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DevSecOps in the Age of Generative AI: A Literature Review of Secure Code Generation, Vulnerability Detection, Compliance Automation, and Software Supply Chain Risk

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Abstract

The convergence of DevSecOps practices and Generative Artificial Intelligence (GenAI) represents a transformative shift in secure software development. This literature review systematically examines the integration of GenAI technologies into DevSecOps workflows, focusing on four critical domains: secure code generation, vulnerability detection, compliance automation, and software supply chain security. We analyze 30 peer-reviewed publications from 2023-2026, identifying key approaches, frameworks, and empirical findings. Our review reveals that GenAI-powered tools demonstrate significant potential in automating security tasks, with reported improvements including 87% reduction in security incidents, 88% higher threat detection accuracy, and 71% faster vulnerability remediation. However, critical challenges persist, including AI hallucination risks (19.7% package hallucination rate), limited context understanding, high false positive rates, and the need for human oversight in security-critical decisions. We present a comprehensive taxonomy of existing approaches, comparative analysis of methodologies, and identify eight major research gaps. The review concludes with future research directions emphasizing explainable AI for security, robust hallucination mitigation, standardized benchmarks for secure code generation, and integration of policy-as-code with infrastructure-as-code security. This work provides researchers and practitioners with a structured understanding of the current landscape and actionable insights for advancing secure AI-augmented software development.

Keywords Devsecops · Generative ai · Secure code generation · Vulnerability detection · Sast · Dast · Sbom · Software supply chain security · Policy-as-code · Infrastructure-as-code security · Compliance automation · Ai hallucination · Large language models · Ci/cd security

1 Introduction

The rapid evolution of software development practices has necessitated the integration of security throughout the Software Development Life Cycle (SDLC), giving rise to the DevSecOps paradigm. DevSecOps extends traditional DevOps by embedding security practices into continuous integration and continuous deployment (CI/CD) pipelines, enabling organizations to deliver secure software at velocity [8, 10]. Concurrently, the emergence of Generative Artificial Intelligence (GenAI), particularly Large Language Models (LLMs), has introduced unprecedented capabilities for code generation, vulnerability analysis, and automated security enforcement [6, 3].

The intersection of DevSecOps and GenAI presents both transformative opportunities and significant challenges. On one hand, AI-driven tools promise to automate labor-intensive security tasks, reduce human error, and accelerate threat detection [2, 19]. On the other hand, the integration of GenAI introduces novel security risks, including AI hallucinations, insecure code patterns, and supply chain vulnerabilities [25, 3, 14].

1.1 Motivation and Context

Modern software systems face an expanding attack surface driven by cloud-native architectures, microservices, containerization, and complex dependency chains [4, 5]. Traditional security approaches struggle to keep pace with the velocity of modern development cycles. The 2023 State of DevSecOps report indicates that 80% of organizations plan to integrate security automation by 2026, with unpatched vulnerabilities costing an average of $4.45 million per incident [5]. This economic and operational pressure has accelerated the adoption of AI-driven security solutions.

GenAI technologies, particularly LLMs like GPT-4, Claude, and open-source alternatives, have demonstrated remarkable capabilities in understanding and generating code [11, 15]. However, their application in security-critical contexts requires rigorous evaluation. Recent studies reveal concerning trends: 19.7% of AI-generated packages contain hallucinations [25], and current AI agents achieve only 23.8% success rates in producing correct and secure code [23].

1.2 Scope and Objectives

This literature review systematically examines the integration of GenAI into DevSecOps practices, with specific focus on:

• **Secure Code Generation:** AI-assisted development tools, security-aware training policies, and frameworks for generating vulnerability-free code

• **Vulnerability Detection:** Static Application Security Testing (SAST), Dynamic Application Security Testing (DAST), and AI-enhanced threat identification

• **Compliance Automation:** Policy-as-code enforcement, regulatory compliance, and automated security auditing

• **Software Supply Chain Security:** Software Bill of Materials (SBOM), dependency management, provenance tracking, and supply chain attack mitigation

Our objectives are threefold: (1) to provide a comprehensive taxonomy of existing approaches, (2) to synthesize empirical findings and comparative insights, and (3) to identify critical research gaps and future directions for the field.

1.3 Contributions

This review makes the following contributions:

A systematic analysis of 30 peer-reviewed publications spanning 2023-2026, representing the most recent advances in GenAI-augmented DevSecOps

A novel taxonomy organizing approaches by security focus area, methodology, and integration strategy

Comparative analysis of frameworks, tools, and empirical results across diverse application domains

Identification of eight major research gaps and corresponding future research directions

Actionable insights for practitioners implementing AI-driven security in production environments

The remainder of this paper is organized as follows: Section II provides background and theoretical foundations. Section III describes our review methodology. Section IV presents technical background on key concepts. Section V introduces our taxonomy of existing approaches. Section VI provides a detailed literature review organized by security domain. Section VII presents comparative analysis. Section VIII discusses findings and implications. Section IX identifies research gaps. Section X outlines future research directions, and Section XI concludes.

2 Background and Theoretical Foundations

2.1 DevSecOps Paradigm

DevSecOps represents the evolution of DevOps practices to incorporate security as a first-class concern throughout the SDLC [8]. The paradigm is built on three foundational principles: (1) shift-left security, where security testing occurs early in development; (2) automation of security controls within CI/CD pipelines; and (3) continuous monitoring and feedback loops [9].

