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Masterthesis

Generative AI for Security Automation in Hyperscale Cloud Platforms

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Declaration of Authorship

I, Daniel VERA GILLIARD, in lieu of an oath that I have written the Master's thesis presented here independently and exclusively using the literature and other aids provided. The thesis has not been submitted in the same or a similar form to any other examination authority for the award of an academic degree.

Signed:

Date:

Declaration on the Use of Generative AI

I, Daniel VERA GILLIARD, hereby declare that generative artificial intelligence (AI) was employed as a writing assistant in the development of this manuscript. The use of these tools was exclusively for linguistic enhancement, such as refining sentence structure, correcting grammar, and improving overall style. The conceptual framework, original ideas, research methodology, data analysis, and final conclusions presented in this work are the product of my own intellectual effort. I have critically reviewed, edited, and validated all content to ensure its accuracy and originality, and I bear complete responsibility for the entirety of this thesis.

Signed: _____

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"*Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism.*"

Dave Barry

HOCHSCHULE KARLSRUHE

Abstract

Faculty Name
Business Information Systems

Master of Business Information Systems

Generative AI for Security Automation in Hyperscale Cloud Platforms

by Daniel VERA GILLIARD

The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too...

Acknowledgements

The acknowledgments and the people to thank go here, don’t forget to include your project advisor. . .

Contents

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Listings

Glossary

cloud-native An approach to building and running applications that exploits the advantages of the cloud computing delivery model. Cloud-native technologies empower organizations to build and run scalable applications in modern, dynamic environments such as public, private, and hybrid clouds. 34

false positive An alert or detection that incorrectly identifies normal, benign activity as malicious or threatening. High false positive rates can overwhelm security teams and reduce the effectiveness of security systems. 36, 41

orchestration The automated arrangement, coordination, and management of complex computer systems, middleware, and services. In cloud computing, this often refers to managing containers, services, and infrastructure. 35, 38, 39

Rego A high-level declarative language used by the Open Policy Agent (OPA) to express policies over complex data structures, such as JSON.. 35, 37, 38, 41, 42

security automation The use of technology to perform security tasks with minimal human intervention. It includes automated threat detection, incident response, compliance monitoring, and vulnerability management. 38

Acronyms

AI Artificial Intelligence. 3–8, 10, 13–17, 24–26, 30, 31, 37–39

AI RMF Artificial Intelligence Risk Management Framework. 5–8, 14–16

API Application Programming Interface. 6, 26, 35–39, 41

APP Australian Privacy Principles. 7

AWS Amazon Web Services. 4, 7, 8, 35–38, 41

CI/CD Continuous Integration/Continuous Deployment. 21, 23, 25, 26, 31, 32, 34–38, 41, 42

CoE Center of Excellence. 6, 8

DevOps Development and Operations. 21

DevSecOps Development, Security, and Operations. 10, 11, 34, 41

GDPR General Data Protection Regulation. 12

GenAI Generative Artificial Intelligence. 3–17, 23, 24, 26, 30–38, 41

GitHub GitHub platform. 35, 37, 41

HITL Human-in-the-Loop. 30, 31, 33–37

IaC Infrastructure-as-Code. 21, 23, 24, 26–29, 31, 33, 35–37, 42

IAM Identity and Access Management. 37

IDPS Intrusion Detection and Prevention System. 9

IP Internet Protocol. 8

ISO International Organization for Standardization. 7

IT Information Technology. 9

JSON JavaScript Object Notation. 35

KB Knowledge Base. 37, 38, 41

KMS Key Management Service. 37

LLM Large Language Model. 6, 8, 10–12, 14, 15, 21, 24–29, 33, 36, 37

MLOps Machine Learning Operations. 7, 8, 26, 35

MTTD Mean Time to Detect. 11

MTTR Mean Time to Resolve. 11

NIST U.S. National Institute of Standards and Technology. 5–8, 14–16

OPA Open Policy Agent. 35–38, 41, 42

OWASP Open Web Application Security Project. 6–8

PaC Policy-as-Code. 21, 26, 31, 35

PG Policy Generation. 33, 38, 41

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses. 11

RAG Retrieval-Augmented Generation. 7, 10, 26, 27, 33, 36–38, 41

RMF Risk Management Framework. 14, 15

S3 Simple Storage Service. 37

SAIF Secure AI Framework. 5–8

SAST static analysis security testing. 23, 24, 30, 34, 36, 38, 41

SOC Security Operations Center. 5

SP System Prompt. 37

SQL Structured Query Language. 11

SRM Shared Responsibility Model. 7, 8, 37

Terraform Terraform infrastructure as code. 33–38, 41, 42

YAML YAML Ain't Markup Language. 8, 35

ZTA Zero Trust Architecture. 15

For/Dedicated to/To my. . .

Chapter 1

Introduction

1.1 Instead of an introduction

First of all: The introduction should be short!

State the problem, describe the organization and structure of the document and thats it. Anything more thatn 3 pages needs justification.

Chapter 2

Background and Related Work

2.1 Foundational Concepts in Cloud Security

TBD

2.2 Foundational Concepts in Generative AI

TBD

2.3 State of Cloud Provider Ecosystems

TBD

2.4 Literature State of the Art

The convergence of Generative Artificial Intelligence (GenAI) and hyperscale cloud platforms presents a rapidly evolving frontier for cybersecurity. As organizations increasingly rely on complex cloud environments, the scale and sophistication of threats necessitate advanced automation capabilities. GenAI offers promising avenues for enhancing security posture through intelligent automation, but its integration also introduces challenges and risks. A comprehensive understanding of the existing research landscape is therefore essential to identify established practices, emerging trends, and critical gaps in knowledge.

This literature review synthesizes current academic and industry contributions pertinent to the application of GenAI for security automation within hyperscale and multi-cloud contexts. It begins by outlining the methodology employed to select and analyze relevant works. Subsequently, the review dives into several key thematic areas: the evolution from traditional security methods to Artificial Intelligence (AI)-driven approaches, specific frameworks for scoping and managing GenAI security implementations, architectural patterns and techniques for security automation, a critical examination of the unique security risks associated with GenAI itself, risk management frameworks and the ongoing crucial discussion regarding the necessary balance between automation and human oversight.

By examining these facets, this review aims to provide a foundational understanding of the state-of-the-art, highlighting both the potential of GenAI in cloud security automation and the significant considerations that must be addressed for its responsible and effective deployment. This synthesis will builds the basis for the subsequent research presented in this thesis.

2.4.1 Methodology

This literature review followed a structured approach to identify relevant publications, focusing on peer-reviewed articles addressing GenAI applications in hyperscale cloud security published primarily within the last five years. The search utilized academic databases with key search terms related to generative AI, cloud security automation, hyperscale platforms, and multi-cloud orchestration.

Papers were selected based on their relevance to:

- GenAI applications specifically in cloud security contexts
- Hyperscale or multi-cloud environments
- Technical solutions for security automation
- Empirical evidence or theoretical frameworks with substantial methodological rigor

The selection process involved initial screening of titles and abstracts followed by full-text review of promising papers. The analysis employed a thematic approach, identifying recurring concepts, methodological approaches, and gaps in existing research. Particular attention was paid to identifying the theoretical foundations underpinning GenAI applications in security contexts, empirical evidence of effectiveness, and limitations of current approaches.

2.4.2 AI-Driven Security Approaches

The landscape of cloud security is undergoing a significant transformation, shifting from traditional, often reactive methods towards more proactive and adaptive strategies powered by AI, particularly GenAI. This evolution marks a move beyond basic anomaly detection towards sophisticated security postures capable of learning from and responding dynamically to novel threat vectors in complex cloud environments.

Foundational work by Khanna [1] explores the integration of GenAI into cloud security, outlining its core applications. According to Khanna, modern GenAI implementations focus on key capabilities such as processing vast amounts of data (e.g., log entries, network packets) for advanced anomaly detection and threat intelligence, enabling automated response mechanisms that dynamically adjust security protocols, and facilitating predictive security measures to forecast potential vulnerabilities. While highlighting these advancements, Khanna also acknowledges inherent challenges, including the need for large datasets and mitigating potential adversarial manipulation.

Building upon these foundational capabilities, [2] also concludes that the integration of GenAI represents a significant leap beyond conventional rule-based security systems. Its research indicates that GenAI enhances security automation, particularly within multi-cloud and hybrid architectures. It allows systems to adapt infrastructure dynamically in response to varying traffic patterns and implements AI-powered defenses against continuously evolving cyber threats. This adaptive capability directly addresses persistent challenges in cloud security related to optimizing workload distribution, ensuring performance, and managing costs effectively.

Furthermore, recent studies underscore the practical impact of integrating GenAI with established cloud-native security tools. Patel et al. [3] demonstrate how layering GenAI onto platforms like Amazon Web Services (AWS) GuardDuty and Google

Cloud Security Command Center significantly boosts automated threat detection, enables real-time incident response, and improves comprehensive vulnerability management across distributed cloud infrastructures. Their work provides empirical evidence, citing examples like Netflix and JPMorgan Chase, which reported measurable improvements in detection accuracy and notable reductions in security incidents following the adoption of GenAI-driven security automation strategies [3]. This convergence of GenAI with existing security frameworks highlights its potential to transform Security Operations Centers (SOCs) by enhancing both efficiency and effectiveness.

2.4.3 GenAI Security Frameworks

The rapid integration of GenAI into various domains, including security automation within hyperscale cloud platforms, necessitates robust frameworks to govern its development, deployment, and operation securely. Unlike traditional software, GenAI systems introduce unique risks stemming from their data dependency, complexity, potential for emergent behaviors, and socio-technical nature [4]. These risks include prompt injection, data leakage through model inversion or training data extraction, adversarial attacks, generation of harmful or biased content, and insecure code generation [5, 6]. Consequently, a multi-faceted approach to security is required, encompassing foundational risk management principles, organizational governance structures, technical control implementation, and context-specific guidance. This subchapter reviews several key frameworks and guides that collectively address the challenge of securing GenAI systems.

A foundational element in managing AI risks is provided by the Artificial Intelligence Risk Management Framework (AI RMF) 1.0 developed by the U.S. National Institute of Standards and Technology (NIST) [4]. This voluntary, non-sector-specific framework aims to help organizations manage AI risks and promote trustworthy and responsible AI development and use. It is structured around four core functions: GOVERN, MAP, MEASURE, and MANAGE. The GOVERN function is cross-cutting, establishing a risk management culture and processes throughout the organization. MAP involves contextualizing risks and understanding potential impacts. MEASURE employs qualitative and quantitative tools to analyze, assess, and track AI risks. MANAGE focuses on prioritizing and acting on risks based on the previous functions [4]. The NIST AI RMF emphasizes characteristics of trustworthy AI systems, including validity and reliability, safety, security and resilience, accountability and transparency, explainability and interpretability, privacy-enhancement, and fairness with harmful bias managed [4]. It acknowledges the challenges specific to AI risk management, such as difficulties in risk measurement (especially with third-party components and emergent risks), defining risk tolerance, prioritizing risks, and integrating AI risk management into broader enterprise strategies [4].

Building upon similar principles but offering a perspective from a major cloud provider, Google's Secure AI Framework (SAIF) presents a conceptual framework inspired by security best practices applied to software development, adapted for AI-specific risks [6]. SAIF proposes six core elements for secure AI systems[6]:

1. Expand strong security foundations to the AI ecosystem by applying and adapting existing controls.

2. Extend detection and response to include AI-specific threats and outputs.

3. Automate defenses using AI itself where appropriate, while keeping humans in the loop.

4. Harmonize platform-level controls to ensure consistency and prevent fragmentation.

5. Adapt controls with faster feedback loops, incorporating insights from red teaming and novel attack awareness.

6. Contextualize AI system risks within surrounding business processes, including model risk management and shared responsibility.

