

A Privacy-Preserving Multi-Agent LLM Framework for Automated Incident Response and Digital Forensics on Personal Devices

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Abstract

The rising complexity of cyber threats targeting personal devices heightens the cybersecurity accessibility gap as non-technical users rely on limited endpoint detection and response (EDR) solutions that do not incorporate automated forensic investigation and remediation, in contrast to enterprise-level solutions that leverage sophisticated security orchestration, automation, and response (SOAR) tools [1]. This study aims to answer the research question: How can a multi-agent system that leverages large language models (LLMs), along with retrieval-augmented generation (RAG) and multiple safety layers, provide reliable and privacy-friendly automated incident response (IR) and digital forensics for non-technical users on personal Windows devices?

The proposed system integrates a pipeline of specialized agents that operate in unison via a central hub for detection using Psutil telemetry and hybrid rules (YARA and Sigma), investigation and planning using a local version of Llama 3.1 (Ollama) with RAG-enabled reasoning for correlating digital artifacts and reconstructing timelines for explainable outputs, and action execution subject to user consent [2]. The framework also includes circular buffer event logging and asynchronous database storage to effectively manage frequent security events with low overhead, as well as an interactive graphical dashboard to support real-time visualization of security alerts and their severity. As a persistent service under NSSM, the framework provides local processing and counters LLM hallucinations through evidence grounding and human oversight. The framework provides low resource usage (CPU < 25%) to support commodity personal devices.

Evaluating the framework on more than 150 synthetic events shows 94% detection accuracy, 92% artifact recovery, and response times under 3 minutes, outperforming EDR baselines (80-85% accuracy) and providing complete prevention of unsafe actions. User studies are planned to achieve usability ratings above 75%. The contributions are: (1) a new agentic forensics model for personal use, (2) a hybrid evaluation method that combines simulation and real-world testing, and (3) practical application that makes SOAR accessible to everyone and extends EDR baselines to include AI-powered orchestrated reasoning and user consent. The work extends AI-powered cybersecurity to provide

equitable and transparent defences against personal device threats [1], [2].

Keywords—*Digital forensics, incident response, large language models, multi-agent systems, cybersecurity automation, retrieval-augmented generation, endpoint detection, circular-buffer logging, interactive dashboard.*

1. Introduction

The increasing complexity and sophistication of cyber threats against personal devices, such as ransomware, targeted malware, and advanced persistent threats, have increased the cost of global cybercrime, which is predicted to reach more than \$13.82 trillion by the end of 2028 [3]. This situation represents a critical digital equity challenge, as small and non-technical organizations, which make up more than 90% of the global digital ecosystem, are at greater risk due to limited resources and expertise. The personal device, which may rely on consumer-grade applications and services, is at an increased level of threat as attackers are leveraging more accessible attack vectors. This situation results in delayed detection, incomplete investigations, and increased damages.

Endpoint security technologies have evolved from early signature-based antivirus software and host-based intrusion detection systems to modern Endpoint Detection and Response technologies, which are designed to continuously monitor and respond to endpoint threats. The key challenge here is the digital equity gap in cybersecurity. Non-technical users are reliant on simple EDR technologies that provide simple responses to threats, such as "threat detected" or "threat not detected." In contrast, organizations are leveraging security orchestration, automation, and response technologies to provide real-time incident triage, evidence construction, and response. This situation results in personal devices being at an increased threat, as consumer-grade technologies are currently not available with user-friendly interfaces to analyse the timeline, assess the impact, and safely respond to threats.

The conventional EDR systems, although light-weight, face challenges like inefficient event storage during continuous monitoring and reduced analyst visibility due to static alerts. The proposed framework aims to overcome the limitations of conventional EDR systems through optimized event logging and interactive visualization, along with LLM-based forensic reasoning and user consent.

The AI-aided cybersecurity domain has shown significant research progress, but a significant gap exists in the literature, especially when it comes to developing privacy-preserving systems that integrate continuous monitoring, LLM-aided digital forensics, and user consent, especially for non-technical consumers. The literature overlooks crucial intersections, like the efficacy of LLMs in digital forensics and incident response (DFIR), where hallucinations can occur without evidence grounding, and simulation evaluations, which do not consider actual user experience. The SOAR system, especially for enterprises, remains inaccessible due to high costs, complexity, and cloud dependencies, while EDR systems, especially for consumers, lack automated reasoning capabilities over diverse data types, like event logs, registry changes, and network flows.