Traditional security approaches relied on manual code reviews and post-deployment security assessments, creating bottlenecks and delaying releases. DevSecOps addresses these limitations by embedding automated security testing, policy enforcement, and compliance checks directly into development workflows [10]. Key practices include pre-commit security scanning, container security validation, infrastructure-as-code (IaC) security analysis, and runtime threat detection [2, 13].

2.2 Generative AI and Large Language Models

Generative AI refers to machine learning models capable of creating new content, including text, code, and structured data. Large Language Models (LLMs) such as GPT-4, Claude, and open-source alternatives like Llama have demonstrated remarkable capabilities in code understanding, generation, and transformation [11, 15].

LLMs are trained on vast corpora of code and natural language, enabling them to perform tasks such as code completion, bug detection, vulnerability identification, and security policy generation [6]. The transformer architecture underlying modern LLMs enables contextual understanding across long sequences, making them suitable for analyzing complex codebases and security configurations [20].

However, LLMs exhibit inherent limitations including hallucinations (generating plausible but incorrect information), limited context windows, training data biases, and difficulty with novel or domain-specific security patterns [25, 15]. These limitations necessitate careful integration strategies and human oversight in security-critical applications.

2.3 Software Supply Chain Security

Software supply chain security encompasses the protection of all components, dependencies, and processes involved in software development and delivery [1, 7]. Modern applications typically incorporate hundreds of third-party dependencies, creating

extensive attack surfaces. High-profile supply chain attacks such as SolarWinds and Log4Shell have demonstrated the catastrophic potential of compromised dependencies [26].

Key concepts in supply chain security include:

• **Software Bill of Materials (SBOM):** A comprehensive inventory of software components, dependencies, and metadata [21, 26]

• **Provenance Tracking:** Documentation of software origin, build processes, and custody chain [1]

• **Dependency Analysis:** Identification of vulnerable or malicious dependencies [17]

• **Artifact Integrity:** Cryptographic verification of software artifacts [9]

Frameworks such as SLSA (Supply-chain Levels for Software Artifacts), in-toto, and SBOM standards (SPDX, CycloneDX) provide structured approaches to supply chain security [1, 21].

2.4 Security Testing Methodologies

Security testing in DevSecOps environments employs multiple complementary approaches:

Static Application Security Testing (SAST) analyzes source code without execution, identifying vulnerabilities such as SQL injection, cross-site scripting, and buffer overflows [9, 13]. SAST tools integrate into pre-commit hooks and CI/CD pipelines, providing immediate feedback to developers.

Dynamic Application Security Testing (DAST) examines running applications, simulating attacks to identify runtime vulnerabilities and configuration issues [19]. DAST complements SAST by detecting issues that only manifest during execution.

Software Composition Analysis (SCA) identifies vulnerabilities in third-party dependencies and open-source components [9, 21]. SCA tools analyze dependency manifests and compare components against vulnerability databases.

Container Security Scanning validates container images for vulnerabilities, misconfigurations, and compliance violations [27, 19].

Infrastructure-as-Code (IaC) Security analyzes infrastructure definitions (Terraform, CloudFormation, Kubernetes manifests) for security misconfigurations and policy violations [19, 27].

3 Review Methodology

3.1 Search Strategy and Data Sources

This literature review is based on a comprehensive search conducted across three major academic databases: SciSpace, Google Scholar, and ArXiv. The search focused on publications addressing the intersection of DevSecOps and Generative AI, with emphasis on secure code generation, vulnerability detection, compliance automation, and software supply chain security.

Search queries combined terms including: "DevSecOps," "Generative AI," "LLM security," "secure code generation," "AI vulnerability detection," "SBOM," "software supply chain security," "policy-as-code," "infrastructure-as-code security," and "compliance automation." The search covered publications from 2023 to 2026, capturing the most recent advances in this rapidly evolving field.

3.2 Selection Criteria and Filtering

The initial search yielded 88 unique papers after deduplication. Papers were included if they met the following criteria:

• Focus on integration of AI/ML technologies into DevSecOps practices

• Address at least one of the four primary security domains (secure code generation, vulnerability detection, compliance automation, supply chain security)

• Present novel frameworks, empirical evaluations, or systematic analyses

• Published in peer-reviewed venues or reputable preprint repositories

• Available in English

Papers were excluded if they focused solely on general DevOps automation without security considerations, addressed AI security in non-software contexts, or lacked technical depth.

3.3 Data Extraction and Analysis

The combined paper table was relevance-ranked, and the top 30 papers were selected for detailed analysis. For each paper, we extracted:

- Research methodology and technical approach
- Key contributions and empirical findings
- Security focus areas and application domains
- Tools, frameworks, and technologies employed
- Evaluation metrics and performance results
- Identified limitations and challenges

Papers were systematically categorized according to our taxonomy (Section V) and analyzed to identify common themes, methodological patterns, and research gaps.

3.4 Quality Assessment

Quality assessment considered publication venue, methodological rigor, empirical validation, reproducibility, and practical applicability. Papers presenting frameworks without evaluation were noted as conceptual contributions, while those with empirical results were prioritized for quantitative analysis.

4 Technical Background

4.1 AI-Driven Security Analysis

AI-driven security analysis leverages machine learning and deep learning techniques to automate vulnerability detection, threat identification, and security policy enforcement [10, 19]. Key approaches include:

Supervised Learning trains models on labeled datasets of vulnerable and secure code, enabling classification of security issues [18]. Common architectures include convolutional neural networks (CNNs) for pattern recognition and recurrent neural networks (RNNs) for sequential code analysis.

Unsupervised Learning identifies anomalies and outliers in code patterns, security logs, and system behavior without requiring labeled training data [2]. Techniques include clustering, autoencoders, and isolation forests.

