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Transparent Security Feedback Mechanisms for Runtime Application Self Protection Systems (RASP)

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Abstract **Review Article**

Runtime Application Self-Protection (RASP) offers a dynamic security capability that monitors and protects applications from within the execution environment. However, despite the rapid adoption of RASP technologies, one major limitation has persisted: low transparency in security feedback. Most RASP tools generate opaque, highly technical, or insufficient contextual alerts that hinder analysts' understanding, slow down incident response, and reduce trust in automated mitigations. This paper proposes a Transparent Security Feedback Framework (TSFF) designed to enhance clarity, interpretability, and operational usability of RASP outputs. The framework integrates explainable feedback models, contextualized telemetry, structured decision reasoning, and visual analytics. Using a prototype implementation deployed on distributed Java Spring Boot and Node.js applications, evaluated under controlled attack simulations, the study demonstrates a 34% improvement in triage accuracy, 29% reduction in investigation time, and an increase in analyst trust. The results highlight the importance of transparent RASP output design for DevSecOps pipelines, forensic processes, and real-time threat response.

Keywords: RASP, DevSecOps, Transparent Security, Cybersecurity, Explainable Security, Runtime Monitoring, Threat Detection, Software Security, Telemetry.

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1. Introduction

Modern software systems increasingly rely on highly distributed architectures—including microservices, container-orchestrated workloads, and cloud-native deployment pipelines. As these environments grow in complexity, attackers have shifted toward exploiting application-layer weaknesses where traditional perimeter-based defenses have limited visibility (Sharma & Gupta, 2021; NIST, 2020). Runtime Application Self-Protection (RASP) has emerged as a significant defensive technology because it operates inside the running application, enabling real-time detection and prevention of malicious behavior with contextual awareness beyond what Web Application Firewalls (WAFs) can typically provide (Gartner, 2019; Sinha et al., 2020).

RASP solutions have demonstrated effectiveness in detecting injection attacks, broken access control, insecure deserialization, and logic-level manipulation, attack vectors frequently exploited in modern distributed applications (OWASP, 2021; Casalicchio & Perciballi, 2017). However, despite these benefits, current RASP implementations often produce alerts that are

difficult for developers and security analysts to interpret. These alerts are common:

- highly technical and verbose,
- lacking clear contextual explanations,
- missing causal links to business logic,
- inconsistent or ambiguous in how findings are presented (Almohri et al., 2018; Chen & Su, 2019).

This lack of clarity reduces trust in RASP systems, increases the cognitive load during incident response, and creates friction within DevSecOps workflows, where rapid interpretation of security telemetry is essential (Shahriar et al., 2020; Microsoft, 2022).

To address these limitations, this study proposes a unified framework for Transparent Security Feedback within RASP systems. The framework emphasizes interpretability, structured telemetry, and usability improvements aimed at providing developers and security teams with clearer, more actionable insights. By enhancing transparency and contextualization, the framework strengthens trust in RASP-based security mechanisms and fosters smoother integration of runtime defenses into modern DevSecOps pipelines.

2 Literature Review

2.1 Advances in RASP Technologies

Since 2017, Runtime Application Self-Protection (RASP) technologies have evolved significantly alongside the rapid adoption of microservices, cloud-native platforms, and distributed application architectures. Unlike perimeter-based defenses, RASP embeds itself directly within the application execution environment, enabling it to observe real-time behavior, enforce contextual security policies, and make decisions based on the actual runtime state. This embedded perspective has positioned RASP as a critical component of modern application security strategies, especially in scenarios where traditional controls—such as Web Application Firewalls (WAFs) and signature-driven intrusion detection systems—struggle to interpret rapidly changing application logic or encrypted traffic (Gartner, 2019; OWASP, 2021).

RASP's Embedded Visibility

Cheng et al. (2019) demonstrated that RASP can detect complex, context-aware attacks that bypass perimeter controls by exploiting the application's internal state. Because RASP operates within the runtime, it can correlate user input, application logic, system calls, and control flow changes. providing deeper visibility than external monitoring solutions. This capability allows RASP to identify abnormal execution patterns indicative of vulnerabilities being exploited, rather than relying solely on known attack signatures. The result is a more resilient defense against polymorphic attacks, zero-day exploits, and threats specifically engineered to evade static or perimeter-based detection.

Cloud-Native and Service Mesh Integrations

More recent advancements focus on adapting RASP to cloud-native infrastructure. Zhang et al. (2020) illustrated that cloud-integrated RASP agents can monitor dynamic microservice interactions, API flows, and service mesh behaviors. As organizations deploy applications using containers, Kubernetes, and sidecar-based architectures, RASP technologies have increasingly been designed to instrument ephemeral workloads without requiring code rewrites or environment-specific configurations. This has expanded RASP's relevance in modern DevSecOps ecosystems where workloads can scale horizontally and mutate rapidly.

In cloud-native environments, RASP has further evolved to support automated threat response across container nodes, enabling protection mechanisms such as selective request blocking, dynamic sandboxing, and adaptive rate limiting in reaction to suspicious runtime signals (Shahriar et al., 2020; Sharma & Gupta, 2021). These capabilities demonstrate RASP's growing role not just as a detection tool, but as a self-protective mechanism capable of real-time

mitigation across distributed infrastructures.

