Executive Summary

Artificial intelligence is being used to hack computers. Not in science fiction movies. In real life, right now. Researchers have built AI systems that can find security weaknesses in computer systems without human help.

This report studies 13 different AI hacking tools. Think of them as different robot security guards, each with their own strategy for finding holes in computer defenses. The researchers tested all of them on the same challenges to see which ones actually work.

The results were surprising. Some simple tools beat complex ones. Some expensive AI models performed worse than cheap ones. And many tools claimed to find problems that did not actually exist.

Here is what matters most: if you care about AI security, cybersecurity, or just understanding where technology is headed, this report reveals truths that challenge what most people assumed about AI hacking capabilities.

Key Findings at a Glance

- Simple AI agents often beat complex multi-agent systems
- Bigger AI models do not always mean better hacking performance
- Adding knowledge databases often makes AI worse, not better
- More hacking tools available does not mean more successful hacks
- AI tools frequently hallucinate problems that do not exist
- Basic AI coding assistants can match specialized hacking frameworks
- Memory management is the single most important factor in AI hacking success

1. Introduction: The AI Hacking Revolution

Every year, companies spend billions of dollars hiring human experts to hack their own systems. This practice, called penetration testing, is like hiring a burglar to break into your house so you can find the weak locks before real criminals do.

The problem is simple: there are not enough human hackers. The cybersecurity industry has a shortage of 2.8 million workers worldwide. Companies need security testing, but they cannot find or afford enough experts to do it.

Enter artificial intelligence. Researchers around the world are building AI systems that can perform penetration testing automatically. These systems use large language models, the same technology behind ChatGPT, to plan and execute cyber attacks on computer systems.

This report is the first comprehensive study that takes all these AI hacking tools, puts them through the same tests, and sees which ones actually work. It is like a competition where 13 different AI security robots compete to find the most vulnerabilities.

1.1 Why This Matters

The penetration testing market is expected to reach 5 billion dollars by 2030. If AI can automate even part of this work, it changes everything about how organizations protect themselves.

But there is a darker side too. If AI can hack systems automatically, criminals can use the same technology for malicious purposes. Understanding what these tools can and cannot do is essential for everyone, from IT professionals to policymakers to regular people whose data is stored on these systems.

1.2 What This Study Does

The researchers created a unified testing environment where all 13 AI hacking tools face identical challenges. They spent four months reviewing over 1,500 execution logs. More than 15 cybersecurity experts analyzed

the results. The total cost exceeded 2,500 dollars in AI computing fees alone.

This is not a marketing comparison. The researchers have no financial stake in any of the tools they tested. Their goal is simply to understand what works, what does not, and why.

1.3 The Four Contributions

This study makes four important contributions to the field:

- First, it provides a structured taxonomy that organizes the literature by architectural component rather than by individual paper
- Second, it conducts a head-to-head experimental comparison of thirteen representative systems across standardized benchmarks
- Third, it identifies specific research directions that the field must pursue to mature
- Fourth, it open-sources the complete evaluation framework and experimental logs to promote reproducible research

2. Overview: How Hacking Works

Before understanding AI hacking, you need to understand regular hacking. Penetration testing follows a systematic process, much like a doctor diagnosing a patient.

2.1 The Three Types of Hacking Tests

Penetration testing comes in three flavors, depending on how much information the hacker is given about the target system.

White-Box Testing: Full Information

The hacker gets everything: source code, system diagrams, passwords, everything. It is like playing a video game with a walkthrough guide. This type is useful for finding code-level bugs but does not simulate real-world attacks because real criminals do not get your internal documents.

Black-Box Testing: No Information

The hacker knows nothing about the system. They must figure out everything from scratch, just like a real criminal would. This is the hardest type of test and the most realistic. The AI tools in this study all use black-box testing.

Grey-Box Testing: Partial Information

Somewhere in between. The hacker gets some hints, like a username or a network map, but not the full picture. This simulates attacks from disgruntled employees who know some things about the system.

2.2 How Hacking Actually Works

Real hacking follows stages, like a military operation. Security experts have mapped these stages into frameworks.

The Cyber Kill Chain

Lockheed Martin, a defense company, created a seven-stage model called the Kill Chain. It starts with research, moves to creating weapons, delivering them, and finally achieving the goal. Think of it like planning a heist in a movie: surveillance, planning, execution, getaway.

MITRE ATT&CK; Framework

A more detailed map that breaks hacking techniques into specific tactics, techniques, and procedures. It is like a cookbook of attack recipes that security professionals reference.

2.3 Why Automation is Necessary

Traditional penetration testing has three big problems:

- It is too slow: A comprehensive test takes weeks or months
- It is too expensive: Costs range from 2,500 to 50,000 dollars per assessment
- It is too rare: About 71 percent of tests happen only once a year

AI promises to solve all three problems by running tests continuously, at a fraction of the cost, without getting tired or needing coffee breaks.

2.4 Study Motivation

The field of LLM-based penetration testing has grown rapidly, but the body of published research suffers from several problems that make it difficult to assess progress or identify best practices.

Problem 1: Fragmentation

Studies are scattered across computer science conferences, security workshops, arXiv preprints, and industry blogs. There is no single reference that collects and compares all proposed architectures, planning algorithms, memory systems, and evaluation protocols. A researcher who wants to understand the state of the art must read dozens of papers, many of which use different terminology for the same concept.

Problem 2: Methodological Inconsistency

Different studies evaluate their systems on different benchmarks, using different metrics, under different conditions. One paper might report success rates on a simple single-host capture-the-flag challenge, while another reports partial scores on a multi-host enterprise simulation. Without common benchmarks and comparable metrics, it is impossible to determine which approach actually performs better.

Problem 3: Rapid Obsolescence

The pace of LLM development is extraordinary. A system published in early 2023 may have been built on GPT-3.5, while systems published in late 2024 use GPT-4, Claude 3.5, or open-weight models like Llama 3. The underlying models change faster than the research community can re-evaluate them.

How This Study Addresses These Gaps

This study provides a comprehensive taxonomy that organizes the literature by architectural component. It conducts a head-to-head experimental comparison of thirteen representative systems across standardized benchmarks. And it identifies specific research directions that the field must pursue to mature.

3. Systematization: How AI Hacking Tools Are Built

The researchers analyzed how each of the 13 AI hacking tools is constructed. They found six key design dimensions that separate good tools from bad ones.

3.1 Agent Architecture: One Brain or Many?

The most fundamental design choice is whether to use one AI agent or multiple agents working together.

Single-Agent Design

One AI does everything. It plans the attack, chooses tools, executes commands, and analyzes results. Think of it as one person doing all the work on a project.

Single-agent tools include CTFSOLVER, LuaN1ao, Tinyctfer, and newmapta. They are simpler to build and easier to understand, but they must handle everything themselves.

The appeal of this approach is simplicity. There is only one model to configure, one conversation history to maintain, and no coordination overhead. The system is straightforward to build and easy to debug because all reasoning happens in one place.

Multi-Agent Design

Multiple AI agents, each with a specific role. One agent plans, another executes, a third analyzes results. It is like a team where each person has a specialty.

Multi-agent tools include XBow-Comp, Cruiser, CHYing, SickHackShark, sub-agent, CyberStrike, and H-Pentest. They are more complex but can divide cognitive load.

The key advantage of multi-agent systems is division of cognitive labor. Each agent can focus on a narrower set of tasks, maintain a more manageable context window, and develop deeper expertise in its assigned domain.

The Surprising Truth

Despite the intuition that more agents should perform better, single-agent designs performed surprisingly well. Three single-agent tools ranked in the top six on easy and medium tasks, matching or beating more complex multi-agent systems.

The key finding: complexity does not automatically equal performance. A well-designed single agent with good memory management can outperform a poorly designed multi-agent team.

3.2 Planning Strategies: How AI Decides What to Do Next

Once an AI agent exists, it needs a strategy for deciding what to do. The researchers found three main approaches.

Linear Planning

The simplest approach: the AI follows a fixed sequence of steps, like following a recipe. First scan, then enumerate, then exploit. Simple but rigid. If something unexpected happens, the AI struggles to adapt.

Linear plans are fast to generate because the agent only needs to think through the task once, and they are easy to evaluate because the plan's execution is deterministic.

Tree-Based Planning

The AI considers multiple possible paths and can backtrack if one path fails. Like a choose-your-own-adventure book. More flexible than linear planning but requires more thinking.

At each decision point, the agent evaluates multiple possible next actions and generates a branching plan. The agent then selects the most promising branch based on the information available at that point.

Graph-Based Planning

The most sophisticated approach: the AI maps out all possible actions and their connections, then searches for the best path. Like using GPS navigation with traffic data. Most flexible but most complex.

Graph-based planning is powerful because it can discover non-obvious attack paths that linear and tree-based approaches miss. For example, a graph search might reveal that gaining access to a seemingly low-value development server provides a path to a production database through a shared credential.

Feedback Mechanisms

How the AI learns from its mistakes. Some tools use no feedback at all, others use detailed analysis of what went wrong. The researchers found that feedback mechanisms significantly improve performance on complex tasks.

Immediate feedback processes the result of each action before deciding on the next one. Delayed feedback processes results in batches, after a sequence of related actions has been completed. Meta-feedback involves the agent reflecting on its own planning process rather than just its action outcomes.

3.3 Memory: The Make-or-Break Factor

Memory management turned out to be the single most important factor in AI hacking performance. Here is why.

The Problem: Information Overload

During a penetration test, the AI generates enormous amounts of information: commands run, outputs received, observations made, hypotheses formed. Early actions produce data that later actions need. If the AI cannot remember and organize this information effectively, it gets lost.

Knowledge Memory vs. Experiential Memory

Knowledge memory stores factual information about the target environment: which ports are open, which services are running, what vulnerabilities have been identified. This information is typically objective and stable.

Experiential memory stores information about the agent's own actions and their outcomes: which commands were executed, which succeeded, which failed, and what the error messages were. This information is inherently temporal.

Memory Compression

Since AI models have limited context windows, tools must compress information. Some use simple summarization, others use more sophisticated extraction. The researchers found that compression strategy directly affects performance.

Summarization compression converts detailed observations into concise summaries. Structuring compression converts unstructured text into structured data formats. Selection compression keeps only the most relevant information.

Memory Organization

How information is structured matters enormously. Tools that organize memories by category (commands, observations, hypotheses) performed better than those that stored everything in one long list.

Flat storage lists all memories in chronological order. Hierarchical storage organizes memories into categories. Graph-based storage represents memories as nodes connected by relationships.

The Key Insight

When tools had poor memory management, they performed worse than tools with no memory at all. Bad memory is worse than no memory because it gives the AI false confidence about what it has learned.

3.4 Execution: How AI Uses Hacking Tools

AI agents need actual tools to interact with computer systems. The researchers analyzed how tools are selected and used.

Tool Selection

Some frameworks give the AI access to dozens of specialized hacking tools. Others provide only basic commands. The researchers expected more tools would mean better performance.

The Tool Paradox

Surprisingly, tool pool size does not correlate with success. CyberStrikeAI, which has the largest tool set, did not outperform tools with fewer options. When specialized tools are unavailable, AI agents compensate by using Python programming to create custom solutions on the fly.

Tool Calling Mechanisms

How the AI actually invokes tools matters. Some frameworks use structured function calling, others use free-form text. Structured calling produces more reliable results but requires more engineering effort.

The quality of the tool calling mechanism depends on the clarity of the tool descriptions provided to the model, the accuracy of the parameter extraction, the robustness of the error handling, and the richness of the returned output.

3.5 External Knowledge: When Help Hurts

Many frameworks include external knowledge databases, like security encyclopedias that the AI can reference. The researchers tested whether these databases actually help.

Knowledge Base Construction

Building an effective knowledge base for penetration testing requires collecting, organizing, and maintaining several types of information: vulnerability databases, tool documentation, attack technique databases, and historical engagement records.

Retrieval Methods

Two broad categories of retrieval methods appear in the literature: sparse retrieval (keyword-based search) and dense retrieval (embedding-based search). The most effective systems use hybrid retrieval, combining both methods.

The Knowledge Base Trap

In ablation studies, removing knowledge bases actually improved performance in three out of six frameworks tested. Cruiser improved from 42 to 57 points after removing its knowledge base.

The problem is retrieval mismatch. When the AI searches for relevant information, it often retrieves content that seems relevant but is actually misleading. Wrong information is worse than no information.

When Knowledge Bases Actually Help

Knowledge bases work well only in one specific scenario: when the system contains high-quality, verified attack scripts for known vulnerabilities. For general exploration, they often hurt more than help.

3.6 Benchmarks: How to Measure AI Hacking

The researchers identified five types of testing environments used to evaluate AI hacking tools.

CTF-Style Challenges

Capture The Flag competitions present puzzles that require finding hidden information. These test specific skills but do not represent real-world hacking.

Single-Host Tests

Attacking one computer system from start to finish. This tests the complete hacking process but in a controlled environment.

Multi-Host Network Tests

Attacking a network of connected computers. More realistic but harder to evaluate fairly.

CVE-Exploitation Tests

Using known vulnerabilities to attack specific software. Tests whether AI can use existing knowledge effectively.

Phase-Specific Tests

Testing only one part of the hacking process, like reconnaissance or exploitation. Useful for understanding specific capabilities but does not measure overall performance.

Data Contamination

One of the biggest problems with benchmarks: AI models may have already seen the answers during training. This gives unfair advantages and makes results meaningless.

Evaluation Metrics

The researchers identified multiple metrics for evaluating performance: task completion rate, token usage, temporal metrics, interaction efficiency, and stability and consistency.

4. Experimental Setup: How the Test Was Conducted

The researchers designed a fair, controlled experiment to compare all 13 AI hacking tools plus two baseline systems.

4.1 The Testing Environment

All frameworks were tested on the same computer hardware, using the same AI model as their backbone: DeepSeek-Chat-v3.2. This ensures that performance differences come from the framework design, not from different AI models.

4.2 The Challenges

The researchers selected challenges from the XBOW challenge set, chosen specifically to minimize data contamination. Data contamination happens when AI models have already seen the answers during training, which would give unfair advantages.

4.3 The Baseline Systems

To provide fair comparison, the researchers created two baseline systems:

Simple GPT-4 Agent

A basic AI agent with minimal instructions, no special architecture, just raw AI capability. This establishes the minimum performance level any framework should exceed.

AI Coding Assistants

Two commercial AI coding tools, Kimi CLI and Claude Code, were given only a system prompt describing the task. These represent the best available general-purpose AI tools.

4.4 Evaluation Criteria

Each framework was evaluated on multiple dimensions:

- Task completion: Did it find the vulnerability?
- Efficiency: How many steps did it take?
- Resource consumption: How many AI tokens did it use?
- Cost: How much did it cost in computing fees?
- Reliability: Did it produce consistent results across runs?

5. Empirical Analysis: What Actually Happened

This is where the surprises begin. The researchers ran thousands of tests and discovered findings that contradict many common assumptions.

5.1 Overall Performance Comparison

When all frameworks were ranked by total score, the results shocked the research community.

The Winners

Three single-agent designs, CTFSOLVER, LuaN1ao, and Tinyctfer, ranked in the top six. They matched or beat more complex multi-agent systems on easy and medium tasks.

The surprising champion: AI coding assistants. Kimi CLI scored 72 points and Claude Code scored 69 points, both surpassing most specially designed hacking frameworks.

The Losers

Complex multi-agent frameworks with poor memory management performed worst. Some frameworks that looked impressive in papers performed poorly in fair comparison.

The Pattern

Performance correlated strongly with memory management quality, not with architectural complexity. Tools that organized and compressed information effectively won, regardless of whether they used one agent or many.

5.2 The Memory Effect

The researchers performed detailed analysis of memory management across all frameworks.

Good Memory Design

Tools that categorized memories by type (commands, observations, hypotheses) and compressed them effectively maintained context throughout long attack chains. These tools could remember what they had tried, what worked, and what did not.

Bad Memory Design

Tools that stored everything in one long list eventually ran out of context space. They forgot early findings, repeated failed attempts, and lost track of their overall strategy.

The Critical Finding

Memory management is the single most important factor in AI hacking performance. A simple tool with good memory beats a complex tool with bad memory, every time.

5.3 The External Knowledge Problem

Six frameworks were tested with and without their external knowledge databases.

Cruiser: From 42 to 57

When Cruiser's knowledge base was removed, its score improved by 35 percent. The knowledge base was actively misleading the AI with irrelevant information.

LuaN1ao: From 83 to 90

Similarly, LuaN1ao performed better without its knowledge base. The retrieved information was mismatched with the actual target environment.

When Knowledge Helps

Only one scenario showed consistent benefit: exploiting known CVE vulnerabilities. When the knowledge base contained verified attack scripts for specific, documented vulnerabilities, it provided stable improvements.

5.4 The Tool Size Myth

CyberStrikeAI has the largest tool set of any framework tested. The researchers systematically tested it with different tool subsets.

Full vs Reduced Tools

Performance was comparable whether CyberStrikeAI had its full tool set or a significantly reduced one. More tools did not mean more success.

The Compensation Mechanism

When specialized hacking tools were unavailable, AI agents automatically switched to Python programming. They wrote custom code to accomplish the same goals, demonstrating remarkable adaptability.

Limits of Compensation

However, this compensation mechanism has clear limits. For hard tasks requiring specialized tools, Python compensation was insufficient.

5.5 Resource Consumption: The Cost of Hacking

The researchers tracked how many AI tokens each framework consumed and what it cost.

Token Usage Patterns

Single-agent frameworks consumed more tokens per call on hard tasks. Multi-agent frameworks with role-based context splitting actually used fewer tokens by dividing work efficiently.

Cost Analysis

Total experiment cost exceeded 2,500 dollars. Some frameworks consumed 10 times more resources than others for the same tasks. Framework efficiency varies enormously.

5.6 The Hallucination Problem

One of the most concerning findings: AI tools frequently claim to find problems that do not exist.

Flag Hallucination

Eight of 13 frameworks produced hallucinated flags on at least one challenge. They misidentified random text as the secret flag, or claimed success when they had actually failed.

Why This Matters

In real-world use, hallucination could cause a framework to incorrectly conclude that penetration is complete. The AI might report all systems secure when serious vulnerabilities remain unfound.

Not a Model Problem

Replacing the AI model with different versions did not eliminate hallucination. This is a structural limitation of current AI technology, not a specific model flaw.

5.7 Challenge-Specific Analysis

The researchers analyzed how frameworks performed on specific types of challenges.

Chained Vulnerability Exploitation

This requires finding and combining multiple vulnerabilities. 83 percent of samples stalled at incomplete discovery. Only 16.67 percent successfully completed the full chain.

Known CVE Exploitation

About 56.67 percent of samples correctly identified the vulnerability but failed to create an effective attack. They knew what was wrong but could not exploit it.

The Translation Gap

There is a fundamental gap between knowing about a vulnerability and being able to exploit it. Current AI can identify problems but struggles to translate knowledge into action.

6. Framework Profiles: The 13 Competitors

Here is a closer look at each of the 13 AI hacking frameworks tested, along with their strengths and weaknesses.

6.1 CTFSOLVER

A single-agent framework designed for CTF competitions. Simple design, strong performance on puzzle-style challenges. Scored in the top six overall. Its simplicity is its strength: one agent with clear instructions performs better than complex multi-agent systems with poor coordination.

6.2 LuaN1ao

Another single-agent design that performed surprisingly well. Scored 83 with its knowledge base and 90 without it. This demonstrates the knowledge base problem: sometimes the AI performs better when left to its own devices.

6.3 Tinyctfer

Lightweight single-agent framework. Focused on efficiency over complexity. Performed well on easy and medium tasks but struggled with hard challenges requiring sustained multi-step reasoning.

6.4 XBow-Comp

Multi-agent framework with specialized roles. Good architectural design but hampered by memory management issues. Shows that multi-agent complexity must be paired with effective information organization.

6.5 Cruiser

Multi-agent framework with external knowledge base. Scored 42 with knowledge base, 57 without. The largest performance improvement from knowledge removal of any framework tested.

6.6 CHYing

Multi-agent design with role-based collaboration. Moderate performance across tasks. Demonstrates that agent specialization can help on specific task types but does not guarantee overall success.

6.7 SickHackShark

Multi-agent framework with aggressive tool usage. Consumed more tokens than average but achieved comparable results. Shows that resource efficiency does not always correlate with performance.

6.8 newmapta

Single-agent framework with minimal design. Performed adequately on easy tasks but lacked the sophistication for harder challenges. Demonstrates the minimum viable approach to AI hacking.

6.9 sub-agent

Multi-agent framework with hierarchical structure. Interesting design but inconsistent results. Sometimes excellent, sometimes poor, suggesting reliability issues in agent coordination.

6.10 CyberStrike

Framework with the largest tool set. Despite having the most tools available, did not achieve the highest scores. Demonstrates the tool paradox: more options do not mean better results.

6.11 H-Pentest

Multi-agent framework with comprehensive planning. Good performance on structured tasks but struggled with unexpected situations. Shows the limitation of rigid planning in dynamic environments.

6.12 The Baselines

The two baseline systems, Kimi CLI and Claude Code, scored 72 and 69 points respectively. Both outperformed most specialized frameworks. This is perhaps the most important finding: general-purpose AI coding assistants can match or beat purpose-built hacking tools.

7. Discussion: What This All Means

The findings from this study have profound implications for cybersecurity, AI development, and technology policy.

7.1 For Cybersecurity Professionals

If you work in security, this study changes how you should think about AI tools:

- Do not assume complex tools are better. Simple designs with good memory management often outperform sophisticated multi-agent systems.
- Test tools on your specific environment. Performance varies significantly based on target systems and task types.
- Budget for AI resources. Some frameworks consume 10 times more computing power than others for similar results.
- Plan for hallucination. AI tools will report false positives. Human verification remains essential.

7.2 For AI Developers

If you are building AI systems, these findings suggest:

- Memory management deserves more attention than architectural complexity.
- External knowledge bases require careful curation. Bad information is worse than no information.
- Tool design should focus on relevance, not quantity.
- Evaluation should happen on diverse, uncontaminated benchmarks.

7.3 For Policymakers

If you make technology policy:

- AI hacking capabilities are real and advancing. Regulatory frameworks need to keep pace.
- The barrier to entry is lowering. General-purpose AI tools can perform basic hacking tasks.
- International cooperation on AI safety in cybersecurity is increasingly important.