SAIF advocates a practical implementation approach involving understanding the specific use case, assembling a multidisciplinary team, providing an AI primer for all stakeholders, and applying the six core elements iteratively [6]. Like the NIST AI RMF, SAIF highlights the socio-technical nature of AI risks and the importance of context.

While NIST and Google provide overarching frameworks, securing GenAI, particularly Large Language Models (LLMs), requires specific organizational structures and practices. The LLM and Generative AI Security Center of Excellence (CoE) Guide from OWASP addresses this by outlining how to establish a dedicated CoE [7]. The primary objective of such a CoE is "to develop and enforce security policies and protocols for generative AI applications, facilitate cross-departmental collaboration to harness expertise from various fields, educate and train teams on the ethical and secure use of generative AI technologies, and serve as an advisory body for AI-related projects and initiatives within the organization" [7, p.4]. This guide emphasizes the necessity of a multidisciplinary team, bringing together expertise from Cybersecurity, AI/ML Development, IT Operations, Legal, Compliance, Ethics, Governance, Risk Management, Data Science, and various other user groups[7]. Establishing clear objectives, Key Performance Indicators, roles, and responsibilities is crucial for the CoE's success. The guide suggests a phased implementation (Planning, Integration, Operationalization, Evaluation) and highlights the importance of leveraging both internal and external expertise to address challenges like communication barriers, resistance to change, and skill gaps [7]. The CoE structure directly supports the GOVERN function described in the NIST AI RMF and aligns with SAIF's recommendation to assemble a cross-functional team.

To translate high-level governance and risk management principles into concrete verification steps, the Open Web Application Security Project (OWASP) LLM Applications Cybersecurity and Governance Checklist provides a practical, actionable tool [8]. Derived from the well-known OWASP Top 10 for LLM Applications project, this checklist offers a structured approach to assessing the security posture of LLM-based systems. It covers a wide array of control areas critical for LLM security, extending beyond purely technical vulnerabilities to encompass essential governance aspects [8]. Key domains addressed include Input Validation and handling, Output Encoding and Handling, Access Control and Authorization, Data Privacy and Confidentiality, Model Training and Fine-tuning Security, Application Programming Interface (API) and Integration Security, robust Logging and Monitoring, Incident Response Planning, and overall Governance, Risk, and Compliance[8]. The checklist serves as a valuable resource for development teams, security assessors, and governance bodies to systematically identify potential weaknesses, guide the implementation of specific security controls, and perform gap analyses against established best practices [8]. In the context of broader frameworks, this checklist acts as a practical instrument for the MEASURE and MANAGE functions outlined in the NIST AI RMF [4], providing specific checks aligned with the risks highlighted by SAIF [6] and the technical controls advocated by SecGenAI [5]. It furnishes the CoE[8] with a concrete tool for enforcing

security policies and protocols. Regarding a specific GenAI architecture, the SecGenAI framework focuses on enhancing the security of cloud-based GenAI applications, particularly Retrieval-Augmented Generation (RAG) systems, within the context of Australian critical technologies [5]. SecGenAI adopts an end-to-end perspective covering Functional, Infrastructure, and Governance requirements. Functionally, it analyzes RAG components and identifies root causes for security concerns like injection attacks, data leakage, and model inversion [5]. It proposes specific countermeasures such as input validation, robust access controls, data protection techniques, and model security measures[5]. On the infrastructure side, SecGenAI details requirements for sandboxing, secure database connections, network segmentation, external attack prevention, and disaster recovery within a cloud environment[5]. Governance requirements emphasize alignment with Australian AI Ethics Principles and Australian Privacy Principles (APP), advocating for fairness, accountability, traceability, data protection, regular audits, reliability, transparency, and compliance, structured using the International Organization for Standardization (ISO) 38500 Evaluate-Direct-Monitor cycle [9]. SecGenAI explicitly incorporates the Shared Responsibility Model, detailing Cloud Service Provider and customer obligations for GenAI security[5]. This framework provides a detailed blueprint for securing a specific, common GenAI patters by integrating technical and governance controls, reflecting a practical application of the principles found in NIST AI RMF and SAIF.

The successful implementation of these security frameworks inherently depends on the underlying platform architecture. The paper "Integration patterns in unified AI and cloud platforms" provides context by reviewing how AI, Machine Learning Operations (MLOps), workflow orchestration, and data processing converge in cloud-native environments[10]. It highlights the importance of MLOps frameworks for lifecycle management, workflow orchestration engines for process automation, and robust data processing systems as core components [10]. Security considerations must be embedded within these components and their integration patterns. For instance, securing data pipelines within MLOps, ensuring secure communication in federated learning setups, or implementing access controls within workflow orchestration are crucial [5, 6, 10]. The paper implicitly underscores that security cannot be an afterthought but must be integrated into the design and automation processes of these unified platforms, aligning with the principles of secure-by-design advocated by frameworks like SAIF and SecGenAI. Facilitating this integration within a specific hyperscale cloud platform, the AWS GenAI Security Scoping Matrix serves as a practical aid for organizations utilizing AWS[11]. This matrix is designed explicitly to help customers navigate the complexities of the Shared Responsibility Model (SRM) as it applies to GenAI workloads deployed on AWS. It systematically maps common GenAI architectural components and layers against key security domains[11]. For each intersection of a GenAI component and a security domain, the matrix clarifies whether the responsibility for implementing controls lies primarily with AWS, the customer, or is shared between them [11]. This structured delineation is crucial for organizations to understand their specific security obligations when building and operating GenAI systems on AWS. Furthermore, the matrix guides customers in identifying and scoping the relevant AWS security services needed to fulfill their responsibilities [11]. It acts as a translator, converting the high-level principles of frameworks like NIST AI RMF [4] and SAIF [6], and the specific control requirements suggested by SecGenAI [5] or the OWASP Checklist [8], into actionable configurations and service selections within the AWS ecosystem. It directly supports the practical implementation of the SRM, a concept emphasized across multiple frameworks [4–6, 8], thereby enabling organizations to effectively manage risks within their AWS environment.

In summary, these frameworks and guides offer a layered approach to GenAI security. The NIST AI RMF provides a foundational, risk-based structure and defines trustworthiness. Google's SAIF offers a conceptual implementation path with core security elements, emphasizing adaptation and integration. The OWASP LLM CoE Guide focuses on the essential organizational and collaborative structures needed for effective governance. SecGenAI provides a detailed, integrated blueprint for securing a specific architecture, demonstrating how broader principles can be applied in context, including alignment with regional regulations. Practical tools like the OWASP LLM Checklist and provider-specific resources like the AWS Scoping Matrix aid in the MEASURE and MANAGE functions by providing concrete checks and configurations. The insights from [10] remind us that these security measures must be seamlessly integrated within the complex fabric of unified AI and cloud platforms, particularly within MLOps and automation workflows, to be effective. The recurring theme of the SRM across multiple frameworks [4–6, 8] highlights the collaborative nature of securing GenAI in cloud environments. Collectively, these resources provide a comprehensive toolkit for organizations aiming to leverage GenAI for security automation and other critical tasks on hyperscale cloud platforms, enabling them to manage risks effectively and build trustworthy AI systems.

2.4.4 Approaches for Automated Cloud Security

This subsection details specific technical approaches and architectural patterns crucial for enabling automated cloud security. It reviews research on unified platforms integrating AI and MLOps across multi-cloud environments, techniques for automated policy orchestration in complex Kubernetes setups, and the application of digital twins for robust security policy validation. These approaches represent concrete mechanisms for realizing the potential of automation in dynamic cloud infrastructures. For organizations operating containerized workloads across multiple clusters, particularly in multi-domain architectures involving different administrative entities, research from 2023 proposes an automated approach for generating network security policies in Kubernetes deployments[12]. Manually configuring security in such environments is complex, often leading to inconsistencies between policies defined in different clusters and requiring domain administrators to possess knowledge about other domains' configurations (like service locations or Internet Protocol (IP) addresses), which is not always feasible[12]. This approach addresses two critical challenges in multi-cluster security: reducing the configuration errors commonly made by human administrators and creating transparent cross-cluster communications without requiring extensive information sharing between domains[12].

The proposed solution involves a top-level entity named the "Multi-Cluster Orchestrator"[12]. This orchestrator acts as a central management point, receiving inputs from managers of different domains[12]. These inputs include:

- A description of each domain's structure[12].
- High-level security requirements specifying allowed communications[12]. These requirements can be defined using an extended YAML Ain't Markup Language (YAML) syntax with special labels that abstract away low-level details[12].

Based on these inputs, the Multi-Cluster Orchestrator refines the high-level requirements into concrete configurations through a two-step process[12]:

1. It generates a "Global Configuration" that tracks communication pairs between services and required links between clusters, optimizing the overall cluster mesh setup[12].

2. It derives "Single Configurations" for each individual cluster, containing the specific parameters needed to connect the cluster to the mesh, the Kubernetes Network Policies to enforce the desired security rules, and commands to create local service entries that enable transparent name resolution for services located in external clusters[12].

The implementation, known as Multi-Cluster Orchestrator, demonstrates how automated policy generation can improve security consistency across distributed environments while reducing the cognitive load on security administrators by handling the complexity of multi-domain interactions transparently[12]. This research is particularly relevant for hyperscale cloud platforms and organizations that utilize container orchestration technologies like Kubernetes to manage numerous workloads across multiple clusters, potentially spanning different regions, availability zones, or administrative boundaries[12].

Another approach to security automation in the context of policies involves the use of digital twins for validating security policies before deployment in production environments[13]. This approach utilizes an emulation system specifically designed to create high-fidelity digital replicas of target Information Technology (IT) infrastructures[13]. These digital twins replicate key functionalities of the corresponding physical or virtual systems, allowing security teams to play out complex security scenarios, such as intrusion attempts and defense responses, within a safe and controlled environment[13]. This capability avoids impacting operational workflows on the real-world infrastructure[13]. The digital twin approach, following the research by Hammar and Stadler, enables a closed-loop learning process for crafting and refining security policies[13]. It starts with generating a digital twin of the target infrastructure. This is achieved using an emulation system constructed with virtualization tools like Docker containers, alongside virtual links and switches[13]. Within this digital twin, various security scenarios involving emulated attackers, defenders, and client populations are executed[13]. During these runs, monitoring agents collect detailed system measurements and logs, channeling this data through pipelines for analysis[13]. The gathered data and statistics are then used to build simulations[13]. Reinforcement learning techniques are applied to these simulations to learn potentially optimal security policies[13]. Finally, the performance of these learned policies is rigorously evaluated back in the digital twin, allowing for validation and further iteration[13]. This methodology provides continuous, iterative feedback and improvement cycles, as the results from validation can inform further scenario runs and learning phases, enhancing policy effectiveness over time[13]. The authors demonstrate this by applying the approach to an intrusion response scenario, showing that the digital twin provided the necessary evaluative feedback to learn near-optimal policies that outperformed baseline systems like the SNORT Intrusion Detection and Prevention System (IDPS)[14]. This represents a significant advancement in validation mechanisms, particularly relevant for potentially complex GenAI-driven security automation strategies, by bridging the gap between simulation-based learning and real-world applicability[13].

