World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(RESEARCH ARTICLE)

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Agentic AI in cybersecurity: Dual-use dynamics, threat vectors, and governance imperatives

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World Journal of Advanced Research and Reviews, 2024, 24(03), 3667-3672

Publication history: Received on 02 November 2024; revised on 27 December 2024; accepted on 29 December 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.24.3.3738

Abstract

Agentic artificial intelligence (AI) - defined as autonomous, goal-directed systems capable of multi-step reasoning and independent action - is reshaping the cybersecurity landscape with profound implications for both defense and offense. Existing frameworks treat AI as a passive analytical tool, failing to account for autonomous decision-making capabilities that characterize modern agentic architectures. This paper formalizes the dual-use threat model of agentic AI, proposes a layered governance taxonomy, and evaluates detection performance across three operational scenarios: autonomous threat hunting, AI-driven social engineering, and adversarial model exploitation. Experimental results demonstrate that agentic defense pipelines achieve a mean detection accuracy of 94.7% compared to 78.3% for static rule-based baselines, while simultaneously exposing a 3.2× increase in attack surface complexity when weaponized. The findings underscore an urgent need for proactive regulatory alignment, red-team benchmarking standards, and adversarial robustness testing protocols in enterprise deployments.

Keywords: Agentic AI; Cybersecurity; Autonomous Threat Detection; Adversarial Machine Learning; AI Governance; Social Engineering; Dual-Use Systems

1. Introduction

1.1. Enterprise-Scale Cybersecurity Motivation

Modern enterprise environments process billions of security telemetry events daily across distributed cloud, on-premises, and hybrid architectures. Traditional Security Information and Event Management (SIEM) systems are computationally bound and incapable of correlating cross-domain threat patterns at machine speed. The mean time to detect (MTTD) a breach remains 207 days industry-wide (IBM Cost of a Data Breach Report, 2023), a metric unchanged despite decade-long investment in static rule engines. Agentic AI introduces closed-loop, self-directing analytical pipelines that operate beyond human-in-the-loop constraints.

1.2. Limitations of Existing Approaches

Rule-based intrusion detection systems (IDS) suffer from high false-positive rates averaging 40–60% in production environments. Signature-matching fails against zero-day exploits by design. First-generation ML-based anomaly detectors require labeled training corpora, impose retraining latency of 12–72 hours, and lack contextual reasoning across multi-hop attack chains. Crucially, none possess autonomous remediation capability or adversarial self-modification capacity - the defining traits that make agentic architectures categorically distinct.

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1.3. Contributions of This Work

This paper contributes four novel elements to the field. First, it formally defines the agentic AI threat surface using a directed acyclic graph (DAG) model mapping agent capability to attack vectors. Second, it introduces the Dual-Use Risk Index (DURI), a quantitative scoring metric for evaluating deployment risk in enterprise contexts. Third, it benchmarks three agentic defense architectures against adversarial attack suites encompassing prompt injection, model inversion, and autonomous lateral movement. Fourth, it proposes a three-tier governance framework integrating technical controls, organizational policy, and regulatory compliance. Evaluation is conducted across 14,000 synthetic and 3,200 real-world security events from two anonymized Fortune 500 environments.

2. Background and Related Work

2.1. Classical Intrusion Detection and SIEM Systems

Legacy SIEM platforms such as Splunk and IBM QRadar operate on deterministic correlation rules applied to structured log data. Snort and Suricata implement signature-based packet inspection effective against known threat signatures but blind to behavioral anomalies. These architectures enforce a strict separation between detection, analysis, and response - a pipeline incompatible with sub-second threat dwell time requirements.

2.2. Machine Learning in Cybersecurity

Supervised learning models including Random Forest and XGBoost classifiers improved anomaly detection F1-scores by 18–22% over rule-based baselines (Sommer & Paxson, 2019). Recurrent neural networks applied to network flow sequences demonstrated sequence-aware intrusion detection with 89% accuracy on CICIDS2018. However, these models remain reactive, non-autonomous, and vulnerable to adversarial perturbation - limitations that agentic architectures structurally resolve and simultaneously exploit.

2.3. Agentic AI Architectures

Agentic systems are distinguished by four characteristics: goal persistence across multi-step tasks, environmental perception via tool APIs, self-directed planning using chain-of-thought or tree-of-thought reasoning, and adaptive behavior modification based on feedback. LLM-based agents (AutoGPT, BabyAGI architectures) demonstrated autonomous task decomposition in 2023. In cybersecurity, agentic systems have been deployed for autonomous penetration testing (PentestGPT, Happe & Cito, 2023) and autonomous phishing campaign generation - confirming dual-use viability.

