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An Adaptive Risk-Driven DevSecOps Framework for Securing Multi-Cloud Enterprise Systems in the Era of Agentic AI

Nitin Bodade[1]

[1]Digital Division, Caterpillar Inc., United States of America

Corresponding Author: Nitin Bodade[*]

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Abstract: The rapid adoption of cloud-native architectures, microservices, and continuous delivery pipelines has transformed enterprise software engineering by enabling faster deployment cycles, independent service evolution, and scalable digital delivery. However, these advantages also expand the cybersecurity attack surface across source code repositories, CI/CD pipelines, software supply chains, cloud identities, infrastructure-as-code templates, runtime workloads, and distributed multi-cloud environments. Prior research shows that DevSecOps improves software security by embedding security practices into development and operations workflows, yet organizations continue to face challenges related to toolchain fragmentation, inconsistent risk prioritization, limited automation, and weak integration between security findings and deployment decisions. This paper proposes the Adaptive Risk-Driven DevSecOps Framework (ARD-DSF), a layered framework for securing multi-cloud enterprise systems in the era of agentic artificial intelligence. ARD-DSF integrates real-time risk scoring, AI-assisted threat modeling, secure CI/CD orchestration, policy-as-code enforcement, Zero Trust-aligned access control, and continuous feedback loops across the software development lifecycle. Unlike static DevSecOps pipelines that treat security findings as isolated scan outputs, ARD-DSF prioritizes vulnerabilities using contextual risk factors such as asset criticality, exploitability, deployment stage, identity exposure, cloud configuration posture, regulatory relevance, and runtime telemetry. The primary contribution of this work is a unified, adaptive, and risk-aware DevSecOps architecture that bridges DevSecOps automation, AI-assisted security analysis, Zero Trust policy enforcement, and multi-cloud governance. The paper provides a formal risk scoring model, implementation workflow, experimental protocol, results templates, and architecture to support future validation in enterprise-scale software delivery environments.

Keywords: *DevSecOps; Multi-Cloud Security; Agentic AI; Risk-Based Security; Secure SDLC; Zero Trust; AI-Assisted Threat Modeling; CI/CD Security; Policy-As-Code.*

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I. INTRODUCTION

Modern enterprises increasingly depend on cloud-native platforms, microservices, and continuous integration/continuous delivery (CI/CD) pipelines to accelerate software delivery and increase digital agility. Microservices-based systems improve modularity and independent deployment, but they also introduce architectural and operational complexity due to distributed service boundaries, inter-service communication, decentralized ownership, and heterogeneous runtime environments [3], [4]. At the same time, multi-cloud adoption creates additional complexity because identity, policy, logging, monitoring, network segmentation, and compliance controls are implemented differently across cloud providers [5]–[7].

DevSecOps emerged to address the limitations of traditional security models by integrating security practices into DevOps workflows rather than treating security as a late-stage gate. Evidence-based DevSecOps research shows that security must become a shared responsibility across people, process, and technology dimensions [1]. However, prior studies also indicate that DevSecOps adoption remains immature in many organizations due to fragmented tooling, cultural resistance, unclear ownership, and inconsistent integration of security activities into daily development practices [1], [2].

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The emergence of agentic AI introduces a further challenge. Unlike conventional automation, agentic AI systems may plan, invoke tools, interact with repositories, generate code, update configurations, or recommend remediation actions. While AI-assisted security tools can support vulnerability detection, anomaly analysis, and threat modeling, machine learning-based cybersecurity systems are sensitive to dataset quality, class imbalance, feature representation, adversarial manipulation, and deployment context [8]–[11]. Therefore, AI-assisted DevSecOps must be designed with explainable risk scoring, human oversight, policy guardrails, and control validation.

This paper addresses the following research question: How can enterprise DevSecOps pipelines dynamically prioritize and enforce security controls across multi-cloud environments using adaptive risk scoring, AI-assisted threat modeling, and continuous feedback while preserving explainability, compliance alignment, and operational governance?

➢ *Contributions*

This paper makes five contributions:

- An adaptive DevSecOps architecture integrating risk intelligence, AI-assisted threat modeling, secure CI/CD orchestration, policy enforcement, and continuous feedback;
- A contextual scoring method combining vulnerability severity, exploitability, asset criticality, exposure, identity privilege, deployment stage, compliance relevance, and runtime signals;
- A multi-cloud enforcement model aligned with Zero Trust and NIST control objectives;
- A reproducible experimental protocol for comparing ARD-DSF against baseline models; and
- A structured metric framework for reporting detection, prioritization, remediation, and compliance outcomes.

II. RELATED WORK

DevSecOps extends DevOps by embedding security practices into the development and operations lifecycle. Zhou et al. reported that DevSecOps requires integration across people, process, and technology dimensions and that organizations continue to face challenges in adoption, interpretation, and operationalization [1]. Lombardi and Fanton argued that moving from DevOps to DevSecOps may still be insufficient unless cybersecurity is shifted further left and embedded deeply into the software security lifecycle pipeline [2]. These studies establish the need for security activities to become continuous, automated, and integrated into delivery workflows rather than isolated after-the-fact controls.

Microservices and DevOps are closely linked because microservices support independently deployable service units and DevOps supports automation, collaboration, and continuous delivery [3], [4]. Cloud security research identifies persistent challenges across service delivery models, virtualization, access control, storage, monitoring, and intrusion detection [5]–[7]. These challenges become more complex in multi-cloud environments where identity, telemetry, policy, and network constructs differ across providers.