Regarding policies, ensuring the trustworthiness and accuracy of GenAI-generated security policies and responses remains a significant challenge. The already mentioned SecGenAI framework demonstrates how advanced machine learning techniques can be combined with robust security measures to enhance the reliability of

GenAI systems while maintaining compliance with regulatory requirements.[5] As described, this approach integrates continuous validation processes throughout the AI lifecycle, from model development to deployment and monitoring, creating multiple checkpoints that verify the integrity and effectiveness of security responses. By emphasizing explainability alongside accuracy, the framework addresses one of the primary concerns associated with GenAI applications in security contexts: the "black box" nature of complex models.[5]

While not specifically focused on cloud security, research on GenAI applications in the energy sector offers transferable insights into implementation approaches for complex operating environments. This comprehensive literature review identifies how GenAI enhances productivity through data creation, forecasting, optimization, and natural language understanding, while also addressing challenges such as hallucinations, data biases, privacy concerns, and system errors [15]. The proposed solutions including improving training data quality, implementing system fine-tuning processes, establishing human oversight mechanisms, and deploying robust security measures provide a valuable framework for GenAI implementations in cloud security contexts. These approaches are particularly relevant for hyperscale environments where scale and complexity amplify both the benefits and risks of GenAI adoption [15].

2.4.5 Agent-Based Approaches

A recent paper from 2024 introduces and validates the concept of employing GenAI-driven agentic workflows to achieve comprehensive security automation, particularly in complex modern environments. A notable example is the Development, Security, and Operations (DevSecOps) Sentinel system[16], specifically designed to address the mounting security challenges inherent in modern software supply chains. Challenges coming from microservices, containerization, and cloud-native architectures that often outpace traditional DevSecOps practices[16].

The DevSecOps Sentinel system exemplifies this approach by utilizing intelligent agents integrated into automated workflows. These agents are powered by advanced GenAI models, such as LLMs enhanced with RAG, enabling sophisticated analysis capabilities[16]. Key characteristics of these agents include:

- **Autonomy:** Operating independently based on predefined goals and policies.
- **Reactivity:** Responding in real-time to environmental changes like new vulnerability disclosures.
- **Proactivity:** Taking initiative, such as preemptively scanning for risks or suggesting improvements[16].

These agents execute critical security tasks throughout the software development lifecycle, including:

- **Automated Vulnerability and Impact Analysis:** Leveraging GenAI to analyze code, dependencies and infrastructure configurations for potential threats, assessing their potential impact in context[16].
- **Adaptive Compliance and Release Gating:** Enforcing security policies and compliance requirements dynamically, acting as automated checks before deployment[16].
- **Predictive Security:** Utilizing AI to identify potential future risks based on historical data and emerging threat patterns[16].

The implementation and testing of DevSecOps Sentinel demonstrate several key points relevant to broader security automation:

1. **Viability for Complexity:** Agentic workflows powered by GenAI are shown to be a viable and effective method for tackling the intricate and rapidly evolving security issues found in modern, distributed systems[16].

2. **Synergy of AI and Agents:** The integration of GenAI's deep analysis capabilities with the autonomous, proactive nature of agentic systems offers a powerful paradigm for strengthening organizational security posture[16]. While Sentinel focuses on the supply chain, the principle applies broadly to automating security operations in complex cloud environments.

3. **Measurable Improvements:** Such systems can contribute to building and deploying software that is simultaneously faster, safer, and more reliable. The DevSecOps Sentinel study reported significant quantitative improvements in key security and operational metrics, including reduced Mean Time to Detect (MTTD) and Mean Time to Resolve (MTTR) for vulnerabilities, lower false positive rates, increased compliance pass rates, higher deployment frequency, and reduced change failure rates[16].

This approach, exemplified by DevSecOps Sentinel, highlights a promising direction for leveraging GenAI to automate and enhance security functions, moving beyond traditional limitations to offer more adaptive, context-aware, and efficient security management in demanding environments like hyperscale clouds.

2.4.6 Security Risks

The increasing integration of GenAI into various domains, including cybersecurity, presents significant opportunities but also introduces complex and multifaceted risks. Insights from recent literature reviews highlight these emerging challenges. A systematic literature review by Nyoto et al. [17], analyzing 17 relevant studies according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [18], identifies several significant cybersecurity threats stemming primarily from the irresponsible application of GenAI technology. Complementing this, Surathunmanun et al. [15], while reviewing GenAI in the energy sector, outline key challenges that possess direct and critical relevance to security implementations, particularly within cloud environments reliant on third-party models and data. Synthesizing these findings provides a comprehensive overview of the risks:

- **Enhanced Malicious Content Generation and Misuse:** GenAI significantly lowers the barrier for creating sophisticated malicious content and tools. It can be abused to generate highly personalized and convincing phishing messages and social engineering tactics, increasing their effectiveness even with minimal target information [17]. Furthermore, GenAI facilitates the creation of effective ransomware and diverse forms of malware, potentially empowering individuals with limited coding expertise to launch attacks [17]. Beyond typical malware, it can also generate other executable attack code, such as Structured Query Language (SQL) injection scripts [17]. This potential for misuse is a major concern, where uncontrolled access or improper application can lead to significant harm [15]. This includes leveraging GenAI to bypass security controls through techniques like prompt injection or jailbreaking, as highlighted in literature concerning LLMs. [15].

- **Information Integrity:** GenAI poses substantial risks to information integrity. It enables the creation of highly realistic deepfake audio and video content, often without clear legal frameworks or consent, leading to potential fraud, manipulation, reputational damage, and the spread of disinformation [17]. Concurrently, GenAI models are prone to generating plausible but factually incorrect or nonsensical information, known as hallucinations [15, 17]. This issue often arises from poor quality training data or suboptimal parameter settings [15] and can be exacerbated by data poisoning during the model training phase [17]. In a security context, hallucinations can manifest as faulty threat analyses, incorrect vulnerability assessments, or misleading security recommendations [15]. Compounding this is the issue of data bias, where biases inherent in training data or introduced during feature selection lead to skewed or unfair outputs [15]. For security applications, this could result in certain threat types being consistently overlooked or specific user groups being unfairly flagged, thereby undermining the reliability of automated systems [15]. These challenges are often exacerbated by the inherent 'black box' nature of many LLMs, characterized by their complexity, lack of transparency in internal decision-making, and limited explainability, making it difficult to fully diagnose or prevent issues like hallucinations or bias [19].

- **Data Privacy, Security Vulnerabilities, and Intellectual Property:** The foundation of GenAI models, vast datasets, introduces significant privacy and security risks. Models are often trained on data scraped without explicit consent, potentially including sensitive personal information or copyrighted material [17]. User interactions and prompts can also be incorporated into training data, leading to potential data leakage and privacy violations [17]. This raises substantial intellectual property concerns and challenges compliance with regulations like General Data Protection Regulation (GDPR) [17]. The lack of transparency and control over how data is utilized presents considerable privacy risks [17]. Furthermore, insecure data handling practices can create security vulnerabilities [15]. Specific risks associated with LLMs, often used in cloud-hosted GenAI services, include inference attacks, data extraction attacks, data poisoning, supply chain vulnerabilities [15] and vulnerabilities to adversarial attacks stemming from the models complex and often opaque nature [19].

- **Systemic and Operational Risks:** Beyond content generation and data issues, GenAI systems can introduce operational risks. Logical inconsistencies within the model or unforeseen external events can cause GenAI systems to produce errors or fail entirely [15]. In automated security workflows operating in cloud environments, such errors could propagate rapidly, leading to service disruptions, critical misconfigurations, or a failure to respond effectively to genuine threats [15].

These diverse risks, spanning malicious misuse, information integrity compromises, privacy violations, intellectual property infringements, and operational failures, underscore the critical need for robust countermeasures and responsible governance. Addressing these challenges necessitates comprehensive approaches, including rigorous data governance frameworks, cross-verification of GenAI outputs, continuous model monitoring and updating, incorporating human-in-the-loop validation processes, implementing strong security measures [15] and architectures like Zero Trust [15, 19], establishing clear ethical guidelines, and potentially developing new regulations specific to GenAI development and deployment [17]. Ensuring the

responsible use of GenAI is paramount to harnessing its benefits while mitigating the significant emerging cybersecurity challenges, particularly in sensitive contexts like cloud security where the consequences of unreliable or misused AI can severely impact organizational risk posture and operational integrity [15].

Another significant challenge in implementing GenAI for security automation is the comprehensive identification and management of the unique risks these systems introduce, which differ significantly from traditional software risks. The NIST Artificial Intelligence Risk Management Framework (AI RMF) 1.0 [4] provides a structured, voluntary approach to address these challenges.

The AI RMF defines an AI system as an "engineered or machine-based system that can, for a given set of objectives, generate outputs such as predictions, recommendations, or decisions influencing real or virtual environments" [4, p.1]. It acknowledges that while AI offers transformative potential, it also poses distinct risks due to factors like data dependency, complexity, opacity, and the socio-technical context of deployment [4].

In the paper, the NIST describes some key points relevant to GenAI Security Risks in Cloud Computing.

1. **Unique AI Risk Landscape:** The framework highlights that AI risks differ from traditional software risks. Appendix B specifically notes challenges pertinent to GenAI and cloud environments, including:

    - Dependency on vast datasets which may harbor biases or quality issues, and are susceptible to poisoning attacks [4].
    - Risks associated with using pre-trained models, which can "increase levels of statistical uncertainty and cause issues with bias management, scientific validity, and reproducibility" [4, p.38]. This is crucial in cloud settings where models might be sourced from third parties.
    - Increased opacity and difficulty in predicting failure modes or emergent behaviors, complicating security validation [4]. This aligns with the widely recognized 'black box' problems of LLMs, encompassing their complexity, lack of transparency, and limited explainability [19]. Specific security concerns not fully addressed by traditional frameworks, such as "evasion, model extraction, membership inference, availability, or other machine learning attacks" [4, p.39], including adversarial vulnerabilities common in LLMs [19].
    - Specific security concerns not fully addressed by traditional frameworks, such as "evasion, model extraction, membership inference, availability, or other machine learning attacks" [4, p.39].
    - Risks associated with "third-party AI technologies, transfer learning, and off-label use," which are highly relevant when using GenAI models hosted or integrated via cloud services [4, p.39].

2. **Trustworthiness Characteristics:** The Risk Management Framework (RMF) emphasizes achieving trustworthy AI by balancing several characteristics [4]. For security, the most critical are:

    - **Secure and Resilient:** AI systems should maintain "confidentiality, integrity, and availability" and be able to "withstand unexpected adverse events or unexpected changes" [4, p.15]. This includes protecting against data poisoning, adversarial examples, and model exfiltration key threats for GenAI. The RMF notes applicability of existing standards like the NIST Cybersecurity Framework here [4, p.15].
    - **Accountable and Transparent:** While distinct from security, transparency and accountability are vital for security incident analysis, understanding

vulnerabilities, and assigning responsibility, especially in complex cloud supply chains [4].

- **Privacy-Enhanced:** GenAI often processes vast amounts of data, potentially including sensitive information. Privacy risks are intertwined with security, as data breaches impact both. The RMF advocates for privacy considerations throughout the lifecycle and mentions Privacy-Enhancing Technologies[4].
- **Valid and Reliable:** Systems must perform accurately and consistently. Unreliable GenAI could produce insecure code, faulty security recommendations, or fail in ways that create security openings [4].