Reinforcement Learning enables adaptive security policies that balance security effectiveness with operational overhead [1]. RL agents learn optimal mitigation strategies through interaction with simulated or real environments.

Transfer Learning adapts pre-trained models to security-specific tasks, reducing training data requirements and improving generalization [6].

4.2 LLM-Based Code Analysis

LLMs enable semantic understanding of code, going beyond syntactic pattern matching to comprehend intent, context, and security implications [11, 15]. Key capabilities include:

Vulnerability Detection: LLMs can identify security vulnerabilities by analyzing code patterns, data flows, and API usage [22, 12]. They excel at detecting complex vulnerabilities that require contextual understanding, such as authentication bypasses and logic flaws.

Code Generation: LLMs generate code from natural language descriptions, potentially introducing security vulnerabilities if not properly constrained [3, 16]. Security-aware training and post-generation validation are critical.

Threat Modeling: LLMs automate threat discovery at the design stage by analyzing system architectures and identifying potential attack vectors [11].

Explainability: LLMs provide natural language explanations of security findings, improving developer understanding and facilitating remediation [2].

4.3 Policy-as-Code and Compliance Automation

Policy-as-code represents security policies, compliance requirements, and governance rules as executable code [2, 24]. This approach enables:

- Automated enforcement of security policies in CI/CD pipelines
- Version control and auditing of policy changes

• Consistent policy application across environments

• Integration with IaC tools for infrastructure validation

Frameworks such as Open Policy Agent (OPA), Sentinel, and Kyverno enable declarative policy definition and enforcement [27]. AI enhances policy-as-code by automatically generating policies from regulatory requirements, adapting policies based on threat intelligence, and providing intelligent policy conflict resolution [24].

4.4 Agentic AI Architectures

Agentic AI refers to autonomous systems capable of reasoning, planning, and executing complex tasks with minimal human intervention [1, 7]. In DevSecOps contexts, agentic architectures typically comprise:

Specialized Security Agents: Domain-specific agents for vulnerability scanning, policy enforcement, threat detection, and incident response [1].

Orchestration Layer: Frameworks like LangChain and LangGraph coordinate multi-agent workflows, managing task decomposition, agent communication, and result aggregation [1].

Integration Interfaces: Model Context Protocol (MCP) and similar standards enable agents to interact with CI/CD systems, version control, and security tools [1].

Memory and Learning: Persistent storage of security findings, mitigation strategies, and feedback enables continuous improvement [1].

5 Taxonomy of Existing Approaches

We propose a multi-dimensional taxonomy organizing GenAI-augmented DevSecOps approaches along four axes: security focus area, AI methodology, integration strategy, and deployment context.

5.1 Security Focus Area Taxonomy

Secure Code Generation approaches focus on generating vulnerability-free code through security-aware training, multi-stage generation pipelines, and automated validation [16, 6, 3]. Subcategories include code completion, template generation, and full application scaffolding.

Vulnerability Detection encompasses SAST, DAST, and hybrid approaches leveraging AI for improved accuracy and reduced false positives [22, 12, 15]. Subcategories include static analysis, dynamic testing, and runtime monitoring.

Compliance Automation addresses regulatory requirements, policy enforcement, and audit readiness through AI-driven policy generation and validation [24, 27, 19]. Subcategories include policy-as-code, compliance monitoring, and audit trail generation.

Supply Chain Security protects against dependency vulnerabilities, malicious packages, and provenance violations [1, 7, 25, 21]. Subcategories include SBOM generation, dependency analysis, and provenance tracking.

5.2 AI Methodology Taxonomy

LLM-Based Approaches leverage large language models for code understanding, generation, and analysis [11, 15, 14]. Variants include prompt engineering, fine-tuning, and retrieval-augmented generation (RAG).

Traditional ML Approaches employ supervised and unsupervised learning for vulnerability classification and anomaly detection [18, 19].

Hybrid Approaches combine LLMs with traditional security tools, rule-based systems, and domain-specific models [2, 13].

Agentic Systems implement multi-agent architectures with autonomous reasoning and coordination [1, 7].

5.3 Integration Strategy Taxonomy

Pre-Commit Integration embeds security checks in developer IDEs and pre-commit hooks [2, 12].

CI/CD Pipeline Integration incorporates security testing and policy enforcement in continuous integration workflows [5, 20].

Runtime Integration provides continuous monitoring and threat detection in production environments [19].

Platform Integration offers comprehensive security platforms spanning multiple SDLC stages [13, 27].

5.4 Deployment Context Taxonomy

Cloud-Native Applications focus on containerized, microservices-based architectures [4, 19].

Regulated Industries address compliance-critical domains such as healthcare and finance [27].

Open-Source Ecosystems target specific language ecosystems and package repositories [17, 21].

Enterprise Environments provide scalable solutions for large organizations with complex security requirements [2].

6 Detailed Literature Review

6.1 Secure Code Generation

The integration of GenAI into code generation workflows presents both opportunities and risks for software security. Alwageed et al. [6] conducted a systematic study examining how GenAI strengthens secure coding practices, analyzing AI-driven code generation tools through literature review, industry applications, and empirical studies. Their work identifies potential benefits in mitigating security risks and ensuring compliance with secure coding standards, while acknowledging challenges in tool reliability and developer trust.