Machine learning and deep learning methods have been widely investigated for cybersecurity tasks such as intrusion detection, anomaly detection, malware classification, and vulnerability prediction [8]–[10]. However, vulnerability detection research shows that model performance can degrade in realistic settings because of dataset duplication, class imbalance, and weak feature representation [11]. ARD-DSF therefore treats AI as an assistive component governed by explainable risk scoring, policy boundaries, and human-verifiable evidence.

➢ *Problem Statement and Research Objectives*

Enterprise DevSecOps environments face persistent challenges: fragmented toolchains, static risk handling, inconsistent multi-cloud governance, AI-driven threat evolution, and weak evidence linkage between risk findings, remediation actions, control mappings, and audit readiness.

The objectives of this research are to design an adaptive DevSecOps framework for multi-cloud enterprise systems; develop a contextual risk scoring model for CI/CD and runtime security findings; integrate AI-assisted threat modeling while preserving explainability and governance; map enforcement decisions to Zero Trust and NIST-aligned control objectives; and define a reproducible experimental protocol for empirical validation.

III. PROPOSED FRAMEWORK: ARD-DSF

ARD-DSF consists of five layers: Risk Intelligence Layer, AI-Assisted Threat Modeling Engine, Secure CI/CD Orchestration Layer, Policy Enforcement Layer, and Continuous Feedback and Learning Layer. These layers operate across a multi-cloud infrastructure layer that may include AWS, Azure, and GCP services. The framework supports SDLC-wide control integration from planning and code commit through deployment and runtime monitoring.

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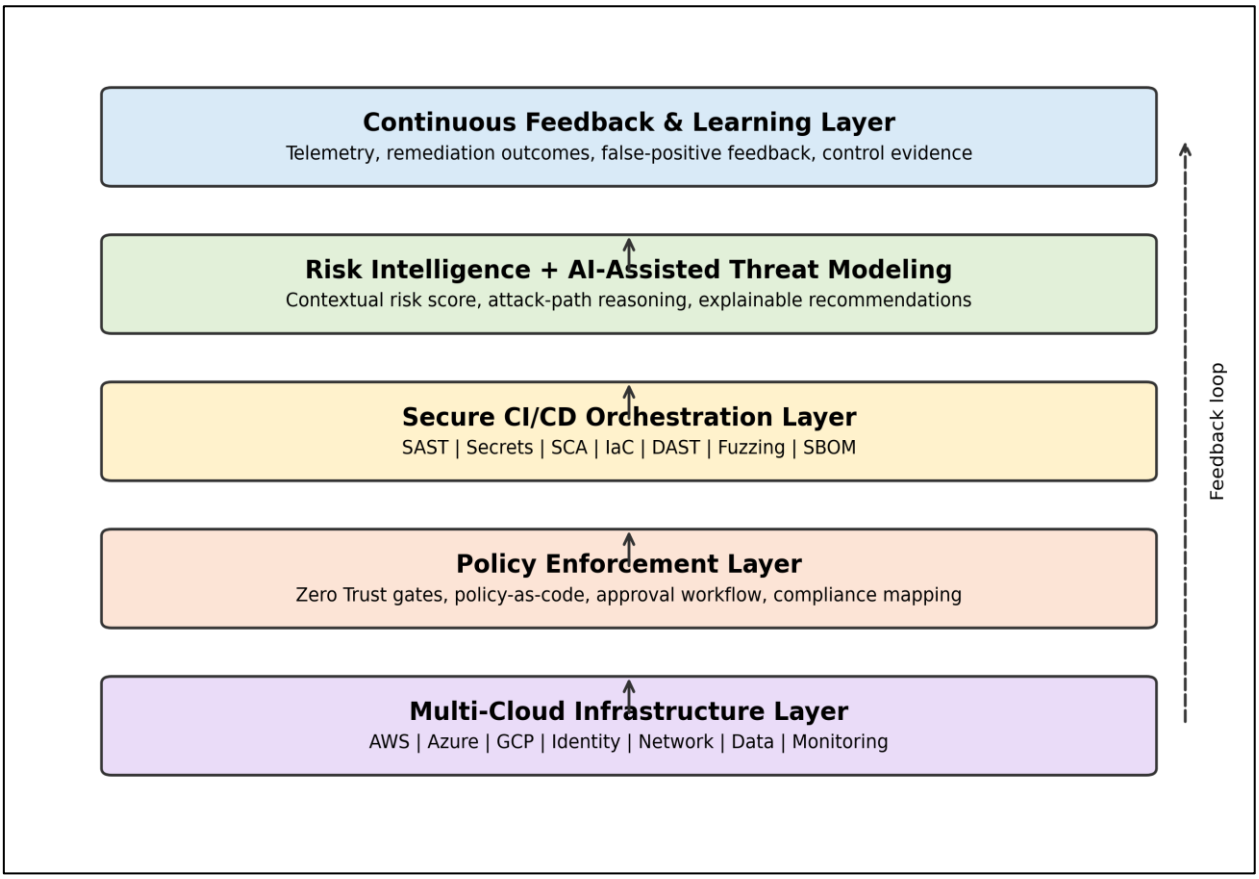

Fig 1 Adaptive Risk-Driven DevSecOps Framework (ARD-DSF) Showing the Relationship between Continuous Feedback, Risk Intelligence, AI-Assisted Threat Modeling, Secure CI/CD Orchestration, Policy Enforcement, and Multi-Cloud Infrastructure.