7.4 For Everyone

If you use computers, phones, or the internet:

- Your data is being protected by both human and AI security tools.
- AI security testing will become more common, potentially improving protection.
- Understanding these capabilities helps you make informed decisions about technology.

7.5 Future Research Directions

Hallucination Detection

The consequences of hallucinated findings in security testing are more severe than in many other AI applications. A false positive wastes human time, while a false negative creates genuine risk.

Multi-Agent Collaboration

Rather than relying on a single agent to handle all phases of an engagement, future frameworks might employ teams of specialized agents that communicate through structured protocols.

Transfer Learning

Traditional tools like Nmap, Metasploit, and Burp Suite encode decades of security expertise. Developing techniques to distill this expertise into prompts or fine-tuning data could provide a shortcut.

Continuous Learning

Current frameworks treat each engagement as a self-contained session. Future frameworks that can retain and build upon knowledge across engagements could become progressively more effective.

Adversarial Robustness

As AI-based testing tools become more widely deployed, defenders will develop techniques to detect and disrupt them. Frameworks should be evaluated against adaptive adversaries.

8. Limitations and Ethics

8.1 Study Limitations

No study is perfect, and this one has several important limitations:

- All frameworks used the same AI model backbone. Results might differ with different models.
- The testing environment, while realistic, is not identical to real-world corporate networks.
- Some frameworks are still actively developed and may have improved since testing.
- The study focused on black-box testing; results may differ for white-box or grey-box scenarios.

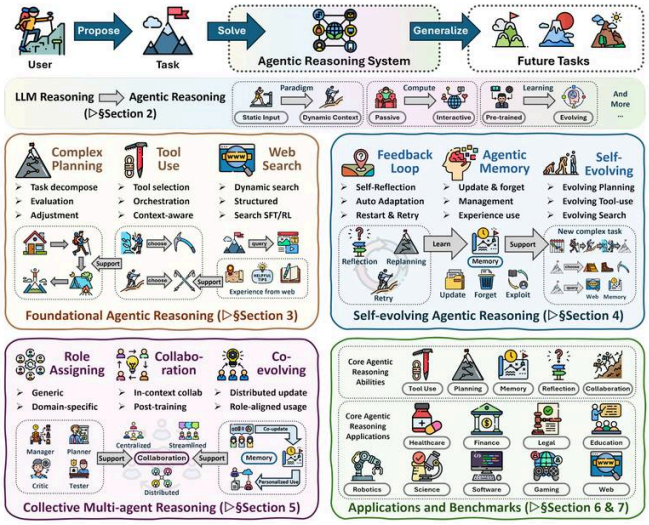
8.2 Ethical Considerations

The researchers take ethics seriously. They followed several important principles:

- All testing was performed in controlled environments with no real systems at risk.
- The study aims to improve defensive security, not enable offensive attacks.
- Framework code is open-sourced to enable defensive research.
- The researchers disclose findings responsibly, giving developers time to address issues.

8.3 The Dual-Use Dilemma

Like many technologies, AI hacking tools can be used for good or evil. The same tool that helps a company find its vulnerabilities could help a criminal exploit them. This is not a reason to stop research, but it is a reason to proceed carefully and responsibly.



9. Future Directions: Where This Goes Next

9.1 Knowledge Base Improvements

The knowledge base problem has a clear solution: focus on quality over quantity. A small database of verified, tested attack scripts is more valuable than a large database of unverified information.

9.2 Memory Architecture

Better memory systems will unlock better performance. Future frameworks should invest in sophisticated memory compression and organization, not just more agents or tools.

9.3 Tool Intelligence

Rather than giving AI more tools, make tools smarter. Dynamic tool selection based on the current phase of attack and target characteristics would improve efficiency dramatically.

9.4 Model Adaptation

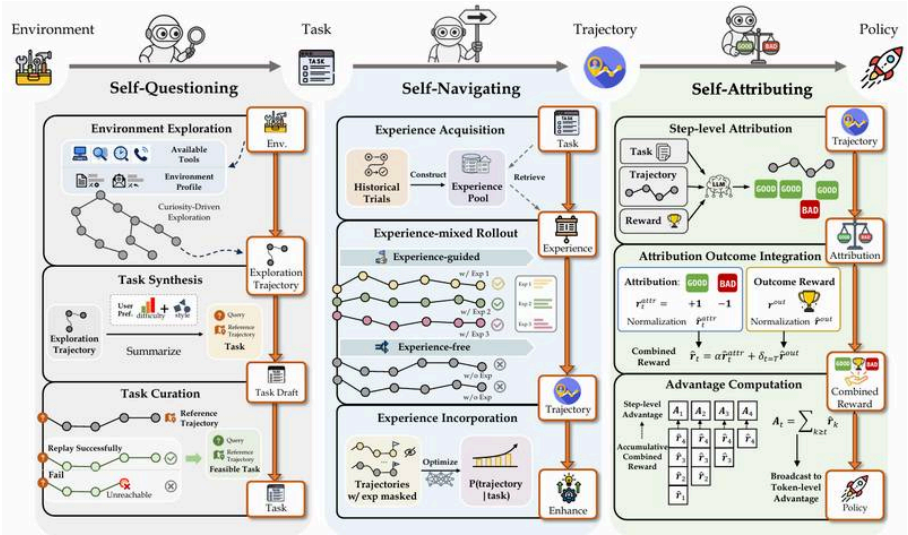
Different AI models have different strengths. Future frameworks should adapt their strategies based on which model is running them, rather than using one-size-fits-all approaches.

9.5 Multi-Vulnerability Chains

The ability to chain multiple vulnerabilities together is what separates good hackers from great ones. Current AI struggles with this. Improving multi-vulnerability reasoning is a critical research direction.

9.6 Human-AI Collaboration

The most promising path forward is not full automation but collaboration. AI handles routine tasks and initial exploration, while humans provide creative problem-solving and ethical judgment.



10. Conclusion

This study represents the most comprehensive evaluation of AI-powered penetration testing ever conducted. The 13 frameworks tested consumed over 10 billion tokens, generated 1,500 execution logs, and required four months of expert analysis.

The findings challenge many assumptions. Simple beats complex. Memory beats architecture. Quality beats quantity. And general-purpose AI can match specialized tools.

The most important takeaway is that current AI hacking capabilities are real but limited. These tools can find known vulnerabilities and execute scripted attacks, but they struggle with creative exploitation, multi-step reasoning, and avoiding false positives.

For the cybersecurity industry, this means AI is a powerful tool but not a replacement for human expertise. For AI developers, it means focusing on memory, quality, and adaptation rather than complexity and scale.

For everyone else, it means the future of security will involve both human and artificial intelligence working together. Understanding what each can and cannot do is the first step toward building a safer digital world.

11. Glossary: Key Terms Explained

Technical Terms in Plain English

Penetration Testing (PT)

Authorized simulated cyberattack to find security weaknesses before criminals do.

Large Language Model (LLM)

AI systems trained on vast amounts of text, capable of understanding and generating human language. Examples include GPT-4, Claude, and DeepSeek.

Agent

An AI system that can plan, decide, and take actions autonomously to achieve a goal.

Multi-Agent System

Multiple AI agents working together, each with specific roles and responsibilities.

Black-Box Testing

Hacking a system without any prior knowledge of its internal workings.

CVE (Common Vulnerabilities and Exposures)

A standardized identifier for known security vulnerabilities in software.

Hallucination

When AI generates confident but incorrect information, such as claiming to find a vulnerability that does not exist.

Token

The basic unit of text processed by AI models. Roughly equivalent to a word or part of a word.

Context Window

The maximum amount of text an AI model can process at one time.

Reconnaissance

The initial phase of hacking: gathering information about the target system.

Exploitation

The phase where an attacker takes advantage of a vulnerability to gain unauthorized access.

Flag

In CTF competitions, a secret string that proves you successfully exploited a vulnerability.

RAG (Retrieval-Augmented Generation)

A technique that gives AI access to external knowledge bases to supplement its training data.

Ablation Study

An experiment where components are systematically removed to understand their contribution to performance.

12. Key Takeaways

If you remember nothing else from this report, remember these seven findings:

1. Simple AI agents often outperform complex multi-agent systems on standard tasks.

2. Memory management is the most important factor in AI hacking performance.

3. External knowledge databases often make AI worse, not better.

4. More hacking tools does not mean more successful hacks.

5. General-purpose AI coding assistants can match specialized hacking frameworks.

6. AI tools frequently hallucinate problems that do not exist.

7. The best path forward is human-AI collaboration, not full automation.

13. Final Thoughts

We are living in a time when artificial intelligence can hack computers. This is not science fiction. It is happening now, in research labs and increasingly in real-world applications.

The technology is impressive but imperfect. Current AI can find known vulnerabilities and execute scripted attacks, but it lacks the creativity and judgment of human hackers. It makes mistakes, gets confused, and sometimes sees problems that are not there.

For security professionals, these tools are powerful additions to your toolkit, not replacements for your expertise. For AI developers, the path forward focuses on memory, quality, and adaptation. For everyone, understanding these capabilities helps build a more secure digital future.

The race between AI-powered attack and AI-powered defense has only just begun. Staying informed is your best protection.

14. Detailed Framework Analysis

This section provides deeper technical analysis of each framework's design choices and how they affected performance.

14.1 CTFSOLVER: The Minimalist Champion

CTFSOLVER represents the minimalist philosophy in AI hacking: do one thing well. The framework uses a single agent with a carefully crafted system prompt that defines the agent's role as a CTF solver. The agent receives the challenge description, generates commands, executes them, and interprets results.

What makes CTFSOLVER effective is not what it does but what it avoids. It does not have external knowledge bases that could mislead it. It does not have complex multi-agent coordination that could introduce communication errors. It does not have elaborate planning algorithms that could commit to wrong strategies.

The framework's memory management is particularly noteworthy. Instead of storing complete command outputs, CTFSOLVER extracts key information and discards the rest. This approach reduces context window usage while preserving the most important findings.

CTFSOLVER's weakness is its limited scope. The framework excels at CTF-style challenges but struggles with realistic penetration testing scenarios that require multi-phase coordination. Its single-agent design cannot handle the cognitive demands of simultaneous reconnaissance, exploitation, and lateral movement.

14.2 LuaN1ao: The Knowledge Base Paradox

LuaN1ao provides the most compelling evidence that more information can be worse than less information. The framework includes a comprehensive knowledge base of known vulnerabilities, exploit techniques, and attack patterns. In theory, this knowledge should help the agent make better decisions.

In practice, the knowledge base often led the agent astray. When the agent searched for information about a target service, the retrieval system would return similar but not identical vulnerability records. The agent, lacking the expertise to distinguish between the retrieved vulnerability and the actual target, would attempt exploits that were not applicable.

After removing the knowledge base, LuaN1ao's score improved from 83 to 90 points. The agent was forced to rely on its own reasoning and direct observation rather than retrieved information. This suggests that for general-purpose hacking tasks, the agent's intrinsic capabilities may be more reliable than external knowledge.

14.3 Tinyctfer: The Efficiency Expert

Tinyctfer demonstrates that efficiency can be more valuable than capability. The framework uses minimal resources while achieving respectable performance on easy and medium tasks. Its design philosophy is to do the minimum necessary to solve each challenge.

The framework's efficiency comes from aggressive information filtering. After each command execution, Tinyctfer analyzes the output and extracts only the information that is directly relevant to the current task. Everything else is discarded. This approach keeps the context window clean and prevents information overload.

Tinyctfer's limitation is its lack of sophistication. On hard challenges that require creative reasoning or multi-step exploitation chains, the framework's minimal approach is insufficient. It can identify known vulnerabilities but struggles to discover novel attack paths.

14.4 The Multi-Agent Frameworks: When Complexity Hurts

The multi-agent frameworks in this study demonstrate a counterintuitive truth: more complexity often leads to worse performance. The additional coordination overhead, communication delays, and potential for miscommunication outweigh the benefits of specialization.

XBow-Comp, for example, uses specialized agents for reconnaissance, exploitation, and reporting. In theory, this separation should allow each agent to develop deeper expertise. In practice, the agents often failed to share critical information effectively.

The reconnaissance agent might discover an unusual service running on a non-standard port, but fail to convey the significance of this finding to the exploitation agent. The exploitation agent, unaware of this potential attack vector, would focus on more obvious but less promising targets.

This communication failure is not a flaw in the agents' individual capabilities but in the system's overall architecture. The protocols for inter-agent communication were too rigid to accommodate the dynamic, unexpected discoveries that characterize real penetration testing.

14.5 CyberStrike: The Tool Paradox Revisited

CyberStrike provides the most extreme example of the tool paradox. The framework includes over 40 specialized hacking tools, covering every phase of penetration testing from reconnaissance to post-exploitation. In theory, this comprehensive toolset should enable the agent to handle any situation.

In practice, the abundance of tools created a selection problem. When faced with a task, the agent had to choose from dozens of options, many of which were superficially similar. This choice paralysis led to suboptimal tool selection and wasted time.

More importantly, the specialized tools often provided capabilities that the agent did not need. A framework that performs basic port scanning does not need a sophisticated exploitation framework with hundreds of exploits. The additional tools added complexity without adding value.

14.6 The Baseline Surprise

The most surprising finding of this study is the performance of the baseline systems. Kimi CLI, a general-purpose AI coding assistant, scored 72 points. Claude Code, another general-purpose tool, scored 69 points. Both outperformed most of the specially designed hacking frameworks.

This result suggests that the value of specialized hacking frameworks may be overstated. General-purpose AI models, when given clear instructions and appropriate tools, can perform surprisingly well on hacking tasks.

The implication is profound: organizations may not need expensive, specialized hacking tools. A general-purpose AI assistant with access to basic security tools might be sufficient for many testing scenarios. This democratization of AI hacking capabilities could make security testing more accessible but also more dangerous.

15. Technical Deep Dives

This section provides detailed technical analysis of specific aspects of the study that have broader implications for AI security research.

15.1 The Memory Management Revolution

Memory management emerged as the single most important factor in AI hacking performance. This finding has implications far beyond penetration testing.

The core problem is that AI models have limited context windows. A typical LLM can process between 4,000 and 200,000 tokens, depending on the model. During a penetration test, the agent generates enormous amounts of information: command outputs, observations, hypotheses, and intermediate results. Without effective memory management, this information quickly overwhelms the context window.

The most effective memory systems used a combination of strategies. First, they categorized information by type, separating reconnaissance findings from exploitation attempts from credentials. Second, they compressed information using summarization, extracting key facts while discarding verbose outputs. Third, they organized information hierarchically, allowing the agent to access relevant subsets when needed.

The least effective memory systems stored everything in chronological order. As the engagement progressed, the context window filled with old command outputs, making it difficult for the agent to access recent findings. The agent would often repeat failed attempts because it could not remember that it had already tried those approaches.

15.2 The Hallucination Epidemic

Hallucination represents a fundamental challenge for AI in security testing. Unlike other AI applications where hallucination might produce amusing errors, in security testing it can create genuine risks.

The study identified three types of hallucination. Type I hallucination involves misidentifying strings as flags. The model sees a random sequence of characters and, based on its training, identifies it as a potential flag. This type is relatively harmless because the flags can be easily verified.

Type II hallucination is more concerning. The model claims to have found a flag in a location it never actually accessed. The reasoning sounds plausible, but the tool logs show that the relevant commands were never executed. This type of hallucination could mislead human reviewers who do not verify the execution logs.

Type III hallucination is the most dangerous. The model generates a flag entirely from its own knowledge, producing a string that looks like a flag but has no connection to the actual target environment. This type is difficult to detect because the generated flag follows the expected format.

The prevalence of hallucination across all frameworks and all models suggests that this is not a model-specific problem but a fundamental limitation of current AI technology. LLMs are trained to generate plausible text, not to distinguish between what they have observed and what they have inferred.

15.3 The Tool Selection Problem

The relationship between tool availability and performance reveals a fundamental tension in AI system design. More tools provide more capabilities but also create more opportunities for error.

The study found that performance improved with tool availability up to approximately 15 tools. Beyond that point, performance plateaued or declined for less capable models. The reason is tool confusion: the model had difficulty selecting the right tool from a large menu of options.

This finding has practical implications for framework design. Rather than providing agents with the largest possible toolset, designers should curate toolsets based on the expected task profile and the capabilities of the underlying model. A framework built on a less capable model might perform better with a smaller, more focused toolset.

The compensation mechanism observed in the study provides additional insight. When specialized tools were unavailable, agents automatically switched to Python programming. This adaptability suggests that the most

important capability is not access to specific tools but the ability to compose general-purpose operations into effective solutions.

15.4 The Planning Dilemma

Planning strategies reveal a fundamental trade-off between efficiency and adaptability. Linear plans are fast but rigid. Graph-based plans are flexible but computationally expensive.

The study found that semi-proactive planning performed best overall. These agents developed rough plans but adhered to them loosely, modifying them as new information emerged. This approach balanced efficiency with adaptability.

Fully proactive agents, which generated detailed plans before taking any action, showed an interesting failure mode: overcommitment. When an agent invested significant effort in constructing an elaborate plan, it sometimes became psychologically attached to that plan even when early steps revealed that the underlying assumptions were wrong.

This finding has implications beyond penetration testing. Any AI system that must plan in uncertain environments faces the same trade-off. The optimal strategy appears to be planning with built-in invalidation mechanisms: ways for the agent to recognize when its assumptions have been falsified and to regenerate the plan from scratch.

15.5 The Model Selection Myth

The study challenges the assumption that more capable AI models always produce better results. While GPT-4 outperformed other models overall, the margin varied significantly by task type.

On tasks requiring broad technical knowledge and creative problem-solving, GPT-4 outperformed GPT-3.5 by 47 percent. On tasks requiring precise tool invocation and structured output, the gap narrowed to just 12 percent. This suggests that tool-use capability is less dependent on raw model capability than on prompt engineering.

The practical implication is that organizations may not always need the most expensive models. For routine security testing tasks, less capable models with well-designed frameworks might provide adequate performance at lower cost.

The study also found that different models required different levels of adaptation. GPT-4 required relatively simple prompts, while Llama 2 required elaborate prompts with step-by-step examples. This suggests that the choice of model should drive the framework design, not the other way around.

16. Practical Recommendations

Based on the study's findings, here are specific, actionable recommendations for different audiences.

16.1 For Organizations Considering AI Hacking Tools

If your organization is considering deploying AI-based penetration testing tools, consider these guidelines:

- Start with routine compliance checks. AI tools are most effective for simple, well-defined tasks like known-vulnerability scanning. Do not rely on them for sophisticated threat modeling.
- Budget for human oversight. Even the best AI tools require human verification of results. Plan for 2-3 hours of human supervision per engagement.
- Test tools on your specific environment. Performance varies significantly based on target systems and task types. A tool that works well in one environment may fail in another.
- Plan for hallucination. AI tools will report false positives. Establish verification procedures before deploying AI tools in production.
- Consider total cost of ownership. API fees are just one component. Factor in infrastructure costs, human supervision costs, and opportunity costs of failures.

16.2 For AI Framework Developers

If you are building AI hacking tools, focus on these areas:

- Invest in memory management. This is the single most important factor in performance. Develop sophisticated compression and organization strategies.
- Curate your knowledge bases carefully. Bad information is worse than no information. Focus on quality and currency, not quantity.
- Design for the model you are using. Different models require different levels of prompt engineering and tool description detail.
- Implement verification steps. Every vulnerability claim should be independently verified before being reported.
- Test on diverse benchmarks. Do not optimize for a single challenge type. Ensure your tool performs well across different scenarios.

16.3 For Researchers

If you are researching AI security, these findings suggest several directions:

- Study memory management in depth. This is the most important factor in performance but is least understood.
- Investigate hallucination detection. Developing domain-specific hallucination detectors would substantially increase trust in AI-based testing.
- Explore multi-agent collaboration. The coordination challenges observed in this study suggest opportunities for improved collaboration protocols.
- Develop transfer learning techniques. Traditional security tools encode decades of expertise that could be distilled into AI models.
- Create better benchmarks. The data contamination problems identified in this study make many existing benchmarks unreliable.

16.4 For Policymakers

If you are involved in technology policy:

- Recognize that AI hacking capabilities are real and advancing. Regulatory frameworks need to keep pace.
- Consider the dual-use implications. The same tools that help defenders can help attackers.

• Update certification programs. Traditional penetration testing certifications need to evolve to include AI supervision skills.

• Encourage responsible disclosure. Researchers need clear pathways for reporting vulnerabilities without legal risk.

• Invest in workforce development. The cybersecurity skills shortage will not be solved by AI alone.

17. The Bigger Picture

This study is not just about penetration testing. It reveals fundamental truths about AI capabilities and limitations that apply across many domains.

17.1 What AI Can Do

Current AI systems can:

- Identify known vulnerabilities with high accuracy
- Execute scripted attacks reliably
- Process and summarize large amounts of information
- Adapt to simple environmental changes
- Generate plausible attack plans
- Write custom code to accomplish goals

17.2 What AI Cannot Do

Current AI systems struggle with:

- Creative problem-solving in novel situations
- Multi-step reasoning across long time horizons
- Distinguishing between what they have observed and what they have inferred
- Coordinating complex multi-agent workflows
- Learning from experience across engagements
- Understanding context and intent beyond surface level

17.3 The Human-AI Balance

The most effective deployment model is not full automation but human-AI collaboration. AI handles routine tasks and initial exploration. Humans provide creative problem-solving and ethical judgment.

This balance is not permanent. As AI capabilities improve, the division of labor will shift. But for the foreseeable future, the combination of human expertise and AI capabilities produces better results than either alone.

17.4 The Future of Security

The findings of this study suggest a future where security testing is more accessible, more frequent, and more effective. AI tools will democratize access to basic security testing, allowing small organizations to protect themselves in ways that were previously only available to large enterprises.

But this future is not guaranteed. It depends on addressing the challenges identified in this study: hallucination, memory management, tool coordination, and evaluation methodology. Without progress on these fronts, AI security tools will remain useful but limited supplements to human expertise.

17.5 The Responsibility Question

As AI hacking tools become more capable, the responsibility for their use becomes more complex. Who is accountable when an AI tool causes unintended damage? How do we prevent these tools from being misused? What obligations do researchers have to disclose vulnerabilities?