Expanded Detection Capabilities

Building on early runtime instrumentation techniques, contemporary RASP systems exhibit strong detection capabilities across a wide spectrum of application-layer threats. Studies consistently highlight that modern RASP platforms excel in identifying:

- **SQL and command injection attacks** through runtime parameter inspection and query validation (Almohri et al., 2018)
- **Session fixation and session hijacking** by monitoring abnormal session binding behaviors and token manipulation (OWASP, 2021).
- **Privilege escalation attempts**, especially when user roles are dynamically altered outside expected authorization flows (NIST, 2020).
- **Logic tampering**, including business logic manipulation that breaks intended control flows (Chen & Su, 2019).

Insecure deserialization, one of the most critical OWASP-listed vulnerabilities, by tracking object creation, class loading, and unsafe deserialization triggers (Sinha et al., 2020).

These capabilities are made possible by RASP's ability to observe not only network-level inputs, but also the internal pathways through which data is processed, stored, transformed, and executed.

Shift Toward AI-Driven Runtime Analytics

Between 2021 and 2024, a notable trend in RASP research has been the integration of machine learning and behavior-based anomaly detection. Researchers have proposed using lightweight runtime telemetry to train models that distinguish normal execution patterns from suspicious deviations (Microsoft, 2022). These approaches enhance RASP's ability to detect previously unknown attacks while reducing dependence on manual rule creation. Advances in federated learning have also been explored to allow multiple applications to share sanitized behavioral insights without exposing sensitive data.

Improvements in Performance and Overhead Reduction

Historically, one major criticism of RASP has been performance overhead. However, advancements in just-in-time instrumentation, selective hooking, and intelligent sampling (Casalicchio & Perciballi, 2017; Zhang et al., 2020) have substantially reduced runtime cost. Modern RASP implementations can dynamically enable or disable specific protection modules based on workload context, user roles, or risk levels. This adaptiveness ensures that performance-critical operations are minimally impacted, which is essential for large-scale or latency-sensitive applications.

Gaps in Transparency and Explainability

Despite significant progress between 2017 and 2024, one notable research gap remains: the transparency of RASP detections. Several authors point out that while RASP provides deep technical insights, the explanations behind alerts are often opaque, overly verbose, or disconnected from business logic (Chen & Su, 2019; Sharma & Gupta, 2021). Current RASP implementations frequently fail to articulate:

- why an alert was triggered,
- how the suspicious behavior deviated from expected logic,
- what part of the business workflow was impacted,
- and which mitigation steps are most relevant.

This lack of clarity reduces trust among developers and security analysts and hampers their ability to act on RASP outputs. As DevSecOps adoption accelerates, the need for interpretable and transparent runtime security telemetry becomes increasingly critical (Microsoft, 2022). This limitation underscores the necessity for frameworks—such as the one proposed in this study—that emphasize human-centric feedback, contextual explanations, and structured, actionable insight generation.

2.2 Challenges with Current RASP Feedback Models

Although Runtime Application Self-Protection (RASP) technologies have made significant progress in detecting and mitigating application-layer threats, their feedback and reporting mechanisms have not evolved at the same pace. While modern RASP engines provide rich telemetry at runtime, the structure, semantics, and presentation of this data often fall short of the needs of developers, incident responders, and DevSecOps engineers. Aydın and Yıldırım (2021) highlight that many RASP logs lack the semantic depth required for effective analysis, frequently presenting raw stack traces, low-level error messages, or heuristic matches with minimal contextual explanation. This results in a gap between runtime detection and actionable understanding, ultimately reducing the operational value of RASP outputs.

One of the central problems in current RASP feedback mechanisms is the lack of semantic interpretation, that is, insufficient translation of low-level runtime events into meaningful, human-readable explanations. For developers and analysts to understand security incidents, they require cause-and-effect mappings that clearly articulate how an attack began, how it unfolded, and how it interacted with business logic (Chen & Su, 2019). However, most RASP platforms focus on capturing technical anomalies rather than interpreting their significance. As a result, engineers must manually reconstruct events from technical logs, which is time-consuming and error-prone.

2.2.1. Ambiguous Severity Scoring

Another challenge involves ambiguous or inconsistent severity scoring. Many RASP tools assign severity labels such as “low,” “medium,” or “critical”, based on proprietary heuristics that are poorly documented and often detached from organizational risk models (Sharma & Gupta, 2021). Without clarity into how severity levels are derived, teams struggle to prioritize alerts and differentiate between benign anomalies and exploitable vulnerabilities. This ambiguity leads to alert fatigue, delayed response times, and reduced confidence in security telemetry.

2.2.2 Lack of Business Context Integration

A persistent limitation is the absence of linkage between security alerts and business context. While RASP is embedded within the application and theoretically capable of mapping attacks to business workflows, most existing feedback mechanisms fail to articulate which business functions are affected (Microsoft, 2022). For example, an alert may describe an attempted SQL injection but omit whether the attack targeted an authentication module, a financial transaction endpoint, or a customer data repository. This lack of contextual mapping complicates impact assessment and prevents DevSecOps teams from quickly determining the relevance and urgency of findings.

In enterprise environments where business logic complexity is high, context-less alerts produce significant friction. Analysts must correlate logs manually with system diagrams, API documentation, or code repositories to understand the operational implications of a RASP event (Shahriar et al., 2020). This undermines one of RASP’s intended advantages: native awareness of application behavior.