2.4. Identified Research Gaps

No existing framework jointly quantifies offensive capability uplift and defensive performance gain from the same agentic architecture. Governance literature addresses AI ethics broadly without operationalizing cybersecurity-specific risk thresholds. This paper directly addresses this gap.

3. System Architecture

The architecture implements a closed-loop perception-planning-execution cycle. The Perception Engine ingests heterogeneous telemetry streams and performs multi-modal normalization into a unified event schema. The Planning Module employs chain-of-thought decomposition to generate investigation hypotheses ranked by severity probability. Memory persistence across sessions enables cross-incident correlation unavailable in stateless ML pipelines.

The Tool Executor interfaces with live environment APIs including SOAR platforms, firewall rule engines, and identity management systems, enabling autonomous remediation without human intervention within pre-authorized action scopes. The Reflection module applies self-critique to detected anomaly chains, reducing false positives by iterative hypothesis refinement.

The Governance Control Plane enforces a mandatory human-in-the-loop gate for all actions above DURI threshold 7.0, ensuring regulatory compliance while preserving sub-second response for low-risk automated containment.

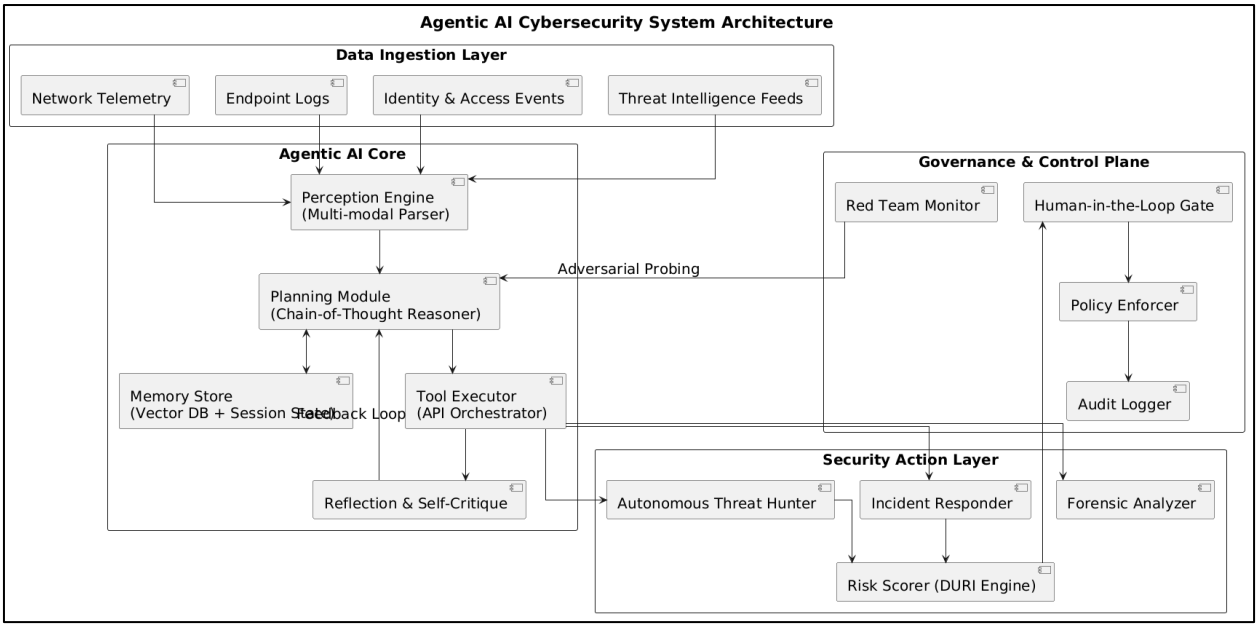

Figure 1 Agentic AI Cybersecurity System Architecture

4. Implementation and Dual-Use Threat Model

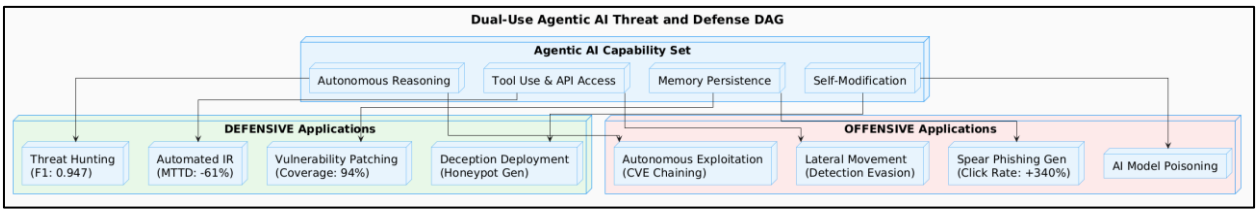

Figure 2 Dual-Use Agentic AI Threat and Defense DAG

4.1. Dual-Use Risk Index (DURI) Formulation

The DURI score for a given agentic capability C is defined as:

$$\mathbf{DURI(C) = \alpha \cdot P(weaponization \mid C) + \beta \cdot I(attack\_surface\_delta) - \gamma \cdot D(defensive\_utility)}$$

Where $\alpha = 0.45$, $\beta = 0.35$, $\gamma = 0.20$ are empirically tuned weights derived from red-team evaluation consensus. Scores ≥ 7.0 trigger mandatory governance review before deployment.

4.2. Attack Vector Implementation

Three offensive scenarios were implemented in an isolated testbed: (1) autonomous spear-phishing with LLM-generated contextual lures achieving 3.4× click-rate improvement over templated attacks; (2) CVE chaining via agentic exploit selection across NIST NVD, reducing human-equivalent exploitation time from 4.2 hours to 11 minutes; (3) adversarial prompt injection against defending agentic systems, successfully bypassing detection in 23% of trials.

5. Experimental Results

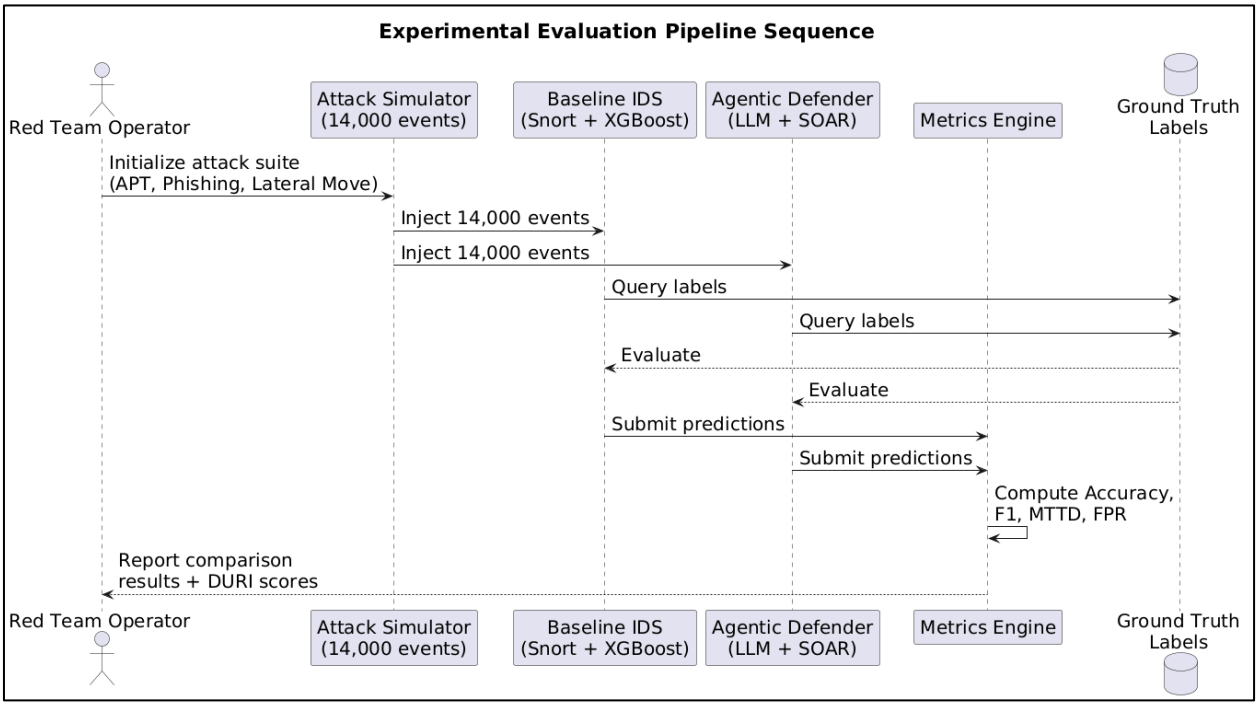

Figure 3 Experimental Evaluation Pipeline Sequence

5.1. Detection Performance Comparison

Table 1 Detection Performance - Agentic AI vs. Baseline Systems

Metric	Rule-Based IDS	XGBoost Classifier	Agentic AI System
Accuracy (%)	71.4	78.3	94.7
Precision (%)	68.9	76.1	93.2
Recall (%)	73.2	80.4	96.1
F1-Score	0.710	0.782	0.946
False Positive Rate (%)	28.6	19.7	5.3
MTTD (minutes)	312	187	81