3. **Risk Management Core Functions:** The RMF outlines four functions to operationalize risk management:

   - **Govern:** Establishing a risk management culture, policies, accountability structures, and processes. Crucially, this includes policies addressing risks from "third-party software and data and other supply chain issues", vital for cloud-based GenAI [4, pp.21-24].
   - **Map:** Establishing context, categorizing the AI system, understanding capabilities and limitations, and mapping risks/benefits, explicitly including those from third-party components[4].
   - **Measure:** Applying methods and metrics to assess risks and evaluate trustworthy characteristics, including specific evaluations for security and resilience and privacy[4].
   - **Manage:** Prioritizing and responding to risks, including managing risks from third-party entities and implementing incident response and recovery plans[4].

In essence, the NIST AI RMF 1.0 provides a comprehensive framework that, while voluntary and high-level, guides organizations in systematically considering the multifaceted risks, including significant security and privacy challenges, inherent in developing, deploying, and using complex AI systems like GenAI, particularly within the context of third-party dependencies common in cloud computing environments. It stresses the importance of integrating risk management throughout the AI lifecycle and addressing the unique characteristics and vulnerabilities of AI technologies. Adding to frameworks like the NIST AI RMF, specific architectural approaches are emerging to address the unique security challenges of GenAI in cloud environments. One prominent example is Zero Trust Architecture (ZTA) [19]. ZTA moves away from traditional perimeter-based security towards a model where trust is never assumed, and verification is continuously required[19]. This aligns well with the NIST RMF's emphasis on secure and resilient systems and proactive risk management, particularly given the "black box" nature and dynamic deployment of many GenAI models [4, 19]. Key tenets include strict identity verification, micro-segmentation to limit lateral movement, least privilege access control, and continuous monitoring [19]. Implementing ZTA for LLMs involves specific considerations such as unified identity management across cloud platforms, AI-driven dynamic access policies, automated network segmentation, robust data encryption and classification, continuous threat monitoring tailored to LLM vulnerabilities, and ensuring compliance [19]. Interestingly, AI itself can enhance ZTA through behavioral analytics for continuous authentication or threat intelligence processing[19]. However, implementing ZTA effectively presents its own

challenges, including complexity, integration with legacy systems, resource requirements, and potential performance impacts [19].

2.4.7 Balance of Automation and Human Oversight

The integration of AI, particularly GenAI, into cybersecurity presents a significant paradigm shift, offering powerful automation capabilities to counter increasingly sophisticated cyber threats. A recurring theme in the literature, however, is the inherent tension between the compelling benefits derived from this automation and the indispensable necessity of human oversight [2]. While AI-powered security automation provides crucial safeguards against evolving cyber dangers, the unique characteristics and potential risks associated with AI systems, especially GenAI, underscore the continued importance of human expertise and intervention [2, 3].

A fundamental principle, strongly articulated within risk management frameworks, is that no "high-risk" AI system should be operated without substantial human oversight [4, p.7]. This necessitates careful deliberation regarding whether the potential benefits of deploying such systems truly outweigh the potential negative impacts and risks [4]. In cybersecurity contexts, high-risk applications might include automated incident response systems with the potential for disruptive countermeasures, security policy generation influencing critical infrastructure, or threat analysis tools whose outputs directly inform high-stakes decisions. The NIST AI RMF emphasizes that in situations where AI systems present unacceptable negative risk levels, such as imminent significant negative impacts or the occurrence of severe harms, their development and deployment should cease until these risks can be sufficiently managed [4].

Despite the promising applications of GenAI for security automation such as generating security reports, suggesting code fixes, or creating configuration scripts significant challenges remain in striking the right balance between automation and appropriate human oversight. Research highlights several critical issues stemming from the use of GenAI in automated security operations [3]. One major concern is the potential for over-dependence on AI tools, which could lead to complacency or a degradation of human skills [3]. Furthermore, GenAI models themselves are susceptible to adversarial risks, including data poisoning or prompt injection attacks designed to manipulate their outputs, presenting unique security challenges [3]. The inherent complexity and often opaque nature of decision-making processes within sophisticated AI systems, including GenAI, can also hinder effective oversight and accountability [4] [3].

Effectively managing GenAI in cybersecurity demands a recognition that complete automation without human intervention introduces unacceptable risks [3]. Human oversight is crucial not merely as a final checkpoint but throughout the AI lifecycle. This includes defining system goals and constraints, interpreting ambiguous or novel situations that fall outside the AI's training data, providing contextual understanding that the AI may lack, and making ethical judgments, particularly when potential actions have significant consequences [4]. The NIST AI RMF emphasizes the importance of clearly defined human roles and responsibilities within human-AI configurations, acknowledging the influence of human cognitive biases and the need for systems that are explainable and interpretable to those operating or overseeing them [4].

Frameworks like the NIST AI RMF provide structured approaches to managing these challenges. The `GOVERN` function stresses establishing a risk management culture, defining roles, and ensuring accountability [4, p. 21-24]. The `MAP` function

requires establishing context, understanding system limitations, and defining processes for human oversight [4, p. 24-28]. `MEASURE` involves ongoing monitoring of performance, safety, and fairness, incorporating feedback mechanisms [4, p. 28-31]. Crucially, the `MANAGE` function includes planning risk responses and implementing mechanisms to supersede, disengage, or deactivate AI systems demonstrating performance inconsistent with intended use, alongside robust post-deployment monitoring and incident response plans [4, p. 31-33].

Ultimately, the effective use of GenAI in cybersecurity hinges on achieving a balanced, symbiotic relationship between automated capabilities and human expertise. This balanced approach acknowledges the complementary strengths of humans and AI. GenAI can process vast amounts of data and automate repetitive tasks at scale and speed, while humans provide critical thinking, contextual awareness, ethical guidance, and ultimate accountability [3]. Preventive efforts and well-planned action plans, incorporating robust human oversight mechanisms, are essential to harness the benefits of GenAI for cybersecurity while mitigating its inherent risks [3].

2.4.8 Summary Literature State of the Art

This literature review demonstrates that GenAI represents a transformative technology for security automation within hyperscale cloud environments. The analysis reveals significant potential for GenAI to enhance security operations through automated threat detection, policy generation, and incident response, particularly across complex multi-cloud settings. Research highlights notable advancements in conceptual frameworks for multi-cloud policy orchestration, validation mechanisms to ensure trust and accuracy, and technical approaches for implementing GenAI at scale. The most promising strategies often leverage multi-cloud architectures, zero-trust principles, and comprehensive security frameworks, while necessarily acknowledging the unique infrastructure requirements of GenAI itself. However, despite this progress, persistent challenges related to trust, validation, data privacy and quality, and the crucial balance between automation and human oversight remain significant considerations. As this field continues its rapid evolution, interdisciplinary collaboration will be essential to develop robust ethical norms and innovative defense mechanisms, addressing current issues while guiding the responsible application of GenAI in cybersecurity.

2.5 Research Gaps

Chapter 3

Methodology

3.1 Main Section 1

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3.1.1 Subsection 1

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3.1.2 Subsection 2

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3.2 Main Section 2

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Chapter 4

Conceptual Framework for GenAI-Driven Security Automation

4.1 Architectural Overview of the Proposed Framework

This chapter introduces the conceptual framework designed to address the critical challenges of automated security analysis and policy generation for cloud infrastructure. The proposed architecture presents a comprehensive, multi-layered approach that systematically processes Infrastructure-as-Code (IaC) artifacts and automatically generates corresponding security policies. At its core, the framework leverages the power of traditional static analysis tools and advanced LLMs to create a robust security automation pipeline.

This hybrid model is intentionally designed for efficacy, combining the reliability of established security scanners for identifying known vulnerability patterns with the contextual intelligence of generative AI [1]. This allows for deeper analytical capabilities, necessary for uncovering complex, context-dependent security issues that traditional tools often miss [20]. Furthermore, the architecture is conceived for seamless integration into modern Development and Operations (DevOps) workflows, particularly Continuous Integration/Continuous Deployment (CI/CD) pipelines, to operationalize a Policy-as-Code (PaC) model and enforce security throughout the development lifecycle [1].

As illustrated in Figure 4.1, the conceptual framework is visualized to provide an overview of its architectural layers and data flow.

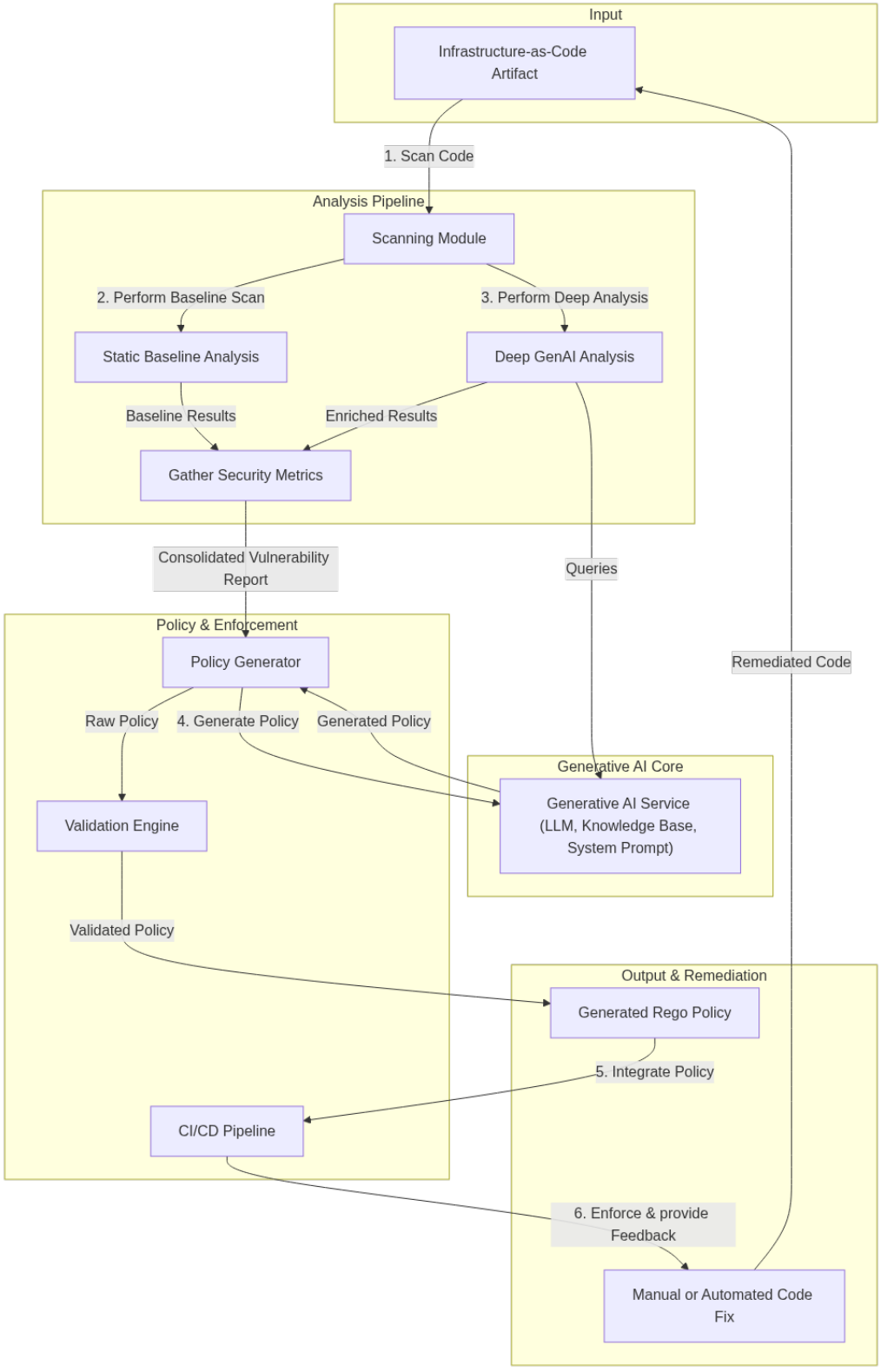

FIGURE 4.1: Architectural Overview of the Proposed GenAI-Driven Security Automation Framework

The framework is organized into a logical pipeline comprising four distinct layers: the Data Ingestion Layer, the Data Processing Layer, the Code Generation Layer, and the Validation Layer. Each layer performs a specific function, building upon the output of the preceding one to create an end-to-end workflow. This process

begins with the intake of infrastructure configuration definitions, proceeds through multi-stage static and AI-driven analysis, generates preventative security policies in a declarative, machine-readable format, and concludes with the strict validation of these AI-generated artifacts. This layered design aims to provide a comprehensive and efficient system for enhancing cloud security posture by translating identified vulnerabilities directly into enforceable controls [21]. The following subsections will detail the specific roles and functions of each of these core layers.

