Survey Perspective: The Role of Explainable AI in Threat Intelligence

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Abstract

The increasing reliance on AI-based security tools in Security Operations Centers (SOCs) has transformed threat detection and response, yet analysts frequently struggle with alert overload, false positives, and lack of contextual relevance. The inability to effectively analyze AI-generated security alerts lead to inefficiencies in incident response and reduces trust in automated decision-making. In this paper, we show results and analysis of our investigation of how SOC analysts navigate AI-based alerts, their challenges with current security tools, and how explainability (XAI) integrated into their security workflows has the potential to become an effective decision support. In this vein, we conducted an industry survey. Using the survey responses, we analyze how security analysts' process, retrieve, and prioritize alerts. Our findings indicate that most analysts have not yet adopted XAI-integrated tools, but they express high interest in attack attribution, confidence scores, and feature contribution explanations to improve interpretability, and triage efficiency. Based on our findings, we also propose practical design recommendations for XAI-enhanced security alert systems, enabling AI-based cybersecurity solutions to be more transparent, interpretable, and actionable.

CCS Concepts

• Information systems \rightarrow Retrieval models and ranking; • Security and privacy \rightarrow Intrusion detection systems; Cybersecurity and defense; • Computing methodologies \rightarrow Explainable AI (XAI); Machine learning.

Keywords

Explainable Threat Intelligence, Explainable AI Security Operation Center, Security Analysts, Threat Intelligence, Alert Fatigue, False Positives, Alert Triage

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1 Introduction

Artificial Intelligence (AI), sometimes interchangeably used with machine learning, has significantly reshaped cybersecurity, enabling automated threat detection, anomaly identification, and realtime incident response [3, 20]. Security analysts rely on AI-based tools such as SIEM, XDR, and EDR to retrieve and process vast amounts of security event data, prioritize alerts, and detect cyber threats efficiently [1]. However, despite AI's ability to enhance searchability and retrieval in security workflows, its lack of explainability remains a fundamental barrier to trust and effective decision-making [7]. Here, explainability refers to unraveling the decision making of the machine learning model [10]. For example, in a phishing detection system, an AI model might flag an email as malicious with 98% confidence, but without explainability, analysts cannot determine whether this decision was based on suspicious sender metadata, anomalous text patterns, or embedded links. Using an XAI method such as SHAP, LIME, DeepLIFT, GradCAM [11, 16, 18, 19], analysts can identify key contributing factors-such as an unusual sender domain or phishing-like language allowing them to validate the threat, improve response time, and fix detection rules.

The effectiveness of AI-based security alerts depends on their ability to provide relevant, interpretable, and actionable insights. Current security systems generate a flood of alerts, many of which lack sufficient context, requiring analysts to manually investigate and correlate security logs to determine relevance [15]. This results in alert fatigue, increased manual triage efforts, and overlooked critical threats [2, 13]. From an information retrieval (IR) perspective, the challenge is not only to retrieve relevant security signals but also to rank them effectively, provide supporting explanations, and integrate historical context to improve decision-making [17, 21].

To investigate these challenges, we conducted a survey of security professionals to examine how they process, retrieve, and interpret AI-based security alerts. Our study explores the extent to which analysts trust AI-generated results, their frustrations with existing security tooling, and the explainability features they find most valuable. The findings reveal a strong demand for XAI-enhanced information retrieval in SOC environments, where analysts require

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contextual explanations, confidence scores, and attack attribution mechanisms to filter and rank alerts effectively.

Secondly, we evaluate the integration of XAI using mock SOC dashboards (see Fig. 1, 2), assessing how different retrieval and ranking mechanisms affect usability. Based on security analyst feedback, we identify preferred approaches for visualizing and interacting with AI-based alerts. These can be used to design usable XAI methods that have a higher utility compared to current methods that have resulted purely from XAI research on non-security use cases. Finally, we provide design recommendations for XAI-integrated retrieval and ranking models that can improve trust, efficiency, and decision-making in cybersecurity operations. This paper makes the following contributions:

- (1) We present empirical insights into how security analysts handle and prioritize AI-generated alerts, highlighting frustrations related to false positives, lack of context, and trust issues.
- (2) We evaluate using mock SOC dashboard designs (Fig. 1, 2) integrating XAI-based explanations to assess how different explainable approaches impact usability.
- (3) We propose design recommendations for XAI-integrated retrieval and ranking systems, enabling AI-based cybersecurity tools to be more transparent, interpretable, and actionable.