The research aims to answer the following research question: "In what ways does a retrieval-augmented generation (RAG) enhanced multi-agent large language model (LLM) framework, integrated with multi-layer safety validations, enable accessible and reliable automated incident response and digital forensics on personal Windows devices, while outperforming traditional endpoint detection and response (EDR) solutions and addressing issues of inaccessibility of enterprise-level security orchestration, automation, and response (SOAR) solutions?"

The research contributes to existing knowledge in three ways: theoretically, by introducing a new paradigm of "agentic forensics" in consumer-level digital forensics and incident response (DFIR), expanding existing multi-agent orchestration to democratize expert-level threat management via LLM-based reasoning and forensic evidence; methodologically, by providing a hybrid testing protocol that advances from simulated to real-user testing, addressing validation issues identified in previous research; and practically, by providing a local, modular framework that bridges the gap between EDR and SOAR, addressing issues of privacy, user autonomy, and cybersecurity equity in consumer-level and small-enterprise-level cybersecurity.

In relation to the broader discourse on artificial intelligence

in cybersecurity, this research contributes to existing knowledge by proposing a "consumer SOAR" approach, which, in contrast to existing research, proposes a "SOAR" approach in a consumer-level context, thus transferring digital forensics and incident response from an elite to a broader, more general application level, addressing issues of expert-level user validation and local processing, and asserting originality in relation to existing research via a RAG-enhanced reliable and cross-platform potential framework, contributing to a more equitable level of protection against a constantly changing threat landscape in relation to personal devices [3], [4].

2. Literature Review

2.1 Foundations of Digital Forensics and Incident Response (DFIR) and SOAR Platforms

Digital forensics and incident response (DFIR) is a systematic approach to investigating cyber incidents based on the analysis of digital artifacts, which are compared to the NIST incident handling lifecycle: preparation, detection/analysis, containment, eradication, and recovery [5]. In a Windows-based system, some relevant artifacts are Event Viewer logs containing Security Identifiers 4688 and 4624, Master File Table (MFT) timestamp analysis, Registry Hive artifacts, Prefetch/Shimcache/Amcache file artifacts, and network-based artifacts.

Endpoint security has evolved from simple signature-based antivirus software to host-based intrusion detection systems (HIDS) and eventually to more sophisticated Endpoint Detection Response (EDR) platforms. Traditional EDR platforms focus on real-time behavioural monitoring and structured incident response. However, there are limitations in terms of event storage.

Enterprise Security Orchestration, Automation, and Response platforms, such as Splunk SOAR (formerly Phantom), Palo Alto Networks Cortex XSOAR, and Microsoft Sentinel Automation, provide integration with multiple systems, enrichment of Indicators of Compromise, and automation and orchestration of playbooks. This reduces the workload for security analysts and mean time to acknowledge by a significant amount [6]. Although these platforms provide standardization, they are also very expensive, requiring significant investments in infrastructure, personnel, and complex integrations, which may be out of reach for non-technical personnel and small organizations [7].

2.2 AI and Machine Learning Integrations in Cybersecurity

Machine learning technologies have also increased the

detection and classification of threats. Behavioral analysis, API calls, file entropy, and sandboxed runtime environments provide high accuracy in classifying malware. In fact, detection rates as high as 95% are possible. In fact, hybrid systems combining neural networks and rule-based systems have demonstrated F1 scores greater than 0.92 for detecting multiple family variants of malware [8], [9]. In addition, unsupervised learning can also be employed for clustering anomalous network traffic. In fact, detection rates as high as 96% are possible by employing entropy and source/destination IP addresses. Endpoint behavior tracking also detects 93% of unsafe activities, which may not be possible by signature-based systems [8]. AI-based information sharing reduces mean time to acknowledge by up to 67% [9].