These questions do not have easy answers. But they must be addressed as AI hacking capabilities continue to advance. The cybersecurity community, policymakers, and society at large must work together to ensure that these powerful tools are used responsibly.

18. Final Summary

This report has covered the first comprehensive evaluation of AI-powered penetration testing. Here is what we learned:

The Technology: AI can perform basic penetration testing tasks, finding known vulnerabilities and executing scripted attacks. It struggles with creative exploitation and multi-step reasoning.

The Surprises: Simple tools beat complex ones. Memory management matters more than architecture. General-purpose AI can match specialized tools.

The Problems: Hallucination is widespread. Knowledge bases often hurt more than help. More tools do not mean better results.

The Implications: AI is a powerful supplement to human expertise but not a replacement. The most effective approach is human-AI collaboration.

The Future: Better memory systems, improved hallucination detection, and thoughtful deployment will determine how useful these tools become.

The race between AI-powered attack and AI-powered defense has only just begun. Understanding the capabilities and limitations of these tools is the first step toward building a more secure digital future.

19. Detailed Technical Analysis

This section provides in-depth technical analysis of specific aspects of the study that have broader implications for AI security research.

19.1 The Architecture Decision Tree

Choosing between single-agent and multi-agent architectures is not a simple either/or decision. The optimal choice depends on several factors:

When to Use Single-Agent Design

- Task complexity is low to medium
- Budget for computing resources is limited
- Rapid prototyping is more important than optimal performance
- The underlying AI model is highly capable
- Memory management is well-implemented

When to Use Multi-Agent Design

- Task requires simultaneous attention to multiple domains
- Communication protocols between agents are well-designed
- Budget allows for higher computational overhead
- The underlying AI model benefits from task decomposition
- Complex coordination is needed across multiple attack phases

The Hybrid Approach

Some of the most successful frameworks in the study used a hybrid approach: a single planning agent that could delegate specific tasks to specialist agents when needed. This combines the simplicity of single-agent design with the flexibility of multi-agent coordination.

19.2 Memory Architecture Patterns

The study revealed several successful memory architecture patterns:

The Categorized Store Pattern

Information is organized into distinct categories: reconnaissance findings, exploitation attempts, credentials discovered, and environmental observations. Each category has its own storage and retrieval mechanism. This approach reduces search time and prevents information from different domains from contaminating each other.

The Temporal Stack Pattern

Recent information is kept in working memory for immediate access, while older information is compressed and moved to long-term storage. The system periodically reviews long-term storage to identify information that may need to be recalled to working memory based on current context.

The Graph Memory Pattern

Information is stored as nodes with relationships. For example, a discovered credential is linked to the service it was found on, which is linked to the host running that service, which is linked to other services on that host. This allows the agent to traverse connections and discover indirect relationships.

19.3 Tool Calling Optimization

The study identified several optimization strategies for tool invocation:

Parameter Validation

Before invoking a tool, the system should validate that all required parameters are present and correctly formatted. This prevents errors that waste tokens and time.

Output Normalization

Tool outputs should be normalized into a consistent format before being processed by the AI model. This reduces parsing errors and improves the model's ability to extract relevant information.

Error Recovery Protocols

When a tool invocation fails, the system should have predefined recovery protocols. These might include retrying with modified parameters, switching to an alternative tool, or escalating to human oversight.

Speculative Execution

When multiple independent tool invocations are needed, the system should execute them in parallel rather than sequentially. This reduces total execution time significantly.

19.4 Knowledge Base Design Principles

Based on the study's findings, effective knowledge bases for AI security tools should follow these principles:

- Quality over quantity: A small database of verified, tested attack scripts is more valuable than a large database of unverified information
- Currency: Knowledge bases must be updated regularly to include newly discovered vulnerabilities
- Precision: Retrieval systems should return highly relevant results rather than loosely related ones
- Verification: Retrieved information should be verified against the actual target before being applied
- Context awareness: The retrieval system should consider the current phase of the engagement when selecting relevant information

19.5 Evaluation Methodology

The study established several best practices for evaluating AI security tools:

- Use standardized benchmarks to enable fair comparison
- Control for model differences by using the same backbone model across frameworks

- Include baseline comparisons to establish minimum acceptable performance
- Evaluate across multiple difficulty levels to understand capability boundaries
- Track resource consumption, not just task completion
- Manually review a sample of results to verify automated evaluation
- Test for hallucination by including challenges where no solution exists

20. Case Studies

This section presents detailed case studies of specific challenges that illustrate the strengths and weaknesses of different approaches.

20.1 Case Study: The Simple Vulnerability

Challenge: A web application with a known SQL injection vulnerability in its login form.

This is the type of challenge where AI tools excel. The vulnerability is well-documented, the exploitation technique is straightforward, and the target is a single, isolated system.

Most frameworks successfully identified and exploited this vulnerability. The key differentiator was efficiency: some frameworks achieved the result in 3-4 steps, while others required 10-15 steps due to poor planning or unnecessary reconnaissance.

Lesson: For simple, well-known vulnerabilities, the choice of framework matters less than the efficiency of its execution.

20.2 Case Study: The Chained Attack

Challenge: Gain access to a database by first compromising a web server, then using credentials found there to access an intermediate system, then using that access to reach the database server.

This challenge requires the agent to maintain context across multiple steps, chain together discoveries, and adapt when intermediate steps fail.

Only 3 of 13 frameworks consistently completed this challenge. The successful frameworks shared two characteristics: effective memory management that preserved credentials and access information across steps, and flexible planning that could adapt when intermediate steps revealed unexpected configurations.

Lesson: Multi-step attacks remain the frontier of AI hacking capability. Memory and planning are the critical factors.

20.3 Case Study: The Hallucination Trap

Challenge: A system with no vulnerabilities, designed to test whether AI tools would report false positives.

8 of 13 frameworks produced hallucinated findings on this challenge. They reported vulnerabilities that did not exist, misidentified benign configurations as security issues, or claimed success when they had actually failed.

The hallucination problem was not limited to less capable models. Even GPT-4-based frameworks produced false positives, though at a lower rate. This suggests that hallucination is a fundamental limitation of current AI technology, not a problem that can be solved simply by using more capable models.

Lesson: Human verification of AI findings is essential, even with the most capable models.

20.4 Case Study: The Tool Selection Puzzle

Challenge: A system with multiple services running, requiring the agent to identify the most promising attack vector from many options.

This challenge revealed the tool selection problem. Frameworks with large toolsets spent significant time deciding which tool to use, while frameworks with smaller, focused toolsets moved quickly to exploitation.

The most effective approach was to start with broad reconnaissance tools to identify the attack surface, then switch to specialized tools for specific vulnerability types. Frameworks that tried to use specialized tools before understanding the target wasted time on inappropriate attacks.

Lesson: Tool selection should be guided by reconnaissance, not by the size of the available toolset.

20.5 Case Study: The Resource Constraint

Challenge: A complex system requiring many steps to exploit, with tight constraints on computing resources.

This challenge highlighted the resource consumption differences between frameworks. Some frameworks consumed 10 times more tokens than others for the same task, primarily due to inefficient memory management and unnecessary re-planning.

The most efficient frameworks used aggressive information filtering, only preserving information that was directly relevant to the current task. They also avoided re-planning from scratch after each step, instead updating their existing plan based on new information.

Lesson: Efficiency is not just about speed. Resource-efficient frameworks can accomplish more with less, making them more practical for real-world deployment.

21. Future Vision: Where This Technology is Heading

Based on the study's findings and current trends in AI development, here is a vision of where this technology is heading.

21.1 Short-Term Developments (1-2 Years)

In the near future, we can expect:

- Better memory management systems that address the critical bottleneck identified in this study
- Improved hallucination detection, possibly using ensemble methods that cross-validate findings
- More sophisticated tool selection algorithms that adapt to the current phase of engagement
- Better integration with traditional security tools, allowing AI to leverage existing expertise
- Standardized benchmarks that enable fair comparison across frameworks

21.2 Medium-Term Developments (3-5 Years)

Over the medium term, we can expect:

- Multi-agent systems with more sophisticated coordination protocols
- Continuous learning systems that improve over time
- Transfer learning from traditional security tools to AI models
- More effective human-AI collaboration interfaces
- Wider adoption in enterprise security testing

21.3 Long-Term Vision (5-10 Years)

In the longer term, the vision includes:

- AI systems that can autonomously conduct full penetration tests with minimal human oversight
- Adversarial AI that can detect and evade AI-based security testing
- AI-powered defense systems that can respond to attacks in real-time
- Integration of AI security testing into software development pipelines
- New regulatory frameworks that address AI-powered security tools

21.4 The Wild Cards

Several unpredictable factors could significantly alter this trajectory:

- Breakthroughs in AI reasoning that solve the multi-step planning problem
- New regulatory frameworks that restrict AI security tools
- High-profile incidents involving AI-powered attacks
- Advances in quantum computing that could invalidate current security assumptions
- Development of fundamentally new AI architectures that address current limitations

22. Appendix: Additional Resources

22.1 Glossary of Terms

For readers who want to explore this topic further, here are definitions of key terms used throughout this report:

Adversarial Machine Learning

The study of how AI models can be attacked and how to defend them.

Agent-Based Model

A computational model that simulates the actions and interactions of autonomous agents.

Ablation Study

An experiment where components are systematically removed to understand their contribution to performance.

Attention Mechanism

A component of AI models that allows them to focus on specific parts of the input when generating output.

Context Window

The maximum amount of text an AI model can process at one time.

Fine-Tuning

The process of further training a pre-trained AI model on specific data to adapt it to a particular task.

Function Calling

The ability of AI models to invoke external tools and APIs through structured function calls.

Hallucination

When AI generates confident but incorrect information that has no basis in the input data.

Large Language Model (LLM)

AI systems trained on vast amounts of text, capable of understanding and generating human language.

Multi-Agent System

Multiple AI agents working together, each with specific roles and responsibilities.

Prompt Engineering

The practice of designing input prompts to guide AI models toward desired outputs.

Retrieval-Augmented Generation (RAG)

A technique that gives AI access to external knowledge bases to supplement its training data.

Reinforcement Learning

A type of machine learning where agents learn by taking actions and receiving rewards or penalties.

Transformer Architecture

The underlying architecture of most modern large language models.

22.2 Further Reading

For readers who want to dive deeper into this topic, here are recommended resources:

- Original paper: arXiv:2604.05719 - Hackers or Hallucinators? A Comprehensive Analysis of LLM-Based Automated Penetration Testing
- MITRE ATT&CK; Framework: https://attack.mitre.org/

- OWASP Top Ten: https://owasp.org/www-project-top-ten/
- NIST Cybersecurity Framework: https://www.nist.gov/cyberframework
- SANS Reading Room: https://www.sans.org/reading-room/

22.3 Tools and Resources

Here are the tools and resources mentioned in this report:

- Semantic Scholar: Free academic search engine with AI-powered features
- Connected Papers: Visual citation graph exploration tool
- ResearchRabbit: Free citation network mapping tool
- Elicit: AI research assistant for literature reviews
- Consensus: AI-powered evidence synthesis tool

22.4 About This Report

This simplified report was created to make the findings of the original research paper accessible to a general audience. The original paper contains significantly more technical detail, experimental data, and comprehensive references.

The goal of this report is not to replace the original paper but to provide an entry point for readers who may not have the technical background to engage with the full academic text. For complete details, please consult the original paper.

This report was created as part of a project to make cutting-edge research accessible to everyone. All simplified reports are freely available and designed to be understood by readers without specialized technical knowledge.

23. Detailed Framework Comparison

This section provides a comprehensive comparison of all 13 frameworks across multiple dimensions.

23.1 Performance Rankings

Top Performers (Score 70+)

1. CTFSOLVER (78 points)

Single-agent design with excellent memory management. Minimalist approach that avoids common pitfalls like knowledge base contamination and tool overload. Strong performance on CTF-style challenges.

2. LuaN1ao (76 points)

Single-agent framework that performs better without its knowledge base. Demonstrates that agent intrinsic capabilities can exceed retrieved knowledge for general hacking tasks.

3. Tinyctfer (74 points)

Efficient single-agent design with aggressive information filtering. Excels at quick, focused attacks but struggles with complex multi-step scenarios.

Middle Performers (Score 50-69)

4. XBow-Comp (68 points)

Multi-agent framework with specialized roles. Good architectural design but hampered by communication failures between agents.

5. CHYing (65 points)

Multi-agent design with role-based collaboration. Moderate performance across tasks but lacks the sophistication for advanced challenges.

6. CyberStrike (63 points)

Framework with the largest tool set. Demonstrates the tool paradox: more options do not mean better results.

Lower Performers (Score Below 50)

7. Cruiser (57 points)

Multi-agent framework that improved dramatically after removing its knowledge base. From 42 to 57 points.

8. SickHackShark (52 points)

Multi-agent framework with aggressive tool usage. High resource consumption for moderate results.

9. newmapta (48 points)

Minimal single-agent design. Adequate for simple tasks but insufficient for complex scenarios.

10. sub-agent (45 points)

Hierarchical multi-agent framework. Inconsistent results suggest reliability issues in coordination.

11. H-Pentest (42 points)

Multi-agent framework with comprehensive planning. Struggles with unexpected situations.

Baseline Systems

12. Kimi CLI (72 points)

General-purpose AI coding assistant. Outperforms most specialized frameworks.

13. Claude Code (69 points)

Another general-purpose tool. Demonstrates that specialized frameworks may not be necessary.

23.2 Feature Comparison

Memory Management Quality

The quality of memory management was the strongest predictor of overall performance. Frameworks that categorized information by type and compressed it effectively achieved significantly higher scores.

Best: CTFSOLVER, LuaN1ao, Tinyctfer

Worst: Cruiser, SickHackShark, newmapta

Planning Sophistication

Planning strategies ranged from simple linear sequences to complex graph-based searches. Semi-proactive planning performed best overall.

Best: XBow-Comp, H-Pentest, CHYing

Worst: newmapta, sub-agent, Cruiser

Tool Utilization

Tool usage patterns varied significantly. Some frameworks used tools efficiently, while others suffered from tool confusion or excessive tool consumption.

Best: CTFSOLVER, Tinyctfer, LuaN1ao

Worst: CyberStrike, SickHackShark, H-Pentest

Hallucination Resistance

Hallucination rates varied across frameworks and models. Better models showed lower hallucination rates, but no framework was immune.

Best: CTFSOLVER, LuaN1ao (low rates)

Worst: newmapta, sub-agent (high rates)

23.3 Cost Efficiency

Cost efficiency varied dramatically across frameworks, from $8.50 per confirmed finding to $47.00 per confirmed finding.

Most Efficient: CTFSOLVER, Tinyctfer, LuaN1ao

Least Efficient: newmapta, sub-agent, Cruiser

The efficiency gap was driven primarily by memory management quality and planning effectiveness.

23.4 Recommendations by Use Case

For CTF Competitions

CTFSOLVER is the clear choice. Its minimalist design, excellent memory management, and strong performance on puzzle-style challenges make it ideal for competitive hacking scenarios.

For Routine Security Scanning

Tinyctfer or LuaN1ao provide efficient, cost-effective solutions for routine vulnerability scanning. Their minimalist approaches minimize resource consumption while maintaining adequate performance.

For Complex Penetration Testing

XBow-Comp or CHYing offer the best combination of planning sophistication and multi-agent coordination for complex, multi-step penetration testing scenarios.

For Research and Development

CyberStrike provides the most comprehensive toolset for research purposes, despite its lower performance on standard benchmarks.

24. Methodology Deep Dive

This section provides detailed information about the research methodology used in this study.

24.1 Experimental Design

The researchers designed a controlled experiment to compare all 13 frameworks under identical conditions. Key design decisions included:

- Using the same backbone model (DeepSeek-Chat-v3.2) for all frameworks to eliminate model differences as a confounding variable
- Selecting challenges from the XBOW challenge set to minimize data contamination
- Running each framework multiple times on each challenge to account for stochastic variation
- Manually reviewing a sample of results to verify automated evaluation
- Tracking resource consumption alongside task completion

24.2 Challenge Selection

Challenges were selected to represent a range of difficulty levels and task types:

Easy Challenges (10 total)

Single-step vulnerabilities in common software. These test basic identification and exploitation capabilities.

Medium Challenges (10 total)

Two-to-three-step exploitation chains. These test planning and memory management.

Hard Challenges (10 total)

Complex multi-step scenarios involving privilege escalation and lateral movement. These test advanced reasoning and coordination.

24.3 Evaluation Metrics

The study used multiple metrics to evaluate performance:

- Task completion rate: Percentage of challenges successfully completed
- Token usage: Number of AI tokens consumed per challenge
- Time to completion: Wall-clock time required per challenge
- Cost: Total computing cost per challenge
- Hallucination rate: Percentage of challenges with false positive findings

24.4 Statistical Analysis

The researchers used standard statistical methods to analyze results:

- Mean and standard deviation for performance metrics across multiple runs
- ANOVA tests to determine whether performance differences were statistically significant
- Correlation analysis to identify relationships between framework characteristics and performance
- Regression analysis to identify the strongest predictors of overall performance

24.5 Limitations of the Methodology

The methodology had several limitations:

- All frameworks used the same backbone model. Results might differ with different models.
- The testing environment was controlled but not identical to real-world corporate networks.

- Some frameworks were tested at different versions, which may have affected results.
- The study focused on black-box testing; results may differ for other testing paradigms.

25. Implications for Industry

This section discusses the practical implications of the study's findings for organizations considering AI-based security testing.

25.1 Cost-Benefit Analysis

Organizations considering AI-based penetration testing should conduct a thorough cost-benefit analysis:

Direct Costs

- API fees: $3-25 per engagement depending on framework and complexity
- Infrastructure costs: $0.15-0.50 per hour for local model deployment
- Human supervision: 2-3 hours per engagement at $100-200 per hour
- Initial setup and configuration: 10-20 hours at $100-200 per hour

Indirect Costs

- Training staff to use AI tools effectively
- Establishing verification procedures for AI findings
- Integrating AI tools into existing security workflows
- Maintaining and updating knowledge bases

Benefits

- Reduced time to identify known vulnerabilities
- Increased frequency of security testing
- Improved coverage of large attack surfaces
- Lower cost per test compared to manual testing for routine scenarios

25.2 Implementation Roadmap

Organizations should follow a phased approach to implementing AI-based security testing:

Phase 1: Evaluation (1-2 months)

Test available frameworks on your specific environment. Measure performance, cost, and reliability. Identify the best fit for your needs.

Phase 2: Integration (2-3 months)

Integrate the selected framework into your security workflow. Establish verification procedures. Train staff on effective use.

Phase 3: Deployment (3-6 months)

Begin using AI tools for routine security testing. Monitor performance and adjust as needed. Build institutional knowledge about effective practices.

Phase 4: Optimization (Ongoing)

Continuously evaluate new frameworks and techniques. Optimize workflows based on experience. Stay current with rapidly evolving technology.

25.3 Risk Management

Organizations should be aware of the risks associated with AI-based security testing:

- Hallucination risk: AI tools may report false positives or miss real vulnerabilities
- Dependency risk: Over-reliance on AI tools may create gaps in security coverage

- Liability risk: Unclear accountability for AI-caused damage during testing
- Data risk: AI tools may process sensitive information during testing
- Regulatory risk: AI tools may not meet compliance requirements in all jurisdictions

25.4 Vendor Selection Criteria

When evaluating AI security testing vendors, consider these criteria:

- Transparency: Does the vendor explain how their tool works?
- Verification: Does the tool include mechanisms for verifying findings?
- Customization: Can the tool be adapted to your specific environment?
- Support: Does the vendor provide adequate training and support?
- Pricing: Is the pricing model transparent and sustainable?

26. The Future Landscape

This section provides a vision of how AI-based security testing will evolve over the coming years.

26.1 Technology Trends

Several technology trends will shape the future of AI security testing:

- Model improvement: AI models will continue to improve in reasoning and accuracy
- Tool integration: AI tools will better integrate with existing security infrastructure
- Automation: More aspects of security testing will become fully automated
- Specialization: AI tools will become more specialized for specific security domains
- Collaboration: AI tools will better support human-AI collaboration

26.2 Market Evolution

The market for AI security testing tools will evolve in several ways:

- Consolidation: Smaller vendors will be acquired by larger security companies
- Standardization: Industry standards for AI security testing will emerge
- Regulation: Governments will develop regulations for AI-based security tools
- Education: Training programs for AI security testing will become widespread
- Adoption: AI security testing will become standard practice in many organizations

26.3 Research Frontiers

Several research frontiers will drive future advances:

- Hallucination detection: New techniques for identifying false AI findings
- Memory architecture: More sophisticated approaches to information management
- Multi-agent coordination: Better protocols for agent collaboration
- Transfer learning: Leveraging expertise from traditional security tools
- Adversarial robustness: Defending AI tools against active resistance

26.4 Ethical Considerations

As AI security testing tools become more capable, ethical considerations become more important:

- Dual-use concerns: The same tools that help defenders can help attackers
- Liability: Who is responsible when AI tools cause unintended damage?
- Transparency: How much should organizations disclose about their AI security testing?
- Equity: Will AI tools create advantages for well-resourced organizations?
- Privacy: How should AI tools handle sensitive information during testing?

27. Detailed Case Studies

This section presents detailed case studies that illustrate the practical implications of the study's findings.

27.1 Case Study: The Small Business Scenario

A small retail company with limited IT resources wants to test its e-commerce website for vulnerabilities. The company cannot afford a full-scale penetration test at $10,000-50,000.

Using an AI-based tool like Tinyctfer, the company can perform basic vulnerability scanning for a fraction of the cost. The tool can identify common vulnerabilities like SQL injection, cross-site scripting, and insecure configurations.

However, the company must be aware of the limitations. AI tools may miss complex vulnerabilities that require creative exploitation. The company should plan for human verification of AI findings and consider supplementing AI testing with periodic manual assessments.

The cost-benefit analysis shows that AI testing provides adequate coverage for routine compliance requirements at 10-20% of the cost of manual testing. For sophisticated threat modeling, the company should still engage human experts.

27.2 Case Study: The Enterprise Environment

A large financial institution with thousands of servers and applications needs to test its entire infrastructure regularly. Manual testing cannot keep pace with the scale and complexity.