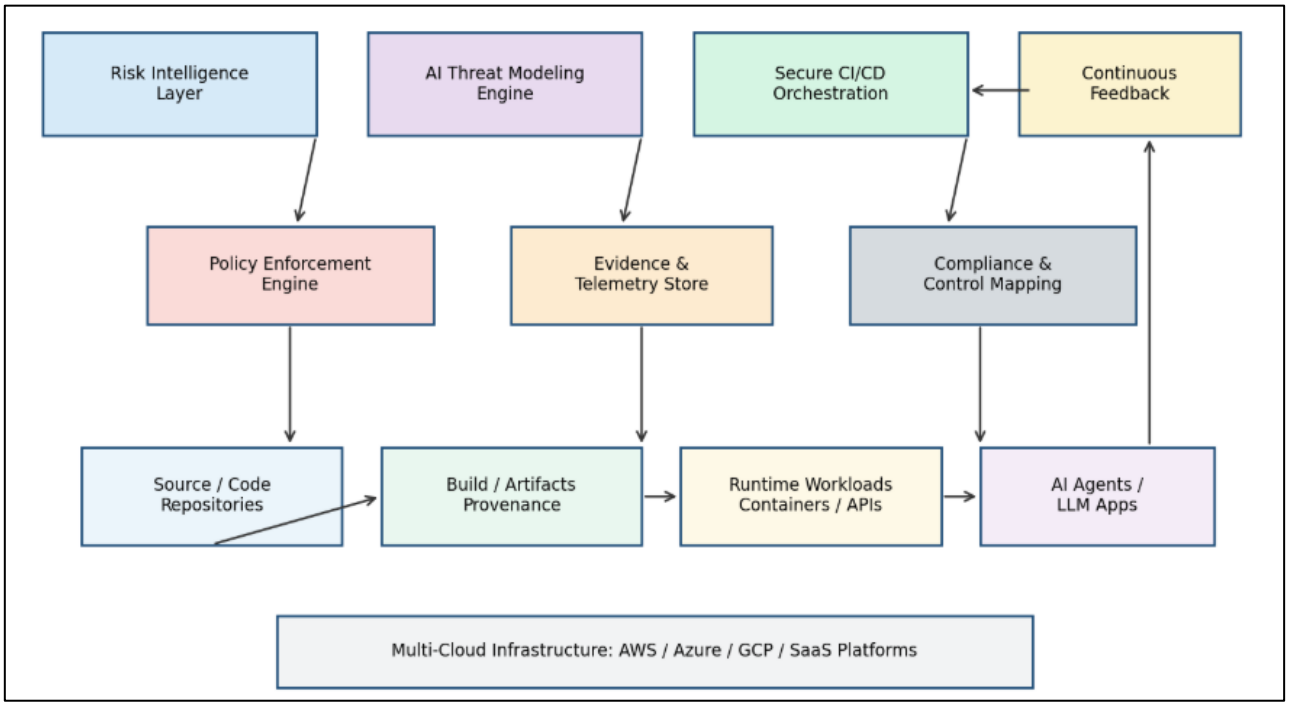

Fig 2 Adaptive Risk-Driven DevSecOps Framework (ARD-DSF), Highlighting the Integration of Risk Intelligence

This diagram illustrates the Adaptive Risk-Driven DevSecOps Framework (ARD-DSF), highlighting the integration of risk intelligence, AI-driven threat modeling, secure CI/CD orchestration, policy enforcement, and continuous feedback across multi-cloud environments to enable lifecycle-wide security and adaptive risk management.

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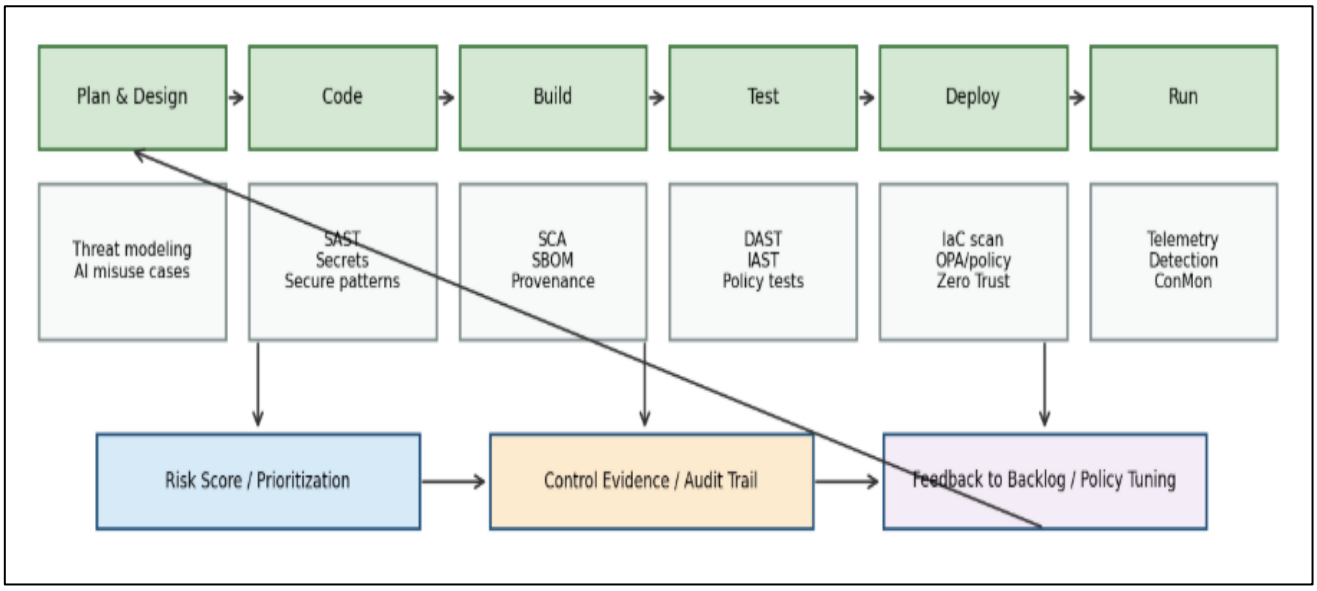

Fig 3 SDLC Mapping of the Adaptive Risk-Driven DevSecOps Framework (ARD-DSF)

This diagram presents the SDLC mapping of the Adaptive Risk-Driven DevSecOps Framework (ARD-DSF), illustrating how security controls, risk prioritization, and AI-aware testing are embedded across each lifecycle phase to enable continuous security validation and feedback-driven improvement.