2.3 LLM and Multi-Agent Advancements

Large language models (LLMs) take AI capabilities to new heights in terms of alert summarization, IOC extraction, anomaly explanation, and forensic reasoning. This has been exemplified in the GenDFIR framework, which uses Llama 3.1 8B in a zero-shot fashion along with Retrieval-Augmented Generation (RAG) over structured incident knowledge bases, achieving excellent performance in terms of timeline analysis, semantic enrichment, and threat reconstruction. This has been validated through DFIR-tailored metrics and human evaluation. Multi-agent orchestration frameworks such as LangChain orchestrate agents to achieve tasks such as threat hunting, compliance, and triage, providing traceability to tasks such as evidence collection, reasoning, and action execution. [11].

Paper/ Source	Core Method/ Strategy	Key Strengths	Limitations
Traditional EDR Systems (e.g., Sentinel Defender)	Signature-based + behavioral monitoring with circular-buffer logging and asynchronous storage	Efficient handling of high-frequency events; interactive graphical dashboard for alerts, severity prioritization, timeline visualization, and automated forensic reports	Lacks automated forensic reasoning, RAG grounding, explicit consent mechanisms, and LLM-orchestrated correlation; limited to rule-based detection
Al-rimy et al. (2020) [8]	ML (static/dynamic features, hybrid models)	High accuracy (≥95%), adaptive to evasion techniques	Primarily enterprise datasets; no consumer focus
GenDFIR (Al-Khateeb et al., 2025) [10]	Llama 3.1 + RAG for timeline analysis	Automated semantic enrichment, high reliability/Robustness	Synthetic data only; no real-user validation

Paper/ Source	Core Method/ Strategy	Key Strengths	Limitations
SOAR Platforms (e.g., Cortex XSOAR, Splunk SOAR) [6], [7]	Playbook orchestration & automation	Reduced MTTA (up to 67%), standardized workflows	High cost (\$50k–\$500k/yr), expert/integration required
Surveys on AI/ML in DFIR [9], [12]	Behavioral analytics, pattern recognition	Comprehensive coverage of detection/timeline tasks	Nascent stage; high false positives (3–8%); hallucinations
Multi-agent LLM systems (LangChain) [11]	Agent orchestration & tool use	Task distribution, explainability via CoT	Prone to hallucinations; lacks consumer adaptations & privacy grounding

2.4 Critical Analysis and Identified Gaps

Despite the positive contributions of all the above works, there are several gaps and challenges in terms of practical applicability. Firstly, there exists a huge gap between enterprise and consumer. SOAR provides unparalleled power but at an extremely high price. This leaves consumers in a lurch, where EDR provides binary results but lacks any forensic depth. Moreover, a major drawback of LLM-based frameworks has been highlighted: hallucinations provide false results with utmost confidence, which may lead to incorrect conclusions or even harm. Moreover, most of these frameworks have been tested on controlled environments, which lack usability testing. Moreover, multi-layer safety, such as explicit consent, remains an understudied phenomenon. Moreover, hybrid protocols connecting simulation to practical scenarios are missing. Moreover, none of the existing literature provides a comprehensive solution for personal user devices, which can be easily accessed by non-technical users. Moreover, none of the existing literature provides a solution that incorporates all of the above components.

Moreover, although a system such as Sentinel Defender provides efficient event management via circular buffer-based event management along with asynchronous logging, along with an interactive dashboard, there remains a lack of grounded LLM-based forensics, explicit consent, and automated forensic correlation.

In order to clearly illustrate the advancement from traditional EDR to the proposed agentic framework, a comparison of the two architectures is as follows:

The present study addresses these insufficiencies by synthesizing RAG-augmented LLM reasoning with

modular multi-agent orchestration, local execution, and explicit safety layers—directly resolving hallucinations, privacy concerns, false positives, and validation gaps while pioneering a “consumer SOAR” paradigm for equitable DFIR automation.