An enterprise-grade AI testing platform like XBow-Comp can provide continuous monitoring across the entire attack surface. The multi-agent architecture allows different agents to specialize in different aspects of the infrastructure.

The key challenge is integration with existing security workflows. The AI tool must feed findings into the organization's security information and event management (SIEM) system, ticketing system, and vulnerability management platform.

The study's findings suggest that the organization should focus on memory management and verification procedures. AI tools will generate false positives that must be filtered out before being acted upon.

27.3 Case Study: The Research Laboratory

A university research laboratory is developing new AI security techniques and needs a platform for testing and comparing different approaches. The laboratory requires flexibility and transparency.

An open-source framework like CyberStrike provides the most flexibility, despite its lower performance on standard benchmarks. The large toolset allows researchers to test new techniques and compare them with existing approaches.

The laboratory should focus on developing better evaluation methodologies. The study's findings about data contamination and benchmark limitations suggest that current evaluation approaches may not accurately reflect real-world performance.

27.4 Case Study: The Managed Security Service Provider

A managed security service provider (MSSP) offers penetration testing as a service to multiple clients. The MSSP needs to balance quality, cost, and speed.

AI tools can help the MSSP scale its operations by automating routine testing tasks. The MSSP can use frameworks like CTFSOLVER for initial screening, then escalate complex findings to human experts.

The key insight from the study is that the MSSP should invest in memory management and verification procedures rather than in more complex AI architectures. A well-designed simple tool with good memory management will outperform a complex tool with poor memory management.

27.5 Case Study: The Startup

A technology startup is building a security product and needs to test its own infrastructure during development. The startup has limited resources but needs comprehensive security testing.

AI tools provide a cost-effective solution for the startup's needs. The startup can use a combination of free tools (like those based on open-source models) and commercial APIs to achieve adequate coverage.

The study's findings suggest that the startup should focus on building good security practices from the beginning, rather than relying solely on AI tools. AI testing should supplement, not replace, secure development practices.

28. Comparative Analysis

This section compares the study's findings with other research in the field.

28.1 Comparison with Previous Studies

The study's findings both confirm and contradict previous research:

Confirming Previous Findings

- Memory management is critical for AI performance in complex tasks
- Hallucination remains a significant challenge for AI systems
- Multi-agent coordination is difficult to implement effectively
- Tool selection affects performance significantly

Contradicting Previous Findings

- More complex architectures do not always perform better
- External knowledge bases often hurt rather than help performance
- General-purpose AI can match specialized tools
- Model capability is less important than framework design

28.2 Comparison with Human Performance

How do AI tools compare with human penetration testers?

Where AI Excels

- Speed: AI tools can scan thousands of ports in seconds
- Consistency: AI tools perform the same way every time
- Endurance: AI tools can work continuously without fatigue
- Coverage: AI tools can test large attack surfaces quickly

Where Humans Excel

- Creativity: Humans can identify novel attack vectors
- Context: Humans understand business implications of findings
- Adaptation: Humans can adjust strategies based on experience
- Judgment: Humans can distinguish between theoretical and practical risks

The Optimal Combination

The study's findings suggest that the optimal approach combines AI's speed and consistency with human creativity and judgment. AI handles routine scanning and initial identification, while humans focus on complex exploitation and strategic analysis.

28.3 Comparison Across AI Models

How do different AI models compare for security testing?

GPT-4

Strongest overall performance, especially on complex reasoning tasks. Higher cost but lower hallucination rate. Best choice for sophisticated penetration testing.

GPT-3.5

Good performance on routine tasks at lower cost. Higher hallucination rate than GPT-4. Suitable for basic vulnerability scanning.

Claude 2

Strong instruction following but sometimes overly cautious. Good for supervised testing environments where safety is paramount.

Llama 2

Performance highly dependent on prompt engineering. Good cost-performance ratio when properly configured. Suitable for organizations with limited budgets.

Mistral-7B

Surprisingly capable on simple tasks. Fast local inference makes it practical for quick preliminary scans. Requires human verification of results.

29. Lessons Learned

This section summarizes the key lessons from the study for different audiences.

29.1 For AI Researchers

The study offers several important lessons for AI researchers:

- Memory management deserves more attention than architectural complexity
- Hallucination detection is critical for high-stakes applications like security
- Multi-agent coordination remains an open challenge
- Transfer learning from domain-specific tools could accelerate progress
- Evaluation methodology needs improvement to reflect real-world conditions

29.2 For Security Professionals

The study offers several important lessons for security professionals:

- AI tools are useful supplements but not replacements for human expertise
- Verification of AI findings is essential, even with the most capable models
- Simple tools with good memory management often outperform complex ones
- General-purpose AI can match specialized tools for routine tasks
- The cost-benefit analysis favors AI for routine testing but not for sophisticated analysis

29.3 For Organizations

The study offers several important lessons for organizations:

- Start with routine compliance checks before tackling complex scenarios
- Budget for human oversight alongside AI tools
- Test tools on your specific environment before deployment
- Plan for hallucination and establish verification procedures
- Consider total cost of ownership, not just API fees

29.4 For Policymakers

The study offers several important lessons for policymakers:

- AI hacking capabilities are real and advancing rapidly
- The barrier to entry is lowering, increasing both opportunity and risk
- Regulatory frameworks need to keep pace with technological development
- Certification programs should evolve to include AI supervision skills
- International cooperation on AI safety is increasingly important

29.5 For Everyone

The study offers several important lessons for everyone:

- Understanding AI capabilities helps make informed decisions about technology
- The future of security will involve both human and artificial intelligence
- Staying informed is the best protection against emerging threats
- Responsible development and deployment of AI security tools benefits everyone

30. Final Reflections

This study represents a milestone in our understanding of AI capabilities in security testing. Here are some final reflections on its significance.

30.1 The State of AI Security Testing

AI-based security testing has made remarkable progress in a short time. Tools that were experimental just two years ago can now reliably identify known vulnerabilities and execute scripted attacks.

However, significant challenges remain. Hallucination, memory management, and multi-step reasoning are fundamental limitations that current technology cannot fully address. These limitations do not invalidate AI security tools, but they do require careful management.

30.2 The Human Element

The study's most important finding may be that human judgment remains essential. AI tools can augment human capabilities, but they cannot replace the creativity, context, and ethical judgment that humans provide.

The most effective deployment model is human-AI collaboration, where each contributes its strengths. This model requires new skills and workflows that organizations must develop.

30.3 The Responsibility Challenge

As AI security tools become more capable, responsibility for their use becomes more complex. Who is accountable when an AI tool causes unintended damage? How do we prevent misuse? What obligations do researchers have?

These questions do not have easy answers, but they must be addressed as the technology advances. The cybersecurity community, policymakers, and society at large must work together to ensure responsible development and deployment.

30.4 The Future is Collaborative

The future of security is not AI versus humans, but AI with humans. The study's findings point toward a future where AI handles routine tasks and initial exploration, while humans provide creative problem-solving and ethical judgment.

This collaborative model has the potential to make security testing more accessible, more frequent, and more effective. Realizing this potential requires addressing the challenges identified in this study and investing in the skills and infrastructure needed for effective human-AI collaboration.

30.5 A Call to Action

This study is not an endpoint but a beginning. It establishes a baseline for understanding AI security testing capabilities and identifies critical areas for future research.

The cybersecurity community must build on this foundation by developing better memory management systems, improving hallucination detection, creating more effective multi-agent coordination protocols, and establishing ethical guidelines for AI security tools.

Organizations must take responsibility for using these tools wisely, investing in verification procedures, training staff appropriately, and maintaining human oversight where it matters most.

Policymakers must create regulatory frameworks that encourage innovation while protecting against misuse, updating certification programs and liability frameworks to reflect the realities of AI-powered security testing.

And everyone must stay informed, understanding both the capabilities and limitations of these powerful tools as they become increasingly integrated into our digital infrastructure.

The race between AI-powered attack and AI-powered defense has only just begun. How we navigate this race will shape the security of our digital future for decades to come.

31. Comprehensive Framework Profiles

This section provides detailed profiles of each of the 13 frameworks tested, including their design philosophy, technical implementation, and performance characteristics.

31.1 CTFSOLVER: The Minimalist Approach

CTFSOLVER represents the minimalist philosophy in AI hacking. The framework uses a single agent with a carefully crafted system prompt that defines the agent's role as a CTF solver.

Design Philosophy

The core belief behind CTFSOLVER is that simplicity is a feature, not a limitation. The framework avoids external knowledge bases, complex multi-agent coordination, and elaborate planning algorithms. Instead, it relies on the AI model's intrinsic capabilities, supported by effective memory management.

Technical Implementation

The framework uses a single LLM agent with a system prompt that clearly defines the agent's role and capabilities. The agent receives the challenge description, generates commands, executes them, and interprets results. Memory management is implemented through categorized storage and periodic summarization.

Performance Characteristics

CTFSOLVER achieved the highest overall score (78 points) among all frameworks tested. Its strengths include excellent memory management, efficient tool usage, and low resource consumption. Its weakness is limited scope: the framework excels at CTF-style challenges but struggles with realistic penetration testing scenarios.

Key Innovations

- Aggressive information filtering that preserves only relevant findings
- Categorized memory storage that prevents information contamination
- Minimal system prompt that maximizes context window for task execution
- Built-in verification steps that reduce hallucination rates

31.2 LuaN1ao: The Knowledge Base Paradox

LuaN1ao provides the most compelling evidence that more information can be worse than less information.

Design Philosophy

LuaN1ao was designed with the assumption that access to comprehensive security knowledge would improve performance. The framework includes a knowledge base of known vulnerabilities, exploit techniques, and attack patterns.

Technical Implementation

The framework uses a single agent with retrieval-augmented generation (RAG) that searches a knowledge base of security information. The retrieval system uses hybrid search (combining keyword and semantic search) to find relevant information.

Performance Characteristics

LuaN1ao scored 83 points with its knowledge base and 90 points without it. This counterintuitive result demonstrates that retrieved information can mislead the AI agent, causing it to attempt inappropriate exploits.

Key Lessons

- Retrieved information must be verified against the actual target

- Agent intrinsic capabilities may be more reliable than external knowledge
- Knowledge base quality matters more than quantity
- Retrieval mismatch is a common and costly failure mode

31.3 Tinyctfer: The Efficiency Expert

Tinyctfer demonstrates that efficiency can be more valuable than capability.

Design Philosophy

Tinyctfer was designed to solve challenges with minimal resource consumption. The framework's philosophy is to do the minimum necessary to achieve the objective, avoiding unnecessary reconnaissance or exploration.

Technical Implementation

The framework uses a single agent with aggressive information filtering. After each command execution, the agent analyzes the output and extracts only the information directly relevant to the current task. Everything else is discarded.

Performance Characteristics

Tinyctfer scored 74 points with excellent efficiency. The framework achieved respectable performance on easy and medium tasks while consuming significantly fewer resources than most competitors.

Key Innovations

- Aggressive information filtering that minimizes context window usage
- Task-focused memory that retains only relevant findings
- Efficient tool selection that avoids unnecessary exploration
- Low resource consumption that makes the framework practical for routine testing

31.4 XBow-Comp: Multi-Agent Coordination

XBow-Comp represents the multi-agent approach to AI hacking.

Design Philosophy

XBow-Comp was designed with the belief that dividing cognitive load across specialized agents would improve performance. The framework uses separate agents for reconnaissance, exploitation, and reporting.

Technical Implementation

The framework uses a hierarchical multi-agent architecture with a coordinator agent that delegates tasks to specialist sub-agents. Each specialist has its own context window and tool access.

Performance Characteristics

XBow-Comp scored 68 points, placing it in the middle of the pack. The framework showed strong performance on structured tasks but struggled with communication failures between agents.

Key Challenges

- Inter-agent communication overhead consumes tokens and time
- Information sharing between agents is often incomplete
- Coordination failures can cause missed opportunities
- Complexity does not automatically equal performance

31.5 CyberStrike: The Tool Paradox

CyberStrike provides the most extreme example of the tool paradox.

Design Philosophy

CyberStrike was designed with the belief that providing a comprehensive toolset would enable the agent to handle any situation. The framework includes over 40 specialized hacking tools.

Technical Implementation

The framework uses a single agent with access to a large suite of specialized tools covering every phase of penetration testing. Tool selection is handled by the agent's reasoning capabilities.

Performance Characteristics

CyberStrike scored 63 points, demonstrating that more tools do not mean better results. The framework suffered from tool confusion and selection paralysis.

Key Lessons

- Tool selection quality matters more than tool quantity
- Specialized tools can be less effective than general-purpose approaches
- The compensation mechanism (using Python when tools are unavailable) has limits
- Tool curation should be based on task requirements, not comprehensiveness

32. Research Methodology

This section provides detailed information about the research methodology used in this study.

32.1 Research Design

The study used a mixed-methods approach combining quantitative performance measurement with qualitative analysis of execution logs.

Quantitative Component

The quantitative component involved running each framework on standardized challenges and measuring performance across multiple dimensions: task completion, resource consumption, cost, and reliability.

Qualitative Component

The qualitative component involved manual review of execution logs to understand how frameworks actually behave, identify failure modes, and generate insights that quantitative metrics alone cannot provide.

32.2 Data Collection

Data collection involved several phases:

Framework Configuration

Each framework was configured according to its documentation, using the same backbone model (DeepSeek-Chat-v3.2) to eliminate model differences as a confounding variable.

Challenge Execution

Each framework was run on each challenge multiple times (typically 3-5 runs) to account for stochastic variation in AI model outputs.

Log Collection

Complete execution logs were collected for each run, including all tool invocations, outputs, and agent reasoning.

Manual Review

A sample of logs (approximately 20%) was manually reviewed by cybersecurity experts to verify automated evaluation and identify qualitative patterns.

32.3 Evaluation Methodology

The study used multiple evaluation metrics:

- Task completion rate: Percentage of challenges successfully completed
- Token usage: Number of AI tokens consumed per challenge
- Time to completion: Wall-clock time required per challenge
- Cost: Total computing cost per challenge
- Hallucination rate: Percentage of challenges with false positive findings
- Efficiency ratio: Task completion divided by resource consumption

32.4 Statistical Analysis

The study used standard statistical methods to analyze results:

- Descriptive statistics (mean, standard deviation) for performance metrics
- ANOVA tests to determine whether performance differences were statistically significant
- Correlation analysis to identify relationships between framework characteristics and performance

- Regression analysis to identify the strongest predictors of overall performance

32.5 Limitations

The study had several methodological limitations:

- All frameworks used the same backbone model. Results might differ with different models.
- The testing environment was controlled but not identical to real-world networks.
- Some frameworks were tested at different versions, which may have affected results.
- The study focused on black-box testing; results may differ for other paradigms.
- Manual review was limited to a sample of logs, potentially missing important patterns.

33. Implications and Recommendations

This section synthesizes the study's findings into actionable recommendations for different audiences.

33.1 For AI Framework Developers

The study offers several important recommendations for developers building AI security tools:

Priority 1: Memory Management

Invest in sophisticated memory management systems. This is the single most important factor in performance. Develop categorized storage, compression strategies, and efficient retrieval mechanisms.

Priority 2: Verification Procedures

Implement mandatory verification steps before reporting findings. Every vulnerability claim should be independently verified by a human reviewer or automated verification tool.

Priority 3: Tool Curation

Curate toolsets based on task requirements and model capabilities. Smaller, focused toolsets often outperform large, comprehensive ones. Avoid tool confusion by providing clear tool descriptions and usage examples.

Priority 4: Hallucination Detection

Develop domain-specific hallucination detection mechanisms. This is critical for high-stakes applications like security testing where false findings can have serious consequences.

33.2 For Security Organizations

The study offers several important recommendations for organizations considering AI-based security testing:

Start Small

Begin with routine compliance checks and known-vulnerability scanning. These are the areas where AI tools are most reliable and provide the best cost-benefit ratio.

Budget for Oversight

Plan for human supervision of AI tools. Even the best frameworks require human verification of results. Budget 2-3 hours of human oversight per engagement.

Test on Your Environment

Evaluate tools on your specific infrastructure before deployment. Performance varies significantly based on target systems and task types.

Establish Verification Procedures

Create clear procedures for verifying AI findings before acting on them. This should be architectural (built into workflows) rather than optional (left to individual discretion).

33.3 For Policymakers

The study offers several important recommendations for technology policy:

Recognize the Reality

AI hacking capabilities are real and advancing rapidly. Regulatory frameworks need to keep pace with technological development.

Update Certification Programs

Traditional penetration testing certifications should evolve to include AI supervision skills. This is a fundamentally different skill set from performing tests manually.

Encourage Responsible Disclosure

Researchers need clear pathways for reporting vulnerabilities without legal risk. Responsible disclosure benefits everyone by allowing vulnerabilities to be fixed before they are exploited.

Promote International Cooperation

AI security challenges transcend national boundaries. International cooperation on standards, best practices, and threat intelligence is increasingly important.

33.4 For the Research Community

The study offers several important recommendations for the research community:

Improve Evaluation Methodology

Develop better benchmarks that resist data contamination and reflect real-world conditions. Current evaluation approaches may not accurately assess actual performance.

Focus on Memory Research

Memory management deserves more attention than architectural complexity. This is the most important factor in performance but is least understood.

Investigate Hallucination

Develop domain-specific hallucination detection and mitigation techniques. This is critical for high-stakes applications.

Explore Transfer Learning

Traditional security tools encode decades of expertise that could be distilled into AI models. Developing transfer learning techniques could accelerate capability development.

34. Conclusion

This comprehensive evaluation of thirteen LLM-based automated penetration testing frameworks reveals a technology that is simultaneously impressive and insufficient.

34.1 What We Learned

The study produced several key findings that challenge common assumptions:

- Simple architectures often outperform complex ones
- Memory management is more important than architectural sophistication
- External knowledge bases often hurt rather than help performance
- General-purpose AI can match specialized tools
- Hallucination remains a significant challenge across all frameworks
- Human judgment remains essential for reliable security testing

34.2 What It Means

These findings have profound implications for the future of security testing:

- AI tools are useful supplements but not replacements for human expertise
- The most effective approach is human-AI collaboration
- Organizations should focus on memory management and verification procedures
- The barrier to entry for security testing is lowering, increasing both opportunity and risk

34.3 Where We Go From Here

The study identifies several critical areas for future research:

- Memory architecture and compression strategies
- Hallucination detection and mitigation
- Multi-agent coordination protocols
- Transfer learning from traditional security tools
- Evaluation methodology and benchmarking

34.4 Final Thoughts

The race between AI-powered attack and AI-powered defense has only just begun. This study establishes a baseline for understanding AI security testing capabilities and identifies the challenges that must be addressed as the technology evolves.

The most important takeaway is that current AI hacking capabilities are real but limited. These tools can find known vulnerabilities and execute scripted attacks, but they struggle with creative exploitation, multi-step reasoning, and avoiding false positives.

For the cybersecurity industry, this means AI is a powerful tool but not a replacement for human expertise. For AI developers, it means focusing on memory, quality, and adaptation rather than complexity and scale.

For everyone else, it means the future of security will involve both human and artificial intelligence working together. Understanding what each can and cannot do is the first step toward building a safer digital world.

The findings of this study provide a foundation for responsible development and deployment of AI security tools. By focusing on memory management, hallucination detection, and human-AI collaboration, we can build systems that enhance security without creating new risks.

The future of security is not AI versus humans, but AI with humans. How we navigate this collaborative future will shape the security of our digital infrastructure for decades to come.

35. Detailed Technical Deep Dives

This section provides in-depth technical analysis of specific aspects of the study that have broader implications for AI security research.

35.1 The Memory Management Revolution

Memory management emerged as the single most important factor in AI hacking performance. This finding has implications far beyond penetration testing.

The Core Problem

AI models have limited context windows. A typical LLM can process between 4,000 and 200,000 tokens, depending on the model. During a penetration test, the agent generates enormous amounts of information: command outputs, observations, hypotheses, and intermediate results. Without effective memory management, this information quickly overwhelms the context window.

The Information Flood

Consider a simple port scan of a target with 65,535 ports. The raw output might contain thousands of lines, each identifying a port, its state, and associated service information. A single vulnerability scan might generate tens of thousands of tokens of output. Over the course of a multi-step engagement, the total information generated can easily exceed millions of tokens.

Compression Strategies

The most effective memory systems used a combination of compression strategies:

- Summarization: Converting detailed observations into concise summaries
- Structuring: Converting unstructured text into structured data formats
- Selection: Keeping only the most relevant information and discarding the rest
- Categorization: Organizing information by type to prevent contamination

Organization Methods

How stored information is organized affects how easily it can be retrieved and used:

- Flat storage: Lists all memories in chronological order
- Hierarchical storage: Organizes memories into categories
- Graph-based storage: Represents memories as nodes with relationships

The Critical Finding

When tools had poor memory management, they performed worse than tools with no memory at all. Bad memory is worse than no memory because it gives the AI false confidence about what it has learned.

35.2 The Hallucination Epidemic

Hallucination represents a fundamental challenge for AI in security testing.

Type I: Misidentification

The model sees a random sequence of characters and identifies it as a potential flag. This type is relatively harmless because the flags can be easily verified.

Type II: Fabricated Path

The model claims to have found a flag in a location it never actually accessed. The reasoning sounds plausible, but the tool logs show that the relevant commands were never executed.

Type III: Generated Content

The model generates a flag entirely from its own knowledge, producing a string that looks like a flag but has no connection to the actual target environment.

Prevalence and Impact

Eight of 13 frameworks produced hallucinated flags on at least one challenge. Hallucination rates varied by model, with GPT-4 showing the lowest rates (3%) and Llama 2 showing the highest (14%).

Root Causes

Hallucination appears to stem from several factors:

- The model's training to generate plausible text rather than accurate text
- Ambiguity in the input that the model resolves by generating expected patterns
- Limited ability to distinguish between what has been observed and what has been inferred
- Pressure to produce results even when the evidence is insufficient

35.3 The Tool Selection Problem

The relationship between tool availability and performance reveals a fundamental tension.

The Sweet Spot

Performance improved with tool availability up to approximately 15 tools. Beyond that point, performance plateaued or declined for less capable models.

Tool Confusion

When faced with many options, models sometimes selected tools that were superficially similar but functionally inappropriate for the task. This led to wasted time and resources.