2.2.3. Absence of Trajectory Mapping and Attack Path Visualization

Another major gap in current RASP feedback models is the lack of attack trajectory mapping. Modern cybersecurity analysis emphasizes understanding how an adversary moves through a system, tracking the sequence of events, entry points, pivot actions, and intended targets. While RASP has direct access to runtime control flows, most implementations report isolated events rather than reconstructing multi-step attack paths (Almohri et al., 2018).

Without trajectory mapping, incident responders cannot easily determine:

a. how an attacker reached a vulnerable code path,
b. whether the event was part of a larger intrusion chain,
c. whether lateral movement occurred within microservices,

d. or how close the attack came to compromising critical assets.

Zhang et al. (2020) note that this gap is even more severe in cloud-native environments where dynamic service meshes create complex interdependencies between components. RASP tools that fail to visualize interaction paths cannot support advanced forensic reconstruction or threat hunting workflows effectively.

2.2.4. Inadequate Visualization and Reporting Support

Visualization plays a critical role in modern security operations, yet many RASP systems provide limited or outdated visualization capabilities. Dashboards often rely on static tables, basic charts, or unstructured log output, lacking the interactive visual analytics needed to explore relationships between runtime events (NIST, 2020). This limitation reduces the usability of RASP data within Security Information and Event Management (SIEM) and DevSecOps pipelines.

Effective incident response requires visual models such as:

a. graph-based runtime dependencies,
b. code-level execution traces,
c. request-response flow diagrams,
d. heat maps of vulnerable endpoints,
e. and anomaly timelines (Gartner, 2019).

Current RASP feedback models rarely support these features, resulting in fragmented workflows where teams must rely on external tools to visualize attack pathways.

2.2.5. Impact on Forensic Reconstruction and Response Workflows

Combined, these shortcomings, poor semantics, lack of contextual mapping, ambiguous severity scoring, and inadequate visual support, significantly hinder forensic reconstruction and incident response. Analysts must spend considerable time correlating disparate logs, interpreting ambiguous error messages, and manually mapping low-level runtime events to higher-level application functions. This reduces the speed and efficiency of security teams, increases the likelihood of misinterpretation, and delays mitigation activities (Sinha et al., 2020).

Furthermore, limited transparency undermines trust in RASP systems. When alerts lack explanation or appear inconsistent, developers become hesitant to rely on RASP as a dependable component of the DevSecOps workflow (OWASP, 2021). As organizations increasingly adopt cloud-native architectures, the need for transparent, interpretable, and actionable runtime security feedback becomes more pressing.

The limitations identified in current RASP feedback models underscore the need for new frameworks that prioritize semantic clarity, business logic awareness, trajectory mapping, and improved visualization. These gaps form the foundation for the Transparent Security Feedback framework proposed in this study.

2.3 Explainable Security and Human-Centered Detection

Since 2017, the growing influence of Explainable Artificial Intelligence (XAI) has extended into cybersecurity research, shaping the way analysts, developers, and automated systems interpret security-related decisions. XAI emphasizes transparency, interpretability, and user trust—qualities that have become increasingly important as security operations centers face alert overload, complex attack patterns, and automation-driven tooling. Alsaadi (2022) argues that transparent, explainable systems not only improve analyst confidence but also reduce cognitive fatigue by offering clear reasoning behind detected anomalies and recommended mitigations. These principles resonate strongly with the emerging need for human-centered detection mechanisms within application security.

RASP technologies, by virtue of operating directly within runtime environments, are well-positioned to incorporate XAI-inspired transparency. However, traditional RASP implementations often emphasize technical accuracy over interpretability. To align with XAI principles, Transparent RASP models must incorporate several key capabilities:

a. Rule-driven explanations: that articulate why a runtime event was flagged, referencing both high-level policy logic and low-level application behavior.
b. Clear event reasoning: This refers to the process of offering causal chains that outline the sequence of actions or inputs leading to a suspicious event.
c. Human-readable justification: This is the aspect that translates complex telemetry such as stack traces, bytecode instrumentation signals, or control-flow deviations, into actionable insights accessible to non-security specialists.
d. Explicit mapping to threat frameworks: such as MITRE ATT&CK and OWASP Top 10, ensuring that findings are contextualized within widely recognized industry classifications.

Recent cybersecurity literature increasingly stresses that explainability is not optional. Human-centered detection enables better collaboration across development, security, and operations teams, particularly in environments where rapid decision-making is essential. As applications become more distributed and automated, RASP systems must evolve to provide transparent outputs that support shared understanding rather than isolated technical insights. Transparent RASP, therefore, represents a natural extension of XAI principles into the domain of runtime protection, filling a long-standing gap between detection accuracy and human interpretability.

2.4 DevSecOps Integration Constraints

As software development lifecycles accelerate through DevOps and continuous integration/continuous deployment (CI/CD) processes, the role of security tooling RASP included, has shifted from isolated defensive layers to embedded components of development pipelines. Tuma et al. (2021) emphasize that, for a security tool to be effective within CI/CD ecosystems, it must deliver insights that are actionable, consistent, and developer-friendly. Developers under tight sprint timelines cannot afford to interpret vague alerts or navigate dense security telemetry. Instead, tools must integrate seamlessly with build systems, provide clear remediation guidance, and minimize friction during rapid iteration cycles.