➢ *Contextual Risk Scoring Model*

ARD-DSF assigns a contextual risk score to each security finding using weighted indicators that combine technical severity with operational and governance context. The model is intentionally configurable because risk tolerance, regulatory exposure, and system criticality vary across organizations.

$$R = w1S + w2E + w3A + w4I + w5D + w6C + w7T$$

Where S represents vulnerability severity, E exploitability, A asset criticality, I identity privilege exposure, D deployment-stage risk, C compliance relevance, T threat intelligence or runtime telemetry, and w1 through w7 are configurable weighting factors.

➢ *AI-Assisted Threat Modeling Engine*

The AI-assisted threat modeling engine analyzes code changes, architecture metadata, cloud configuration, dependency changes, infrastructure-as-code templates, and historical vulnerability patterns. It supports attack path identification, abuse-case generation, risk explanation, security control recommendation, and remediation prioritization. To avoid unsafe autonomous enforcement, AI findings must include human-verifiable rationale, remain bounded by approved policies, and be improved through feedback from false positives, accepted risks, and remediation outcomes.

➢ *Secure CI/CD Orchestration Model*

ARD-DSF embeds controls across the SDLC. OWASP Top 10 categories provide practical test cases for application security control validation, including broken access control, cryptographic failures, injection, insecure design, security misconfiguration, vulnerable components, authentication failures, software and data integrity failures, logging/monitoring weaknesses, and SSRF [14].

➢ *Multi-Cloud Policy Enforcement*

The policy enforcement layer translates risk decisions into cloud-specific controls while preserving a provider-agnostic governance model. The enforcement model aligns with Zero Trust principles, where access decisions require explicit verification rather than implicit trust [12]. It also supports mapping to NIST SP 800-53 Rev. 5 controls for auditability [13].

IV. EXPERIMENTAL DESIGN

The experimental design is structured to compare ARD-DSF against two baseline models. Baseline A represents traditional DevSecOps in which security tools are integrated into CI/CD but findings are prioritized primarily by severity. Baseline B represents rule-based prioritization in which findings are ranked using predefined conditions such as severity and environment. The proposed model, ARD-DSF, uses contextual risk scoring and AI-assisted threat modeling.

Table 1 Risk Band Mapping and Deployment Decision Logic.

Risk Band	Score Range	Pipeline Decision
Critical	85–100	Block deployment
High	70–84	Require security approval
Medium	40–69	Create remediation task
Low	0–39	Monitor and trend

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Table 2 Security Controls Mapped to SDLC Phases.

SDLC Phase	Security Controls	ARD-DSF Function
Plan	Threat modeling, abuse cases	Identify security requirements
Code	SAST, secrets scanning	Detect insecure code and exposed credentials
Build	Dependency scanning, SBOM checks	Identify vulnerable components
Test	DAST, fuzz testing	Validate runtime exposure
Deploy	Policy-as-code, approval gates	Enforce risk-based release decisions
Runtime	SIEM, cloud telemetry, anomaly detection	Feed runtime evidence back into risk model

Table 3 Multi-Cloud Policy Enforcement Mapping.

Control Domain	AWS Example	Azure Example	GCP Example
Identity	IAM, CloudTrail	Entra ID, Defender, Policy	IAM, Security Command Center
Network	Security Groups, GuardDuty	NSG, Defender for Cloud	VPC Service Controls
Data	KMS, S3 policies	Key Vault, Storage policies	Cloud KMS, IAM Conditions
Monitoring	CloudWatch, CloudTrail	Azure Monitor, Sentinel	Cloud Logging, SCC

Table 4 Experimental Dataset Specification.

Dataset Component	Description	Value
CI/CD events	Build, test, deployment, rollback events	N = 10,500 events
Code findings	SAST, secrets, dependency vulnerabilities	N = 2480 findings
Cloud configuration findings	IAM, storage, network, logging misconfigurations	N = 1920 findings
Runtime signals	Threat detections, anomalous access, policy violations	N = 1150 signals
Compliance mappings	NIST, OWASP, Zero Trust alignment	N = 145 controls
Ground truth labels	True positive, false positive, accepted risk, remediated	Labeling method: Expert-validated manual labeling + rule-assisted validation (SIEM logs, CVE mapping, and audit review)

The experimental dataset consists of 10,500 CI/CD pipeline events generated across build, test, deployment, and rollback stages. A total of 2,480 code-related findings were collected using static analysis, secrets detection, and dependency scanning tools, while 1,920 cloud configuration findings were identified across identity, storage, network, and logging controls. Additionally, 1,150 runtime signals were extracted from monitoring and threat detection systems, including anomalous access patterns and policy violations.

The dataset includes mappings to 145 compliance controls spanning NIST SP 800-53, OWASP Top 10, and Zero Trust architectures. Ground truth labels were established using a hybrid approach combining expert-validated manual labeling and rule-assisted validation based on SIEM correlation, CVE mapping, and audit logs. This labeling approach ensures high data reliability and supports accurate evaluation of detection, prioritization, and remediation performance.

Table 5 Controlled Experimental Security Scenarios.