4.1.1 Data Ingestion Layer

The Data Ingestion Layer serves as the foundational entry point for security artifacts into the automation framework. Its primary function is to ingest IaC configurations, a prevalent standard for provisioning and managing cloud infrastructure. The reliance on IaC, while enhancing automation and consistency, introduces significant risks such as misconfigurations, coding errors, and embedded secrets, making automated analysis a critical requirement for secure cloud operations.

This layer is designed to support both batch and real-time ingestion modes, a flexible approach that aligns with modern data pipeline architectures emphasizing scalability and performance[22]. Batch ingestion allows for comprehensive, scheduled scans of entire code repositories, while real-time ingestion facilitates immediate analysis within CI/CD pipelines [23]. The framework is designed to receive these IaC configurations via programmatic interfaces, ensuring seamless integration into existing developer workflows and automated systems.

Upon ingestion, the layer initiates a multi-stage preliminary analysis process. First, the raw IaC configuration is parsed for programmatic analysis. Following this step, a suite of established static analysis security testing (SAST) tools is executed. This initial scan generates a baseline vulnerability report by checking the configurations against a comprehensive database of known misconfigurations, security vulnerabilities, and compliance violations. The structured output from this layer includes the original IaC configuration, its parsed form, and the baseline vulnerability report. These results are then passed to the Data Processing Layer. There, deeper, context-aware analysis is performed using GenAI. The following section details the processes of the Data Processing Layer.

4.2 Data Processing Layer

Following the Data Ingestion Layer, the Data Processing Layer is responsible for the core analysis of the ingested IaC artifacts. A central design principle of this framework is the segregation of processing activities into two distinct but complementary sub-layers: a traditional Static Analysis Engine and an advanced GenAI Analysis Engine.

The rationale for this dual-layer architecture is to create a highly efficient and comprehensive security analysis pipeline. This approach leverages the respective strengths of each technology. Static analysis provides a rapid, reliable, and computationally inexpensive method for identifying a wide range of known, pattern-based vulnerabilities. By filtering out these common issues first, the framework can then employ the more resource-intensive GenAI engine to focus on complex, context-dependent security flaws that traditional tools are ill-equipped to detect [24]. This layered methodology optimizes analytical depth while maintaining operational efficiency, ensuring that both well-defined and nuanced vulnerabilities are addressed [1].

The first stage of this layer employs a suite of established SAST tools to conduct an initial scan of the IaC configuration. This engine examines the configuration for syntactic and structural flaws by referencing curated databases of known vulnerabilities, common misconfigurations, and code smells. It validates the configuration against established security benchmarks and standards. The primary output of this stage is a baseline vulnerability report, which provides a structured list of potential issues identified through deterministic, rule-based pattern matching. This report serves as a foundational input for the subsequent, more sophisticated analysis stage.

The second stage is the GenAI Analysis Engine, which represents the core innovation of this framework and directly addresses the research interest in applying generative AI to cloud security. This engine utilizes LLMs to perform a deeper, contextual analysis that transcends the limitations of traditional static scanners [25]. It takes as input both the original IaC configuration and the baseline vulnerability report from the previous stage, using the initial findings to enrich its analytical context [26].

This engine is designed to identify security weaknesses that require an understanding of developer intent, architectural relationships, and complex business logic [27]. Its capabilities include:

- **Identifying Context-Sensitive Flaws:** Detecting risks that emerge from the interaction of multiple configurations. For example, overly permissive network rules may appear acceptable in isolation but create a vulnerability when combined with a specific resource's placement within the network architecture[24].
- **Uncovering Logical and Policy Violations:** Identifying logical flaws in resource deployments, such as potential circular dependencies. The engine can also detect violations of complex, unwritten organizational policies like nuanced tagging and naming conventions [1].
- **Reducing False Positives:** Differentiating between genuine security risks and findings from the static analysis that are benign within a specific operational context. For example, a "hardcoded secret" may simply be a placeholder for a non-production environment.

By synthesizing information from the configuration and the initial scan, the GenAI Analysis Engine bridges the gap between traditional, rule-based detection and adaptive, context-aware threat identification, producing a consolidated and enriched vulnerability report.

4.3 Code Generation Layer

The Code Generation Layer operationalizes the insights derived from the Data Processing Layer, acting as the primary action-oriented component of the framework. Its purpose is to automate the creation of security artifacts, in the context of this prototype, preventative policies using GenAI. This layer directly addresses a core aspect of this research: leveraging LLMs to not only analyze but also actively generate security policies. The integration of GenAI into the security architecture in this manner marks a significant shift, promising to streamline development workflows and accelerate remediation cycles.

This layer leverages LLMs to generate security policies tailored to the vulnerabilities identified in the preceding analysis stages. The generated artifacts are formal policies written in a declarative, machine-readable language, designed for automated

enforcement. The LLM is guided by system prompts and a curated knowledge base of security standards to produce precise, context-aware rules. This process of generating platform-specific policies from a higher-level analysis aligns with established methods in automated systems engineering, where abstract requirements are translated into concrete, executable artifacts for a target platform[21].

A critical aspect of this layer is its multi-stage validation process, designed to mitigate risks associated with AI-generated artifacts, such as factual inaccuracies (hallucinations) or the introduction of new security flaws. Raw, unvalidated output is never trusted for deployment. The workflow, as specified in the prototype design, includes several checkpoints:

- **Automated Validation:** Generated policies undergo initial automated checks for syntactic correctness. Following this, the policies are subjected to the same suite of static analysis tools used in the Data Ingestion Layer to ensure no new vulnerabilities have been introduced.
- **Human-in-the-Loop Review:** The framework mandates a human-in-the-loop review process, which is indispensable for high-impact changes or when the AI model's confidence in its output is low. This approach maintains a crucial balance between automation and human oversight, a central theme identified in the literature [28].
- **Advanced Testing:** For more accuracy, the architecture can incorporate further testing to detect subtle inconsistencies or unintended behaviors in the generated policies.

From a governance standpoint, the layer integrates robust security controls. Access controls and authentication mechanisms restrict the policy generation function to authorized entities and automated processes. Comprehensive audit logs are maintained for all generated and validated artifacts, ensuring traceability for compliance and forensic analysis, a key element in modern data architectures[29]. Ultimately, this layer ensures that only validated, secure, and compliant policies are promoted to subsequent deployment or enforcement stages within a CI/CD pipeline.

4.4 Validation Layer

The Validation Layer is a critical automated quality assurance component that directly follows the Code Generation Layer. Its primary purpose is to rigorously verify the integrity, correctness, and security of the AI-generated security policies before they are committed to a repository or presented for human review. This layer functions as an essential trust and safety mechanism, mitigating the risks associated with AI-generated policies, such as syntactic errors, logical flaws, or the introduction of new security loopholes. It ensures that only high-quality, effective, and secure policies proceed to the final enforcement and review stages within the CI/CD pipeline.

The validation process is executed through a sequence of automated checks, each designed to test a different aspect of the generated policy's quality:

- **Syntactic Validation:** This is the initial and most fundamental check. The layer uses standard parsers and validators to confirm that the generated policy is syntactically correct and adheres to the relevant language specifications. Any policy that fails this check is immediately rejected and logged, preventing malformed policies from entering the system.

- **Security Self-Scan:** To prevent the AI from inadvertently introducing new vulnerabilities, the generated security policy itself is subjected to a security scan. This process uses static analysis tools to check the policy for insecure patterns or anti-patterns that could be exploited. This "self-scan" ensures the remediation policy does not create new security problems while attempting to solve another.

Only after a generated policy successfully passes all stages of this automated validation gauntlet is it considered "validated". The validated policy, along with its comprehensive audit report, is then passed to the CI/CD pipeline, where it can be reviewed and approved by a human expert before being enforced as part of the organization's PaC repository. This structured validation process builds a high degree of trust in the automated system and ensures that human oversight is applied to well-vetted, high-quality security artifacts.

4.5 Integration of GenAI-Driven Security Automation

The core of the proposed security automation framework is centered around the integration of GenAI, specifically through the use of LLMs accessed as a managed cloud service. This approach was deliberately chosen over deploying and managing local, open-source models for several strategic reasons. Utilizing a hyperscale cloud provider's managed AI service offers access to powerful, state-of-the-art models without the substantial computational and financial overhead associated with self-hosting. It abstracts away the complexities of MLOps, such as infrastructure provisioning, scaling, and maintenance, allowing the focus to remain on the application logic. Furthermore, this model aligns with the Shared Responsibility Model discussed in the literature review, where the cloud provider manages the security and availability of the underlying AI service.

To ensure the generation of accurate, contextually relevant, and reliable security policies, the framework employs a RAG architecture. This pattern is crucial for grounding the LLM's output in factual data, thereby mitigating the risk of model "hallucinations"—a significant concern in GenAI systems where plausible but incorrect information may be generated [30]. The RAG process within this framework functions as follows:

1. Upon receiving a vulnerability finding from the Data Processing Layer, the system queries a dedicated Knowledge Base. This knowledge base is a curated repository containing relevant security standards, vulnerability information, best practices for the given IaC technology, and documentation for the target policy language [31].

2. The retrieved documents, which provide specific context for the detected vulnerability, are then combined with a custom System Prompt. This prompt instructs the LLM on its role, the task to be performed (e.g., "You are a security expert. Generate a precise security policy to prevent the following vulnerability"), and the required output format.

3. This enriched context, consisting of the vulnerability data, retrieved knowledge, and the system prompt, is then sent to the selected LLM via the managed service's API to generate the security policy.

This RAG-based approach ensures that the generated policies are not only syntactically correct but are also directly informed by authoritative and up-to-date security guidance, making the system more robust and trustworthy [30]. By externalizing the knowledge base, the framework can be easily updated to reflect new standards or threat intelligence without needing to retrain or fine-tune the underlying LLM [31]. A high-performance foundation model is utilized for its advanced reasoning and code generation capabilities.

4.6 Leveraging LLMs for Deeper Contextual Analysis

The deployment of LLMs within the security automation framework fundamentally transforms the depth and quality of IaC analysis. These models introduce a level of contextual understanding previously unattainable with traditional static analysis tools. Unlike rule-based scanners, which are limited to identifying known vulnerability patterns and syntactic misconfigurations, LLMs can synthesize information across multiple resources, configuration layers, and organizational policies. This enables them to surface nuanced, context-sensitive security issues.