Wang et al. [3] performed the first large-scale empirical study of AI-generated code in production environments, analyzing 1,000 GitHub repositories and 7,000+ CVE-linked code changes from 2022-2025. Their findings reveal that AI-generated code constitutes a substantial fraction of new code, particularly in boilerplate implementations. Critically, they identified "AI-induced vulnerabilities" arising from recurring insecure templates, with certain CWE families overrepresented in AI-generated code. The study emphasizes humans as security gatekeepers, noting that shallow code review leads to persistent AI-introduced defects.

A et al. [16] proposed a generalizable secure code generation framework integrating security-aware training policies, multi-stage generation pipelines, and automated vulnerability detection algorithms. Their framework significantly reduces insecure code patterns while maintaining correctness and efficiency across multiple programming languages. Benchmark testing demonstrated reduced vulnerability rates, offering a practical solution for balancing AI-driven productivity with security requirements.

Chen et al. [23] introduced SecureVibeBench, a benchmark of 105 C/C++ secure coding tasks derived from OSS-Fuzz, designed to evaluate AI agents by reconstructing vulnerability-introducing scenarios. Their evaluation of current agents, including OpenHands with Claude Sonnet 4.5, revealed that the best-performing agent achieved only 23.8% correct and secure solutions, highlighting significant gaps in AI agents' ability to produce secure code.

Neto et al. [12] developed a VSCode extension integrating ChatGPT to support secure software development by analyzing and suggesting fixes for vulnerable code. Qualitative evaluation suggested promise in enhancing developer certainty regarding security issues, though quantitative validation was limited.

6.2 Vulnerability Detection and Threat Analysis

AI-enhanced vulnerability detection represents a major focus area, with multiple approaches demonstrating improved accuracy and reduced false positives compared to traditional tools.

Beljulji et al. [15] conducted a systematic survey of LLM applications in security code review and testing, focusing on vulnerability detection, fuzz testing, and exploit generation. Their analysis compared LLM performance with traditional tools, identifying challenges including high training costs, limited context understanding, high false positive rates due to hallucinations, and data currency issues. Despite these limitations, LLMs showed promise in semantic vulnerability analysis and explainable security findings.

Alevizos et al. [22] investigated open LLMs for detecting source code language errors and deprecated code, assessing their potential to replace traditional security scanners. Findings indicated that while LLMs show promise, they face limitations in memory complexity and handling unfamiliar data patterns. The authors recommend proactive LLM application combined with security databases and continuous updates to fortify supply chain processes.

Bedoya et al. [11] proposed integrating LLMs for automated threat discovery at the design stage and Security Chaos Engineering to identify security flaws missed by traditional tools. Their framework, demonstrated through a retail company use case, aims to enhance DevSecOps practice by improving agile production of secure software and reducing vulnerabilities throughout the SDLC.

Warburton [19] examined AI/ML integration into DevSecOps for cloud-native applications, reporting substantial improvements: 76% fewer false positives, 88% higher threat detection accuracy, and 71% faster vulnerability remediation. The study explored frameworks for AI-driven security controls in CI/CD pipelines, IaC, and real-time threat detection systems, demonstrating significant improvements in security operations and development velocity.

Mittal [2] presented an AI-Augmented DevOps framework combining machine learning with DevSecOps practices for self-managing deployment pipelines. The framework features pre-commit security scanning, AI-powered vulnerability assessment, policy-as-code enforcement, and explainable anomaly detection. Experimental evaluation demonstrated an 87% reduction in security incidents, 340% improvement in deployment frequency, less than 5% false positive rates, and 3.5-month ROI. User studies showed 67% improvement in developers' security understanding.

6.3 Compliance Automation and Policy Enforcement

Compliance automation through AI-driven policy enforcement addresses the challenge of maintaining regulatory adherence in fast-paced development environments.

Automating Security Compliance [24] explored AI-driven policy enforcement in DevSecOps pipelines through a survey of 100 professionals. Findings indicated that AI tools significantly improve security audit efficiency and threat mitigation. However, challenges persist including skilled personnel shortages, high costs, and data quality issues. The study recommends investments in training, data management, and fostering AI adoption to fully realize compliance automation potential.

Kumar [27] presented an AI-augmented DevSecOps toolchain for compliance-critical cloud applications in healthcare and finance. The framework embeds autonomous agents and machine learning models to dynamically enforce regulatory controls, integrating static code analysis, container scanning, and IaC validation. The approach achieves continuous compliance enforcement, reduces manual overhead, and improves audit readiness in regulated environments.

Achbarou et al. [13] introduced SafeOps+, an integrated platform for automated security analysis and compliance in DevSecOps pipelines. The platform facilitates DevSecOps adoption, improves traceability and reproducibility, and is designed for development teams, researchers, and trainers. It addresses automated security analysis, compliance, and policy-as-code within DevSecOps workflows.

Wilson [5] explored AI-enhanced DevSecOps for automating vulnerability management and security policy enforcement in CI/CD pipelines. The study addresses the expanded attack surface and scalability challenges in modern software development, emphasizing real-time security policy enforcement and vulnerability identification. Given that unpatched vulnerabilities cost $4.45 million per incident and 80% of organizations plan to integrate security automation by 2026, the practical implications are substantial.

6.4 Software Supply Chain Security

Software supply chain security has emerged as a critical concern, with AI-driven approaches addressing provenance, dependency management, and attack mitigation.

Syed et al. [1] introduced an agentic AI framework combining LLMs, reinforcement learning, and multi-agent coordination for autonomous software supply chain defense. The system integrates with CI/CD environments via Model Context Protocol and documents observations in a blockchain security ledger. Experimental evaluation on GitHub Actions and Jenkins demonstrated better detection accuracy, shorter mitigation latency, and reasonable build-time overhead compared to rule-based and provenance-only baselines, facilitating proactive, self-defending supply chains.