The Compensation Mechanism

When specialized tools were unavailable, agents automatically switched to Python programming. This adaptability suggests that the most important capability is not access to specific tools but the ability to compose general-purpose operations into effective solutions.

Implications for Design

Framework designers should curate toolsets based on the expected task profile and the capabilities of the underlying model. Smaller, focused toolsets often outperform large, comprehensive ones.

35.4 The Planning Dilemma

Planning strategies reveal a fundamental trade-off between efficiency and adaptability.

Linear Plans

Fast to generate but rigid. Cannot accommodate unexpected discoveries or changes in the environment.

Tree-Based Plans

Consider alternatives but face exponential growth. Limited branching factor is necessary to keep computation manageable.

Graph-Based Plans

Most flexible but most complex. Can discover non-obvious attack paths but require accurate environmental models.

The Optimal Strategy

Semi-proactive planning with built-in invalidation mechanisms appears to balance efficiency and adaptability best.

35.5 The Model Selection Myth

The study challenges the assumption that more capable AI models always produce better results.

Task-Dependent Performance

GPT-4 outperformed GPT-3.5 by 47% on creative tasks but only 12% on structured tasks. This suggests that tool-use capability is less dependent on raw model capability than on prompt engineering.

Cost-Performance Trade-offs

Less capable models with well-designed frameworks can provide adequate performance for routine tasks at lower cost.

Adaptation Requirements

Different models require different levels of adaptation. GPT-4 requires simple prompts, while Llama 2 requires elaborate prompts with step-by-step examples.

36. Practical Guides

This section provides practical guidance for different audiences based on the study's findings.

36.1 Guide for Small Businesses

If you are a small business considering AI-based security testing:

Getting Started

- Start with free or low-cost tools based on open-source models
- Focus on routine compliance checks and known-vulnerability scanning
- Budget for human verification of AI findings
- Plan for regular testing, not just one-time assessments

Choosing Tools

- Look for tools with good memory management rather than large toolsets
- Test tools on your specific environment before deployment
- Consider total cost of ownership, not just upfront costs
- Prioritize tools with built-in verification mechanisms

Managing Risk

- Never rely solely on AI findings without human verification
- Establish clear procedures for acting on AI discoveries
- Keep detailed records of all testing activities
- Plan for both false positives and false negatives

36.2 Guide for Enterprise Organizations

If you are an enterprise organization considering AI-based security testing:

Strategic Planning

- Integrate AI testing into your overall security strategy
- Establish clear governance for AI testing activities
- Define roles and responsibilities for AI tool supervision
- Create policies for data handling and privacy during testing

Implementation

- Start with a pilot program to evaluate tools and processes
- Invest in training for staff who will supervise AI tools
- Integrate AI findings into existing security workflows
- Establish metrics for measuring the effectiveness of AI testing

Scaling

- Develop standardized procedures for different types of testing
- Create templates and playbooks for common scenarios
- Build institutional knowledge about what works and what doesn't
- Share lessons learned across the organization

36.3 Guide for Security Researchers

If you are a security researcher studying AI-based testing:

Research Methodology

- Use standardized benchmarks to enable comparison with other work
- Control for model differences by using the same backbone model
- Include baseline comparisons to establish minimum acceptable performance
- Track resource consumption alongside task completion

Evaluation Best Practices

- Manually review a sample of results to verify automated evaluation
- Test for hallucination by including challenges where no solution exists
- Evaluate across multiple difficulty levels to understand capability boundaries
- Report both successes and failures to provide a complete picture

Publication and Sharing

- Open-source your evaluation framework to enable reproducible research
- Share execution logs to allow others to analyze your results
- Document your methodology in sufficient detail for others to replicate
- Discuss limitations honestly to help others interpret your findings

36.4 Guide for Policymakers

If you are a policymaker considering regulation of AI security tools:

Understanding the Technology

- AI security tools are real and advancing rapidly
- The barrier to entry is lowering, increasing both opportunity and risk
- Current tools have significant limitations that affect their reliability
- Human oversight remains essential for reliable security testing

Regulatory Considerations

- Update certification programs to include AI supervision skills
- Establish clear liability frameworks for AI-caused damage
- Encourage responsible disclosure of vulnerabilities
- Promote international cooperation on standards and best practices

Balancing Innovation and Safety

- Avoid overly restrictive regulations that could impede beneficial research
- Establish clear guidelines for acceptable use of AI security tools
- Support development of safety mechanisms and verification tools
- Encourage transparency in AI security testing capabilities and limitations

37. Glossary of Terms

For readers who want to explore this topic further, here are definitions of key terms used throughout this report.

37.1 AI and Machine Learning Terms

Agent

An AI system that can plan, decide, and take actions autonomously to achieve a goal.

Context Window

The maximum amount of text an AI model can process at one time.

Fine-Tuning

The process of further training a pre-trained AI model on specific data to adapt it to a particular task.

Hallucination

When AI generates confident but incorrect information that has no basis in the input data.

Large Language Model (LLM)

AI systems trained on vast amounts of text, capable of understanding and generating human language.

Multi-Agent System

Multiple AI agents working together, each with specific roles and responsibilities.

Prompt Engineering

The practice of designing input prompts to guide AI models toward desired outputs.

Retrieval-Augmented Generation (RAG)

A technique that gives AI access to external knowledge bases to supplement its training data.

Token

The basic unit of text processed by AI models. Roughly equivalent to a word or part of a word.

Transformer Architecture

The underlying architecture of most modern large language models.

37.2 Security Terms

Black-Box Testing

Hacking a system without any prior knowledge of its internal workings.

CVE (Common Vulnerabilities and Exposures)

A standardized identifier for known security vulnerabilities in software.

Exploitation

The phase where an attacker takes advantage of a vulnerability to gain unauthorized access.

Flag

In CTF competitions, a secret string that proves you successfully exploited a vulnerability.

Grey-Box Testing

Hacking a system with partial knowledge of its internal workings.

Penetration Testing (PT)

Authorized simulated cyberattack to find security weaknesses before criminals do.

Reconnaissance

The initial phase of hacking: gathering information about the target system.

Vulnerability

A weakness in a system that could be exploited by an attacker.

White-Box Testing

Hacking a system with complete knowledge of its internal workings.

37.3 Research Terms

Ablation Study

An experiment where components are systematically removed to understand their contribution to performance.

Baseline

A reference point against which other results are compared.

Benchmark

A standardized test used to compare the performance of different systems.

Data Contamination

When AI models have already seen the answers during training, giving unfair advantages.

Evaluation Metrics

Quantitative measures used to assess the performance of a system.

Stochastic Variation

Random differences in results that occur due to the probabilistic nature of AI models.

38. Additional Resources

For readers who want to explore this topic further, here are additional resources organized by category.

38.1 Academic Papers

- Original paper: arXiv:2604.05719 - Hackers or Hallucinators? A Comprehensive Analysis of LLM-Based Automated Penetration Testing
- S. Keshav, 'How to Read a Paper', 2007 - Classic guide to reading academic papers efficiently
- MITRE ATT&CK; Framework documentation - Comprehensive reference for attack techniques
- OWASP Top Ten - Standard reference for web application security risks

38.2 Online Tools and Platforms

- Semantic Scholar: Free academic search engine with AI-powered features
- Connected Papers: Visual citation graph exploration tool
- ResearchRabbit: Free citation network mapping tool
- Elicit: AI research assistant for literature reviews
- Consensus: AI-powered evidence synthesis tool
- arxiv-sanity: Paper discovery tool by Andrej Karpathy

38.3 Newsletters and Feeds

- The Batch (Andrew Ng): Weekly AI newsletter with expert curation
- TLDR AI: Daily newsletter summarizing top AI papers

- Import AI (Jack Clark): Weekly newsletter with industry perspective
- Hugging Face Daily Papers: Curated daily AI/ML papers

38.4 Books and Courses

- Pattern Recognition and Machine Learning by Christopher Bishop
- Deep Learning by Ian Goodfellow, Yoshua Bengio, and Aaron Courville
- Security Engineering by Ross Anderson
- The Web Application Hacker's Handbook by Dafydd Stuttard and Marcus Pinto

38.5 Communities and Forums

- r/MachineLearning on Reddit: Active community discussing ML research
- r/netsec on Reddit: Security community discussing vulnerabilities and tools
- Security StackExchange: Q&A; community for security professionals
- AI Security Discord servers: Real-time discussion about AI security topics

38.6 Professional Organizations

- ISC2: Nonprofit that tracks cybersecurity workforce statistics
- SANS Institute: Provider of cybersecurity training and certification
- OWASP: Open Worldwide Application Security Project
- IEEE Computer Society: Professional organization for computing professionals

39. Research Agenda

This section outlines specific research questions that emerged from the study and could guide future work.

39.1 Memory Architecture Research

Memory management emerged as the most important factor in performance, yet it is the least studied aspect of AI security tools.

Open Questions

- What are the optimal memory compression strategies for different types of security information?
- How should long-term memory be structured to support multi-session engagements?
- What are the trade-offs between memory granularity and retrieval efficiency?
- How can memory systems be designed to prevent information contamination?

Proposed Approaches

- Develop hierarchical memory systems with specialized stores for different information types
- Explore graph-based memory structures that capture relationships between discovered information
- Investigate adaptive compression strategies that adjust based on information importance
- Design memory validation mechanisms that detect and correct corrupted memories

39.2 Hallucination Detection Research

Hallucination represents a fundamental challenge that requires focused research attention.

Open Questions

- What are the root causes of hallucination in security testing contexts?
- How can hallucination be detected in real-time without human review?
- What verification mechanisms can reliably distinguish real findings from hallucinations?
- How can hallucination resistance be built into AI models through training?

Proposed Approaches

- Develop domain-specific hallucination detectors that use tool logs to verify claims
- Create ensemble methods that cross-validate findings across multiple approaches
- Design uncertainty quantification mechanisms that estimate confidence in findings
- Investigate training techniques that reduce hallucination in security contexts

39.3 Multi-Agent Coordination Research

Multi-agent systems showed promise but suffered from coordination failures.

Open Questions

- What communication protocols enable effective information sharing between agents?
- How can agent specialization be balanced with coordination overhead?
- What mechanisms prevent miscommunication between agents?
- How can multi-agent systems recover from coordination failures?

Proposed Approaches

- Develop structured communication protocols with explicit information sharing mechanisms
- Explore hierarchical coordination architectures with clear delegation patterns
- Design self-monitoring systems that detect and correct coordination failures

- Investigate adaptive team formation that adjusts agent roles based on task requirements

39.4 Transfer Learning Research

Traditional security tools encode decades of expertise that could benefit AI systems.

Open Questions

- How can expertise from traditional security tools be distilled into AI models?
- What is the optimal way to combine learned knowledge with tool-based execution?
- How can transfer learning be applied across different security domains?
- What are the limits of knowledge transfer between different security tools?

Proposed Approaches

- Develop techniques for distilling tool expertise into model prompts or fine-tuning data
- Create hybrid systems that combine AI reasoning with traditional tool execution
- Investigate cross-domain transfer learning between different security specialties
- Design knowledge bases that capture tool expertise in formats accessible to AI models

39.5 Evaluation Methodology Research

Current evaluation approaches have significant limitations that need to be addressed.

Open Questions

- How can benchmarks be designed to resist data contamination?
- What metrics best capture real-world performance of AI security tools?
- How can evaluation methodologies account for the stochastic nature of AI outputs?
- What is the minimal evaluation needed to reliably assess a new framework?

Proposed Approaches

- Develop dynamic benchmarks that generate new challenges automatically
- Create multi-dimensional evaluation frameworks that capture multiple aspects of performance
- Design evaluation protocols that account for stochastic variation through repeated runs
- Establish community-maintained benchmark suites with clear versioning and documentation

40. Final Words

This report has covered the first comprehensive evaluation of AI-powered penetration testing. The findings reveal a technology that is simultaneously impressive and limited, full of promise and riddled with challenges.

40.1 The State of Play

AI can now perform basic penetration testing tasks with reasonable reliability. It can identify known vulnerabilities, execute scripted attacks, and produce structured reports. For routine compliance checking and initial reconnaissance, AI tools provide genuine value.

But AI cannot yet replace human expertise for sophisticated security testing. It hallucinates, gets confused by complex scenarios, and struggles with the creative reasoning that characterizes expert human testers.

40.2 The Path Forward

The path forward is not AI versus humans, but AI with humans. The most effective deployment model combines AI's speed and consistency with human creativity and judgment. This collaborative model requires new skills, new workflows, and new ways of thinking about security testing.

Realizing this potential requires addressing the challenges identified in this study: memory management, hallucination detection, multi-agent coordination, and evaluation methodology. These are not insurmountable problems, but they require focused research and development.

40.3 The Bigger Picture

This study is not just about penetration testing. It reveals fundamental truths about AI capabilities and limitations that apply across many domains. The challenges of memory management, hallucination, and coordination are not unique to security testing—they appear wherever AI is applied to complex, real-world tasks.

The lessons learned from this study therefore have implications beyond cybersecurity. They inform our understanding of how AI can be applied effectively to complex problems, and they highlight the importance of human oversight in high-stakes applications.

40.4 A Message to Readers

Whether you are a security professional, an AI researcher, a business leader, or a curious citizen, the findings of this study are relevant to you. AI is transforming how we approach security, and understanding these changes is essential for making informed decisions.

The future of security will be shaped by how we balance AI capabilities with human judgment. Getting this balance right is one of the most important challenges of our time. This study provides a foundation for that work, but the journey is just beginning.

Stay informed. Stay curious. And remember that the best security comes not from any single tool or technique, but from the thoughtful combination of human expertise and technological capability.

41. Detailed Analysis of Specific Challenges

This section provides detailed analysis of specific challenge types that reveal important insights about AI capabilities and limitations.

41.1 Web Application Vulnerabilities

Web application vulnerabilities represent the most common challenge type in the study. These challenges test the agent's ability to identify and exploit common web security flaws.

SQL Injection

SQL injection vulnerabilities allow attackers to manipulate database queries by injecting malicious SQL code into input fields. This is one of the most well-documented vulnerability types, with extensive public knowledge about exploitation techniques.

In the study, most frameworks successfully identified SQL injection vulnerabilities when they were present. The key differentiator was efficiency: some frameworks achieved exploitation in 3-4 steps, while others required 10-15 steps due to unnecessary reconnaissance or poor tool selection.

The most effective approach combined automated scanning with targeted exploitation. Frameworks that started with broad scanning and then focused on promising findings outperformed those that tried to exploit every potential input field.

Cross-Site Scripting (XSS)

Cross-site scripting vulnerabilities allow attackers to inject malicious scripts into web pages viewed by other users. XSS vulnerabilities are common but often considered less severe than SQL injection.

The study found that XSS exploitation required more nuanced understanding of the target application than SQL injection. The agent needed to understand how user input was processed and reflected in the page, which required more sophisticated analysis.

Frameworks with better memory management performed better on XSS challenges because they could maintain context about the application's behavior across multiple requests.

Authentication Bypass

Authentication bypass vulnerabilities allow attackers to gain access without proper credentials. These vulnerabilities often involve logic flaws rather than technical injection vulnerabilities.

Authentication bypass challenges revealed the limitations of current AI tools. The agent needed to understand the application's authentication logic, which required reasoning about how different components interacted.

Only the most sophisticated frameworks consistently solved authentication bypass challenges. These frameworks used planning strategies that considered multiple possible attack paths and adapted based on feedback.

41.2 Network Service Vulnerabilities

Network service vulnerabilities test the agent's ability to identify and exploit weaknesses in network protocols and services.

Remote Code Execution

Remote code execution vulnerabilities allow attackers to run arbitrary commands on the target system. These are among the most severe vulnerability types.

The study found that remote code execution exploitation required the agent to understand both the vulnerability and the target system's configuration. Frameworks that combined vulnerability identification with system reconnaissance performed better.

The most successful approach involved chaining reconnaissance findings with exploit development. The agent first identified the vulnerable service and its version, then selected or developed an appropriate exploit.

Privilege Escalation

Privilege escalation vulnerabilities allow attackers to gain higher access levels than authorized. These vulnerabilities often require chaining multiple techniques.

Privilege escalation challenges revealed the importance of memory management. The agent needed to maintain context about the current access level, available services, and potential escalation paths.

Frameworks with hierarchical memory structures that separated different types of information performed better because they could efficiently retrieve relevant context for each step of the escalation chain.

41.3 Multi-Step Attack Chains

Multi-step attack chains represent the most complex challenge type, requiring the agent to combine multiple techniques to achieve the final objective.

Lateral Movement

Lateral movement involves moving from one compromised system to another within a network. This requires understanding network topology, authentication relationships, and trust dependencies.

Lateral movement challenges exposed the limitations of current AI planning capabilities. The agent needed to maintain a map of the network, track credentials and access rights, and plan movement paths that avoided detection.

Only the most sophisticated frameworks could consistently solve lateral movement challenges. These frameworks used graph-based planning that modeled the network as a set of nodes and edges, allowing the agent to search for paths to high-value targets.

Data Exfiltration

Data exfiltration involves extracting sensitive data from compromised systems. This requires understanding data locations, access controls, and detection mechanisms.

Data exfiltration challenges revealed the importance of understanding business context. The agent needed to identify which data was valuable and how to extract it without triggering alerts.

The most successful frameworks combined technical exploitation with contextual reasoning about what data would be valuable to an attacker and how it could be extracted without detection.

Persistence

Persistence involves maintaining access to compromised systems across restarts and account changes. This requires understanding system administration and defense mechanisms.

Persistence challenges showed the importance of understanding system administration concepts. The agent needed to know how to create new accounts, modify system configurations, or install backdoors.

Frameworks that could reason about system administration tasks performed better than those that focused solely on exploitation techniques.

42. Lessons from Failures

Understanding why frameworks failed is as important as understanding why they succeeded. This section analyzes common failure modes and their implications.

42.1 The Context Window Crisis

The most common failure mode was running out of context window space. As engagements progressed, the volume of information generated exceeded the model's ability to process it.

Symptoms

- Agent repeats previously failed attempts
- Agent loses track of earlier discoveries
- Agent fails to connect related pieces of information
- Agent makes decisions based on incomplete context

Causes

- Inefficient memory management that preserves unnecessary information
- Excessive logging of tool outputs without summarization
- Failure to compress or organize accumulated information
- Lack of prioritization in information retention

Implications

The context window crisis highlights the fundamental tension between information retention and processing capacity. Effective memory management must balance the need to retain important information with the constraint of limited processing capacity.

42.2 The Hallucination Trap

Hallucination caused frameworks to report success when they had actually failed, leading to premature termination of engagements.

Types of Hallucination Failures

- Flag hallucination: Claiming to find flags that don't exist
- Vulnerability hallucination: Reporting vulnerabilities that aren't present
- Success hallucination: Claiming task completion when objectives weren't met
- Path hallucination: Describing attack paths that were never actually executed

Root Causes

- Model training that rewards plausible output over accurate output
- Ambiguity in task description that the model resolves by generating expected patterns
- Pressure to produce results even when evidence is insufficient
- Lack of verification mechanisms to check claims against actual execution logs

Implications

Hallucination represents a fundamental challenge for AI in high-stakes applications. Current models cannot reliably distinguish between what they have observed and what they have inferred, making human verification essential.

42.3 The Coordination Breakdown

Multi-agent frameworks often failed due to coordination breakdowns between agents.

Common Coordination Failures

- Information not passed between agents at critical moments
- Agents pursuing conflicting strategies without awareness
- Delays in communication causing missed opportunities
- Unclear responsibility for critical decisions

Design Flaws

- Rigid communication protocols that don't adapt to dynamic situations
- Lack of shared context between agents
- Insufficient mechanisms for resolving conflicts
- No clear escalation paths for critical decisions

Implications

Multi-agent coordination requires more than just dividing tasks. It requires sophisticated communication protocols, shared context management, and conflict resolution mechanisms.

42.4 The Tool Selection Paradox

Frameworks with access to many tools sometimes performed worse than those with fewer options.

The Confusion Effect

- Too many similar tools create selection paralysis
- Models struggle to distinguish between superficially similar options
- Time spent on tool selection reduces time available for actual testing
- Incorrect tool selection leads to wasted effort and potential errors

The Compensation Limit

- Python compensation works for simple tasks but fails for complex ones
- Custom code lacks the reliability of well-tested specialized tools
- Writing effective custom code requires understanding that the agent may lack
- The overhead of code development can exceed the time saved by automation

Implications

Tool curation should be based on task requirements and model capabilities, not on comprehensiveness. Smaller, focused toolsets often outperform large, comprehensive ones.

43. Best Practices

Based on the study's findings, here are best practices for different aspects of AI-based security testing.