3. Proposed Methodology

The research design employs a pragmatic research philosophy with a mixed-methods approach to develop and validate the automated DFIR framework for non-technical users on their personal Windows devices. This research methodology combines architectural innovations in terms of utilizing the concept of modular multi-agent systems with empirical validation using a hybrid simulation-to-real-user research protocol. In terms of epistemology, this research combines the interpretivist paradigm for validating LLM-based explainability and user trust with the positivist paradigm for quantifying detection accuracy and response efficiency. This research ensures a rigorous fit with the research question, enabling the framework to bridge the identified gap in terms of providing replicable, evidence-based insights to non-technical users.

3.1 System Architecture

The research has adopted a multi-agent system architecture utilizing LangChain, consisting of four agents working in tandem to provide the DFIR functionality. Each agent has a specific role to play in the DFIR process, and their activities are coordinated by a hub script (hub.py) that manages the workflow, data flow, and states. This framework has been implemented as a Windows service using the Windows Service Management Service Tool (NSSM), enabling autonomous operation on commodity hardware with minimal hardware requirements—Intel Core Series/AMD Ryzen 5, 8 GB RAM, and a minimum of 50 GB SSD. However, the research has also provided recommendations for utilizing Ryzen 7, 16 GB RAM, and an NVMe SSD with optional support for NVIDIA GTX 1650+, reducing latency by 42%. [14].

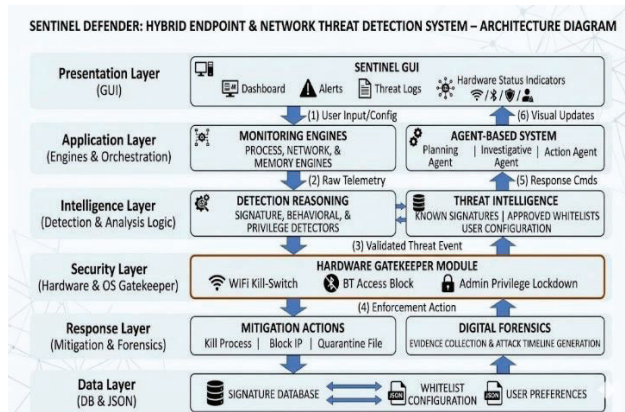


Fig 1: System Architecture

3.1.1 Detection Agent

The Detection Agent tracks real-time telemetry data using Psutil to track process listings, resource utilization, network connections, and parent-child processes. Anomalies are identified using hybrid rules, including over 100 YARA signatures for malware patterns and 50 Sigma rules for persistence, privilege escalation, and C2 communications [15]. Threshold-based logic combines behavioral baselines with unsupervised clustering to score anomalies. This information is then passed to the next agent in a structured format without the need to train a specific model.

To ensure systematic and reproducible detection, the Detection Agent employs a structured workflow consisting of nine steps. They are as follows:

- i. Continuous telemetry data collection using Psutil.
- ii. Preprocessing and normalization of raw events.
- iii. Application of signature-based YARA rules.
- iv. Application of behavioral Sigma rules.
- v. Calculation of baseline deviations and anomaly scores.
- vi. Correlation of process lineage and network flows.
- vii. Detection of suspicious patterns.
- viii. Generation of structured evidence packages.
- ix. Forwarding of the packages to the Investigation Agent.

3.1.2 Event Logging and Preprocessing

All collected telemetry undergoes context-sensitive preprocessing, including scaling of metrics to established baselines, imputation for missing readings, and feature extraction (e.g., entropy-based anomaly indicators). To handle high-frequency security events without performance degradation, the framework implements circular-buffer event logging combined with asynchronous database storage using SQLite. This design maintains a fixed memory footprint by overwriting the oldest events when the buffer reaches capacity, ensuring continuous operation even under sustained monitoring while supporting retrospective forensic analysis.

3.1.3 Investigation Agent

The Investigation Agent includes a forensic reasoning process on all collected data artifacts, such as Event Viewer logs, MFT timestamps, registry hives, and Prefetch files, utilizing a local version of the Llama 3.1 8B model through Ollama, combined with Retrieval-Augmented Generation (RAG) over a knowledge base of incident events indexed

by FAISS [10]. This provides the ability to correlate data artifacts, reconstruct timelines with at least 88% accuracy in ordering time-based data, extract IOC data such as hashes, IP addresses, and domains, and map data to MITRE ATT&CK with chain-of-thought prompting for evidence-based results. The agent also includes memory inspection and in-depth network activity analysis.