Motivation. Security analysts often find that AI-generated alerts provide limited business-relevant context, making it difficult to determine why an event was flagged as suspicious or how it aligns with existing security policies. Without clear explanations, AI operates as a black-box system, forcing analysts to manually cross-check forensic data and validate AI predictions, leading to longer investigation times and slower response rates.

Another major concern is alert fatigue caused by excessive false positives, where AI-based security tools generate overwhelming volumes of alerts, many of which are low-priority or irrelevant [2, 13, 14]. This overload leads to missed critical threats, requiring manual intervention to filter out high-risk events, increasing the cognitive burden on SOC teams. Additionally, issues such as bias in AI models, reliance on static historical data, and inconsistencies in model training sources further contribute to uncertainty in AI-based threat detection. Analysts also report difficulties with cross-tool integration, where AI-based alerts from different security solutions produce conflicting or redundant results, complicating security response efforts. These challenges underscore the need for Explainable AI (XAI) to improve trust and efficiency in SOC workflows.

2 Background and Related Work

Artificial Intelligence (AI) has revolutionized cybersecurity by enabling rapid threat detection, automated incident response, and proactive defense mechanisms. AI-powered security tools such as SIEM, XDR, and EDR analyze large-scale security logs to detect anomalies and malicious activity efficiently. However, their blackbox nature makes it difficult for security analysts to interpret and trust automated decisions, often leading to false positives, misclassifications, and alert fatigue.

Explainable AI (XAI) has emerged as a crucial solution to enhance AI-based security workflows. Explainability techniques like SHAP, LIME, DeepLIFT, GradCAM [11, 16, 18, 19] are helping analysts

understand why alerts were triggered. However, achieving a balance between explainability and real-time operational efficiency remains a challenge, as overly detailed explanations can introduce latency and computational overhead.

To address these limitations, hybrid AI-human decision-making systems have been developed, where XAI assists analysts in refining alerts rather than making fully automated decisions. Industry solutions like IBM Watson AI Explainability 360 [9] and Google's Explainable AI Platform [4] are now integrated into cybersecurity frameworks to enhance transparency. The most commonly used general purpose XAI tools—SHAP [11], LIME [16] provide feature attribution and post-hoc explanations, enabling security teams to better interpret and validate AI-based alerts. Additionally, H2O's Driverless AI [8], Microsoft Defender XDR [12], and Darktrace [6] incorporate explainability features, bridging the gap between blackbox AI models and human decision-making, ultimately improving trust, interpretability, and SOC efficiency.

3 Survey Design and Methodology

We conducted a survey targeting SOC analysts, incident responders, and security engineers. The survey aimed to gather practical insights into AI-based security tools, alert prioritization methods, and explainability needs. Distributed across professional security communities, industry forums, and academic networks, the questionnaire covered participant demographics, challenges in interpreting AI-generated alerts, desired explainability features, tool adoption trends, and usability evaluations of two prototype SOC dashboards integrating XAI-based explanations (Fig. 1, 2).

We received a total of 236 responses, with a mix of human responses and Generative AI generated responses (but submitted by humans). Therefore, to ensure data integrity, we implemented response validation measures. Only human-confirmed responses were included, with three graduate researchers independently reviewing and classifying responses. In cases of disagreement, a third reviewer served as a tiebreaker. The study received Institutional Review Board (IRB) approval from Rochester Institute of Technology, ensuring compliance with ethical research standards, anonymization of participant data before analysis, and completely voluntary participation.