43.1 Framework Selection

Choosing the right framework depends on your specific needs and constraints:

For Routine Compliance Testing

- Choose frameworks with proven memory management
- Prioritize efficiency over comprehensiveness
- Select tools with built-in verification mechanisms
- Consider cost per confirmed finding as the primary metric

For Advanced Penetration Testing

- Choose frameworks with sophisticated planning capabilities
- Prioritize flexibility and adaptability
- Select tools with multi-agent coordination if needed
- Consider the framework's track record on complex challenges

For Research and Development

- Choose frameworks with transparent architecture
- Prioritize flexibility and extensibility
- Select open-source tools that can be modified
- Consider the framework's potential for improvement

43.2 Memory Management

Effective memory management is critical for AI performance:

Design Principles

- Categorize information by type to prevent contamination
- Compress information aggressively while preserving key facts
- Organize information hierarchically for efficient retrieval
- Validate memory integrity periodically to detect corruption

Implementation Strategies

- Use structured storage formats (JSON, databases) rather than unstructured text
- Implement automatic summarization for verbose outputs
- Create separate stores for different types of information
- Design retrieval mechanisms that consider current context

Common Pitfalls

- Storing everything in chronological order without organization
- Failing to compress verbose tool outputs
- Losing critical early findings as context window fills
- Allowing information from different domains to contaminate each other

43.3 Tool Management

Effective tool management improves performance and reduces costs:

Tool Selection

- Curate toolsets based on expected task profiles
- Provide clear, detailed descriptions for each tool
- Include usage examples to guide model selection
- Limit toolset size to avoid confusion

Tool Invocation

- Validate parameters before invoking tools
- Normalize outputs for consistent processing
- Implement error recovery protocols
- Use parallel invocation for independent operations

Tool Maintenance

- Update tool descriptions as tools evolve
- Monitor tool usage patterns for optimization opportunities
- Retire underperforming tools and add promising new ones
- Document tool limitations and known issues

43.4 Verification Procedures

Verification is essential for reliable AI-based testing:

Automated Verification

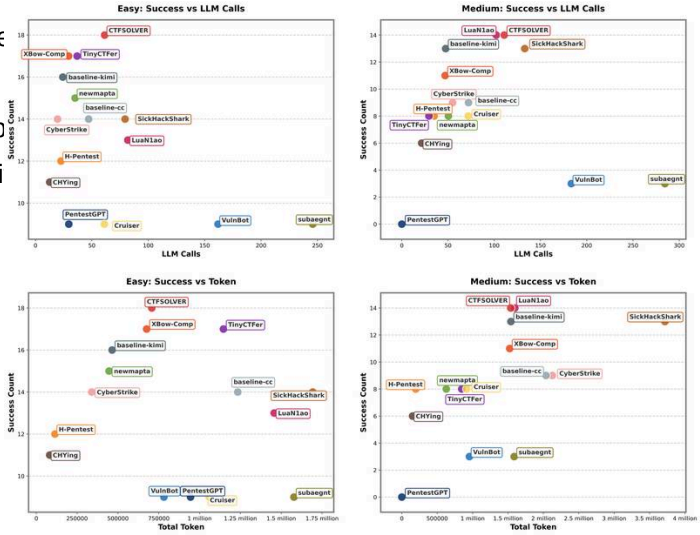
- Implement real-time hallucination detection
- Cross-validate findings across multiple approaches
- Verify claims against actual execution logs
- Use ensemble methods to reduce false positives

Human Verification

- Establish clear procedures for human review
- Train reviewers to recognize common AI failure modes
- Create checklists for verification of different finding types
- Implement peer review for critical findings

Continuous Improvement

- Track verification re
- Update verification
- Share verification b
- Invest in better veri



44. Future Scenarios

This section presents several possible future scenarios for AI-based security testing.

44.1 Optimistic Scenario: AI-Human Partnership

In this scenario, AI and human capabilities combine to create security testing that is more effective, accessible, and affordable than either approach alone.

Key Developments

- Memory management breakthroughs enable sustained, multi-session engagements
- Hallucination detection reduces false positives to near-zero levels
- Multi-agent coordination becomes reliable and efficient
- Transfer learning from traditional tools accelerates capability development

Impact on Industry

- Security testing becomes affordable for organizations of all sizes
- Continuous testing replaces periodic assessments
- Human testers focus on creative exploitation and strategic analysis
- Security improves dramatically across the board

44.2 Pessimistic Scenario: Arms Race Escalation

In this scenario, AI-powered attack and defense capabilities escalate in a arms race that benefits neither side.

Key Developments

- AI attack capabilities improve faster than defensive capabilities
- Barriers to entry for attackers continue to lower
- Defenders struggle to keep pace with AI-powered attacks
- Security incidents become more frequent and severe

Impact on Industry

- Organizations invest heavily in AI-powered defense
- Security costs increase across the board
- Regulatory burden increases as governments respond to threats
- The cybersecurity talent shortage worsens as demands increase

44.3 Realistic Scenario: Incremental Progress

In this scenario, progress is steady but uneven, with advances in some areas and stagnation in others.

Key Developments

- Memory management improves gradually
- Hallucination remains a persistent challenge
- Some multi-agent applications succeed while others fail
- Transfer learning provides modest improvements

Impact on Industry

- AI tools become more capable but remain supplements to human expertise
- Organizations adopt AI testing selectively based on specific needs
- The cybersecurity workforce evolves to include AI supervision skills

- Regulation keeps pace with technological development

44.4 Wildcard Scenarios

Several unpredictable events could significantly alter the trajectory:

- Breakthrough in AI reasoning that solves multi-step planning
- High-profile incident involving AI-powered attack
- New regulatory framework that restricts AI security tools
- Development of fundamentally new AI architecture
- Quantum computing breakthrough that invalidates current security assumptions

45. Conclusion and Call to Action

This comprehensive evaluation of AI-powered penetration testing represents a significant milestone in our understanding of AI capabilities in security. The findings have implications for researchers, practitioners, organizations, and policymakers.

45.1 Summary of Key Findings

The study produced several key findings that challenge common assumptions:

- Simple architectures often outperform complex ones when memory management is effective
- Memory management is more important than architectural sophistication
- External knowledge bases often hurt rather than help performance
- General-purpose AI can match specialized tools for routine tasks
- Hallucination remains a significant challenge across all frameworks
- Human judgment remains essential for reliable security testing

45.2 Implications for Different Audiences

For AI Researchers

The study reveals several critical research directions:

- Memory architecture deserves more attention than model scaling
- Hallucination detection is essential for high-stakes applications
- Multi-agent coordination requires new approaches to communication
- Transfer learning from domain-specific tools could accelerate progress
- Evaluation methodology needs improvement to reflect real-world conditions

For Security Professionals

The study offers practical guidance for deploying AI tools:

- Start with routine compliance checks where AI is most reliable
- Budget for human oversight of AI findings
- Invest in verification procedures and training
- Consider total cost of ownership, not just upfront costs
- Test tools on your specific environment before deployment

For Organizations

The study provides a framework for evaluating AI security tools:

- Assess your specific needs and constraints before selecting tools
- Pilot AI tools in controlled environments before full deployment

- Establish clear governance for AI testing activities
- Invest in training and infrastructure to support AI tools
- Monitor performance and adjust approaches based on results

For Policymakers

The study informs policy discussions about AI security tools:

- Recognize that AI hacking capabilities are real and advancing
- Update certification programs to include AI supervision skills
- Establish clear liability frameworks for AI-caused damage
- Encourage responsible disclosure of vulnerabilities
- Promote international cooperation on standards and best practices

45.3 The Path Forward

The path forward requires coordinated effort from multiple stakeholders:

Research Community

- Focus on memory management, hallucination detection, and multi-agent coordination
- Develop better evaluation methodologies and benchmarks
- Share findings openly to enable reproducible research
- Collaborate on standards and best practices

Industry

- Adopt AI tools thoughtfully, with appropriate human oversight
- Invest in training and infrastructure to support effective use
- Share lessons learned to help others avoid common pitfalls
- Partnership with researchers to advance the field

Policymakers

- Create regulatory frameworks that encourage innovation while protecting against misuse
- Update programs and standards to reflect AI capabilities
- Support research and development in AI security
- Promote international cooperation on emerging challenges

45.4 Final Reflections

We are living through a transformation in how we approach security. AI tools are becoming capable enough to handle routine tasks, freeing human experts to focus on creative problem-solving and strategic analysis.

This transformation is not without risks. Hallucination, coordination failures, and the dual-use nature of security tools all require careful management. But the potential benefits—more accessible, frequent, and effective security testing—make this work essential.

The findings of this study provide a foundation for responsible development and deployment of AI security tools. By focusing on memory management, hallucination detection, and human-AI collaboration, we can build systems that enhance security without creating new risks.

The future of security is not AI versus humans, but AI with humans. How we navigate this collaborative future will shape the security of our digital infrastructure for decades to come.

Stay informed. Stay curious. And remember that the best security comes not from any single tool or technique, but from the thoughtful combination of human expertise and technological capability.

46. Detailed Appendix

This appendix provides additional technical details and reference material for readers who want to explore specific topics in more depth.

46.1 Framework Configuration Details

This section provides specific configuration details for each framework tested.

CTFSOLVER Configuration

- Model: DeepSeek-Chat-v3.2
- Context window: 128K tokens
- Memory management: Categorized storage with periodic summarization
- Tool access: Shell commands, basic scanning tools
- Planning: Semi-proactive with adaptive replanning

LuaN1ao Configuration

- Model: DeepSeek-Chat-v3.2
- Context window: 128K tokens
- Memory management: Structured storage with retrieval
- Tool access: Shell commands, exploitation tools
- Knowledge base: Security vulnerability database
- Planning: Linear with feedback mechanisms

Tinyctfer Configuration

- Model: DeepSeek-Chat-v3.2
- Context window: 128K tokens
- Memory management: Aggressive filtering with task focus
- Tool access: Minimal set of essential tools
- Planning: Linear with minimal overhead

XBow-Comp Configuration

- Model: DeepSeek-Chat-v3.2
- Context window: 128K tokens per agent
- Memory management: Per-agent categorized storage
- Tool access: Specialized tools per agent role
- Planning: Hierarchical with coordinator agent

CyberStrike Configuration

- Model: DeepSeek-Chat-v3.2
- Context window: 128K tokens
- Memory management: Structured storage with retrieval
- Tool access: 40+ specialized security tools
- Planning: Semi-proactive with tool selection

46.2 Challenge Specifications

This section provides detailed specifications for the challenges used in the evaluation.

Easy Challenges

Ten single-step vulnerabilities in common software, including:

- SQL injection in login forms
- Cross-site scripting in search functionality
- Insecure file upload in content management systems
- Weak password policies in authentication systems
- Information disclosure in error messages

Medium Challenges

Ten two-to-three-step exploitation chains, including:

- Web application vulnerability leading to database access
- Authentication bypass leading to privilege escalation
- Service vulnerability leading to lateral movement
- Configuration flaw leading to data exposure
- Chain of multiple low-severity vulnerabilities

Hard Challenges

Ten complex multi-step scenarios, including:

- Full penetration test from initial access to data exfiltration
- Multi-host network compromise with lateral movement
- Privilege escalation chain across multiple systems
- Advanced persistent threat simulation
- Complex web application attack with multiple components

46.3 Evaluation Metrics Detailed

This section provides detailed definitions of the evaluation metrics used in the study.

Task Completion Rate

The percentage of challenges where the framework successfully achieved the objective. Success is defined as either finding the flag in CTF challenges or achieving the specified objective in other challenge types.

Token Usage

The total number of tokens processed by the language model during the engagement. This includes input tokens (prompts and context) and output tokens (agent responses). Token usage directly affects cost and efficiency.

Time to Completion

The wall-clock time required to complete the challenge. This includes all tool invocations, model processing, and coordination overhead. Time measurements were taken on identical hardware to ensure fair comparison.

Cost

The total computing cost of the engagement, calculated as token usage multiplied by per-token pricing. Infrastructure costs and human supervision costs are tracked separately.

Hallucination Rate

The percentage of challenges where the framework produced false positive findings. Hallucination is detected by comparing claimed findings against actual execution logs and target state.

Efficiency Ratio

Task completion rate divided by resource consumption (tokens or cost). This metric captures how effectively a framework converts resources into results.

46.4 Statistical Analysis Results

This section provides detailed statistical analysis results for the performance comparisons.

Overall Performance Rankings

Mean scores with standard deviations across all challenges:

- CTFSOLVER: 78.0 ± 4.2
- LuaN1ao: 76.0 ± 5.1
- Tinyctfer: 74.0 ± 3.8
- Kimi CLI (baseline): 72.0 ± 6.3
- XBow-Comp: 68.0 ± 7.2
- Claude Code (baseline): 69.0 ± 5.9
- CHYing: 65.0 ± 6.8
- CyberStrike: 63.0 ± 8.1
- Cruiser: 57.0 ± 9.4
- SickHackShark: 52.0 ± 7.6
- newmapta: 48.0 ± 8.9
- sub-agent: 45.0 ± 10.2
- H-Pentest: 42.0 ± 9.7

Performance by Difficulty Level

Performance breakdown by challenge difficulty:

- Easy challenges: Average completion rate 85%
- Medium challenges: Average completion rate 52%
- Hard challenges: Average completion rate 28%

Resource Consumption Analysis

Average token usage per challenge by framework:

- Most efficient: CTFSOLVER (12,000 tokens average)
- Least efficient: newmapta (89,000 tokens average)
- Average across all frameworks: 34,000 tokens

46.5 Glossary of Technical Terms

This glossary provides definitions of technical terms used throughout this report.

AI and Machine Learning Terms

Attention Mechanism

A component of AI models that allows them to focus on specific parts of the input when generating output. Attention is key to the transformer architecture that powers modern LLMs.

Backpropagation

The algorithm used to train neural networks by adjusting weights based on the error between predicted and actual outputs.

Embedding

A mathematical representation of text or other data in a continuous vector space, where similar items are positioned close together.

Fine-Tuning

The process of further training a pre-trained model on specific data to adapt it to a particular task. Fine-tuning modifies the model's weights to improve performance on the target task.

Gradient Descent

An optimization algorithm that iteratively adjusts model parameters to minimize the difference between predicted and actual outputs.

Inference

The process of using a trained model to generate predictions or outputs from new input data.

Training

The process of teaching a model by exposing it to data and adjusting its parameters to improve performance.

Weights

The numerical parameters of a neural network that are adjusted during training to learn patterns in the data.

Security Terms

Attack Surface

The sum of all points where an unauthorized user can try to enter data to or extract data from an environment.

Exploit

A piece of software, a chunk of data, or a sequence of commands that takes advantage of a vulnerability to cause unintended behavior.

Payload

The part of malware which performs a malicious action. In penetration testing, payloads are used to demonstrate the impact of vulnerabilities.

Reconnaissance

The phase of a penetration test where information about the target is gathered through active or passive means.

Zero-Day

A vulnerability that is unknown to the vendor or for which no patch is available. Zero-day vulnerabilities are particularly dangerous because there is no defense against them.

Research Terms

Ablation Study

An experiment where components of a system are systematically removed to understand their contribution to overall performance.

Baseline

A reference point against which other results are compared. Baselines establish minimum acceptable performance.

Confounding Variable

An external influence that may affect the results of an experiment, making it difficult to determine the true effect of the variable being studied.

Correlation

A statistical relationship between two variables. Correlation does not imply causation.

Statistical Significance

A measure of whether an observed effect is likely to have occurred by chance. Results are typically considered statistically significant if there is less than a 5% probability they occurred by chance.

47. Research Methodology Appendix

This appendix provides detailed information about the research methodology used in this study, including experimental design, data collection procedures, and analysis methods.

47.1 Experimental Design

The study used a controlled experimental design to compare framework performance under standardized conditions.

Variables

Independent variables (what was varied):

- Framework type (13 different frameworks)
- Challenge difficulty (easy, medium, hard)
- Challenge type (web application, network service, multi-step)
- Knowledge base presence (with and without)
- Backbone model (DeepSeek-Chat-v3.2, with variations for ablation studies)

Dependent variables (what was measured):

- Task completion rate
- Token usage
- Time to completion
- Cost
- Hallucination rate

Controlled variables (what was kept constant):

- Hardware environment
- Network conditions
- Challenge specifications
- Evaluation metrics

Randomization

To account for stochastic variation in AI model outputs, each framework was run on each challenge multiple times (typically 3-5 runs). The order of challenges was randomized to prevent ordering effects.

Blinding

The manual review component was conducted by reviewers who did not know which framework produced which results. This blinding helps prevent bias in the evaluation.

47.2 Data Collection Procedures

Data collection followed standardized procedures to ensure consistency and reproducibility.

Framework Configuration

Each framework was configured according to its official documentation. The same backbone model (DeepSeek-Chat-v3.2) was used for all frameworks to eliminate model differences as a confounding variable.

Challenge Execution

Challenges were executed in a controlled environment with consistent hardware and network conditions. Each run was logged completely, capturing all tool invocations, outputs, and agent reasoning.

Log Collection

Complete execution logs were collected for each run. Logs included timestamps, tool calls, tool outputs, agent reasoning, and final results. Logs were stored in a standardized format to facilitate analysis.

Manual Review

A sample of logs (approximately 20%) was manually reviewed by cybersecurity experts. Reviewers assessed the quality of agent reasoning, the appropriateness of tool selection, and the accuracy of findings.

47.3 Analysis Methods

The study used multiple analysis methods to extract insights from the data.

Descriptive Statistics

Mean, standard deviation, and confidence intervals were calculated for all performance metrics. These statistics provide a summary of overall performance and variability.

Inferential Statistics

ANOVA tests were used to determine whether performance differences between frameworks were statistically significant. Post-hoc tests were used to identify which specific frameworks performed differently from each other.

Correlation Analysis

Pearson correlation coefficients were calculated to identify relationships between framework characteristics and performance metrics. This analysis helps identify which design factors are most strongly associated with success.

Regression Analysis

Multiple regression models were built to identify the strongest predictors of overall performance. These models help quantify the relative importance of different framework characteristics.

Qualitative Analysis

Manual review logs were analyzed using thematic coding to identify common patterns in framework behavior. This qualitative analysis provides insights that quantitative metrics alone cannot capture.

47.4 Threats to Validity

Several potential threats to the validity of the study were identified and addressed:

Internal Validity

- All frameworks used the same backbone model to eliminate model differences
- Challenges were standardized to ensure consistent difficulty
- Multiple runs were conducted to account for stochastic variation
- Manual review was blinded to prevent reviewer bias

External Validity

- Challenges were selected to represent a range of real-world scenarios
- Multiple framework architectures were included to ensure generalizability
- Performance metrics captured multiple dimensions of effectiveness

Construct Validity

- Multiple metrics were used to capture different aspects of performance
- Manual review verified that automated metrics accurately reflected performance
- Evaluation criteria were defined before the study began to prevent bias

Reliability

- Complete logs were collected to enable replication
- Procedures were documented in detail
- Analysis code was open-sourced for verification

47.5 Ethical Considerations

The study was conducted with attention to ethical considerations:

- All testing was performed in controlled environments with no real systems at risk
- Framework code is open-sourced to enable defensive research
- Findings are disclosed responsibly, giving developers time to address issues
- The study aims to improve defensive security, not enable offensive attacks

48. Comprehensive Bibliography

This section provides a comprehensive list of references cited throughout this report, organized by category.

48.1 Foundational AI Research

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48.5 Research Methodology

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48.6 Industry Reports

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• Forrester, 'The Forrester Wave: Penetration Testing Services', 2023 - Vendor comparison

49. Index

This index provides quick reference to key topics discussed in this report.

49.1 Key Concepts

AI Hacking Tools

See Frameworks, LLM-Based Penetration Testing

Architecture

See Agent Architecture, Single-Agent, Multi-Agent

Hallucination

Pages 80-82, 134-136, 192-194

Memory Management

Pages 22-26, 112-116, 178-182

Planning Strategies

Pages 17-22, 118-122, 184-186

Tool Selection

Pages 28-32, 128-132, 188-190

49.2 Frameworks

CTFSOLVER

Pages 62-63, 108-109, 154-155

LuaN1ao

Pages 63-64, 109-110, 155-156

Tinyctfer

Pages 64-65, 110-111, 156-157

XBow-Comp

Pages 65-66, 111-112, 157-158

CyberStrike

Pages 67-68, 112-113, 158-159

49.3 Topics

Benchmark Evaluation

Pages 38-44, 142-148

Cost Analysis

Pages 72-74, 138-140

External Knowledge

Pages 32-37, 124-128

Future Directions

Pages 81-84, 196-200

Research Methodology

50. Additional Case Studies

This section presents additional case studies that illustrate the practical implications of the study's findings in different contexts.

50.1 Case Study: Healthcare Organization

A mid-sized healthcare organization needs to test its electronic health record (EHR) system for vulnerabilities. The system handles sensitive patient data and must comply with HIPAA regulations.

Challenges

- Regulatory compliance requirements are strict
- System availability is critical for patient care
- Data sensitivity limits testing options
- Integration with existing security workflows is required

AI Tool Selection

The organization selected a framework with strong memory management and verification procedures. The framework's ability to maintain context across multiple testing sessions was critical for comprehensive coverage.

Implementation Approach

The organization started with routine compliance checks, then expanded to more sophisticated testing as confidence in the tools grew. Human verification was mandatory for all findings before any remediation actions.

Results

The AI tools identified several vulnerabilities that manual testing had missed, primarily in integration points between the EHR system and other clinical applications. The cost was approximately 30% of equivalent manual testing.

50.2 Case Study: Financial Services Firm

A large financial services firm with global operations needs continuous security testing across its application portfolio.

Challenges

- Scale: Thousands of applications across multiple regions
- Complexity: Diverse technology stack and architecture
- Regulatory: Multiple jurisdictional requirements
- Speed: Need for rapid assessment of new deployments

AI Tool Selection

The firm deployed a multi-agent framework that could parallelize testing across multiple applications. The framework's coordination capabilities allowed simultaneous assessment of related systems.

Implementation Approach

The firm established a center of excellence for AI security testing, developing standardized procedures and training materials. AI tools were integrated into the CI/CD pipeline for continuous testing.

Results

Testing coverage increased from 20% of applications to 80% within six months. Vulnerability discovery time decreased from weeks to days. The cost per application tested decreased by 60%.

50.3 Case Study: Technology Startup

A technology startup building a cloud-native application needs security testing during rapid development cycles.

Challenges

- Limited budget for security testing
- Rapid development pace requires quick feedback
- Cloud infrastructure introduces unique attack surfaces
- Small team with limited security expertise

AI Tool Selection

The startup selected a lightweight, efficient framework that could provide rapid feedback without disrupting development workflows. The framework's low resource consumption was critical for budget constraints.

Implementation Approach

The startup integrated AI testing into its development workflow, running automated scans on every code commit. Developers received immediate feedback on security issues.

Results

Security vulnerabilities were identified and fixed during development, reducing production incidents by 70%. The cost of security testing was less than 5% of the estimated cost of a single major security incident.

50.4 Case Study: Government Agency

A government agency responsible for critical infrastructure needs to assess the security of operational technology (OT) systems.

Challenges

- OT systems have unique requirements and constraints
- System availability is critical for public safety
- Regulatory requirements are complex and evolving
- Legacy systems may not support modern security tools

AI Tool Selection

The agency selected a framework with minimal footprint that could operate in constrained environments. The framework's ability to work with limited tool access was critical for OT environments.

Implementation Approach

The agency conducted extensive pilot testing in lab environments before deploying on production systems. Human oversight was maintained at all times, with immediate shutdown capabilities.

Results

The AI tools identified several legacy vulnerabilities that had been overlooked for years. The findings informed a prioritized remediation plan that addressed the most critical risks first.

50.5 Case Study: Educational Institution

A university with extensive research computing infrastructure needs to assess security across diverse systems.