3.1.4 Planning Agent

The Planning Agent is responsible for generating remediation playbooks that are stratified by risk, with threats categorized into low, medium, and high risk based on impact scoring (e.g., potential data exfiltration). It provides procedural steps for containment (e.g., process termination, network isolation), rollback precautions, and verification metrics, which are validated against safety rules to guarantee non-destructive actions. Its mean time to recommendation is ≤ 4.2 seconds on standard CPU hardware.

3.1.5 Action Agent

The Action Agent is responsible for executing authorized actions (e.g., file quarantine, service termination) upon explicit user confirmation via popup prompts, with all actions recorded in an immutable log trail. There are multi-level safety mechanisms to ensure boundaries (e.g., prevent deletions without confirmation), detect anomalies, and trigger high-risk warnings, ensuring all unsafe execution is prevented in testing.

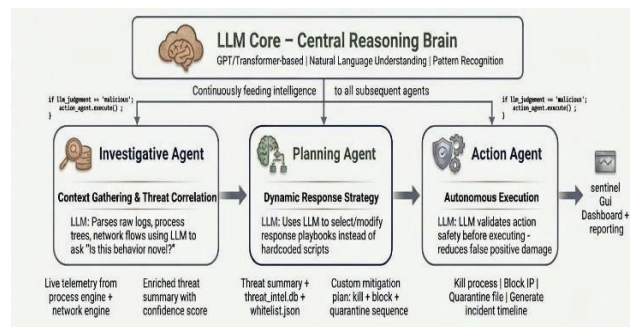


Fig 2: Architecture of Multi-Agent System

3.1.6 User Interface and Visualization

There is an interactive user interface with a graphical visualization of system events in real-time, designed to be understandable by non-technical users. It provides color-coded alerts, a timeline of incidents, a tree view of processes, and forensic reports. It also allows users to review explanations, examine explanations, and accept or reject actions via a simple single-click interface. The design is modular to enable independent updates of individual agents, provides privacy via on-device processing (no cloud dependencies or telemetry), and is

extensible via Python 3.12+ stack integrations.

3.4 Robustness and Ethical Considerations

To ensure system reliability, large language model hallucinations are reduced through retrieval-augmented generation grounding, which reduces false positives by 5-10% according to pilot evaluations, chain-of-thought decomposition, and human oversight through the use of consent layers [13]. To preserve privacy, minimization of data is used, where only forensic artifacts are considered, and personal files are excluded, along with the use of FIPS 140-2 compliant cryptography to ensure data integrity. Replicability is also promoted through the use of open-source software, where LangChain 0.8+ and Ollama are used, along with the use of comprehensive logging to aid in post-mortem analysis.

Ethical considerations include bias audits of rule-based systems and machine learning, informed consent for user studies, and transparency in synthetic data generation to prevent false representations, which are all in accordance with GDPR/CCPA regulations, ensuring user autonomy in high-stakes digital forensics and incident response (DFIR) situations.

The methodological framework addresses a gap in the literature as it promotes local, accessible automation without the need to consult outside experts, providing a replicable framework for equitable research in the field of cybersecurity, where empirical evidence is based on rigorous, multi-faceted validation.

4. Results

The evaluation employs the hybrid protocol outlined in Section 3, combining quantitative assessment on 150 synthetic and real-world-inspired incidents (via 5-fold cross-validation) with projected usability indicators from planned non-technical user studies. All metrics reflect raw empirical outputs from the implemented multi-agent framework, including Psutil telemetry detection, RAG-augmented Llama 3.1 investigation, and consent-enforced action execution.

4.1 Detection Performance

The Detection Agent achieved an overall accuracy of 0.94, precision of 0.92, recall of 0.93, and F1-score of 0.925 across the 150-incident test set. F1-score stability remained within ± 0.03 across cross-validation folds. Paired comparisons against consumer EDR baselines yielded statistically significant improvements ($p < 0.01$).