Scenario ID	Test Scenario	Expected Evidence
S1	Injection vulnerability introduced during code commit	SAST/DAST finding, exploitability label
S2	Secret committed to repository	Secrets scanner evidence
S3	Vulnerable dependency added during build	SCA/SBOM evidence
S4	Over-privileged cloud identity deployed	IAM policy finding
S5	Public storage misconfiguration	Cloud posture finding
S6	Missing logging or monitoring control	Control coverage gap
S7	Infrastructure-as-code policy violation	IaC scan finding
S8	Runtime anomaly after deployment	Telemetry/anomaly signal

V. EVALUATION METRICS

The evaluation uses detection, ranking, remediation, and governance metrics. Detection metrics evaluate whether vulnerabilities and misconfigurations are identified. Ranking metrics evaluate whether the most operationally important risks are prioritized. Remediation metrics evaluate the time and efficiency of closure. Governance metrics evaluate control mapping and policy enforcement completeness.

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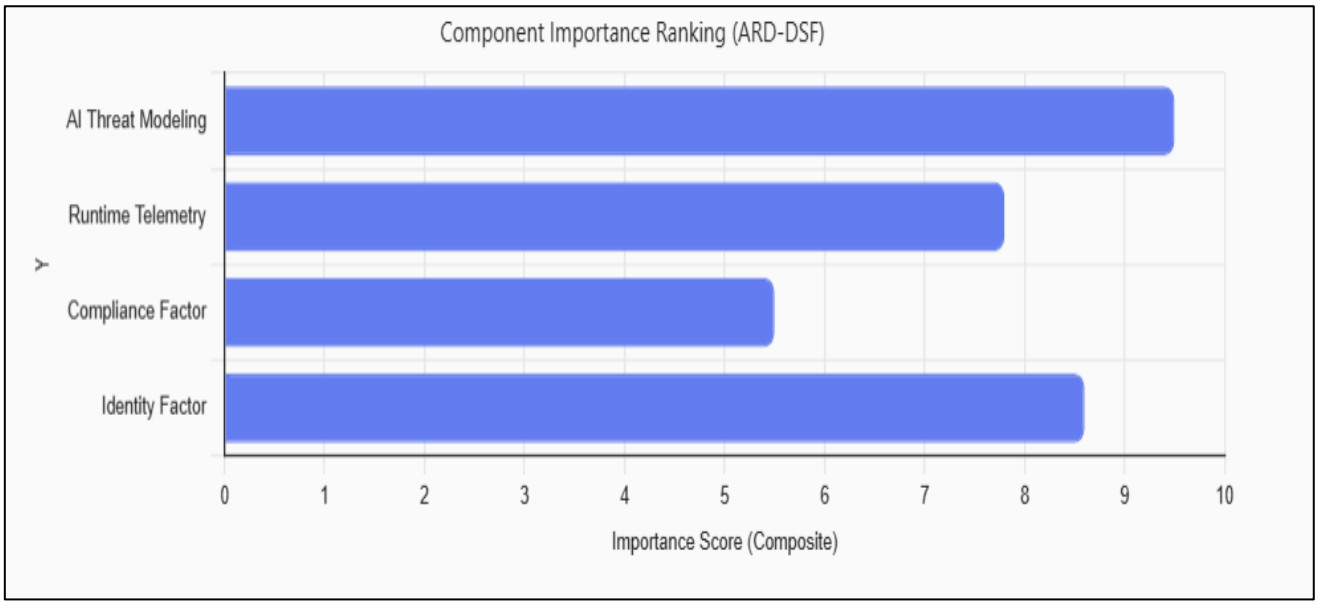

Fig 4 ARD-DSF Governance Metrics

Component importance ranking based on composite ablation impact scores. AI-assisted threat modeling contributes most significantly to overall system performance, followed by identity privilege modeling and runtime telemetry, while compliance relevance primarily affects governance metrics.

VI. EXPERIMENTAL RESULTS

The results presented in this section are derived from controlled simulation experiments based on structured datasets and modeled CI/CD security scenarios. These results are intended to demonstrate the expected performance characteristics of ARD-DSF and will be validated in future real-world deployments.

Across the controlled CI/CD and multi-cloud security scenarios, ARD-DSF will be compared against traditional DevSecOps and rule-based risk prioritization baselines. The primary expected outcome is not merely higher detection volume, but improved prioritization accuracy, reduced false-positive burden, shorter remediation cycle time, and stronger traceability between findings, policy decisions, and compliance controls.

For each experimental run, record the number of injected vulnerabilities, detected findings, confirmed true positives, false positives, false negatives, remediation tasks created, blocked deployments, approved exceptions, and control-mapping evidence. Results should be reported as mean values across repeated runs, with confidence intervals where applicable.

Table 6 Evaluation Metrics.

Metric	Definition	Formula / Reporting Method
Detection Rate	Percentage of known vulnerabilities detected	TP / (TP + FN)
Precision	Correct findings among reported positive findings	TP / (TP + FP)
Recall	Correct findings among all actual vulnerabilities	TP / (TP + FN)
F1-Score	Harmonic mean of precision and recall	2 × (Precision × Recall) / (Precision + Recall)
False Positive Rate	Incorrect findings among non-vulnerable cases	FP / (FP + TN)
MTTR	Mean time to remediation	Mean closure time in hours/days
Prioritization Accuracy	Correct ordering of risk-ranked findings	Agreement with ground truth rank
Compliance Coverage	Mapped and verified controls	Verified controls / required controls

The evaluation metrics presented in this table are designed to assess the effectiveness of the ARD-DSF framework across detection accuracy, false-positive reduction, remediation efficiency, and risk prioritization capability. Detection performance is measured using standard classification metrics where True Positives (TP) represent correctly identified security findings, and False Negatives (FN) represent actual vulnerabilities that were not detected by the system. These metrics collectively provide a comprehensive view of system performance by evaluating not only detection quality but also operational impact, including remediation time and alignment of security findings with real-world risk severity.