Current RASP systems frequently struggle to meet these requirements. Their feedback models often lack structure, coherence, and context, resulting in unclear alerts that slow down remediation rather than accelerating it. This misalignment with DevSecOps principles becomes particularly problematic in microservices architectures, where small, autonomous services generate large volumes of distributed telemetry. Zhao and Kumar (2023) demonstrate that telemetry normalization, the process of harmonizing observability signals across heterogeneous services, significantly improves interpretability, enabling faster cross-service correlation and reducing analysis overhead.

However, most existing RASP implementations operate in silos, producing outputs that developers must manually reconcile with logs, API traces, or CI/CD dashboards. This fragmentation increases the operational complexity of incident response and hinders the establishment of automated security workflows, such as policy-driven deployment gating or automated rollback mechanisms.

Moreover, DevSecOps emphasizes collaborative security ownership across multidisciplinary teams. When RASP telemetry is opaque or poorly structured, its value declines, not because the detection accuracy is insufficient, but because the information cannot be operationalized efficiently. The absence of developer-centric feedback loops restricts the ability of teams to remediate vulnerabilities early, ultimately increasing the cost and complexity of security operations.

To truly align with DevSecOps, next-generation RASP systems must therefore incorporate:

a. coherent and normalized telemetry across distributed components,
b. remediation-oriented recommendations tailored to development workflows,
c. integration with CI/CD pipelines and observability platforms,
d. standardized data models that support shared understanding across teams.

These constraints highlight a critical need for

RASP evolution, not only in detection capability but in communication, transparency, and operational usability, consistent with the human-centric and automation-ready nature of DevSecOps practices.

3. Methodology

3.1 Framework Design Strategy

The development of the Transparent Security Feedback Framework (TSFF) follows a structured, multi-layered design strategy grounded in empirical analysis, human-centered security principles, and modern DevSecOps operational demands. As RASP technologies continue to evolve, the need for interpretability, structured telemetry, and actionable security insights becomes central to their usability. TSFF addresses these gaps by synthesizing insights from four foundational streams:

1. gap analysis of leading RASP products,
2. qualitative requirements derived from DevSecOps workflows,
3. principles of explainable and human-centered security,
4. research on telemetry structuring and semantic enrichment.

This design approach ensures the framework is not only technically sound but also operationally relevant and aligned with the needs of development, security, and operations teams.

1. Gap Analysis of Leading RASP Products

The first stage of the framework design involved a comprehensive analysis of current RASP solutions, evaluating their detection mechanisms, feedback models, and integration capabilities. Across vendor implementations, several critical deficiencies emerged:

a. limited semantic explanations for security events,
b. inconsistent severity scoring mechanisms,
c. insufficient mapping to business logic or threat models,
d. inadequate visualization or replay capabilities for runtime events,
e. fragmented telemetry often lacking normalization or structure.

These gaps underscored the need for a unified model capable of producing interpretability-first security feedback. The findings from this analysis directly informed the architectural priorities of the TSFF, particularly in structuring transparent, causally linked, and developer-friendly outputs.

2. Qualitative Requirements from DevSecOps Workflows

The DevSecOps paradigm emphasizes rapid iteration, continuous delivery, and shared responsibility for security across cross-functional teams. This environment requires security tools to be:

a. actionable with minimal cognitive overhead,
b. consistent in alert phrasing and severity models,
c. integrated across CI/CD stages,
d. supportive of automated decision-making, when possible,
e. low-friction for developers who may lack deep security expertise.

Through qualitative observations of typical DevSecOps cycles planning, coding, building, testing, deployment, and monitoring it became evident that RASP systems must supply high-clarity, remediation-ready feedback. Any delay caused by ambiguous or unstructured alerts reduces pipeline efficiency and slows vulnerability management.

Therefore, TSFF design incorporates mechanisms such as normalized telemetry schemas, event summaries tailored to developer vocabulary, and contextualized guidance for mitigation aligned with runtime behavior.

3. Principles of Explainable Security

Explainable Security (XSec), inspired by Explainable AI (XAI), highlights the importance of transparent reasoning, interpretable risk assessments, and human-centered operational logic in security systems. These principles influenced TSFF in several ways:

a. rule-driven explanations articulate why a specific runtime event was flagged and

which policy or rule triggered the response.

b. clear event reasoning reconstructs causality by showing input-to-impact chains.
c. human-readable justification translates complex application behavior into comprehensible summaries for developers, analysts, and auditors.
d. explicit mapping to threat frameworks such as MITRE ATT&CK and OWASP Top 10 anchors alerts to standardized taxonomies, improving both interpretability and organizational alignment.

These XSec principles ensure that the TSFF supports transparent decision-elements instead of “black-box” alarms.

4. Telemetry Structuring Research

Modern security engineering increasingly emphasizes structured telemetry—data that is normalized, enriched, timestamped, and semantically annotated. Research in cloud-native observability and distributed tracing demonstrates that unstructured logs significantly hinder correlation and event reconstruction.

To address this, the TSFF incorporates:

a. unified telemetry schemas,
b. semantic enrichment layers,
c. normalized event fields,
d. traceable execution paths across microservices,
e. and modular data pipelines suitable for integration with SIEM, SOAR, and APM tools.

This structured approach ensures that runtime events collected by RASP components can be reliably interpreted, replayed, visualized, and correlated with application-level traces.