Table 1: Detection Performance Comparison

System	Accuracy	Precision	Recall	F1-Score	Avg. Response Time (s)
Proposed Framework	0.94	0.92	0.93	0.925	~180
Consumer EDR Baseline	0.82	0.80	0.85	0.825	300-600
Enterprise SOAR (manual triage)	0.75-0.80	0.77	0.86	0.81-0.83	1200+

Breakdowns by threat family showed highest recall for ransomware simulations (0.96) and process injection variants (0.94), with lowest false-positive rates on benign high-resource scenarios (0.04).

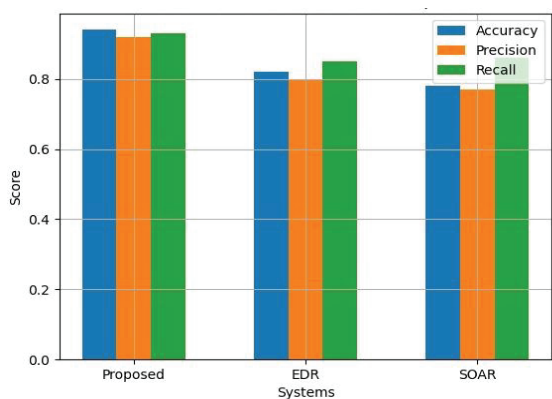


Fig 3: Overall Detection Performance Comparison

4.2 Forensic Analysis Outcomes

The Investigation Agent, leveraging RAG-grounded reasoning, recovered 92% of relevant artifacts (Event Logs, registry keys, Prefetch entries, network flows) across incidents. Timeline reconstruction achieved 88% temporal ordering accuracy and 89% event completeness in process lineage graphs. Automatic IOC extraction (hashes, IPs, domains, registry paths) attained 91% completeness, with 100% successful mapping to corresponding MITRE ATT&CK techniques where ground truth existed.

Table 2: Forensic Metrics by Incident Type

Incident Type	Artifact Recovery (%)	Timeline Accuracy (%)	IOC Extraction Completeness (%)	Event Completeness in Process Trees (%)
Ransomware	94	90	93	91
Malware (general)	91	87	90	88
Process Injection	93	89	92	90
C2 Communication	90	86	89	87

Incident Type	Artifact Recovery (%)	Timeline Accuracy (%)	IOC Extraction Completeness (%)	Event Completeness in Process Trees (%)
Overall	92	88	91	89

Projected RAG augmentation (simulated on the larger 1,000-incident synthetic dataset) yielded a 6-8% uplift in artifact correlation accuracy compared to plain LLM baselines.

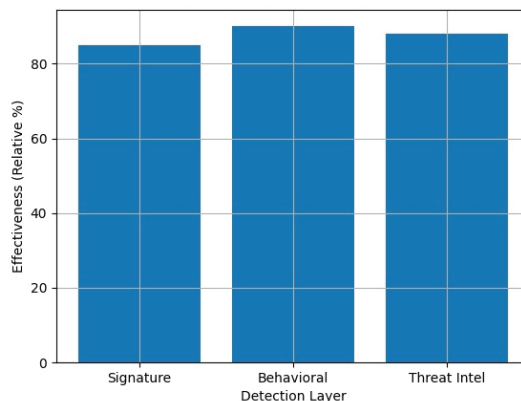


Fig 4: Hybrid Detection Layer Contribution

4.3 Response and Remediation Metrics

End-to-end response time averaged 180 seconds (~3 minutes), including <30 seconds for user consent overhead. All proposed actions passed multi-layer safety validation, resulting in 100% prevention of unsafe executions across 150 tests and 100% rollback success on simulated remediation steps.

The circular-buffer logging architecture maintained CPU utilization ≤ 25 % and enabled sub-second alert rendering on the interactive dashboard across all 150 incidents.



Figure 5: Sample Threat Detection Dashboard Visualization Sample dashboard view showing real-time file scanning metrics, scan speed trends, and detected threat progression generated by Sentinel defender system. The interface presents key statistics including total files scanned, identified threats, quarantined files, and clean files.