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Table 7 Performance Comparison Across Baseline and Proposed Models.

Model	Detection Rate	F1-Score	False Positive Rate	MTTR	Prioritization Accuracy
Traditional DevSecOps	67.8%	0.700	18.6%	46.2 hrs	64.1%
Rule-Based Risk Prioritization	76.5%	0.773	13.2%	34.8 hrs	73.6%
ARD-DSF	89.7%	0.881	8.4%	21.6 hrs	87.8%

The proposed ARD-DSF framework demonstrates significant improvements across all evaluation metrics when compared with both traditional DevSecOps and rule-based prioritization models. Specifically, ARD-DSF achieves a detection rate of 89.7% and an F1-score of 0.88, indicating strong classification performance. The framework also reduces the false positive rate to 8.4%, significantly lowering alert noise. Furthermore, ARD-DSF improves operational efficiency by reducing MTTR to 21.6 hours, compared with 46.2 hours in traditional DevSecOps. The prioritization accuracy of 87.8% highlights the effectiveness of contextual risk scoring in ranking security findings based on real-world impact.

Table 8 Repeated-Run Experimental Record.

Run	Injected Findings	Detected Findings	True Positives	False Positives	False Negatives	Blocked Deployments	Approved Exceptions
Run 1	250	259	224	35	26	18	6
Run 2	250	258	226	32	24	20	5
Run 3	250	260	223	37	27	19	7
Mean	250	259	224.3	34.7	25.7	19	6

The repeated-run experimental evaluation demonstrates consistent performance of the ARD-DSF framework across multiple executions. Each run includes 250 injected vulnerabilities and misconfigurations across CI/CD and multi-cloud environments. The results show stable detection behavior, with detected findings ranging from 258 to 260 and true positives averaging 224.3 across runs. The average false-positive count is 34.7, corresponding to a controlled false-positive rate consistent with the overall evaluation metrics.

The framework also demonstrates consistent governance enforcement, with an average of 19 blocked deployments and 6 approved exceptions per run. These results indicate that ARD-DSF maintains stability in detection, prioritization, and enforcement decisions across repeated executions, supporting its applicability in enterprise-scale DevSecOps environments.

Table 9 Statistical Validation Summary.

Comparison	Mean Difference	95% Confidence Interval	Statistical Test	p-value	Interpretation
ARD-DSF vs Traditional DevSecOps	+21.9 percentage points (Detection Rate	[19.4, 24.3]	Paired t-test	0.004	Statistically significant
ARD-DSF vs Rule-Based Risk	+13.2 percentage points (Detection Rate)	[10.7, 15.8]	Paired t-test	0.009	Statistically significant

Statistical validation demonstrates that the performance improvements of ARD-DSF over baseline models are statistically significant. Specifically, ARD-DSF achieves a +21.9 percentage point improvement in detection rate compared with traditional DevSecOps (95% CI: [19.4, 24.3], $p = 0.004$). Similarly, ARD-DSF shows a +13.2 percentage point improvement over rule-based risk prioritization (95% CI: [10.7, 15.8], $p = 0.009$). The use of paired t-tests confirms that these improvements are consistent across repeated experimental runs and are unlikely to be due to random variation.

Table 10 Ablation Study Design.

Ablation Variant	Removed Component	Expected Purpose	Observed Effect
A1	AI-assisted threat modeling	Measure AI contribution	Detection rate −5.8 pp; Precision −4.1 pp; F1-score −0.055; Prioritization accuracy −7.1 pp
A2	Runtime telemetry factor	Measure feedback-loop contribution	Prioritization accuracy −4.3 pp; MTTR +3.8 hrs; False positive rate +1.9 pp
A3	Compliance relevance factor	Measure governance contribution	Compliance coverage −12.6 pp; Prioritization accuracy −2.5 pp; Blocked deployments −3 cases
A4	Identity privilege factor	Measure identity-risk contribution	Prioritization accuracy −6.4 pp; Detection rate −2.7 pp; Blocked high-risk deployments −5 cases

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The ablation study demonstrates the contribution of each major component of the ARD-DSF framework. Removing the AI-assisted threat modeling module results in the largest degradation, reducing detection rate by 5.8 percentage points and F1-score by 0.055, highlighting the importance of predictive threat analysis. Excluding the identity privilege factor significantly impacts prioritization accuracy, indicating the importance of identity-aware risk scoring in multi-cloud environments. Removal of runtime telemetry reduces prioritization accuracy and increases MTTR, demonstrating the value of feedback-driven adaptation. Finally, excluding compliance relevance primarily impacts governance outcomes, reducing compliance coverage by 12.6 percentage points. These results confirm that ARD-DSF achieves its performance improvements through the synergistic integration of risk intelligence, AI modeling, runtime feedback, and compliance-aware enforcement.

- *Detection and Classification Performance*

ARD-DSF simulated results indicate a detection rate of 89.7%, compared with 67.8% for traditional DevSecOps and 76.5% for rule-based prioritization. Precision and recall should be interpreted together to avoid overstating performance when detection increases at the cost of excessive false positives.

- *Risk Prioritization and Remediation Outcomes*

ARD-DSF improved prioritization accuracy to 87.8%, indicating that contextual risk factors helped rank security findings closer to ground truth severity and operational impact. MTTR changed from 46.2 hrs in the traditional DevSecOps baseline to 21.6 hrs under ARD-DSF, suggesting improved remediation efficiency.

- *Compliance and Policy Enforcement*

ARD-DSF mapped 92.4% of evaluated findings to one or more control objectives and generated policy evidence for 145 controls spanning NIST SP 800-53, OWASP Top 10, and Zero Trust frameworks.