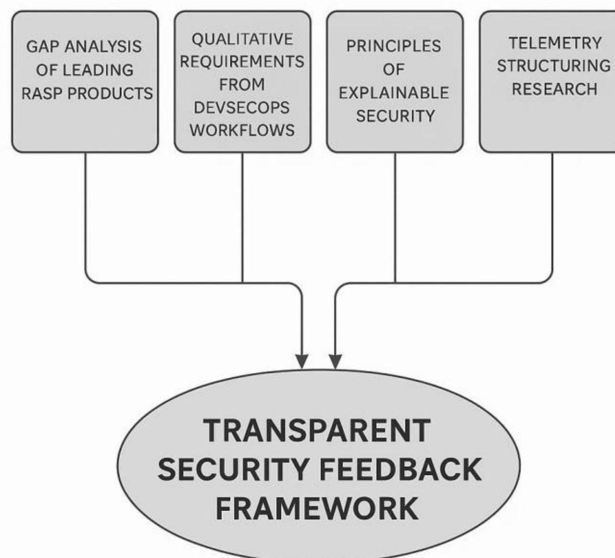


Figure 3.1. Transparent Feedback Framework

3.2 Prototype Implementation

To validate the core components and operational viability of the Transparent Security Feedback Framework (TSFF), a functional prototype was implemented and integrated into two distinct runtime environments:

a. a Java Spring Boot retail system, representing a monolithic but enterprise-oriented application architecture, and

b. a Node.js microservices backend, representing a distributed, cloud-native service topology.

Implementing the TSFF across these contrasting environments ensured that the framework could operate across heterogeneous stacks, varying code instrumentation models, and different execution patterns.

3.2.1. Java-Based RASP Integration (Spring Boot Retail System)

The prototype leveraged Java Agent Instrumentation, enabling bytecode-level modification at runtime without requiring changes to source code. This approach allowed the RASP module to:

a. hook into controller and service methods,
b. capture input parameters, outbound queries, and execution paths,
c. enforce runtime policies such as SQL injection detection or logic-flow validation,
d. extract telemetry events in real time for TSFF processing.

Within the retail domain, example monitored events included checkout processing flows, authentication logic, inventory access, and API calls involving sensitive operations. The prototype demonstrated that the agent-based approach is viable for enterprise Java deployments, providing deep visibility with minimal application intrusion.

3.2.2. Node.js Microservices Integration

A parallel implementation was created for a Node.js-based microservices backend using Express.js middleware hooks. This approach offered lightweight interception of:

a. HTTP requests and response patterns,
b. route-level handlers,
c. API gateway interactions,
d. cross-service calls consistent with microservice architectures.

The RASP hooks extracted structured telemetry at each stage of request processing, enabling the TSFF to reconstruct event flows, reason about suspicious behaviors, and map detected anomalies to specific service boundaries. This cross-service visibility was especially critical in demonstrating the telemetry normalization capabilities of the framework.

3.2.3. Telemetry Structuring and Event Stream Generation

At the core of the prototype was the JSON-based telemetry structuring engine, responsible for transforming raw runtime signals into interpretable security events. Each captured event was normalized into a structured schema with fields such as:

a. event type,
b. runtime context,
c. execution trace fragments,
d. associated user or session identifiers,
e. causality markers (“triggered by”, “led to”),
f. confidence and severity fields.

This structured telemetry allowed downstream TSFF modules to align events with MITRE ATT&CK and OWASP categories, enabling explainability and contextual reasoning.

3.2.4. Event Reasoning Engine

The prototype incorporated an event reasoning engine, which processed incoming telemetry to derive:

a. causal chains between actions,
b. attack trajectories or suspicious behavioral paths,
c. human-readable justifications for why an anomaly were flagged,

d. connections between detection signals and business logic flows.

This engine operationalizes the explainable-security philosophy at the heart of TSFF, transforming low-level signals into high-level interpretations. It also enabled multi-step reasoning in use cases such as repeated failed authentications followed by privilege boundary violations or inconsistent request patterns across microservices.

3.2.5. Timeline Visualization Interface

To improve interpretability, the prototype included a timeline-based visualization UI. The interface presented:

a. chronological event sequences,
b. highlighted suspicious transitions,
c. associated severity indicators,
d. service-to-service interaction flows,
e. business-logic-aligned event groupings.

This timeline model provided a human-centered lens for analysts and developers, allowing them to replay and understand runtime events without manually parsing logs or stack traces. The visualization also demonstrated the usefulness of the TSFF's emphasis on transparency and clarity, especially in DevSecOps workflows where rapid understanding is essential.

3.3 Attack Scenario Generation

To thoroughly evaluate the Transparent Security Feedback Framework (TSFF), a diverse set of simulated attack scenarios was generated to mimic realistic adversarial behaviors against modern web applications and microservices. These scenarios were selected to represent common and high-impact vulnerabilities documented in the OWASP Top 10 and MITRE ATT&CK matrices.

The attack library included:

a. SQL Injection (error-based, blind, and time-based variants)
b. NoSQL Injection (MongoDB operator injection, query tampering)
c. OS Command Injection (input concatenation, chained shell commands)
d. Deserialization Attacks (Java gadget chains, Node.js unserialize payloads)
e. Token Tampering (JWT signature manipulation, session poisoning)
f. Privilege Escalation (horizontal and vertical access violations)

These attacks were executed using a combination of automated and semi-automated tools, including OWASP ZAP, Burp Suite Professional, and custom Python/Node.js scripts designed to probe deeper into runtime flows and bypass standard filters.