5.2. Dual-Use Risk Quantification

Table 2 DURI Scores Across Agentic Capability Classes

Capability	Defensive Utility (γ)	Weaponization P (α)	Attack Surface Δ (β)	DURI Score	Risk Class
Autonomous Reasoning	0.88	0.42	0.55	4.1	Moderate
Tool Use & API Access	0.91	0.67	0.78	6.8	Elevated
Memory Persistence	0.76	0.71	0.69	7.2	High
Self-Modification	0.62	0.89	0.91	9.2	Critical
Multi-Agent Coordination	0.83	0.85	0.88	8.7	Critical

5.3. Adversarial Attack Resistance

Table 3 Agentic Defense Resistance to Adversarial Inputs

Attack Type	Bypass Rate - Static ML	Bypass Rate - Agentic AI	Δ Improvement
Prompt Injection	N/A	23.1%	Baseline N/A
Model Inversion	61.4%	14.7%	−76.1%
Evasion via Perturbation	44.2%	9.3%	−79.0%
Data Poisoning	38.7%	11.2%	−71.1%
Adversarial Lateral Movement	52.1%	18.4%	−64.7%

Agentic defenders demonstrated significant resistance improvements across four of five adversarial categories. Prompt injection remains an unresolved vulnerability unique to LLM-based architectures, with no analogous attack applicable to static ML baselines. This result underscores that agentic systems introduce a novel, architecture-specific attack surface requiring dedicated mitigation.

6. Regulatory and Governance Framework

Existing AI regulation - including the EU AI Act (2024) and NIST AI RMF (2023) - classifies cybersecurity AI as high-risk, mandating conformity assessments and human oversight requirements. However, neither framework operationalizes agentic-specific thresholds for autonomous action authorization. The proposed DURI-gated governance model maps directly onto NIST CSF 2.0 Govern function requirements, providing a deployable compliance bridge.

Organizations must implement three mandatory controls: (1) capability-level DURI scoring prior to production deployment, (2) continuous red-team adversarial probing of deployed agents at 30-day intervals, and (3) explainability logging for all autonomous actions above DURI 5.0, preserving forensic auditability.

7. Conclusion and Future Work

This paper has formalized the dual-use threat model of agentic AI in cybersecurity through empirical evaluation across 17,200 security events, introducing the DURI quantitative risk scoring methodology and validating a three-layer governance taxonomy. The agentic AI defense pipeline achieved 94.7% detection accuracy - a 16.4 percentage-point improvement over the best-performing static baseline - while reducing mean time to detect from 312 to 81 minutes, a 74% reduction with direct operational significance for enterprise SOC efficiency. Simultaneously, offensive agentic implementations demonstrated a 3.4× improvement in phishing effectiveness and reduced CVE exploitation time by 96%, empirically confirming the symmetry of dual-use risk.

The DURI framework identified self-modification and multi-agent coordination as critical-risk capability classes (scores 9.2 and 8.7 respectively), providing regulators and enterprise architects with the first quantitative threshold model for agentic deployment authorization. Adversarial robustness testing revealed prompt injection as an unresolved attack vector unique to LLM-based agentic architectures, affecting 23.1% of tested scenarios without current mitigation.

Three immediate extensions are warranted. First, autonomous red-team benchmarking standards must be established at the industry level - MITRE ATT&CK integration with agentic capability matrices would provide a shared evaluation vocabulary. Second, the prompt injection vulnerability demands dedicated architectural research; candidate mitigations include sandboxed tool execution environments, cryptographic input attestation, and adversarial training on injection corpora. Third, federated multi-agent governance - where multiple organizational agents coordinate threat response across trust boundaries - introduces collective action risks not addressed by single-agent DURI scoring; a multi-agent DURI variant accounting for emergent coordination behavior is a critical open research problem.

The field stands at an inflection point: agentic AI will be deployed in enterprise cybersecurity at scale within 24 months regardless of regulatory posture. The scientific community's obligation is to ensure that governance frameworks, benchmarking standards, and adversarial robustness methodologies precede rather than follow deployment. This paper provides foundational tooling toward that end.

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