Pillala et al. [7] proposed DevSecOps Sentinel, a system utilizing GenAI-driven agentic workflows to holistically improve software supply chain security. The architecture integrates cutting-edge GenAI models and intelligent agentic workflows, impacting the entire SDLC. Results indicate that GenAI-powered agentic workflows are viable for tackling complex security issues, enabling organizations to build faster, safer, and more reliable software.

Spracklen et al. [25] conducted a comprehensive analysis of package hallucinations by code-generating LLMs, identifying them as a novel software supply chain threat. Using 16 different models across two programming languages and 576,000 code samples, they found that 19.7% of generated packages are hallucinated, including 205,474 unique hallucinated package names. Mitigation strategies including RAG, self-detected feedback, and supervised fine-tuning reduced hallucination rates to below 3% for one model, though the phenomenon remains systemic and persistent.

Li et al. [14] investigated eleven potential software supply chain threats from LLM-generated code, finding they persistently exist. They introduced SSCGuard, a tool that generated 439,138 prompts to analyze four LLMs. To mitigate risks, they proposed Chain-of-Confirmation, a novel prompt-based defense to reduce fabrication, alongside a middleware-based defense informing users of supply chain threats.

Benedetti et al. [21] introduced PIP-SBOM, a novel pip-inspired solution for generating SBOMs in Python. Their work performed the first security analysis on SBOM generation tools' impact on vulnerability detection. PIP-SBOM significantly improved accuracy in component identification and dependency resolution, increasing average precision and recall by 60% and reducing false positives tenfold compared to state-of-the-art tools.

Xia et al. [26] conducted the first empirical study to understand practitioners' perceptions of SBOMs, using a mixed qualitative and quantitative method involving 17 interviewees and 65 survey respondents across 15 countries. The study summarized 26 statements on SBOM's states of practice, derived a goal model, and highlighted future directions, aiming to bridge gaps in understanding real-world SBOM adoption challenges.

Cesarano et al. [17] introduced a novel taxonomy of 12 Go-specific software supply chain attack vectors and GoSurf, a static analysis tool to identify them. Evaluation on real-world Go packages provided preliminary insights for securing the Go ecosystem by prioritizing code audits and uncovering hidden malicious behaviors.

6.5 Integrated DevSecOps Frameworks

Several studies proposed comprehensive frameworks integrating multiple security capabilities across the SDLC.

Kakarla et al. [4] proposed an AI-driven DevSecOps framework to automate continuous cloud security and regulatory compliance, addressing increased operational complexity and security exposure from cloud-native systems, microservices, and IaC-oriented CI/CD pipelines.

Airhiavbere et al. [8] synthesized SSDLC, DevSecOps, and AI-driven threat mitigation for secure software engineering. Their mixed-method study combining systematic literature review, quantitative analysis, and case study evaluation found that security-first frameworks effectively mitigate risks, strengthen resilience, and enable predictive analytics and proactive vulnerability detection, leading to measurable reductions in system vulnerabilities and enhanced incident response times.

Shriwastav [9] presented a Zero-Trust framework for automated AI infrastructure deployment in SMEs, demonstrated through a Secure DevOps case study. The framework incorporates a "shift-left" DevSecOps pipeline, automating security tests like SAST, SCA, and container scanning, alongside artifact integrity checks including SBOM generation.

Fu et al. [10] presented a comprehensive landscape study analyzing 99 research papers from 2017 to 2023, identifying 12 security tasks and reviewing existing AI-driven approaches for DevSecOps. The study detailed 65 benchmarks, highlighted 15 challenges, and proposed 15 future opportunities, aiming to enhance security, trust, and efficiency in software development by integrating AI into DevSecOps workflows.

Gurajapu [20] introduced DevGen, a Generative-AI assistant embedding LLMs across four CI/CD stages: feature breakdown, code templating, automated test synthesis, and pipeline authoring. Experimental evaluation demonstrated a 30% reduction in story completion lead time and 25% increase in automated test coverage, alongside improved developer satisfaction, with recommendations for security policy generation to enhance AI-driven delivery.

7 Comparative Analysis

7.1 Methodological Approaches

Table \reftab:comparative presents a comparative analysis of selected frameworks across key dimensions including AI methodology, security focus, evaluation approach, and reported performance metrics.

Table 1. Comparative Analysis of GenAI-Augmented DevSecOps Frameworks

Framework/Study	AI Methodology	Security Focus	Evaluation	Key Results
Agentic AI [1]	LLM + RL + Multi-agent	Supply chain, vulnerability mitigation	Real CI/CD (GitHub Actions, Jenkins)	Better detection accuracy, shorter mitigation latency vs. baselines
AI-Augmented DevOps [2]	ML + Policy-as-code	Vulnerability assessment, anomaly detection	GitHub Actions, Kubernetes, user studies	87% reduction in security incidents, 340% deployment improvement, <5% false positives
AI Code in Wild [3]	Empirical analysis	Secure code generation, AI-induced vulnerabilities	1,000 repos, 7,000+ CVEs (2022-2025)	AI code substantial fraction, recurring insecure templates, humans as gatekeepers
Secure Code Framework [16]	Security-aware training + Multi-stage pipeline	Secure code generation, vulnerability detection	Benchmark across languages	Reduced insecurity rates, maintained correctness and efficiency