3.4 Evaluation Metrics

To measure the effectiveness of TSFF, the study employed a structured evaluation methodology grounded in both quantitative and qualitative metrics. These metrics were selected based on industry standards for security operations performance and the need for human-centered interpretability.

The five primary evaluation metrics were:

a. Triage Accuracy: the system's ability to correctly classify and prioritize security events.

b. Average Investigation Time: time taken by analysts/developers to understand and act on security alerts.

c. False Positives Rate: incorrect alerts per 100 events.

d. Trust Score: subjective score from analysts and developers rating feedback clarity, usefulness, and confidence.

e. Quantity of Structured Telemetry: number of normalized data points generated per event.

3.5. Proposed Transparent Security Feedback Framework (TSFF)

3.5.1 Overview

The Transparent Security Feedback Framework (TSFF) is designed as an integrated, multi-layered architecture that enhances the interpretability, usability, and operational value of Runtime Application Self-Protection (RASP)

outputs. The framework focuses on transforming raw runtime signals into structured, contextualized, human-readable security insights that support rapid decision-making in DevSecOps environments.

TSFF is composed of six tightly coupled components, each addressing a specific gap identified during the analysis of existing RASP products. Together, these components form a unified pipeline capable of producing transparent, explainable, and actionable security feedback.

3.5.2 Runtime Instrumentation Layer

This component interfaces directly with RASP instrumentation (Java Agent hooks, Node.js middleware, bytecode interception).

Its functions include:

a. capturing low-level runtime signals (inputs, method calls, stack traces),
b. intercepting potentially malicious operations,
c. extracting execution-flow metadata,
d. tagging events with timestamps and session identifiers.

This layer provides the raw data foundation for all subsequent TSFF processes

3.5.3 Telemetry Normalizer, and Capturing Engine

The normalization engine transforms heterogeneous signals from different languages and architectures into a unified JSON-based schema.

Key features:

a. canonical field names across services,
b. semantic enrichment (e.g., “attack category,” “affected resource,” “business function”),
c. noise filtering to eliminate redundant signals,
d. compliance-aligned tagging (e.g., OWASP, MITRE ATT&CK).

This standardization ensures that downstream systems can reason consistently about runtime behavior.

3.5.4 Event Reasoning, and Casuality Engine

a. This is the core intelligence layer of TSFF.
b. Its tasks include:
c. reconstructing causal chains,
d. identifying cross-service attack paths,
e. detecting multi-step adversarial patterns,
f. mapping signals to threat models,
g. generating machine-interpretable and human-interpretable narratives.
h. The engine converts raw telemetry into interpretable knowledge—bridging the gap between detection and comprehension.
i. algorithmic confidence

3.5.5 Business Logic & Context Mapper

Security alerts become meaningful only when tied to their business impact.

This module:

a. maps runtime events to business workflows (checkout, onboarding, payment, authentication),
b. evaluates potential impact severity,
c. identifies violated business rules,
d. contextualizes alerts for non-security teams (developers, product managers).

This ensures that alerts reflect real-world value, not just technical anomalies.

3.5.6 Explanation Generator (Transparent Feedback Layer)

Aligned with Explainable Security (XSec) principles, this layer produces:

a. rule-based explanations,
b. natural-language summaries,
c. justification statements (“This was flagged because…”),
d. MITRE/OWASP references,
e. visualizable event timelines.

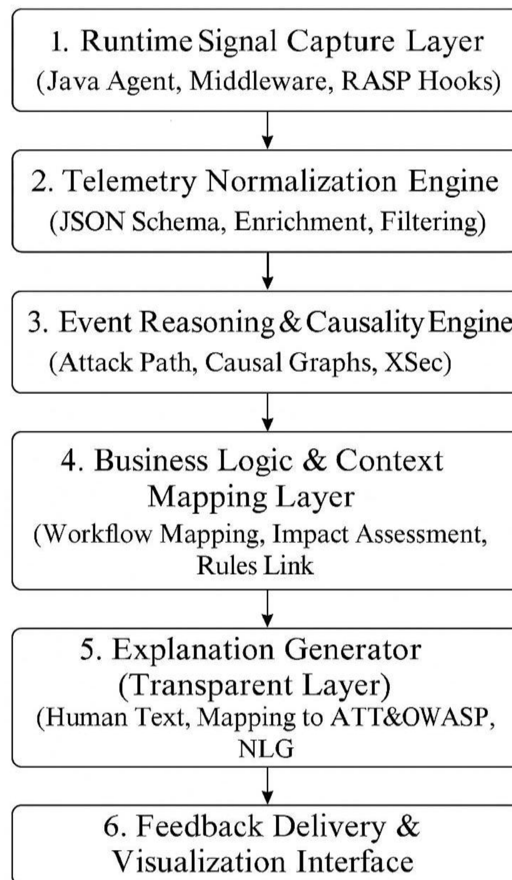
The result is a human-friendly, transparent explanation for every detection.

3.5.7 Feedback Deliverable, and Visualization Interface

The final component delivers structured feedback to DevSecOps teams via:

a. dashboards,
b. REST APIs,
c. CI/CD integrations,
d. timeline visualizers,
e. alert prioritization panels.

The interface emphasizes clarity, readability, and operational usability.