By integrating LLMs with outputs from static code analyzers and a curated knowledge base, the framework is capable of identifying misconfigurations and policy violations that arise from complex interactions within the cloud environment [32]. This deeper insight is made possible by the LLM's ability to reason about architectural relationships, resource dependencies, and the intent behind configurations, allowing it to detect security weaknesses that would otherwise remain hidden.

A key advantage of this approach is the identification of context-sensitive security weaknesses. The LLM is able to analyze configurations in light of their broader environment and operational context, flagging settings that may be technically valid in isolation but become risky when considered alongside other resources or data sensitivity. For example, an overly permissive network rule might not trigger an alert in a development environment, but if linked to production data or exposed to the public internet, it becomes a significant risk—a nuance the LLM can discern by analyzing tags, naming conventions, and architectural metadata.

Beyond identifying outright vulnerabilities, the LLM can uncover suboptimal or inefficient configurations that deviate from best practices for performance, cost-efficiency, or resilience, tailored to the specific needs of the application. It can also interpret and enforce complex internal policies that are difficult to codify with static rules, such as intricate naming conventions, tagging strategies for governance, or architectural patterns mandated by the organization [33]. This capability extends to spotting logical flaws in resource deployment and interconnections, such as circular dependencies, misconfigured network routing, or resource configurations that do not align with their intended purpose.

The LLM's contextual reasoning also enables it to detect deviations from evolving best practices and industry standards by leveraging its knowledge base of security benchmarks and official documentation. This ensures that the framework remains adaptive to new vulnerability patterns and compliance requirements as they emerge. Furthermore, the LLM can analyze how combinations of individually acceptable configurations or permissions might aggregate into an elevated risk profile, identifying attack paths that arise only when multiple minor issues are considered together.

A practical example illustrates this capability: consider a storage resource that appears secure in isolation, with a restrictive access policy allowing permissions only to a specific role. The associated role is properly scoped, and the storage policy

adheres to the principle of least privilege. However, a compute instance in a development environment, which has this role attached, is exposed to the internet via an open management port and is running a vulnerable operating system. While static analyzers might flag the open port and operating system vulnerability separately, and pass the storage resource and role as secure, the LLM can connect these findings. It recognizes that the instance's exposure and vulnerability, combined with its privileged role, create a critical attack path to sensitive data in the storage resource. This context-sensitive weakness would likely be missed or deprioritized by traditional tools, but the LLM's holistic analysis surfaces it as a high-priority risk.

In summary, leveraging LLMs for deeper contextual analysis enables the framework to move beyond pattern-based detection, offering a comprehensive understanding of security posture that accounts for the dynamic and interconnected nature of modern cloud environments. This results in the proactive identification of genuine risks, reduction of false positives, and the continuous alignment of security controls with evolving organizational and industry standards [34].

4.7 Metrics for Security Posture Assessment

In order to meaningfully assess the impact and effectiveness of the GenAI-driven framework described in this chapter, it is crucial to establish a set of quantitative measures that reflect both security improvements and operational performance. Rather than simply listing metrics, this section discusses how these indicators are woven into the framework's validation process, providing concrete evidence of risk reduction, coverage, and the reliability of AI-generated outputs. The metrics below are selected to capture the most relevant aspects of security posture and system efficiency as they pertain to the framework's real-world application:

Vulnerability and Coverage Metrics

These metrics quantify the raw state of security and the comprehensiveness of the analysis.

Vulnerability Count and Severity Distribution This fundamental metric provides a baseline by quantifying the total number of vulnerabilities detected and categorizing them by severity. The change in these counts is a direct measure of risk reduction.

- **Calculation:** Let V_c, V_h, V_m, V_l be the counts of critical, high, medium, and low severity vulnerabilities. The assessment tracks the change (ΔV) in these values pre- and post-policy application.
- **Example:** An initial scan of IaC configurations for a new application deployment reveals $V_{\text{total, pre}} = 15$ vulnerabilities, distributed as $V_c = 2$, $V_h = 5$, $V_m = 8$. After the framework generates and applies security policies, a re-scan shows a new distribution: $V_{\text{total, post}} = 3$, with $V_c = 0$, $V_h = 0$, $V_m = 3$. This represents a risk reduction of 100% for critical and high-severity vulnerabilities and an 80% reduction in total vulnerabilities.

Scan and Policy Coverage This metric assesses the breadth and completeness of the framework's analysis and generation capabilities.

- **Calculation:**

  - Scan Coverage (C_{scan}) is the percentage of IaC resources analyzed relative to the total number of resources defined:

$$C_{\text{scan}} = \left(\frac{R_{\text{analyzed}}}{R_{\text{total}}} \right) \times 100\%$$

  - Policy Coverage (C_{policy}) is the percentage of unique vulnerabilities for which a valid policy was successfully generated:

$$C_{\text{policy}} = \left(\frac{V_{\text{policy\_generated}}}{V_{\text{unique}}} \right) \times 100\%$$

- **Example:** A project contains 120 infrastructure resources (R_{total}). The Data Ingestion Layer successfully parses and analyzes 117 of them, yielding a C_{scan} of 97.5%. The analysis identifies 10 unique vulnerability types (V_{unique}). The Code Generation Layer successfully produces valid security policies for 9 of them, resulting in a C_{policy} of 90%. The one failure may indicate a novel vulnerability requiring refinement of the knowledge base or system prompt.

Efficiency and Speed Metrics

This metric evaluates the framework's contribution to operational agility and responsiveness.

Policy Generation Speed This measures the time required for the Code Generation Layer to produce a syntactically valid policy from a confirmed vulnerability input.

- **Calculation:** The average time $T_{\text{gen}} = \frac{1}{N} \sum_{i=1}^{N} (t_{\text{end},i} - t_{\text{start},i})$, where t_{start} is when the vulnerability is sent to the layer and t_{end} is when the validated policy is output.
- **Example:** In a test run with 50 distinct misconfigurations, the total time for the LLM to generate and validate the syntax of all 50 security policies is 300 seconds. The average T_{gen} is six seconds per policy, demonstrating the system's high-speed performance.

Quality and Accuracy Metrics

These metrics assess the reliability and correctness of the framework's AI-driven outputs.

Policy Accuracy and Effectiveness This composite metric evaluates the quality of the generated policies.

- **Calculation:**
  - Accuracy (A_{policy}) is the percentage of generated policies that are syntactically correct:

$$A_{\text{policy}} = \left(\frac{P_{\text{valid}}}{P_{\text{generated}}} \right) \times 100\%$$

  - Effectiveness (E_{policy}) is the percentage of valid policies that correctly prevent the misconfiguration during testing:

$$E_{\text{policy}} = \left(\frac{P_{\text{effective}}}{P_{\text{valid}}} \right) \times 100\%$$

- **Example:** The system generates 100 policies ($P_{\text{generated}}$). The automated validator confirms 98 are syntactically correct ($A_{\text{policy}} = 98\%$). These 98 policies are then tested in a staging environment. 95 of them successfully block non-compliant configurations while allowing compliant ones, yielding an effectiveness (E_{policy}) of approximately 96.9%.

False Positive Reduction Rate This measures the GenAI Analysis Engine's ability to reduce alert fatigue by filtering out non-issues identified by initial static scans.

- **Calculation:**

$$FP_{\text{reduction}} = \left(\frac{FP_{\text{sast}} - FP_{\text{genai}}}{FP_{\text{sast}}} \right) \times 100\%$$

  A ground truth must be established by human experts.

- **Example:** A baseline SAST scan reports 50 findings. Expert review determines that 15 of these are false positives ($FP_{\text{sast}} = 15$) for the given application context (e.g., a "public" resource in a firewalled development environment). The GenAI engine, using its contextual understanding, processes the 50 findings and correctly dismisses 12 of the 15 false positives, flagging only three ($FP_{\text{genai}} = 3$). This yields a False Positive Reduction Rate of $\left(\frac{15-3}{15}\right) = 80\%$, significantly improving the signal-to-noise ratio for the security team.

4.8 Human-in-the-Loop for Review and Approval

While the framework is designed to maximize automation, the integration of a Human-in-the-Loop (HITL) process for review and approval is a foundational principle, reflecting a core theme identified in the literature review regarding the balance between automation and human oversight [35]. The complete automation of security policy generation and enforcement without human intervention introduces unacceptable risks, particularly in complex cloud environments. This subsection outlines the conceptual design of the HITL workflow, which serves as a critical control point to ensure the safety, accuracy, and contextual appropriateness of the AI-generated security artifacts.

The necessity for human oversight is a principle strongly articulated within established risk management frameworks, which posit that high-risk AI systems should be operated with a meaningful human role [35]. In this framework, the HITL process is not merely a final checkpoint but an integrated function designed to mitigate the inherent risks of GenAI, such as the generation of incorrect policies (hallucinations), the introduction of new security flaws, or the creation of overly restrictive rules that could impede business operations [35]. It operationalizes established governance principles by providing a mechanism to validate, override, or reject the AI's output before it can impact the production environment [36].

The HITL review and approval workflow is triggered under specific, risk-informed conditions. A manual review by a qualified security engineer is mandatory for any AI-generated policies that address high-severity or critical vulnerabilities. A review can

also be triggered when the AI model indicates a low confidence score for its generated output or when the proposed change targets a particularly sensitive component of the cloud infrastructure [35]. This risk-based approach ensures that human expertise is focused where it is most needed, optimizing for both security and operational efficiency [36].

During the review process, the human expert is presented with a comprehensive set of information to facilitate an informed decision. This includes:

1. the original vulnerability report
2. the raw IaC snippet containing the vulnerability
3. the AI-generated security policy for remediation
4. the results of automated validation checks
5. an AI-generated explanation of the policy's logic and how it addresses the issue

This curated context allows the reviewer to assess the generated artifact's accuracy, effectiveness, and potential side effects. The reviewer can then approve the policy, allowing it to proceed to the CI/CD pipeline for enforcement, or reject it [36]. Rejected policies are flagged and can be used as part of a feedback loop to refine the system prompts and knowledge base used by the Code Generation Layer, contributing to the system's continuous improvement. Ultimately, this symbiotic relationship between the automated capabilities of GenAI and the contextual wisdom of human experts ensures that the framework operates not only with speed and scale but also with the necessary accountability and safety [36].

4.9 Integration with CI/CD Pipelines for Policy-as-Code

The ultimate objective of the conceptual framework is to translate its analytical outputs and AI-generated artifacts into tangible, preventative controls that are seamlessly embedded within an organization's development lifecycle. This is achieved by integrating the framework into a CI/CD pipeline, operationalizing a PaC workflow [37]. This approach embodies the "shift left" security principle, where security checks and policy enforcement are automated and moved to the earliest stages of the development process, rather than being an afterthought.

The integration follows a defined workflow, typically initiated within a version control system through a pull request. When a developer proposes changes to the cloud infrastructure by modifying IaC configurations, a CI/CD pipeline is automatically triggered. This pipeline orchestrates the core functions of the framework in a sequence designed to enforce security before insecure configurations are merged:

1. **Automated Scanning and Analysis:** The pipeline first invokes the Data Ingestion and Data Processing layers to scan the proposed infrastructure changes. It generates a comprehensive vulnerability report, leveraging both static analysis and the deeper contextual analysis from the GenAI engine.
2. **Policy Generation and Committing:** If new, unaddressed vulnerabilities are detected, the Code Generation Layer is triggered to produce the corresponding security policies. Following the HITL review and approval process for these policies, the validated policy files are treated as code artifacts themselves. They are committed to a dedicated policy repository, ensuring they are version-controlled, auditable, and consistently applied [37].