SecureVibeBench [23]	LLM agents (Claude)	Secure code generation benchmark	105 C/C++ tasks from OSS-Fuzz	Best agent: 23.8% correct and secure solutions
LLM Security Review [15]	LLM survey	Vulnerability detection, fuzz testing	Systematic literature analysis	High training costs, context limits, false positives, data currency issues
AI/ML DevSecOps [19]	AI/ML integration	Vulnerability detection, IaC security, compliance	Industry research, implementation data	76% fewer false positives, 88% threat detection accuracy, 71% faster remediation
DevSecOps Sentinel [7]	GenAI agentic workflows	Supply chain security	Architecture evaluation	Viable method for complex security issues across SDLC
Package Hallucinations [25]	16 LLMs analysis	AI hallucination, supply chain	576,000 code samples, 2 languages	19.7% hallucination rate, 205,474 unique hallucinated packages; RAG/fine-tuning reduced to <3%
PIP-SBOM [21]	Novel SBOM generator	SBOM, vulnerability assessment	Python ecosystem evaluation	60% precision/recall improvement, 10x fewer false positives vs. state-of-the-art
SafeOps+ [13]	Integrated platform	Automated security analysis, compliance	Platform implementation	Improved traceability, reproducibility, DevSecOps adoption
DevGen [20]	LLM in CI/CD stages	Code generation, test synthesis	GitHub Actions, multiple sprints	30% reduced lead time, 25% increased test coverage

7.2 Performance Metrics and Effectiveness

Quantitative results across studies demonstrate substantial improvements in security metrics:

Incident Reduction: Mittal [2] reported 87% reduction in security incidents through AI-augmented vulnerability assessment and policy enforcement.

Detection Accuracy: Warburton [19] achieved 88% higher threat detection accuracy with AI/ML integration, while reducing false positives by 76%.

Remediation Speed: Warburton [19] demonstrated 71% faster vulnerability remediation through automated AI-driven workflows.

Development Velocity: Mittal [2] showed 340% improvement in deployment frequency, while Gurajapu [20] achieved 30% reduction in story completion lead time.

SBOM Accuracy: Benedetti et al. [21] improved SBOM precision and recall by 60% and reduced false positives tenfold.

However, significant challenges persist:

Secure Code Generation: Chen et al. [23] found that current AI agents achieve only 23.8% success in producing correct and secure code.

Hallucination Rates: Spracklen et al. [25] identified 19.7% package hallucination rate across 16 LLMs, though mitigation strategies reduced this to below 3%.

AI-Induced Vulnerabilities: Wang et al. [3] documented recurring insecure templates in AI-generated code, with certain CWE families overrepresented.

7.3 Integration Strategies and Deployment Contexts

Successful implementations demonstrate diverse integration strategies:

Pre-Commit Integration: Mittal [2] and Neto et al. [12] embedded security checks in developer workflows, providing immediate feedback.

CI/CD Pipeline Integration: Syed et al. [1], Mittal [2], and Gurajapu [20] integrated security automation into GitHub Actions, Jenkins, and Kubernetes environments.

Platform Approaches: Achbarou et al. [13] and Kumar [27] developed comprehensive platforms spanning multiple SDLC stages.

Domain-Specific Solutions: Kumar [27] targeted compliance-critical industries (healthcare, finance), while Cesarano et al. [17] focused on Go ecosystem security.

7.4 Evaluation Methodologies

Studies employed diverse evaluation approaches:

Real-World Deployment: Syed et al. [1], Mittal [2], and Gurajapu [20] evaluated frameworks in production CI/CD environments.

Large-Scale Empirical Analysis: Wang et al. [3] analyzed 1,000 repositories and 7,000+ CVEs, while Spracklen et al. [25] examined 576,000 code samples.

Benchmark Evaluation: Chen et al. [23] introduced a novel benchmark of 105 secure coding tasks, while A et al. [16] tested across multiple programming languages.

User Studies: Mittal [2] conducted user studies measuring developer understanding and satisfaction.

Practitioner Surveys: Xia et al. [26] and Automating Security Compliance [24] surveyed practitioners to understand real-world adoption challenges.

8 Discussion

8.1 Key Findings and Implications

The integration of GenAI into DevSecOps practices demonstrates substantial potential for improving security outcomes, development velocity, and operational efficiency. Quantitative results consistently show significant improvements in threat detection accuracy, false positive reduction, and remediation speed [2, 19]. These improvements translate to measurable business value, with reported ROI periods as short as 3.5 months [2].

However, the literature reveals critical challenges that must be addressed for safe and effective adoption. The 19.7% package hallucination rate [25] and 23.8% secure code generation success rate [23] indicate that current GenAI technologies are not yet reliable enough for autonomous security-critical decision-making. Human oversight remains essential, with Wang et al. [3] emphasizing humans as security gatekeepers who must carefully review AI-generated code.

8.2 Strengths of Current Approaches

Automation and Scalability: AI-driven approaches excel at automating repetitive security tasks, enabling security teams to focus on complex threats [2, 19].

Semantic Understanding: LLMs provide contextual understanding beyond pattern matching, enabling detection of complex vulnerabilities requiring domain knowledge [11, 15].

Explainability: Natural language explanations improve developer understanding and facilitate security knowledge transfer [2].

Adaptive Learning: Reinforcement learning enables adaptive security policies that balance effectiveness with operational constraints [1].

Comprehensive Coverage: Integrated frameworks address multiple security domains across the SDLC [8, 10].

8.3 Limitations and Challenges

Hallucination and Fabrication: LLMs generate plausible but incorrect information, including non-existent packages and insecure code patterns [25, 14]. This poses severe supply chain risks.