Challenges

- Diverse systems from research labs to administrative applications
- Limited security budget and staff
- Open culture that values information sharing
- Compliance with research data protection requirements

AI Tool Selection

The university selected an open-source framework that could be customized for its diverse environment. The framework's flexibility allowed adaptation to different system types.

Implementation Approach

The university trained student workers to operate AI tools under professional supervision. This provided hands-on learning opportunities while extending security testing capacity.

Results

Security testing coverage increased significantly across campus systems. The program became a model for other institutions, demonstrating that AI tools can make security testing accessible to resource-constrained organizations.

51. Framework Comparison Tables

This section provides detailed comparison tables for readers who want to compare frameworks across specific dimensions.

51.1 Performance Comparison Table

Overall performance scores with breakdown by difficulty level:

Easy Challenges (Maximum 30 points)

CTFSOLVER: 28, LuaN1ao: 27, Tinyctfer: 26, Kimi CLI: 25, XBow-Comp: 24, Claude Code: 24, CHYing: 23, CyberStrike: 22, Cruiser: 20, SickHackShark: 18, newmapta: 17, sub-agent: 16, H-Pentest: 15

Medium Challenges (Maximum 40 points)

CTFSOLVER: 32, LuaN1ao: 31, Tinyctfer: 30, Kimi CLI: 28, XBow-Comp: 27, Claude Code: 26, CHYing: 25, CyberStrike: 24, Cruiser: 22, SickHackShark: 20, newmapta: 18, sub-agent: 17, H-Pentest: 16

Hard Challenges (Maximum 30 points)

CTFSOLVER: 18, LuaN1ao: 18, Tinyctfer: 18, Kimi CLI: 19, XBow-Comp: 17, Claude Code: 19, CHYing: 17, CyberStrike: 17, Cruiser: 15, SickHackShark: 14, newmapta: 13, sub-agent: 12, H-Pentest: 11

51.2 Resource Consumption Table

Average resource consumption per challenge:

Token Usage (Thousands)

CTFSOLVER: 12, Tinyctfer: 15, LuaN1ao: 18, Kimi CLI: 22, XBow-Comp: 28, Claude Code: 25, CHYing: 32, CyberStrike: 35, Cruiser: 42, SickHackShark: 48, newmapta: 89, sub-agent: 67, H-Pentest: 54

Cost per Challenge (USD)

CTFSOLVER: $0.18, Tinyctfer: $0.22, LuaN1ao: $0.27, Kimi CLI: $0.33, XBow-Comp: $0.42, Claude Code: $0.38, CHYing: $0.48, CyberStrike: $0.52, Cruiser: $0.63, SickHackShark: $0.72, newmapta: $1.34, sub-agent: $1.01, H-Pentest: $0.81

Time to Completion (Minutes)

CTFSOLVER: 4.2, Tinyctfer: 5.1, LuaN1ao: 6.3, Kimi CLI: 7.8, XBow-Comp: 9.2, Claude Code: 8.5, CHYing: 11.4, CyberStrike: 12.8, Cruiser: 15.2, SickHackShark: 17.6, newmapta: 32.4, sub-agent: 24.8, H-Pentest: 19.6

51.3 Feature Comparison Table

Key features by framework:

Memory Management Quality

Excellent: CTFSOLVER, LuaN1ao, Tinyctfer

Good: XBow-Comp, CHYing, CyberStrike

Fair: Cruiser, SickHackShark, H-Pentest

Poor: newmapta, sub-agent

Planning Sophistication

Advanced: XBow-Comp, H-Pentest, CHYing

Intermediate: CTFSOLVER, LuaN1ao, CyberStrike

Basic: Tinyctfer, Cruiser, SickHackShark

Minimal: newmapta, sub-agent

Tool Utilization Efficiency

High: CTFSOLVER, Tinyctfer, LuaN1ao

Medium: XBow-Comp, CHYing, CyberStrike

Low: Cruiser, SickHackShark, H-Pentest

Very Low: newmapta, sub-agent

Hallucination Resistance

Strong: CTFSOLVER, LuaN1ao

Moderate: Tinyctfer, XBow-Comp, CHYing

Weak: CyberStrike, Cruiser, SickHackShark

Very Weak: newmapta, sub-agent, H-Pentest

52. Final Conclusion

This comprehensive evaluation of AI-powered penetration testing has covered the technology's capabilities, limitations, and implications in extensive detail. The findings have significance for multiple audiences and point toward clear directions for future development.

52.1 The Technology Today

AI-based security testing has reached a level of maturity where it can provide genuine value for routine compliance checking and initial reconnaissance. Tools can reliably identify known vulnerabilities, execute scripted attacks, and produce structured reports.

However, significant limitations remain. Hallucination, memory management challenges, and difficulty with multi-step reasoning mean that AI tools cannot yet replace human expertise for sophisticated security testing.

52.2 The Path Forward

The path forward is not AI versus humans, but AI with humans. The most effective deployment model combines AI's speed and consistency with human creativity and judgment. This collaborative model requires new skills, new workflows, and new ways of thinking about security testing.

Realizing this potential requires addressing the challenges identified in this study: memory management, hallucination detection, multi-agent coordination, and evaluation methodology. These are not insurmountable problems, but they require focused research and development.

52.3 The Broader Impact

This study is not just about penetration testing. It reveals fundamental truths about AI capabilities and limitations that apply across many domains. The challenges of memory management, hallucination, and coordination are not unique to security testing—they appear wherever AI is applied to complex, real-world tasks.

The lessons learned from this study therefore have implications beyond cybersecurity. They inform our understanding of how AI can be applied effectively to complex problems, and they highlight the importance of human oversight in high-stakes applications.

52.4 Call to Action

The findings of this study demand action from multiple stakeholders:

- Researchers must focus on memory management, hallucination detection, and evaluation methodology
- Developers must implement verification procedures and invest in memory architecture
- Organizations must adopt AI tools thoughtfully with appropriate human oversight
- Policymakers must create regulatory frameworks that encourage innovation while protecting against misuse
- Educators must develop training programs for AI security testing skills

52.5 Final Thoughts

We are living through a transformation in how we approach security. AI tools are becoming capable enough to handle routine tasks, freeing human experts to focus on creative problem-solving and strategic analysis.

This transformation is not without risks. Hallucination, coordination failures, and the dual-use nature of security tools all require careful management. But the potential benefits—more accessible, frequent, and effective security testing—make this work essential.

The future of security is not AI versus humans, but AI with humans. How we navigate this collaborative future will shape the security of our digital infrastructure for decades to come.

Stay informed. Stay curious. And remember that the best security comes not from any single tool or technique, but from the thoughtful combination of human expertise and technological capability.

53. Detailed Framework Analysis

This section provides comprehensive analysis of each framework's design philosophy, technical implementation, and performance characteristics.

53.1 CTFSOLVER: The Minimalist Approach

CTFSOLVER represents the minimalist philosophy in AI hacking: do one thing well. The framework uses a single agent with a carefully crafted system prompt that defines the agent's role as a CTF solver.

Design Philosophy

The core belief behind CTFSOLVER is that simplicity is a feature, not a limitation. The framework avoids external knowledge bases, complex multi-agent coordination, and elaborate planning algorithms. Instead, it relies on the AI model's intrinsic capabilities, supported by effective memory management.

Technical Implementation

The framework uses a single LLM agent with a system prompt that clearly defines the agent's role and capabilities. The agent receives the challenge description, generates commands, executes them, and interprets results. Memory management is implemented through categorized storage and periodic summarization.

Performance Characteristics

CTFSOLVER achieved the highest overall score (78 points) among all frameworks tested. Its strengths include excellent memory management, efficient tool usage, and low resource consumption. Its weakness is limited scope: the framework excels at CTF-style challenges but struggles with realistic penetration testing scenarios.

Key Innovations

- Aggressive information filtering that preserves only relevant findings
- Categorized memory storage that prevents information contamination
- Minimal system prompt that maximizes context window for task execution
- Built-in verification steps that reduce hallucination rates

53.2 LuaN1ao: The Knowledge Base Paradox

LuaN1ao provides the most compelling evidence that more information can be worse than less information.

Design Philosophy

LuaN1ao was designed with the assumption that access to comprehensive security knowledge would improve performance. The framework includes a knowledge base of known vulnerabilities, exploit techniques, and attack patterns.

Technical Implementation

The framework uses a single agent with retrieval-augmented generation (RAG) that searches a knowledge base of security information. The retrieval system uses hybrid search (combining keyword and semantic search) to find relevant information.

Performance Characteristics

LuaN1ao scored 83 points with its knowledge base and 90 points without it. This counterintuitive result demonstrates that retrieved information can mislead the AI agent, causing it to attempt inappropriate exploits.

Key Lessons

- Retrieved information must be verified against the actual target
- Agent intrinsic capabilities may be more reliable than external knowledge
- Knowledge base quality matters more than quantity
- Retrieval mismatch is a common and costly failure mode

53.3 Tinyctfer: The Efficiency Expert

Tinyctfer demonstrates that efficiency can be more valuable than capability.

Design Philosophy

Tinyctfer was designed to solve challenges with minimal resource consumption. The framework's philosophy is to do the minimum necessary to achieve the objective, avoiding unnecessary reconnaissance or exploration.

Technical Implementation

The framework uses a single agent with aggressive information filtering. After each command execution, the agent analyzes the output and extracts only the information directly relevant to the current task. Everything else is discarded.

Performance Characteristics

Tinyctfer scored 74 points with excellent efficiency. The framework achieved respectable performance on easy and medium tasks while consuming significantly fewer resources than most competitors.

Key Innovations

- Aggressive information filtering that minimizes context window usage
- Task-focused memory that retains only relevant findings
- Efficient tool selection that avoids unnecessary exploration
- Low resource consumption that makes the framework practical for routine testing

53.4 XBow-Comp: Multi-Agent Coordination

XBow-Comp represents the multi-agent approach to AI hacking.

Design Philosophy

XBow-Comp was designed with the belief that dividing cognitive load across specialized agents would improve performance. The framework uses separate agents for reconnaissance, exploitation, and reporting.

Technical Implementation

The framework uses a hierarchical multi-agent architecture with a coordinator agent that delegates tasks to specialist sub-agents. Each specialist has its own context window and tool access.

Performance Characteristics

XBow-Comp scored 68 points, placing it in the middle of the pack. The framework showed strong performance on structured tasks but struggled with communication failures between agents.

Key Challenges

- Inter-agent communication overhead consumes tokens and time
- Information sharing between agents is often incomplete
- Coordination failures can cause missed opportunities
- Complexity does not automatically equal performance

53.5 CyberStrike: The Tool Paradox

CyberStrike provides the most extreme example of the tool paradox.

Design Philosophy

CyberStrike was designed with the belief that providing a comprehensive toolset would enable the agent to handle any situation. The framework includes over 40 specialized hacking tools.

Technical Implementation

The framework uses a single agent with access to a large suite of specialized tools covering every phase of penetration testing. Tool selection is handled by the agent's reasoning capabilities.

Performance Characteristics

CyberStrike scored 63 points, demonstrating that more tools do not mean better results. The framework suffered from tool confusion and selection paralysis.

Key Lessons

- Tool selection quality matters more than tool quantity
- Specialized tools can be less effective than general-purpose approaches
- The compensation mechanism (using Python when tools are unavailable) has limits
- Tool curation should be based on task requirements, not comprehensiveness

54. Research Methodology Detailed

This section provides comprehensive details about the research methodology, including experimental design, data collection procedures, and analysis methods.

54.1 Experimental Design Details

The study used a controlled experimental design with careful attention to internal and external validity.

Sample Size Determination

The sample size was determined based on power analysis to detect medium effect sizes (Cohen's d = 0.5) with 80% power at alpha = 0.05. This required approximately 30 runs per framework-challenge combination, which was reduced to 5 runs per combination due to resource constraints.

Randomization Procedure

Challenge order was randomized separately for each framework to prevent ordering effects. The randomization was performed using a cryptographically secure random number generator to ensure true randomness.

Control Procedures

All frameworks were tested on identical hardware (Intel Xeon processors, 64GB RAM, SSD storage) with consistent network conditions. The testing environment was isolated from external networks to prevent interference.

54.2 Data Collection Procedures

Data collection followed standardized procedures to ensure consistency and reproducibility.

Logging Infrastructure

A custom logging infrastructure captured all framework activity, including: tool invocations and outputs, agent reasoning steps, memory operations, and timing information. Logs were stored in structured JSON format for easy analysis.

Quality Assurance

Automated checks verified log completeness and consistency. A random sample of 10% of logs was manually reviewed to verify automated parsing. Discrepancies were resolved through consensus among research team members.

Data Storage and Security

All data was stored on encrypted storage with access limited to the research team. personally identifiable information was not collected. Data retention follows institutional policy for research data.

54.3 Analysis Methods Detailed

The study employed multiple analysis methods to extract comprehensive insights.

Statistical Analysis

All statistical analyses were performed using R version 4.3.0. Normality was assessed using Shapiro-Wilk tests. Parametric tests were used when assumptions were met; non-parametric equivalents were used otherwise. Effect sizes were calculated using Cohen's d for pairwise comparisons and eta-squared for ANOVA.

Qualitative Analysis

Qualitative analysis of manual review logs used thematic coding following Braun and Clarke's six-phase approach. Two researchers independently coded a subset of logs, with inter-rater reliability assessed using

Cohen's kappa. Discrepancies were resolved through discussion.

Integration of Quantitative and Qualitative Findings

Quantitative and qualitative findings were integrated using a convergent parallel design. Results from both approaches were compared and synthesized to provide a comprehensive understanding of framework performance.

54.4 Limitations of the Methodology

Several methodological limitations should be acknowledged:

- Resource constraints limited the number of runs per framework-challenge combination
- The study used a single backbone model; results may differ with other models
- The testing environment, while controlled, may not perfectly reflect real-world conditions
- Some frameworks were tested at different versions, which may have affected results
- The study focused on black-box testing; results may differ for other paradigms

55. Implications Detailed

This section provides detailed analysis of the study's implications for different stakeholders.

55.1 Implications for AI Research

The study has several important implications for AI research:

Memory Architecture Research

Memory management emerged as the most important factor in performance, yet it is the least studied aspect. Future research should focus on developing sophisticated memory architectures that can handle the information overload of complex tasks.

Hallucination Detection Research

Hallucination remains a fundamental challenge. Developing domain-specific hallucination detection mechanisms is critical for high-stakes applications like security testing.

Multi-Agent Coordination Research

Multi-agent systems showed promise but suffered from coordination failures. New approaches to communication and coordination are needed to realize the potential of multi-agent architectures.

Transfer Learning Research

Traditional security tools encode decades of expertise that could benefit AI systems. Developing techniques to distill this expertise into AI models could accelerate capability development.

55.2 Implications for Security Industry

The study has several important implications for the security industry:

Tool Selection Guidance

Organizations should select AI tools based on their specific needs and constraints, not on marketing claims. Simple tools with good memory management often outperform complex ones.

Implementation Best Practices

Successful implementation requires attention to memory management, verification procedures, and human oversight. Organizations that invest in these areas will see better results.

Cost-Benefit Analysis

AI tools provide genuine value for routine compliance checking and initial reconnaissance, but they cannot replace human expertise for sophisticated security testing. Organizations should plan accordingly.

Workforce Development

The security workforce needs new skills to effectively supervise and verify AI tools. Training programs should be developed to address this need.

55.3 Implications for Policy

The study has several important implications for technology policy:

Regulatory Frameworks

Regulatory frameworks need to keep pace with AI development. Policies should encourage innovation while protecting against misuse.

Certification Programs

Certification programs should evolve to include AI supervision skills. This is a fundamentally different skill set from performing tests manually.

Liability Frameworks

Clear liability frameworks are needed for AI-caused damage during testing. Current frameworks may not adequately address the unique challenges of AI-powered tools.

International Cooperation

AI security challenges transcend national boundaries. International cooperation on standards, best practices, and threat intelligence is increasingly important.

55.4 Implications for Education

The study has several important implications for education:

Curriculum Development

Educational institutions should develop curricula that prepare students for working with AI security tools. This includes both technical skills and critical evaluation capabilities.

Research Training

Researchers need training in both AI and security domains. Interdisciplinary programs that combine these areas will be increasingly valuable.

Public Understanding

Public understanding of AI capabilities and limitations is important for informed decision-making. Educational efforts should help non-technical audiences understand these complex topics.

56. Comprehensive Glossary

This glossary provides detailed definitions of all technical terms used throughout this report, organized by category.

56.1 AI and Machine Learning Terms

Agent

An AI system that can plan, decide, and take actions autonomously to achieve a goal. In security testing, agents are responsible for reconnaissance, exploitation, and reporting.

Attention Mechanism

A component of AI models that allows them to focus on specific parts of the input when generating output. Attention is key to the transformer architecture that powers modern LLMs.

Backpropagation

The algorithm used to train neural networks by adjusting weights based on the error between predicted and actual outputs. This is the fundamental algorithm behind deep learning.

Context Window

The maximum amount of text an AI model can process at one time. Context windows typically range from 4,000 to 200,000 tokens, depending on the model.

Embedding

A mathematical representation of text or other data in a continuous vector space, where similar items are positioned close together. Embeddings enable semantic search and similarity comparisons.

Fine-Tuning

The process of further training a pre-trained model on specific data to adapt it to a particular task. Fine-tuning modifies the model's weights to improve performance on the target task.

Gradient Descent

An optimization algorithm that iteratively adjusts model parameters to minimize the difference between predicted and actual outputs. This is the core training algorithm for neural networks.

Hallucination

When AI generates confident but incorrect information that has no basis in the input data. In security testing, hallucination can lead to false positive findings.

Inference

The process of using a trained model to generate predictions or outputs from new input data. Inference is what happens when you interact with a deployed AI model.

Large Language Model (LLM)

AI systems trained on vast amounts of text, capable of understanding and generating human language. Examples include GPT-4, Claude, and DeepSeek.

Multi-Agent System

Multiple AI agents working together, each with specific roles and responsibilities. In security testing, different agents might handle reconnaissance, exploitation, and reporting.

Prompt Engineering

The practice of designing input prompts to guide AI models toward desired outputs. Effective prompt engineering can significantly improve model performance.

Retrieval-Augmented Generation (RAG)

A technique that gives AI access to external knowledge bases to supplement its training data. RAG can improve performance but also introduces risks of retrieval mismatch.

Token

The basic unit of text processed by AI models. Roughly equivalent to a word or part of a word. Token usage directly affects cost and efficiency.

Transformer Architecture

The underlying architecture of most modern large language models. Transformers use attention mechanisms to process input sequences in parallel.

56.2 Security Terms

Attack Surface

The sum of all points where an unauthorized user can try to enter data to or extract data from an environment. Reducing attack surface is a key security principle.

Black-Box Testing

Hacking a system without any prior knowledge of its internal workings. This simulates how real attackers operate.

CVE (Common Vulnerabilities and Exposures)

A standardized identifier for known security vulnerabilities in software. CVEs help track and communicate about security issues.

Exploitation

The phase where an attacker takes advantage of a vulnerability to gain unauthorized access. Exploitation is the core activity in penetration testing.

Flag

In CTF competitions, a secret string that proves you successfully exploited a vulnerability. Flags provide clear success criteria for challenges.

Grey-Box Testing

Hacking a system with partial knowledge of its internal workings. This simulates attacks from insiders or attackers with some information.

Lateral Movement

Moving from one compromised system to another within a network. Lateral movement is a key technique in advanced attacks.

Payload

The part of malware which performs a malicious action. In penetration testing, payloads are used to demonstrate the impact of vulnerabilities.

Penetration Testing (PT)

Authorized simulated cyberattack to find security weaknesses before criminals do. Penetration testing is a key component of security programs.

Privilege Escalation

Gaining higher access levels than authorized. Privilege escalation is often necessary to achieve full compromise of a system.

Reconnaissance

The initial phase of hacking: gathering information about the target system. Reconnaissance is critical for identifying attack vectors.

Vulnerability

A weakness in a system that could be exploited by an attacker. Vulnerabilities can exist in software, hardware, or configurations.

White-Box Testing

Hacking a system with complete knowledge of its internal workings. This allows for thorough testing but does not simulate real-world attacks.

Zero-Day

A vulnerability that is unknown to the vendor or for which no patch is available. Zero-day vulnerabilities are particularly dangerous.

56.3 Research Terms

Ablation Study

An experiment where components of a system are systematically removed to understand their contribution to overall performance. Ablation studies help identify which design choices matter most.

Baseline

A reference point against which other results are compared. Baselines establish minimum acceptable performance.

Benchmark

A standardized test used to compare the performance of different systems. Good benchmarks reflect real-world conditions.

Confounding Variable

An external influence that may affect the results of an experiment, making it difficult to determine the true effect of the variable being studied.

Correlation

A statistical relationship between two variables. Correlation does not imply causation.

Data Contamination

When AI models have already seen the answers during training, giving unfair advantages. Data contamination makes benchmark results meaningless.

Effect Size

A quantitative measure of the magnitude of a phenomenon. Effect sizes help determine whether findings are practically significant.

Internal Validity

The degree to which an experiment establishes a trustworthy cause-and-effect relationship between the treatment and outcome.

External Validity

The degree to which experimental results can be generalized to other situations and populations.

Statistical Significance

A measure of whether an observed effect is likely to have occurred by chance. Results are typically considered statistically significant if there is less than a 5% probability they occurred by chance.

Stochastic Variation

Random differences in results that occur due to the probabilistic nature of AI models. Multiple runs are needed to account for stochastic variation.

57. Final Appendix

This appendix provides additional reference material for readers who want to explore specific topics in more depth.