3. **Policy Enforcement as a Quality Gate:** The critical enforcement step is implemented using an automated policy engine as a quality gate within the CI/CD pipeline [38]. The pipeline uses this engine to evaluate the proposed infrastructure plan against the entire set of approved security policies. If the proposed changes violate any policies, particularly those addressing high-severity vulnerabilities, the policy evaluation fails. This failure causes the CI/CD pipeline to halt and blocks the pull request from being merged. This mechanism acts as a powerful preventative control, ensuring that configurations failing to meet security standards cannot be deployed [37] [38].

4. **Metrics and Feedback Loop:** The CI/CD pipeline serves as the practical execution point for capturing the metrics defined in the security posture assessment. By comparing the security scan results against the baseline, the system can quantify the effectiveness of the generated policies and the overall improvement in security posture. This data provides immediate feedback to developers on the impact of their changes and allows security teams to analyze any discrepancies, which in turn informs the refinement of scanning heuristics and the system prompts used by the GenAI models.

By integrating into the CI/CD pipeline, the framework moves beyond being a mere detection tool and becomes an active participant in the development workflow. It creates a closed-loop system where vulnerabilities are automatically detected, preventative policies are generated and validated, and enforcement is programmatically guaranteed, thereby operationalizing a truly automated and responsive cloud security posture [38]

Chapter 5

Implementation & System Architecture

This chapter details the design and implementation of the prototype system, a practical realization of the conceptual framework for GenAI-driven security automation introduced in Chapter 4. The work is implemented through two distinct but interconnected codebases: a cloud-native infrastructure for the GenAI backend, and a Python-based application that orchestrates the analysis and Policy Generation (PG) workflow.

The primary goal of this implementation is to empirically validate the central hypothesis of the theoretical framework: that a hybrid approach, combining traditional static analysis with advanced LLM capabilities, can significantly enhance the automation of security PG for IaC. This chapter will demonstrate how the system architecture directly maps to the four-layered conceptual model Data Ingestion, Data Processing, Code Generation, and Validation. It will further illustrate how this architecture realizes the core principles of leveraging RAG for contextual accuracy and integrating a HITL for safety and oversight.

We will first present the high-level architecture and the technology stack chosen to satisfy the functional requirements of a robust, scalable, and reproducible security pipeline. Subsequently, the chapter will provide a detailed examination of both the cloud infrastructure, deployed via Terraform infrastructure as code (Terraform), and the Python prototype, focusing on the specific modules that implement the core logic of the system. The chapter will conclude by illustrating the end-to-end workflow, from the initial analysis of a Terraform file to the generation and validation of a corresponding Rego security policy, thereby providing a comprehensive account of the system's practical application.

5.1 Design Objectives & Functional Requirements

The practical implementation of the prototype is guided by a set of specific design objectives and functional requirements. These objectives are derived directly from the core research questions and serve to translate the high-level scientific inquiry into concrete, measurable goals for the system. The following objectives define the core functionality of the prototype:

- **Automated, High-Fidelity Policy Generation:** The system's primary function is to automatically generate syntactically correct and logically sound security policies in the Rego language from vulnerabilities found in Terraform files. This objective directly addresses the central research question on the effectiveness of GenAI for security automation **(RQ1)**. A key requirement is to achieve high

fidelity, with a target of $\geq$ 95% of generated policies being effective in mitigating the identified vulnerability, providing a core metric for validation **(RQ3)**. text

- **Hybrid and Reproducible Analysis Architecture:** The system is built on a hybrid analysis model that is both reproducible and architecturally sound. Reproducibility is achieved by defining the entire cloud-native backend as code using Terraform. The analysis engine is hybrid, combining traditional SAST for baseline coverage with GenAI-driven contextual analysis for deeper insights. These architectural choices are fundamental to investigating how to build a trustworthy and effective GenAI-driven system **(RQ2)**.
- **Automated Validation:** To ensure the reliability of the AI-generated artifacts, the system implements a multi-stage, automated validation pipeline. This process checks generated policies for syntactic correctness and performs a security self-scan to ensure they do not introduce new vulnerabilities. This automated validation is a critical mechanism for measuring and ensuring the trustworthiness of the output **(RQ3)**.
- **HITL and CI/CD Integration:** The prototype is designed for seamless integration into a standard CI/CD pipeline, where it can act as an automated quality gate. This integration must also support a HITL workflow, enabling human review and approval of generated policies. This dual requirement is designed to explore the optimal balance between full automation and necessary human oversight in a practical DevSecOps environment **(RQ4, RQ1)**.

This structured set of objectives ensures that the implementation of the prototype directly and comprehensively contributes to answering the core research questions of this thesis.

5.2 Technology & Tooling Stack

The selection of the technology and tooling stack for this project was a deliberate process, guided by the design objectives of creating a reproducible, scalable, and industry-relevant prototype. The choices reflect a modern, cloud-native approach, emphasizing managed services and open standards to validate the conceptual framework effectively. This section briefly justifies the key technologies that constitute the system's foundation. The chosen stack is summarized in Table 5.1.

Component	Technology	Justification
Cloud Platform	AWS	As the leading hyperscale cloud provider, AWS offers a mature and extensive ecosystem of services, robust APIs, and comprehensive documentation. Its managed AI service, AWS Bedrock, is central to the project's architecture.
GenAI Service	AWS Bedrock [39]	Provides API access to a variety of high-performance foundation models without the operational overhead of self-hosting. This aligns with the objective of a fully-managed GenAI pipeline and allows the research to focus on application logic rather than MLOps. The Anthropic Claude model was selected for its advanced reasoning capabilities and large context window.
IaC	HashiCorp Terraform [40]	As the de-facto industry standard for IaC, Terraform's declarative syntax and cloud-agnostic nature ensure the approach is both reproducible and broadly applicable. It is the input format for the security analysis pipeline.
PaC	Open Policy Agent (OPA) (Rego) [41]	The OPA is a CNCF-graduated project and a general-purpose policy engine. Its declarative language, Rego, is purpose-built for expressing policies over complex JavaScript Object Notation (JSON)/YAML data, making it an ideal target for generating preventative controls for IaC.
orchestration	Python 3.12 [42]	Python's extensive ecosystem, including the Boto3 library for AWS, and its strength in scripting and automation makes it the ideal choice for orchestrating the multi-stage workflow, which involves invoking external scanners, calling cloud APIs, and managing file I/O.
CI/CD	GitHub platform (GitHub) [43]	Provides a tightly integrated platform for version control and workflow automation. It enables the seamless implementation of a CI/CD pipeline to trigger scans, orchestrate the policy generation and validation, and manage the HITL approval process.

TABLE 5.1: Technology and Tooling Stack

5.3 High-Level Architecture

This section presents the high-level architecture of the GenAI-driven security automation framework. The design translates the conceptual model from Chapter 4 into a concrete system that orchestrates static analysis tools, GenAI, and validation workflows. The architecture is best understood as a sequential data pipeline, illustrated in Figure 5.1, which depicts the primary components and their interactions.

The diagram illustrates the four-layered architecture that forms the backbone of the security automation system. At the foundation, the Data Ingestion Layer receives Terraform configurations from CI/CD triggers and prepares them for analysis. The Data Processing Layer forms the analytical core, where traditional static analysis tools (Checkov) perform initial vulnerability detection, followed by the GenAI Analysis Engine (AWS Bedrock) conducting deeper contextual analysis to reduce false positives and identify complex misconfigurations. The Code Generation Layer leverages the RAG-enabled knowledge base to construct context-aware prompts for the LLM, ultimately generating targeted Rego policies via the AWS Bedrock API. Finally, the Validation Layer serves as a quality gate, employing OPA syntax validation and security self-scanning before presenting policies to the HITL for final approval. The diagram emphasizes the sequential flow of data transformation from raw Terraform code through vulnerability analysis to validated security policies while highlighting the integration points with cloud services and the critical role of automated validation in ensuring output reliability.

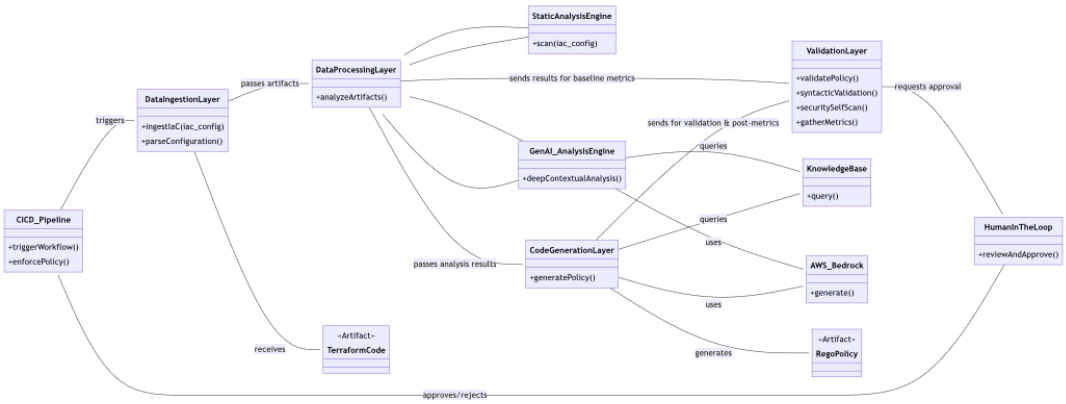

FIGURE 5.1: High-Level Component Diagram

The system's responsibilities are segregated into four logical tiers, directly corresponding to the layers of the conceptual framework. The process begins at the Data Ingestion Layer, which serves as the entry point, receiving Terraform configurations from a CI/CD trigger, parsing the IaC files, and preparing them for analysis. From there, the artifacts are passed to the Data Processing Layer, the core analysis engine. This layer first subjects the IaC to a baseline scan using a traditional SAST tool (Checkov) to identify known vulnerability patterns. The resulting report, along with the original IaC, is then fed into the GenAI Analysis Engine (AWS Bedrock) for a deep, contextual analysis to identify complex misconfigurations and reduce false positives. Subsequently, the Code Generation Layer takes the enriched vulnerability report as input, queries the RAG-enabled knowledge base for relevant security best

practices, and prompts the LLM via the AWS Bedrock API to generate a corresponding Rego policy. Finally, the Validation Layer acts as a quality gate. Here, the newly generated Rego policy is subjected to automated checks, including syntax validation with the OPA parser and a security self-scan, before being presented to the HITL for final approval.

This layered architecture ensures a clear separation of concerns and provides a robust, end-to-end workflow for translating identified risks in IaC into validated, enforceable security policies.

5.4 Cloud-Infrastructure Codebase (IaC)

The cloud infrastructure that underpins the GenAI backend is defined entirely as code, following modern IaC principles to ensure reproducibility, security, and maintainability [44]. The design is centered on a modular architecture, automated lifecycle management, and robust security controls.

The codebase is structured using a modular Terraform approach, where the system is decomposed into discrete, reusable modules. Each module encapsulates a core architectural component: a dedicated module for the vector database, another for the Simple Storage Service (S3) bucket that forms the RAG knowledge base, and a third for the AWS Bedrock service itself. This modularity, a cornerstone of scalable IaC, simplifies management and allows for independent testing and versioning of each component [45].