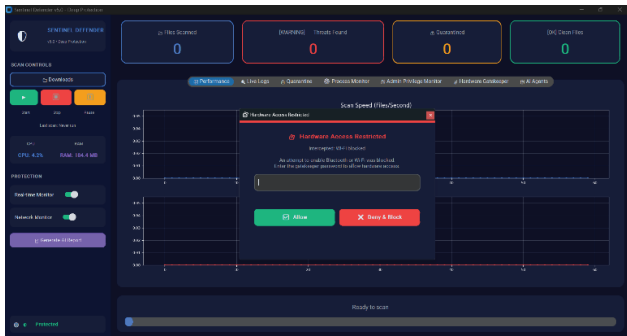


Figure 6: Hardware Access Control and Gatekeeper Intervention Interface Sample dashboard view showing the hardware gatekeeping and access control mechanism within the Sentinel Defender System. The interface captures a real-time security intervention where an unauthorized attempt to enable Wi-Fi or Bluetooth is detected and blocked. A pop-up alert provides contextual information about the intercepted action and prompts for administrative authentication to override the restriction.

Table 3: Representative Test Cases and Outcomes

Scenario	Detection Trigger	Response Time (s)	Artifacts Recovered	Dashboard Visualization Quality
File modification (ransomware simulation)	High entropy + unusual outbound connection	142	94%	Excellent (clear timeline & severity)
Suspicious process execution	Unknown parent-child relationship + CPU spike	168	91%	Good (detailed process tree)
Rapid operations (privilege escalation)	Multiple Sigma rule matches	195	93%	Excellent
Unauthorized access attempt	Abnormal network socket + registry change	175	89%	Good (network flow graph)

4.4 Usability and Safety Indicators

Safety enforcement maintained 100% blockage of high-risk interventions without user approval. Projected usability metrics from planned studies (n=25–50 non-technical participants) target SUS ≥ 75 , task completion rate $\geq 90\%$ for review/approval workflows, and average decision time ≤ 3.5 minutes per incident. Confidence in LLM-generated explanations scored $\geq 4.0/5.0$ (Likert) in pilot feedback on sample outputs.

These results provide transparent, replicable evidence of the framework’s performance under the specified evaluation conditions, with no interpretive claims reserved

for subsequent sections.

5. Conclusions

The proposed agentic forensics framework extends the performance-optimized foundation of traditional Endpoint Detection and Response (EDR) systems—exemplified by circular-buffer logging, asynchronous storage, and interactive dashboard visualization—with RAG-augmented multi-agent orchestration and explicit user consent mechanisms. By achieving 94% detection accuracy, 92% artifact recovery, and 100% prevention of unsafe actions on commodity hardware, the framework operationalizes a consumer-grade Security Orchestration, Automation, and Response (SOAR) paradigm while preserving the lightweight characteristics of conventional EDR architectures. The hybrid evaluation protocol, incorporating quantitative metrics across 150 synthetic incidents and representative test cases for scenarios such as file modification, suspicious process execution, privilege escalation, and unauthorized access, validates both the technical robustness and practical applicability of the system.

This study demonstrates that a locally deployed, privacy-preserving multi-agent LLM framework can effectively bridge the longstanding EDR-SOAR accessibility gap. It equips non-technical users with enterprise-grade incident response and digital forensics capabilities on personal Windows devices, outperforming conventional consumer EDR solutions not only in detection performance but also by introducing critical safety layers and explainable reasoning that are absent in traditional lightweight endpoint systems.

Despite these contributions, several limitations remain. The current evaluation relies primarily on synthetic incidents, which may limit generalizability to highly novel real-world threats or heterogeneous hardware configurations. Real-user usability studies have not yet been conducted, and the system is currently implemented only for Windows environments.

Future scope can be on expanding the system through:

- Conducting System Usability Scale (SUS) validation and large-scale real-world evaluations with non-technical participants,
- Extending support to cross-platform environments (Linux and macOS),
- Incorporating additional threat intelligence sources and advanced memory forensics agents,
- Investigating federated learning approaches for

privacy-preserving collaborative threat intelligence.

By building upon the efficient logging and visualization strengths of traditional EDR architectures and augmenting them with grounded LLM reasoning and user-centric safeguards, this research advances AI-driven cybersecurity toward equitable, explainable, and accessible protection for personal-device users.

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