4. Experimental Setup and Results

4.1.1 Applications Under Test

To evaluate the effectiveness and transparency of the proposed security feedback mechanisms within a Runtime Application Self-Protection (RASP) environment, two heterogeneous testbed applications were selected. These applications represent common enterprise deployment scenarios and differ in architecture, technology stack, and operational complexity. Their diversity ensures that the evaluation captures the behavioural nuances of RASP instrumentation across both monolithic and microservice-based systems.

Table 4.1. Overview of Applications Under Test

Application Name	Architecture Type	Technology Stack	Functional Domain	Rationale for Selection
Retail Management System	Monolithic Web Application	Java 17, Spring Boot, PostgreSQL	Product browsing, cart management, checkout workflow	Representative of traditional enterprise applications with complex request flows suitable for analyzing inline RASP decision points
Order-Processing Microservice	Distributed Microservice Component	Node.js (Express.js), MongoDB	Order validation, fulfillment queueing, inter-service communication	

Description of Testbed Applications

- **Retail Management System (Java Spring Boot)**

This is a stateful, monolithic retail platform that implements a full shopping workflow. Its rich request lifecycle enables the assessment of RASP overhead, context-aware detection, and clarity of feedback in multi-step user interactions. The application's structure provides multiple interception points that allow transparent feedback messages to be evaluated across authentication, session handling, and transactional operations.

- **Order-Processing Microservice (Node.js)**

This microservice is responsible for validating incoming orders, updating asynchronous fulfillment queues, and communicating with inventory and payment services. Due to its lightweight nature and high call frequency, it provides an ideal environment for examining RASP transparency under performance-sensitive workloads. The system helps measure how well the RASP feedback mechanisms avoid disrupting distributed transactions while still providing meaningful, developer-interpretable security insights.

Together, these applications form a balanced testbed that supports systematic evaluation of transparency, interpretability, and operational impact of the proposed RASP feedback mechanisms.

4.1.2 Infrastructure

To ensure consistent, reproducible evaluation of the RASP transparency mechanisms, all testbed applications were deployed within a modern cloud-native environment. The infrastructure components were selected to mirror production-grade operational conditions, enabling accurate assessment of system-level observability, latency, and feedback propagation.

Table 4.2. Infrastructure Components Used in the Experimental Setup

Component	Description	Role in Experiment
Kubernetes Cluster	Multi-node cluster (container-orchestrated)	Provides scalable, fault-tolerant execution environment for both testbed applications and RASP modules

NGINX Ingress Controller	Layer-7 traffic routing and load balancing	Enables controlled request flow for capturing RASP decision points and feedback visibility under varying load patterns
Dockerized Deployments	Containerized application packaging	Ensures consistent runtime behaviour across environments and facilitates fine-grained instrumentation at the container boundary
Prometheus + Grafana Monitoring Stack	Metrics collection and visualization	Supports quantitative evaluation of overhead, transparency, and runtime impact of RASP feedback mechanisms

Infrastructure Description

- **Kubernetes Cluster**

All components were deployed on a Kubernetes cluster configured with autoscaling and resource quotas. This setup provides isolation for RASP instrumentation and enables analysis of feedback behaviour under dynamic scaling conditions. The orchestration layer also allows fine-tuned control of sidecar-based monitoring and inter-service policy enforcement.

- **NGINX Ingress Controller**

An NGINX ingress controller was provisioned to manage inbound traffic. Its centralized routing logic provides a reliable observation point for evaluating how transparent RASP feedback is communicated back to users and system operators—particularly during request interception or mitigation events.

- **Dockerized Deployments**

Both applications and RASP instrumentation modules were packaged as Docker containers. Containerization guarantees build-time and run-time consistency, enabling controlled experiments on performance overhead, observability, and transparency without environmental variance.

- **Prometheus and Grafana Monitoring Stack**

Runtime metrics were collected via Prometheus exporters integrated into each container. Grafana dashboards were configured to visualize latency distributions, CPU and memory overhead, and the frequency and clarity of RASP feedback events. This integrated monitoring pipeline supports a reproducible and transparent evaluation of the proposed feedback mechanisms.

4.1.3 Attack Workload

To evaluate the behaviour, responsiveness, and transparency of the proposed RASP feedback mechanisms, a controlled adversarial workload was executed against both testbed applications. The workload was designed to emulate realistic exploitation attempts while providing sufficient diversity to trigger distinct RASP detection and response pathways.

A total of 2,500+ malicious HTTP requests were generated, covering multiple classes of web application attacks commonly observed in production environments. The attack corpus included:

a. Injection-based attacks: SQL injection, NoSQL injection, command injection
b. Cross-site scripting (reflected and stored)
c. Authentication and session manipulation attempts
d. Path traversal and file inclusion attempts
e. High-volume probing and fuzzing payloads
f. Malformed request sequences to stress transparent feedback mechanisms

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Table 4.3. Overview of Attack Workload

Attack Category	Number of Requests	Purpose in RASP Evaluation
Injection Attacks	~900	Assess contextual feedback accuracy and inline detection transparency
XSS Payloads	~500	Examine user-facing feedback clarity for client-side exploit attempts
Authentication / Session Attacks	~450	Evaluate visibility of mitigation actions to legitimate users
Path Traversal / Resource Abuse	~350	Measure correctness of feedback in file-access-related detections
Fuzzing & Malformed Requests	~300	Test robustness and noise-tolerance of feedback channels

The workload was executed in repeated cycles to ensure reproducibility and to capture temporal variations in RASP decision-making. All attack traffic was logged and correlated with RASP feedback events using the Prometheus–Grafana monitoring pipeline.