A key aspect of the architecture is the management of the GenAI's knowledge and instructions. The System Prompt (SP), which provides the LLM with its core instructions and persona, is externalized into a dedicated system_prompt.txt file. This separation of concerns is critical, as it allows for the prompt to be version-controlled and iterated upon independently from the infrastructure code. This practice of "prompt engineering" is central to refining the AI's output without altering the system's architecture. The RAG Knowledge Base (KB) itself is implemented using an S3 bucket, which stores a curated collection of documents. This corpus includes security best practice guides, vulnerability documentation, and technical manuals for the target technologies (e.g., Terraform and Rego). This design choice is strategic: it allows the KB to be easily updated with new threat intelligence or standards, thereby keeping the AI's responses grounded in current, factual information without the need for costly model fine-tuning [46].

Security is integrated throughout the IaC design, following the principle of least privilege. Identity and Access Management (IAM) roles and policies are narrowly scoped to grant each component only the permissions necessary for its function. All data, both at rest in the S3 bucket and in transit, is encrypted using Key Management Service (KMS), and logging is enabled across all services to provide a comprehensive audit trail, adhering to the SRM [47].

The entire lifecycle of this infrastructure is automated via GitHub Actions, implementing a GitOps workflow. The CI/CD pipeline handles the provisioning and updating of the environment, ensuring that the deployed infrastructure always reflects the state defined in the main branch of the repository. This automated deployment workflow guarantees consistency and environment parity, forming a reliable foundation for the prototype's operation [48].

5.5 Prototype Application Codebase (Python)

The Python application serves as the orchestration engine for the entire security automation framework. It is designed as a command-line tool that implements the logic of the multi-layered conceptual model, connecting the static analysis, GenAI, and validation stages into a cohesive workflow. The codebase adheres to modern software engineering best practices, emphasizing modularity, clear separation of concerns, and robust quality assurance.

The application's architecture is inherently modular, with functionality partitioned into distinct, single-responsibility components. This design enhances maintainability and testability [49]. The core modules include:

- An **Analyzer** module, which acts as an adapter for the underlying SAST tool (Checkov). It is responsible for invoking the scanner on a given Terraform file and normalizing the output into a standardized data structure for consumption by the rest of the application.
- A **PG** module, which represents the core intelligence of the system. This component orchestrates the interaction with the GenAI. It constructs a detailed, context-rich prompt by combining the findings from the analyzer with relevant information retrieved from the RAG KB. It then communicates with the AWS Bedrock API to obtain the generated Rego policy.
- A **Validator** module, which functions as an automated quality gate for the AI-generated artifact. It performs crucial checks to ensure the reliability of the output, primarily by using the OPA toolchain to validate the syntactic correctness of the generated Rego code.

A main control loop in the application's entry point script (‘main.py‘) orchestrates these modules in sequence, executing the end-to-end process from analysis to generation and validation.

To ensure code quality and the reliability of the prototype, a comprehensive testing strategy is employed. The project utilizes the pytest framework to implement a suite of unit tests that verify the functionality of each module in isolation [50]. Fixtures are used to create consistent and reusable test setups, and test coverage is monitored as a quality gate within the CI/CD pipeline. Furthermore, dependency management is handled through a requirements.txt file, which pins the specific versions of all external libraries. This practice guarantees a reproducible and stable runtime environment, which is critical for consistent behavior and scientific validation.

5.6 End-to-End Workflow

The practical application of the framework is best understood by examining the end-to-end workflow of the command-line tool. This process describes the sequence of operations from the moment a user invokes the application to the final output of a validated security policy. The entire sequence is designed to be a self-contained, automated process, as illustrated in the sequence diagram 5.2.

The sequence diagram depicts the temporal flow of interactions between the key actors in the system: the User, the Python Command-Line Application, and the external services (Checkov, AWS Bedrock, and OPA). The diagram illustrates how control and data flow through the system in a step-by-step manner, beginning with the user's

command-line invocation and proceeding through each processing stage. The vertical lifelines represent the different system components, while the horizontal arrows show the sequence of method calls, API requests, and data exchanges. This visualization clearly demonstrates the orchestration role of the Python application as it coordinates between traditional security tools, cloud-based AI services, and validation frameworks to deliver a comprehensive security policy generation workflow.

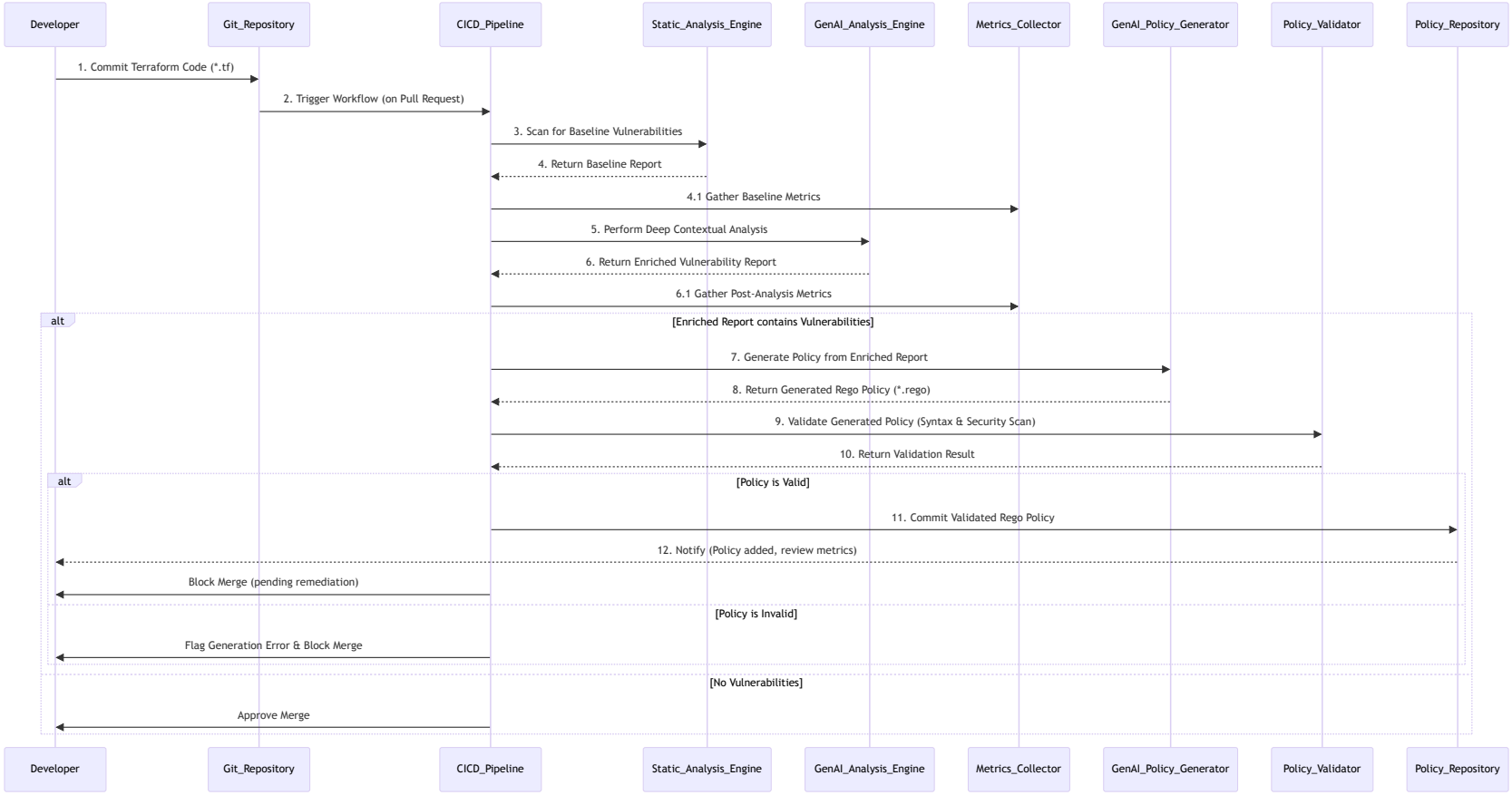

FIGURE 5.2: End-to-End Workflow Sequence Diagram

The workflow is initiated when a user executes the main Python script from the command line, providing the path to a target Terraform (‘.tf‘) file as an argument. The application then proceeds through the following automated steps:

1. **Static Scan:** The **Analyzer** module is invoked. It runs the Checkov SAST tool on the specified Terraform file to identify any known misconfigurations or vulnerabilities.
2. **GenAI Contextual Analysis:** The structured findings from the static scan are fed into the GenAI Analysis Engine (AWS Bedrock) for deep, contextual analysis to reduce false positives and identify complex misconfigurations that traditional tools might miss.
3. **Policy Generation:** The enriched vulnerability report from the GenAI analysis is passed to the **PG** module. This component constructs a detailed, context-rich prompt by combining the analysis findings with relevant information retrieved from the RAG KB, then communicates with the AWS Bedrock API to generate a targeted Rego policy specifically designed to mitigate the identified risks.
4. **Validation:** The raw, generated Rego policy is immediately passed to the **Validator** module. This component uses the OPA toolchain to verify that the policy is syntactically correct and well-formed.
5. **Output:** If the policy successfully passes validation, the application saves the new Rego policy as a ‘.rego‘ file to a designated output directory. The application’s execution concludes by printing the path to the generated file to the console.

This self-contained workflow from file input to policy output is designed for both interactive use by a security analyst and for integration into larger automated systems. For example, it can be executed as a script within a CI/CD pipeline, where the resulting policy artifact can then be automatically committed to a repository and used as a quality gate.

5.7 CI/CD & DevSecOps Integration

While the prototype is a self-contained command-line tool, its primary intended application is within a CI/CD pipeline to enable a proactive DevSecOps workflow. This integration automates the process of security analysis and policy enforcement, "shifting left" to catch and remediate vulnerabilities before they reach production. The implementation uses GitHub Actions as the CI/CD platform.

The integration is achieved through a GitHub Actions workflow that is triggered whenever a developer opens a pull request containing changes to Terraform files. This workflow acts as an automated quality gate and performs the following steps:

1. **Code Checkout & Setup:** The pipeline begins by checking out the source code and setting up the Python environment, including installing the dependencies from ”requirements.txt”.
2. **Execute Security Scan:** The core command-line application is executed. It is pointed at the modified Terraform files within the pull request, running the end-to-end workflow of scanning, generation, and validation.

3. **Commit New Policy:** If the tool successfully generates a new, validated Rego policy, the workflow commits this new policy file to a dedicated directory within the repository.

4. **Enforce Policy as a Quality Gate:** The pipeline then uses the OPA toolchain to evaluate the proposed Terraform changes against the entire set of Rego policies in the repository, including the one that was just generated. If the proposed changes violate any policy, the OPA evaluation fails.

5. **Block or Approve:** A failure in the OPA evaluation causes the entire CI/CD pipeline to fail. This automatically blocks the pull request from being merged and provides immediate feedback to the developer that their changes are not compliant with security standards. This gating mechanism ensures that only secure and compliant IaC can be merged into the main branch.

By integrating the command-line tool in this manner, the framework moves from being a simple analysis utility to a powerful, automated control that is seamlessly embedded in the software development lifecycle.

5.8 Observability & Runtime Telemetry

5.9 Limitations & Trade-offs

5.10 Summary

Chapter 6

Results

6.1 Main Section 1

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Chapter 7

Discussion

7.1 Main Section 1

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Chapter 8

Conclusion

8.1 Main Section 1

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8.2 Main Section 2

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Appendix A

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