Context Limitations: Limited context windows restrict LLMs' ability to analyze large codebases and complex security configurations [15].

Training Data Biases: Models trained on public code repositories inherit vulnerabilities and insecure patterns from training data [3].

False Positives: While AI reduces false positives compared to traditional tools, rates remain significant in some contexts [15].

Skill Requirements: Effective adoption requires skilled personnel capable of configuring, monitoring, and validating AI-driven security tools [24].

Cost and Complexity: High training costs, computational requirements, and integration complexity create barriers to adoption [15, 24].

Regulatory and Compliance Concerns: Lack of standardized benchmarks and certification processes complicates adoption in regulated industries [27].

8.4 Practical Implications for Practitioners

Based on the reviewed literature, we offer the following recommendations for practitioners:

Adopt Hybrid Approaches: Combine AI-driven tools with traditional security controls and human oversight [2, 13].

Implement Multi-Stage Validation: Use multiple validation layers for AI-generated code, including automated testing, security scanning, and human review [16].

Prioritize Explainability: Select tools providing clear explanations of security findings to facilitate developer understanding and trust [2].

Address Hallucination Risks: Implement mitigation strategies such as RAG, fine-tuning on domain-specific data, and middleware-based warnings [25, 14].

Invest in Training: Develop organizational capabilities in AI security, including understanding of model limitations and validation techniques [24].

Start with Low-Risk Applications: Begin AI adoption in non-critical contexts, gradually expanding to security-critical applications as confidence and capabilities grow.

Maintain Human Oversight: Ensure security-critical decisions involve human review, particularly for code deployment and policy changes [3].

Establish Continuous Monitoring: Implement feedback loops to detect and correct AI-introduced vulnerabilities [1].

8.5 Theoretical Contributions

This review contributes to theory by:

• Synthesizing fragmented research into a coherent taxonomy of GenAI-augmented DevSecOps approaches

• Identifying the tension between automation benefits and hallucination risks as a fundamental challenge requiring architectural solutions

• Highlighting the critical role of human oversight in AI-augmented security workflows

• Demonstrating the value of multi-agent architectures for complex security tasks

• Establishing the need for domain-specific benchmarks and evaluation frameworks

9 Research Gaps

Despite significant progress, we identify eight major research gaps requiring attention:

9.1 Gap 1: Standardized Benchmarks for Secure Code Generation

Current evaluations use diverse, often proprietary benchmarks, limiting comparability across studies [23, 16]. The field lacks standardized, comprehensive benchmarks covering multiple languages, vulnerability types, and complexity levels. SecureVibeBench [23] represents progress but covers only C/C++.

9.2 Gap 2: Hallucination Mitigation in Security Contexts

While mitigation strategies show promise [25, 14], systematic approaches to preventing and detecting hallucinations in security-critical contexts remain underdeveloped. Research is needed on architectural patterns, validation frameworks, and real-time hallucination detection.

9.3 Gap 3: Explainable AI for Security Decisions

Most studies report improved explainability [2] but lack rigorous evaluation of explanation quality, developer comprehension, and impact on security outcomes. Research is needed on explanation frameworks, evaluation metrics, and human factors.

9.4 Gap 4: Long-Term Impact and Sustainability

Studies typically report short-term results (weeks to months). Long-term impacts on security posture, technical debt, developer skills, and organizational culture remain unexplored. Longitudinal studies are needed to assess sustainability and evolution of AI-augmented security practices.

9.5 Gap 5: Integration of Policy-as-Code with IaC Security

While individual studies address policy-as-code [2, 24] and IaC security [19, 27], integrated approaches combining both remain limited. Research is needed on unified frameworks, conflict resolution, and cross-domain policy enforcement.

9.6 Gap 6: Adversarial Robustness and Security of AI Systems

The reviewed literature focuses on using AI for security but largely ignores security of AI systems themselves. Research is needed on adversarial attacks against AI security tools, model poisoning, and defensive strategies.

9.7 Gap 7: Economic Models and ROI Analysis

While Mittal [2] reports 3.5-month ROI, comprehensive economic models accounting for implementation costs, training requirements, operational overhead, and risk reduction remain lacking. Research is needed on cost-benefit frameworks and decision support tools.

9.8 Gap 8: Cross-Domain Transfer and Generalization

Most studies focus on specific domains or languages [17, 21]. Research is needed on transfer learning approaches, domain adaptation techniques, and frameworks enabling generalization across diverse contexts.

10 Future Research Directions

Based on identified gaps and emerging trends, we propose the following research directions:

10.1 Direction 1: Robust Hallucination Detection and Mitigation

Develop architectural patterns and runtime systems for detecting and mitigating hallucinations in security contexts. Research should explore:

- Real-time hallucination detection using ensemble methods and cross-validation
- Confidence scoring and uncertainty quantification for AI-generated security artifacts
- Middleware architectures providing safety guarantees for AI-augmented workflows
- Formal verification techniques for AI-generated code and policies

10.2 Direction 2: Comprehensive Security Benchmarks

Establish standardized, multi-dimensional benchmarks for evaluating AI security tools. Benchmarks should:

- Cover multiple programming languages, frameworks, and vulnerability types
- Include realistic, multi-file scenarios reflecting production complexity
- Provide both functional correctness and security validation
- Enable reproducible, comparable evaluations across studies
- Incorporate adversarial test cases and edge conditions

10.3 Direction 3: Explainable AI for Security

Advance explainable AI techniques specifically for security contexts. Research should address:

- Explanation frameworks tailored to security concepts and developer mental models
- Evaluation metrics for explanation quality, completeness, and actionability
- Interactive explanation systems supporting developer learning and decision-making
- Causal reasoning and counterfactual explanations for security findings

10.4 Direction 4: Agentic Security Architectures

Extend agentic AI architectures [1, 7] with enhanced capabilities:

- Multi-agent coordination protocols for complex security workflows
- Learning and adaptation mechanisms based on security outcomes
- Integration with threat intelligence and security knowledge bases
- Formal verification of agent behaviors and security properties

10.5 Direction 5: Unified Policy and Infrastructure Security

Develop integrated frameworks combining policy-as-code and IaC security:

- Unified policy languages spanning application and infrastructure domains
- Automated policy generation from regulatory requirements and threat models
- Conflict detection and resolution across policy domains
- Continuous compliance validation across SDLC stages

10.6 Direction 6: Adversarial Robustness Research

Investigate security of AI security tools themselves:

- Adversarial attacks against AI vulnerability detectors and code generators
- Model poisoning and backdoor attacks in security contexts
- Defensive techniques including adversarial training and input validation
- Security certification frameworks for AI security tools

10.7 Direction 7: Human-AI Collaboration Models

Develop frameworks optimizing human-AI collaboration in security workflows:

- Task allocation strategies balancing automation and human oversight
- Interface designs supporting effective security review and decision-making
- Training programs developing AI-augmented security skills
- Organizational models and governance structures for AI-augmented security

10.8 Direction 8: Domain-Specific Adaptation

Advance techniques for adapting general-purpose AI models to specific security domains:

- Transfer learning and few-shot learning for domain-specific vulnerabilities
- Domain-specific fine-tuning strategies and training data curation
- Hybrid architectures combining general and domain-specific models
- Evaluation frameworks for domain adaptation effectiveness

10.9 Direction 9: Longitudinal Impact Studies

Conduct long-term studies assessing sustained impacts of AI-augmented DevSecOps:

- Evolution of security posture over extended periods (years)
- Impact on developer skills, security culture, and organizational practices
- Technical debt accumulation and maintenance challenges
- Adaptation strategies as threats and technologies evolve

10.10 Direction 10: Economic and Decision Support Models

Develop comprehensive frameworks for evaluating AI security investments:

- Total cost of ownership models including implementation, training, and operations
- Risk quantification and reduction metrics
- Decision support tools for technology selection and deployment strategies
- Comparative analysis of AI-augmented vs. traditional security approaches

11 Conclusion

This literature review has systematically examined the integration of Generative AI into DevSecOps practices, analyzing 30 peer-reviewed publications spanning 2023-2026. Our analysis reveals a rapidly maturing field with substantial demonstrated benefits and persistent challenges.

11.1 Summary of Key Findings

GenAI-augmented DevSecOps approaches demonstrate significant quantitative improvements: 87% reduction in security incidents [2], 88% higher threat detection accuracy [19], 71% faster vulnerability remediation [19], and 340% improvement in deployment frequency [2]. These results indicate that AI-driven automation can substantially enhance security outcomes while accelerating development velocity.

However, critical challenges temper this optimism. Current AI agents achieve only 23.8% success in producing correct and secure code [23], and 19.7% of AI-generated packages contain hallucinations [25]. AI-induced vulnerabilities arising from recurring insecure templates pose supply chain risks [3]. These findings underscore the necessity of human oversight, multi-stage validation, and robust mitigation strategies.

11.2 Theoretical and Practical Contributions

This review contributes a comprehensive taxonomy organizing approaches by security focus area, AI methodology, integration strategy, and deployment context. Our comparative analysis synthesizes empirical findings across diverse studies, enabling evidence-based decision-making. We identify eight major research gaps and propose ten future research directions, providing a roadmap for advancing the field.

For practitioners, we offer actionable recommendations emphasizing hybrid approaches, multi-stage validation, explainability, hallucination mitigation, and sustained human oversight. These recommendations balance the benefits of AI automation with the imperative of maintaining security assurance.

11.3 The Path Forward

The integration of GenAI into DevSecOps represents a fundamental shift in how organizations approach software security. Success requires not only technological advances but also organizational adaptation, skill development, and cultural change. The field must address hallucination risks, establish standardized benchmarks, advance explainable AI techniques, and develop robust human-AI collaboration models.

As GenAI technologies continue to evolve, their role in DevSecOps will expand. The challenge for researchers and practitioners is to harness AI's potential while maintaining rigorous security assurance. This requires sustained research, careful evaluation, and responsible deployment practices.

11.4 Limitations of This Review

This review has limitations that should be acknowledged. First, the rapid pace of AI research means that new developments may have emerged since our search was conducted. Second, our focus on peer-reviewed publications may have excluded relevant industry reports and gray literature. Third, the top-30 selection criterion, while necessary for depth, may have omitted relevant work. Finally, the heterogeneity of evaluation methodologies across studies limits quantitative meta-analysis.

11.5 Closing Remarks

DevSecOps in the age of Generative AI stands at a critical juncture. The demonstrated benefits are substantial, but so are the risks. Moving forward requires a balanced approach that embraces innovation while maintaining security rigor. By addressing identified research gaps, advancing proposed research directions, and following evidence-based practices, the field can realize the transformative potential of AI-augmented security while safeguarding against emerging threats.

The convergence of DevSecOps and GenAI is not merely a technological evolution but a fundamental reimagining of secure software development. Success will require collaboration across disciplines—computer science, security, human factors, and organizational science—to create systems that are not only intelligent and efficient but also trustworthy and secure.

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