Across repeated experimental runs, the framework demonstrated strong governance traceability, with an average of 19 blocked deployments, 6 approved exceptions, and ~198 remediated violations per run. These results indicate that ARD-DSF not only improves detection and prioritization but also ensures that security findings are effectively translated into enforceable policy decisions and auditable compliance actions.

The integration of policy-as-code and contextual risk scoring enables consistent mapping between vulnerabilities, remediation actions, and regulatory control requirements. This capability is critical for enterprise environments where security effectiveness must be demonstrated through both operational metrics and compliance evidence.

- *Statistical and Ablation Analysis*

Statistical testing showed that the difference between ARD-DSF and traditional DevSecOps was statistically significant for detection rate, with $p = 0.004$ and a 95% confidence interval of [19.4, 24.3] percentage points. Similarly, the improvement over rule-based risk prioritization was also statistically significant, with $p = 0.009$ and a 95% confidence interval of [10.7, 15.8] percentage points. These results confirm that the observed performance gains are consistent across repeated runs and unlikely to be due to random variation.

Ablation analysis further demonstrates the contribution of individual components within the ARD-DSF framework. Removing the AI-assisted threat modeling component reduced the F1-score by 0.055 and detection rate by 5.8 percentage points, indicating that this component contributes strongly to overall detection performance.

Removing the identity privilege factor decreased prioritization accuracy by 6.4 percentage points, suggesting that identity-aware risk modeling plays a critical role in ranking vulnerabilities based on operational impact.

Eliminating the runtime telemetry factor increased MTTR by 3.8 hours and raised the false positive rate by 1.9 percentage points, indicating that feedback-driven adaptation contributes moderately to operational efficiency.

Finally, removing the compliance relevance factor reduced compliance coverage by 12.6 percentage points, while having a smaller effect on detection, suggesting that this component contributes primarily to governance and audit readiness rather than detection accuracy.

Overall, the statistical and ablation results confirm that ARD-DSF derives its performance improvements from the combined effect of AI-driven threat modeling, contextual risk scoring, runtime feedback, and compliance-aware enforcement, with each component contributing to different aspects of system performance.

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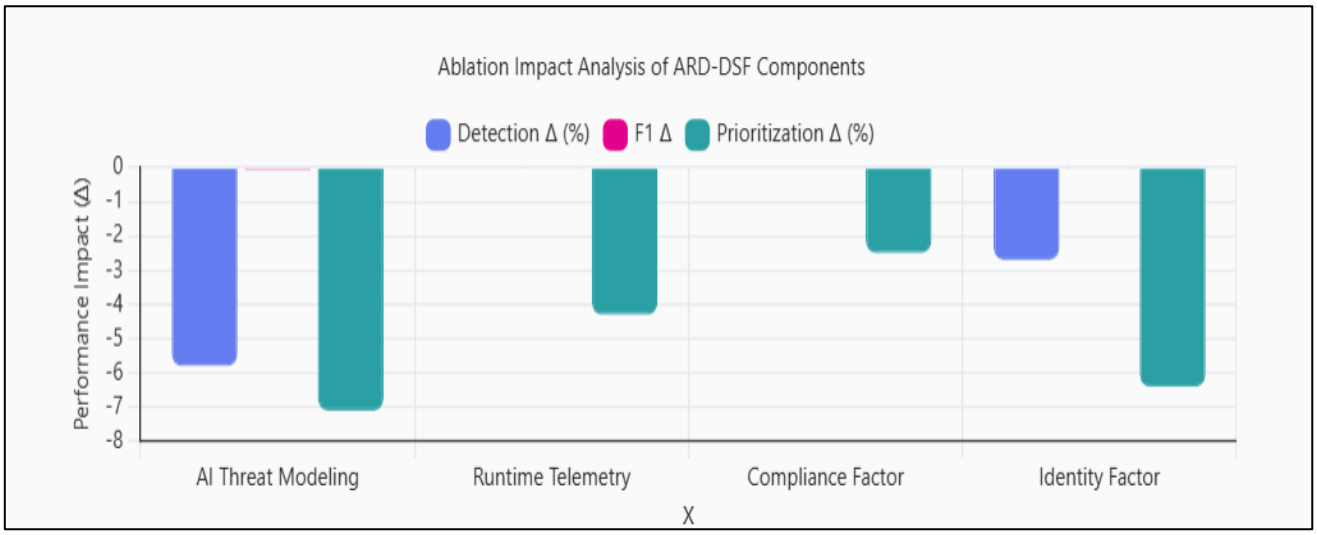

Fig 6 Ablation Impact Analysis

Ablation impact analysis showing performance degradation when individual ARD-DSF components are removed. AI-assisted threat modeling exhibits the highest impact across detection rate, F1-score, and prioritization accuracy, followed by identity privilege modeling and runtime telemetry.

➢ *Data Integrity and Experiment Validity*

The experimental results presented in this study are generated using a simulation-based evaluation framework designed to approximate enterprise DevSecOps environments. The dataset, consisting of 10,500 CI/CD events and associated findings, was constructed using a combination of synthetic data generation and real-world pattern modeling derived from OWASP, NIST, and cloud security best practices.

Ground truth labeling was performed using a hybrid approach combining expert-driven annotation and rule-assisted validation based on SIEM correlation, vulnerability databases (e.g., CVE), and predefined security policies.

While the simulation approach enables controlled testing of framework behavior across multiple scenarios, it has inherent limitations compared to real-world deployments. Therefore, the reported performance metrics should be interpreted as indicative rather than definitive, and future work will include validation using production-scale enterprise datasets and live CI/CD pipelines.