We employed a mixed-method analysis [5], using descriptive statistics to identify trends in security tool adoption and explainability preferences, while qualitative coding extracted themes related to analysts' frustrations and desired XAI features. This methodological approach provides empirical, unbiased insights into how explainability can enhance information retrieval and decision-making in AI-based cybersecurity operations.

4 Key Findings from the Survey

Our study explores the challenges security professionals face with AI-based security operations, focusing on alert fatigue, lack of integration, slow response times, false positives, and high operational costs. We examine how analysts navigate AI-generated alerts, validate threats, and manage prioritization inefficiencies within SOC environments. Additionally, we analyze the impact of poor interoperability, high-latency detections, and usability limitations on security workflows.

4.1 Immediate Steps after a Security Alert

The **initial triage phase** is essential for distinguishing real threats from false positives. Analysts cross-reference log data from firewalls, SIEMs, and endpoint security tools while assessing severity, asset impact, and historical attack patterns. However, false positives and alert fatigue remain major challenges, requiring better automation and contextual intelligence in AI-driven alerts. Once validated, containment measures focus on isolating affected systems, blocking malicious entities, and disabling compromised credentials to prevent lateral movement. Despite these efforts, integration issues between security tools often delay containment, highlighting the need for seamless automation in SOC workflows.

After containment, **root cause analysis (RCA) and forensic investigation** help determine the attack's scope and origin. Analysts examine logs, identify indicators of compromise (IoCs), and map tactics to MITRE ATT&CK techniques to reconstruct the attack timeline. However, many professionals noted that explainability in RCA is lacking, making it difficult to pinpoint attack vectors and apply effective mitigation. Eradication efforts include removing malicious artifacts, patching vulnerabilities, and restoring affected systems from clean backups. While AI-based remediation could accelerate this phase, concerns about false positives disrupting legitimate processes hinder its full adoption.

The **post-incident review phase** is often underutilized but plays a crucial role in enhancing security posture. Updating SIEM detection rules, refining incident response playbooks, and leveraging continuous monitoring improve resilience against future threats. Additionally, threat intelligence feeds help SOC teams validate alerts by correlating them with known IoCs, though delays in processing intelligence can limit real-time effectiveness. Despite automation, manual review remains critical for ambiguous alerts, where human expertise ensures accurate risk assessment. These findings emphasize the need for adaptive, risk-based prioritization mechanisms that combine AI-based triage with expert validation, reducing false positives while maintaining security accuracy.

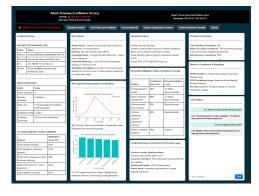


Figure 1: SoC dashboard mock up 1. It shows multiple XAI visualization options, immediate actions after an attack, and an integrated LLM Chatbot.

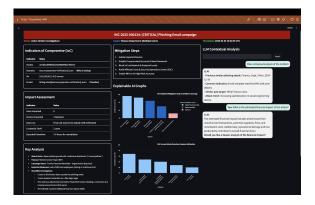


Figure 2: SoC dashboard mock up 2. It shows impact assessment, mitigation after an attack, and an integrated LLM Chathot

4.2 Alert Prioritization in AI-based Security Tools

Our survey reveals that analysts rely on a combination of automated AI-based triage and manual validation to assess and rank security alerts. The most important factors include severity, asset criticality, historical attack patterns, and integration with threat intelligence feeds. Critical threats such as malware infections or privilege escalations are handled first, while alerts involving high-value assets receive elevated priority. Analysts also consider whether an alert corresponds to a recurring threat pattern, leveraging past incidents and external intelligence sources to determine its significance.

Despite these prioritization mechanisms, analysts face persistent challenges that hinder efficient triage. False positives remain a major issue, as many AI-based alerts lack contextual intelligence, overwhelming analysts with excessive noise. Additionally, crosstool integration challenges prevent seamless correlation of alerts across security platforms, requiring analysts to manually validate AI-generated decisions. The absence of interoperability between different security solutions further complicates this process, forcing SOC teams to invest significant time in manual threat correlation. Addressing these limitations requires XAI-based triage enhancements, including context-aware prioritization, confidence-based scoring, and improved alert correlation across tools.