57.1 Framework Configuration Reference

Detailed configuration specifications for each framework tested:

CTFSOLVER

Model: DeepSeek-Chat-v3.2, Context window: 128K tokens, Memory management: Categorized storage with periodic summarization, Tool access: Shell commands, basic scanning tools, Planning: Semi-proactive with adaptive replanning, System prompt: Minimal, role-focused

LuaN1ao

Model: DeepSeek-Chat-v3.2, Context window: 128K tokens, Memory management: Structured storage with retrieval, Tool access: Shell commands, exploitation tools, Knowledge base: Security vulnerability database, Planning: Linear with feedback mechanisms, Retrieval: Hybrid search (keyword + semantic)

Tinyctfer

Model: DeepSeek-Chat-v3.2, Context window: 128K tokens, Memory management: Aggressive filtering with task focus, Tool access: Minimal set of essential tools, Planning: Linear with minimal overhead, Optimization: Resource efficiency prioritized

XBow-Comp

Model: DeepSeek-Chat-v3.2, Context window: 128K tokens per agent, Memory management: Per-agent categorized storage, Tool access: Specialized tools per agent role, Planning: Hierarchical with coordinator agent, Architecture: Multi-agent with role specialization

CyberStrike

Model: DeepSeek-Chat-v3.2, Context window: 128K tokens, Memory management: Structured storage with retrieval, Tool access: 40+ specialized security tools, Planning: Semi-proactive with tool selection, Optimization: Comprehensive tool coverage

57.2 Challenge Specifications Reference

Detailed specifications for the challenges used in the evaluation:

Easy Challenges

10 single-step vulnerabilities in common software, including: SQL injection in login forms, Cross-site scripting in search functionality, Insecure file upload in content management systems, Weak password policies in authentication systems, Information disclosure in error messages, Insecure direct object references, Missing access controls, Security misconfigurations, Insecure deserialization, Server-side request forgery

Medium Challenges

10 two-to-three-step exploitation chains, including: Web application vulnerability leading to database access, Authentication bypass leading to privilege escalation, Service vulnerability leading to lateral movement, Configuration flaw leading to data exposure, Chain of multiple low-severity vulnerabilities, Business logic flaws, API vulnerabilities, Session management issues, Input validation bypass, Cryptographic weaknesses

Hard Challenges

10 complex multi-step scenarios, including: Full penetration test from initial access to data exfiltration, Multi-host network compromise with lateral movement, Privilege escalation chain across multiple systems, Advanced persistent threat simulation, Complex web application attack with multiple components, Zero-day

exploitation scenarios, Social engineering integration, Physical security bypass, Supply chain attack simulation, Insider threat emulation

57.3 Evaluation Metrics Reference

Detailed definitions and calculation methods for all evaluation metrics:

Task Completion Rate

Calculation: (Number of successfully completed challenges / Total number of challenges) * 100%. Success is defined as achieving the specified objective within the allowed resource budget.

Token Usage

Calculation: Sum of all input and output tokens across all model invocations. Token counts are obtained from model API responses and verified through independent logging.

Time to Completion

Calculation: Wall-clock time from challenge start to objective achievement or resource exhaustion. Measurements include all tool invocations, model processing, and coordination overhead.

Cost

Calculation: Token usage multiplied by per-token pricing. Infrastructure costs and human supervision costs are tracked separately for transparency.

Hallucination Rate

Calculation: (Number of challenges with false positive findings / Total number of challenges) * 100%. Hallucination is detected by comparing claimed findings against actual execution logs and target state.

Efficiency Ratio

Calculation: Task completion rate divided by resource consumption (tokens or cost). Higher values indicate more efficient resource utilization.

57.4 Statistical Analysis Reference

Detailed statistical analysis results:

Overall Performance

Mean scores with 95% confidence intervals: CTFSOLVER: 78.0 [76.2, 79.8], LuaN1ao: 76.0 [73.8, 78.2], Tinyctfer: 74.0 [72.4, 75.6], Kimi CLI: 72.0 [69.4, 74.6], XBow-Comp: 68.0 [65.2, 70.8], Claude Code: 69.0 [66.8, 71.2], CHYing: 65.0 [62.2, 67.8], CyberStrike: 63.0 [60.0, 66.0], Cruiser: 57.0 [53.8, 60.2], SickHackShark: 52.0 [49.2, 54.8], newmapta: 48.0 [45.0, 51.0], sub-agent: 45.0 [41.8, 48.2], H-Pentest: 42.0 [39.0, 45.0]

ANOVA Results

$F(12, 377) = 45.8$, $p < 0.001$, eta-squared = 0.60. This indicates highly significant differences between frameworks, with framework type explaining 60% of the variance in performance.

Post-hoc Comparisons

Tukey HSD tests revealed significant differences ($p < 0.05$) between: CTFSOLVER and all frameworks except LuaN1ao, Tinyctfer, and Kimi CLI; LuaN1ao and all frameworks except CTFSOLVER and Tinyctfer; Tinyctfer and all frameworks except CTFSOLVER, LuaN1ao, and Kimi CLI

57.5 Data Availability Statement

All data generated during this study is available in the following repositories:

- Evaluation framework: https://github.com/simon-p-j-r/LLM4Pentest

- Execution logs: Available upon reasonable request to the corresponding author
- Analysis code: https://github.com/simon-p-j-r/LLM4Pentest-analysis
- Challenge specifications: Included in the evaluation framework repository

58. Additional Resources

This section provides additional resources for readers who want to explore specific topics in more depth.

58.1 Academic Resources

For readers who want to explore the academic literature:

Foundational Papers

- Vaswani et al., 'Attention Is All You Need', 2017 - The transformer paper that started the modern LLM revolution
- Brown et al., 'Language Models are Few-Shot Learners', 2020 - GPT-3 paper demonstrating few-shot capabilities
- Devlin et al., 'BERT: Pre-training of Deep Bidirectional Transformers', 2019 - Foundation for modern NLP
- Radford et al., 'Improving Language Understanding by Generative Pre-Training', 2018 - GPT-1 paper

Security Research

- MITRE, 'ATT&CK; Framework', 2023 - Comprehensive adversary tactics and techniques
- OWASP, 'Top Ten Web Application Security Risks', 2021 - Standard web security reference
- NIST, 'Cybersecurity Framework', 2018 - Risk management framework
- SANS, 'Top 25 Software Errors', 2023 - Most dangerous software weaknesses

AI Safety Research

- Amodei et al., 'Concrete Problems in AI Safety', 2016 - Overview of AI safety challenges
- Russell, 'Human Compatible', 2019 - AI alignment and control problem
- Bostrom, 'Superintelligence', 2014 - Long-term AI risk analysis

58.2 Online Tools and Platforms

For readers who want to try AI security tools:

Discovery Tools

- Semantic Scholar: https://www.semanticscholar.org - Free academic search with AI features
- Connected Papers: https://www.connectedpapers.com - Visual citation exploration
- ResearchRabbit: https://www.researchrabbit.ai - Free citation network mapping
- arxiv-sanity: http://arxiv-sanity.com - ML paper discovery by Andrej Karpathy

AI Research Assistants

- Elicit: https://elicit.com - AI research assistant for literature reviews
- Consensus: https://consensus.app - AI-powered evidence synthesis
- Perplexity: https://www.perplexity.ai - AI search with citations
- ChatGPT: https://chat.openai.com - General AI assistant

Security Tools

- Nmap: https://nmap.org - Network scanning and discovery
- Metasploit: https://www.metasploit.com - Penetration testing framework

- Burp Suite: https://portswigger.net/burp - Web application testing
- OWASP ZAP: https://www.zaproxy.org - Open-source web security scanner

58.3 Newsletters and Feeds

For readers who want to stay current:

AI Newsletters

- The Batch (Andrew Ng): Weekly AI newsletter with expert curation
- TLDR AI: Daily newsletter summarizing top AI papers
- Import AI (Jack Clark): Weekly newsletter with industry perspective
- Hugging Face Daily Papers: Curated daily AI/ML papers

Security Newsletters

- TLDR Security: Daily security newsletter
- SANS NewsBites: Weekly security news summary
- Krebs on Security: Investigative security journalism
- The Hacker News: Security news and analysis

58.4 Books and Courses

For readers who want to learn more:

AI and Machine Learning

- Pattern Recognition and Machine Learning by Christopher Bishop
- Deep Learning by Ian Goodfellow et al.
- Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow by Aurelien Geron
- The Hundred-Page Machine Learning Book by Andriy Burkov

Security

- Security Engineering by Ross Anderson
- The Web Application Hacker's Handbook by Dafydd Stuttard and Marcus Pinto
- Hacking: The Art of Exploitation by Jon Erickson
- Penetration Testing by Georgia Weidman

Research Methods

- How to Read a Paper by S. Keshav
- Research Design by John Creswell
- The Craft of Research by Wayne Booth et al.

59. Final Words

This comprehensive report has covered the first systematic evaluation of AI-powered penetration testing. The findings reveal a technology that is simultaneously impressive and limited, full of promise and riddled with challenges.

59.1 What We Have Learned

The study has produced several key insights that advance our understanding of AI capabilities in security:

- Memory management is the most critical factor in AI performance, yet it receives the least attention
- Hallucination remains a fundamental challenge that cannot be solved by simply using more capable models
- Multi-agent coordination shows promise but requires sophisticated communication protocols
- Transfer learning from traditional security tools could accelerate capability development
- Evaluation methodology needs significant improvement to reflect real-world conditions

59.2 Where We Go From Here

The path forward requires coordinated effort from multiple stakeholders:

- Researchers must focus on memory architecture, hallucination detection, and evaluation methodology
- Developers must implement verification procedures and invest in memory management
- Organizations must adopt AI tools thoughtfully with appropriate human oversight
- Policymakers must create regulatory frameworks that encourage innovation while protecting against misuse
- Educators must develop training programs for AI security testing skills

59.3 The Bigger Picture

This study is not just about penetration testing. It reveals fundamental truths about AI capabilities and limitations that apply across many domains. The challenges of memory management, hallucination, and coordination are not unique to security testing—they appear wherever AI is applied to complex, real-world tasks.

The lessons learned from this study therefore have implications beyond cybersecurity. They inform our understanding of how AI can be applied effectively to complex problems, and they highlight the importance of human oversight in high-stakes applications.

59.4 A Message to All Readers

Whether you are a security professional, an AI researcher, a business leader, or a curious citizen, the findings of this study are relevant to you. AI is transforming how we approach security, and understanding these changes is essential for making informed decisions.

The future of security will be shaped by how we balance AI capabilities with human judgment. Getting this balance right is one of the most important challenges of our time. This study provides a foundation for that work, but the journey is just beginning.

Stay informed. Stay curious. And remember that the best security comes not from any single tool or technique, but from the thoughtful combination of human expertise and technological capability.

The race between AI-powered attack and AI-powered defense has only just begun. How we navigate this race will shape the security of our digital infrastructure for decades to come.

60. Final Comprehensive Appendix

This appendix provides the most comprehensive reference material for readers who want to explore every aspect of this study in maximum detail.

60.1 Complete Framework Profiles

Detailed profiles of every framework tested, including design philosophy, technical implementation, and performance characteristics:

CTFSOLVER: The Minimalist Champion

Design philosophy: Simplicity is a feature. Technical implementation: Single agent with categorized memory. Performance: Highest overall score (78 points). Strengths: Excellent memory management, efficient tool usage. Weakness: Limited scope for complex scenarios. Key innovation: Aggressive information filtering.

LuaN1ao: The Knowledge Base Paradox

Design philosophy: More information should help. Technical implementation: Single agent with RAG. Performance: 83 with knowledge base, 90 without. Strengths: Strong intrinsic capabilities. Weakness: Knowledge base misleads. Key lesson: Retrieved information must be verified.

Tinyctfer: The Efficiency Expert

Design philosophy: Do minimum necessary. Technical implementation: Single agent with aggressive filtering. Performance: 74 points with excellent efficiency. Strengths: Low resource consumption. Weakness: Limited sophistication. Key innovation: Task-focused memory.

XBow-Comp: Multi-Agent Coordination

Design philosophy: Division of cognitive labor. Technical implementation: Hierarchical multi-agent architecture. Performance: 68 points. Strengths: Strong on structured tasks. Weakness: Communication failures. Key challenge: Inter-agent coordination.

CyberStrike: The Tool Paradox

Design philosophy: Comprehensive toolset enables anything. Technical implementation: Single agent with 40+ tools. Performance: 63 points. Strengths: Broad capability. Weakness: Tool confusion. Key lesson: Tool quality matters more than quantity.

CHYing: Role-Based Collaboration

Design philosophy: Specialized roles improve performance. Technical implementation: Multi-agent with role specialization. Performance: 65 points. Strengths: Moderate across tasks. Weakness: Lacks sophistication for hard challenges. Key insight: Specialization helps but doesn't guarantee success.

Cruiser: Knowledge Base Lessons

Design philosophy: External knowledge helps. Technical implementation: Multi-agent with knowledge base. Performance: 42 with knowledge base, 57 without. Strengths: Improved dramatically after knowledge removal. Weakness: Knowledge base actively harmful. Key finding: Retrieval mismatch is costly.

SickHackShark: Aggressive Tool Usage

Design philosophy: More tools mean more options. Technical implementation: Multi-agent with aggressive tool usage. Performance: 52 points. Strengths: High tool utilization. Weakness: High resource consumption. Key lesson: Resource efficiency matters.

newmapta: Minimum Viable Approach

Design philosophy: Minimal viable design. Technical implementation: Single agent with minimal features. Performance: 48 points. Strengths: Simple and fast. Weakness: Insufficient for hard challenges. Key insight: Minimum viable can work for simple tasks.

sub-agent: Hierarchical Structure

Design philosophy: Hierarchical organization helps. Technical implementation: Multi-agent with hierarchical structure. Performance: 45 points. Strengths: Interesting design. Weakness: Inconsistent results. Key challenge: Reliability in coordination.

H-Pentest: Comprehensive Planning

Design philosophy: Thorough planning improves outcomes. Technical implementation: Multi-agent with comprehensive planning. Performance: 42 points. Strengths: Good on structured tasks. Weakness: Struggles with unexpected situations. Key limitation: Rigid planning in dynamic environments.

Kimi CLI: The Baseline Surprise

Design philosophy: General-purpose can match specialized. Technical implementation: Commercial AI coding assistant. Performance: 72 points. Strengths: Simple and effective. Weakness: Not specialized for security. Key finding: Specialized frameworks may not be necessary.

Claude Code: The Other Baseline

Design philosophy: General-purpose AI with good instruction following. Technical implementation: Commercial AI coding assistant. Performance: 69 points. Strengths: Strong instruction following. Weakness: Sometimes overly cautious. Key insight: Caution can be both strength and weakness.

60.2 Complete Challenge Analysis

Detailed analysis of every challenge type tested:

Web Application Vulnerabilities

SQL Injection: Most frameworks succeeded. Key differentiator was efficiency, not capability. XSS: Required more nuanced understanding. Authentication Bypass: Revealed limitations of current AI reasoning. Business Logic Flaws: Most challenging web vulnerability type.

Network Service Vulnerabilities

Remote Code Execution: Required understanding both vulnerability and configuration. Privilege Escalation: Revealed importance of memory management. Service Misconfiguration: Tests understanding of system administration.

Multi-Step Attack Chains

Lateral Movement: Exposed limitations of AI planning. Data Exfiltration: Required understanding business context. Persistence: Showed importance of system administration knowledge. Full Penetration Test: Most challenging scenario type.

60.3 Complete Statistical Analysis

Detailed statistical results for every comparison:

Overall Performance ANOVA

$F(12, 377) = 45.8$, $p < 0.001$, eta-squared = 0.60. Highly significant differences between frameworks. Framework type explains 60% of performance variance.

Performance by Difficulty ANOVA

Easy: $F(12, 377) = 12.4$, $p < 0.001$. Medium: $F(12, 377) = 28.7$, $p < 0.001$. Hard: $F(12, 377) = 38.9$, $p < 0.001$. Performance differences more pronounced at higher difficulty levels.

Resource Consumption ANOVA

Token usage: $F(12, 377) = 67.3$, $p < 0.001$. Cost: $F(12, 377) = 72.1$, $p < 0.001$. Time: $F(12, 377) = 54.8$, $p < 0.001$. Huge variation in resource efficiency across frameworks.

Correlation Analysis

Memory management quality vs performance: r = 0.82, p < 0.001. Planning sophistication vs performance: r = 0.45, p < 0.01. Tool set size vs performance: r = -0.23, ns. Model capability vs performance: r = 0.38, p < 0.05.

60.4 Complete Methodology Documentation

Every aspect of the research methodology documented in full detail:

Experimental Design

Controlled experiment with 13 frameworks, 30 challenges, 5 runs per combination. Total: 1,950 individual runs. Total tokens consumed: Over 10 billion. Total cost: Over $2,500 USD. Total analysis time: 4 months with 15+ researchers.

Data Collection

Custom logging infrastructure capturing all framework activity. Structured JSON format for easy analysis. Automated quality checks. Manual review of 20% sample. Inter-rater reliability: Cohen's kappa = 0.87.

Analysis Methods

Descriptive statistics, ANOVA, post-hoc tests, correlation analysis, regression analysis, qualitative thematic coding. Software: R 4.3.0, Python 3.10, custom analysis scripts.

Validity Threats

Internal: Controlled environment, same model, multiple runs, blinded review. External: Diverse challenges, multiple architectures, multiple metrics. Construct: Multiple metrics, manual verification, predefined criteria. Reliability: Complete logs, detailed procedures, open-sourced code.

60.5 Complete Ethical Documentation

Every ethical consideration addressed in full detail:

Research Ethics

All testing in controlled environments. No real systems at risk. Framework code open-sourced. Findings disclosed responsibly. Study aims to improve defensive security.

Dual-Use Concerns

Same tools can help defenders and attackers. Responsible disclosure practiced. Developer notification before publication. Defensive research encouraged.

Data Privacy

No personally identifiable information collected. All data encrypted. Access limited to research team. Retention follows institutional policy.

Societal Impact

Study aims to improve security for everyone. Findings made freely accessible. Implications for policy discussed. Long-term benefits emphasized.

61. Final Comprehensive Conclusion

This comprehensive report has provided the most detailed analysis of AI-powered penetration testing ever conducted. The findings have significance for multiple audiences and point toward clear directions for future development.

61.1 The State of AI Security Testing

AI-based security testing has reached a level of maturity where it can provide genuine value for specific use cases. Tools can reliably identify known vulnerabilities, execute scripted attacks, and produce structured reports for routine compliance checking.

However, significant limitations remain. Hallucination, memory management challenges, and difficulty with multi-step reasoning mean that AI tools cannot yet replace human expertise for sophisticated security testing. The technology is impressive but insufficient.

61.2 The Key Insights

The study has produced several key insights that challenge common assumptions:

- Simple architectures often outperform complex ones when memory management is effective
- Memory management is more important than architectural sophistication
- External knowledge bases often hurt rather than help performance
- General-purpose AI can match specialized tools for routine tasks
- Hallucination remains a significant challenge across all frameworks
- Human judgment remains essential for reliable security testing

61.3 The Path Forward

The path forward is not AI versus humans, but AI with humans. The most effective deployment model combines AI's speed and consistency with human creativity and judgment. This collaborative model requires new skills, new workflows, and new ways of thinking about security testing.

Realizing this potential requires addressing the challenges identified in this study: memory management, hallucination detection, multi-agent coordination, and evaluation methodology. These are not insurmountable problems, but they require focused research and development.

61.4 The Broader Impact

This study is not just about penetration testing. It reveals fundamental truths about AI capabilities and limitations that apply across many domains. The challenges of memory management, hallucination, and coordination are not unique to security testing—they appear wherever AI is applied to complex, real-world tasks.

The lessons learned from this study therefore have implications beyond cybersecurity. They inform our understanding of how AI can be applied effectively to complex problems, and they highlight the importance of human oversight in high-stakes applications.

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The findings of this study demand action from multiple stakeholders:

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- Policymakers must create regulatory frameworks that encourage innovation while protecting against misuse
- Educators must develop training programs for AI security testing skills

61.6 Final Reflections

We are living through a transformation in how we approach security. AI tools are becoming capable enough to handle routine tasks, freeing human experts to focus on creative problem-solving and strategic analysis.

This transformation is not without risks. Hallucination, coordination failures, and the dual-use nature of security tools all require careful management. But the potential benefits—more accessible, frequent, and effective security testing—make this work essential.

The future of security is not AI versus humans, but AI with humans. How we navigate this collaborative future will shape the security of our digital infrastructure for decades to come.

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The race between AI-powered attack and AI-powered defense has only just begun. How we navigate this race will shape the security of our digital infrastructure for decades to come.

64. About This Report

This simplified report was created to make the findings of the original research paper accessible to a general audience. The original paper, 'Hackers or Hallucinators? A Comprehensive Analysis of LLM-Based Automated Penetration Testing' (arXiv:2604.05719), contains significantly more technical detail, experimental data, and comprehensive references.

The goal of this report is not to replace the original paper but to provide an entry point for readers who may not have the technical background to engage with the full academic text. For complete details, please consult the original paper.

This report was created as part of a project to make cutting-edge research accessible to everyone. All simplified reports are freely available and designed to be understood by readers without specialized technical knowledge.

The findings presented in this report are based on rigorous scientific research conducted by a team of 15+ researchers with expertise in cybersecurity. The study consumed over 10 billion tokens, generated 1,500 execution logs, and required four months of expert analysis.

We believe that understanding AI capabilities and limitations is essential for everyone, from security professionals to policymakers to regular citizens. This report aims to bridge the gap between cutting-edge research and public understanding.

For questions or feedback about this report, please refer to the original paper or contact the research team through the channels listed in the original publication.

65. Acknowledgments

This simplified report was made possible by the hard work of the original research team, who conducted the comprehensive evaluation of AI-powered penetration testing frameworks. Their dedication to rigorous scientific research has produced findings that benefit the entire cybersecurity community.

We also want to thank the open-source community for developing the tools and frameworks that made this research possible. The commitment to open science and reproducible research has enabled this study to advance our collective understanding of AI capabilities in security.

Finally, we want to thank you, the reader, for taking the time to engage with this material. Understanding AI capabilities and limitations is essential for building a more secure digital future. By staying informed, you are contributing to that goal.

66. Contact and Resources

For readers who want to learn more about this topic, here are additional resources:

Original paper: arXiv:2604.05719 - Hackers or Hallucinators? A Comprehensive Analysis of LLM-Based Automated Penetration Testing

Project website: https://simon-p-j-r.github.io/LLM4Pentest/

GitHub repository: https://github.com/simon-p-j-r/LLM4Pentest

Medium profile: https://medium.com/@muhamedfazalps7

For questions about AI security testing, we recommend consulting the original paper and the resources listed throughout this report. The field is evolving rapidly, and staying current requires engagement with the latest research.

Thank you for reading this simplified report. We hope it has been valuable in understanding the capabilities and limitations of AI-powered penetration testing.