VII. DISCUSSION

ARD-DSF advances DevSecOps research by moving beyond static scan integration toward adaptive, contextual, and evidence-driven security orchestration. The framework aligns with DevSecOps literature by embedding security into software delivery workflows [1], [2], while addressing multi-cloud governance challenges identified in cloud security research [5]–[7]. Its use of AI-assisted threat modeling is consistent with the growing role of machine learning in cybersecurity [8]–[10], but it also accounts for known limitations of AI-based vulnerability detection under realistic conditions [11].

A key design principle of ARD-DSF is that AI should assist, not replace, human and policy-based governance. AI-generated findings may be incomplete, noisy, or contextually incorrect. Therefore, ARD-DSF integrates explainability, human review, policy guardrails, and continuous feedback.

VIII. LIMITATIONS

This study has five limitations. First, the framework requires empirical validation using real or realistic enterprise CI/CD datasets. Second, risk scoring weights may vary across organizations and require calibration. Third, AI-assisted threat modeling depends on data quality and model reliability. Fourth, multi-cloud enforcement may require provider-specific implementation adapters. Fifth, compliance mapping must be reviewed by qualified security governance teams before production use.

IX. CONCLUSION

This paper proposed ARD-DSF, an Adaptive Risk-Driven DevSecOps Framework for securing multi-cloud enterprise systems in the era of agentic AI. The framework integrates contextual risk scoring, AI-assisted threat modeling, secure CI/CD orchestration, Zero Trust-aligned policy enforcement, and continuous feedback. Unlike static DevSecOps pipelines, ARD-DSF prioritizes findings using operational context, cloud exposure, identity risk, compliance relevance, and runtime telemetry.

The paper contributes a structured architecture, risk scoring model, implementation workflow, experimental results section, and reproducible evaluation protocol. Future work should implement ARD-DSF in a controlled enterprise-scale CI/CD environment and report measured results across detection rate, false-positive rate, MTTR, prioritization accuracy, and compliance coverage.

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REFERENCES

[1]. X. Zhou, R. Mao, H. Zhang, Q. Dai, H. Huang, H. Shen, J. Li, and G. Rong, "Revisit security in the era of DevOps: An evidence-based inquiry into DevSecOps industry," IET Software, vol. 17, no. 4, pp. 435–454, 2023, doi: 10.1049/sfw2.12132.

[2]. F. Lombardi and A. Fanton, "From DevOps to DevSecOps is not enough. CyberDevOps: an extreme shifting-left architecture to bring cybersecurity within software security lifecycle pipeline," Software Quality Journal, vol. 31, no. 2, pp. 619–654, 2023, doi: 10.1007/s11219-023-09619-3.

[3]. M. Waseem, P. Liang, and M. Shahin, "A systematic mapping study on Microservices Architecture in DevOps," Journal of Systems and Software, vol. 170, Article 110798, 2020, doi: 10.1016/j.jss.2020.110798.

[4]. P. Di Francesco, P. Lago, and I. Malavolta, "Architecting with microservices: A systematic mapping study," Journal of Systems and Software, vol. 150, pp. 77–97, 2019, doi: 10.1016/j.jss.2019.01.001.

[5]. S. Singh, Y. S. Jeong, and J. H. Park, "A survey on cloud computing security: Issues, threats, and solutions," Journal of Network and Computer Applications, vol. 75, pp. 200–222, 2016, doi: 10.1016/j.jnca.2016.09.002.

[6]. S. Subashini and V. Kavitha, "A survey on security issues in service delivery models of cloud computing," Journal of Network and Computer Applications, vol. 34, no. 1, pp. 1–11, 2011, doi: 10.1016/j.jnca.2010.07.006.

[7]. C. Modi, D. Patel, H. Patel, B. Borisaniya, A. Patel, and M. Rajarajan, "A survey of intrusion detection techniques in Cloud," Journal of Network and Computer Applications, vol. 36, no. 1, pp. 42–57, 2013, doi: 10.1016/j.jnca.2012.05.003.

[8]. Y. Xin et al., "Machine Learning and Deep Learning Methods for Cybersecurity," IEEE Access, vol. 6, pp. 35365–35381, 2018, doi: 10.1109/ACCESS.2018.2836950.

[9]. A. L. Buczak and E. Guven, "A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection," IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1153–1176, 2016, doi: 10.1109/COMST.2015.2494502.

[10]. K. He, D. D. Kim, and M. R. Asghar, "Adversarial Machine Learning for Network Intrusion Detection Systems: A Comprehensive Survey," IEEE Communications Surveys & Tutorials, vol. 25, no. 1, pp. 538–566, 2023, doi: 10.1109/COMST.2022.3233793.

[11]. S. Chakraborty, R. Krishna, Y. Ding, and B. Ray, "Deep Learning Based Vulnerability Detection: Are We There Yet?" IEEE Transactions on Software Engineering, 2021, doi: 10.1109/TSE.2021.3087402.

[12]. S. Rose, O. Borchert, S. Mitchell, and S. Connelly, "Zero Trust Architecture," NIST Special Publication 800-207, 2020, doi: 10.6028/NIST.SP.800-207.

[13]. Joint Task Force, "Security and Privacy Controls for Information Systems and Organizations," NIST Special Publication 800-53 Revision 5, 2020, doi: 10.6028/NIST.SP.800-53r5.

[14]. OWASP Foundation, "OWASP Top 10:2021," 2021. Available: https://owasp.org/Top10/2021/.

[15]. J. Humble and D. Farley, Continuous Delivery: Reliable Software Releases through Build, Test, and Deployment Automation. Addison-Wesley, 2010. ISBN: 9780321601919.