While explainability has the potential to improve SOC workflows, XAI adoption remains limited. Many security professionals reported little to no experience with explainability frameworks such as SHAP, LIME, IBM Watson AI Explainability, and Google's Explainable AI platform. The primary barriers include lack of awareness, limited integration with existing security tools, and the perceived complexity of interpretability methods. In addition to these explainability concerns, security teams continue to rely on a diverse range of detection and response tools, including SIEM, XDR, EDR, IDS/IPS, and SOAR. While these tools enhance visibility, detection accuracy, and response automation, analysts report ongoing struggles with high alert volumes, false positives, and integration gaps, reinforcing the need for smarter, more explainable AI-based security solutions.

4.3 Preferred Explainability Features in SOC Workflows

Security analysts require interpretable AI-based alerts to enhance decision-making and reduce investigation time. Our survey highlights that analysts prefer explanations that provide clear justifications, contextual relevance, and actionable insights to improve the efficiency of Security Operations Center (SOC) workflows. The most valued explainability features include confidence scores, which help analysts assess the reliability of AI-generated alerts, and attack attribution, which links detections to known threat actors, tactics, or past incidents. Additionally, feature contribution analysis provides insight into which factors affected the AI's decision, while alternative explanations help reduce reliance on a single interpretation, increasing trust in AI-based outputs.

When evaluating SOC dashboards integrating XAI (Fig. 1, 2), analysts favored context-aware alerts that include historical attack patterns, affected systems, and relevant intelligence feeds to provide a broader understanding of threats. Runbook-style mitigation steps were preferred over generic response recommendations, ensuring that analysts receive structured and actionable remediation guidance. Additionally, interactive LLM-based contextual analysis emerged as a valuable feature, enabling analysts to retrieve tailored explanations and insights through chatbot-style interactions. Visual representations, such as attack probability graphs and feature attribution charts, were preferred over text-heavy explanations, as they facilitate faster interpretation of security alerts.

These findings emphasize that explainability in AI-based security tools must prioritize clarity, usability, and contextualization. Effective integration of XAI in SOC workflows requires balancing technical depth with ease of interpretation, ensuring that security analysts can quickly retrieve, understand, and act on AI-generated alerts without additional cognitive overhead.

5 Discussion and XAI Design Recommendations

Our survey reveals several persistent challenges in AI-based security tools that hinder their effectiveness in SOC operations. The most pressing issue is lack of transparency, where analysts struggle to trust AI-generated alerts due to the absence of clear explanations, making it difficult to justify or act on AI-based decisions. Additionally, AI models remain vulnerable to adversarial risks, where attackers can manipulate training data or exploit explainability mechanisms to evade detection. Another significant challenge is alert fatigue, as high volumes of low-confidence AI alerts create inefficiencies, leading to delays in response and increased manual validation efforts.

To address these issues, AI-based security tools must incorporate explainability as a core feature. Confidence scores, feature attribution, and alternative explanations can enhance interpretability, providing analysts with insights into why an alert was triggered and how it aligns with past incidents. SOC dashboards should integrate attack attribution and contextual analysis, enabling analysts to link alerts to known threat actors, similar past incidents, and adversary tactics. Additionally, human-AI collaboration workflows should allow analysts to refine AI outputs by providing feedback, ensuring that models continuously improve while maintaining expert oversight.

Future research should focus on adaptive XAI models that tailor explanations based on analyst expertise, improving usability across different experience levels. Additionally, standardized explainability frameworks will help ensure consistency across security tools, allowing for better interoperability and evaluation. Lastly, adversarially robust AI must be developed to prevent explainability mechanisms from being exploited by attackers. Advancing XAI in cybersecurity will be key to enhancing trust, improving decision-making, and reducing the manual burden on SOC analysts.

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