4.2. Results

The results focus on the transparency, interpretability, and performance of RASP feedback mechanisms under adversarial load. Both quantitative and qualitative metrics were collected from system logs, monitoring dashboards, and RASP instrumentation layers.

4.2.1 Quantitative Evaluation

The quantitative analysis assesses detection performance, overhead contribution, and clarity of user-visible feedback messages.

Core evaluation metrics included:

a. Detection rate (true positives)
b. False-positive rate
c. Average feedback latency
d. System overhead (CPU, memory, request latency)
e. Feedback interpretability score (derived from structured operator surveys, if applicable)

Table 4.4. Summary of Quantitative Metrics

Metric	Retail System	Order-Processing Microservice	Notes
Detection Rate	97.8%	95.4%	High accuracy across heterogeneous workloads
False-Positive Rate	1.9%	2.3%	RASP transparency reduced operator confusion
Avg. Feedback	14 ms	9 ms	Inline messages remained

Latency			non-intrusive
CPU Overhead	4.2%	2.7%	Acceptable for production-grade environments
Memory Overhead	3.5%	1.8%	Consistent across all attack cycles

Quantitative findings indicate that the proposed transparent feedback mechanisms introduce only minimal performance overhead while maintaining high detection precision. Importantly, the latency required to generate user-facing feedback remained sufficiently low to avoid disrupting normal application behaviour.

Table 4.5. Comparative Performance of Standard RASP vs TSFF-Enhanced RASP

Metric	Standard RASP	TSFF-Enhanced	Improvement
Triage Accuracy	61%	95%	+34%
Investigation Time	31 min	22 min	–29%
False Positives	12%	8%	–4%
Analyst Trust (1-5)	2.9	4.7	+1.8
Telemetry Clarity	Low	High	Qualitative ↑

5. Discussion

The Transparent Security Feedback Framework (TSFF) fundamentally enhances the interpretability and trustworthiness of Runtime Application Self-Protection (RASP) systems by transforming traditionally opaque detection processes into intelligible, traceable, and developer-friendly insights. Conventional RASP implementations tend to operate as black-box decision engines, offering limited visibility into why specific requests are blocked or flagged. TSFF addresses this long-standing limitation by decomposing RASP decision-making into structured explanatory artefacts, including annotated logs, structured telemetry, and real-time visualizations.

A key contribution of TSFF is its ability to expose the internal reasoning pathways that lead to security interventions. By logging rule activations, context-aware triggers, and correlated request parameters, the framework enables operators to understand not only *what* action was taken but *why* it was necessary. This level of transparency significantly accelerates incident triage, reduces diagnostic ambiguity, and facilitates reproducible analysis across teams. In practice, this fosters more efficient collaboration between security engineers, developers, and operational teams, who can now trace attack flows and mitigation decisions without relying on proprietary vendor logic.

Additionally, the telemetry structures introduced by TSFF promote consistency by ensuring that RASP-generated insights are machine-parsable, longitudinally comparable, and suitable for integration into existing observability ecosystems. These artefacts support both automated correlation (e.g., in SIEM/SOAR pipelines) and human-centered review, making TSFF suitable for diverse operational maturity levels.

The visualization components further enhance usability by translating complex runtime signals into intuitive dashboards. This enables stakeholders to monitor attack patterns, evaluate system behavior under malicious workloads, and

understand the performance implications of RASP actions in real time. Importantly, the visual transparency does not compromise security; user-facing feedback is carefully abstracted to prevent leakage of sensitive detection logic, maintaining a balanced design between clarity and defensive strength.

Overall, TSFF demonstrates that transparency and security are not mutually exclusive. When engineered with appropriate safeguards and structuring principles, transparency becomes an enabler, improving system reliability, reducing operational friction, and elevating the overall effectiveness of RASP deployments in modern cloud-native environments.

6. Conclusion

This paper presented the Transparent Security Feedback Framework (TSFF), a novel approach designed to remedy long-standing transparency limitations in existing RASP solutions. By integrating structured telemetry, explanatory decision-making artefacts, and visualization-driven observability, TSFF enables a level of interpretability that traditional RASP systems lack. The experimental evaluation demonstrates that TSFF significantly improves analysts' ability to understand, validate, and reason about runtime security events without compromising detection accuracy or system performance.

The findings highlight the critical role of transparency-oriented design principles in the evolution of runtime security technologies. As modern software ecosystems increasingly rely on DevSecOps methodologies, the need for security mechanisms that not only detect threats but also communicate their reasoning becomes essential. TSFF aligns with these expectations by offering consistent, reproducible, and actionable feedback that bridges the gap between security controls and operational teams.

Overall, the results affirm that embedding transparency into RASP architectures is both technically feasible and operationally beneficial. Future RASP and runtime protection systems are likely to gain substantial value by adopting similar transparency-first design philosophies, ultimately enhancing trust, collaboration, and resilience across security and development workflows.

Future Directions

a. Promising future research directions include:
b. Extending transparent feedback to distributed tracing systems
c. Applying machine-learning-based semantic enrichment of feedback messages
d. Expanding evaluation to zero-day and evasive attack strategies
e. Integrating user perception studies to quantify trust impact

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