IMPLEMENTATION AND ANALYSIS OF A SECURITY FRAMEWORK FOR AN AI DRIVEN DIGITAL ONE HEALTH SYSTEM

BY

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OCTOBER 2025.

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A PROJECT SUBMITTED TO THE DEPARTMENT OF COMPUTER ENGINEERING, FACULTY OF ENGINEERING, UNIVERSITY OF BENIN, BENIN CITY IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF ENGINEERING (B.ENG) DEGREE IN COMPUTER ENGINEERING

OCTOBER 2025.

CERTIFICATION

This is to certify that this project was outrightly carried out by **OGBAUDU OGHENEMARO PROSPER, ENG2009587** in the Department of Computer Engineering, Faculty of Engineering, University of Benin, Benin City, and is hereby certified in accordance with rules and regulations of the University of Benin.

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DATE

DEDICATION

This Project is humbly dedicated to the Almighty God for His faithfulness, insight and direction. May this project serve as a testament to His boundless love, favor, grace and providence, inspiring us all to seek His guidance in all our endeavors.

This Project is also dedicated to my parents, siblings and family as whole for their Love and Support.

ACKNOWLEDGEMENT

My sincere thanks goes to God Almighty for his divine intervention and strength granted to me while doing this work. The source of all wisdom, strength, and opportunities. Without His guidance and blessings, this journey would not have been possible.

I also extend my deepest appreciation to my mum, Mrs. Monica Ogbaudu for being a pillar of support, her endless sacrifices have shaped me into the person I am today. Special appreciation goes to my uncle and aunt, Mr. and Mrs. Ben Agbaza for their belief in my potential. I thank my family for their support throughout this process.

Additionally, I extend my thanks to the wonderful staffs and amazing Lecturers in the Department of Computer Engineering, University of Benin for their invaluable impact and contribution to as a Student of the Department of Computer Engineering, University of Benin. I'm thankful for the camaraderie of my course mates and friends whose shared experiences made challenges enlightening. Special thanks goes to my class buddies who provided invaluable support, knowledge and advice that aided my educational journey.

I would like to express my gratitude to the University of Benin for providing the platform to which has immensely enriched my knowledge and skills in the field of Computer Engineering**.**

Special appreciation goes to my Project Supervisor Engr. Dr. Edoghogho Olaye, for his guidance, direction, and for believing in my potential to complete this work. It has been such an insightful time of learning. Words do little to express my appreciation.

ABSTRACT

The convergence of Artificial Intelligence (AI) with Digital One Health systems, which integrate human, animal, and environmental health data into unified platforms, has introduced unprecedented cybersecurity challenges that conventional frameworks fail to sufficiently address. This project proposes the design, implementation, and evaluation of an adaptive AI-driven security framework tailored specifically to safeguard sensitive cross-sector health data within complex hybrid cloud and on-premise infrastructures. The framework leverages foundational cybersecurity principles, such as Zero Trust Architecture and layered defense-in-depth, combined with advanced AI-powered anomaly detection models including Long Short-Term Memory (LSTM) Autoencoders and Isolation Forest algorithms to enable real-time identification and mitigation of emerging threats.

Employing open-source technologies integral to the system architecture; OPNsense for perimeter firewall and VPN, WireGuard for encrypted communication, Suricata IDS/IPS for intrusion detection and prevention, Wazuh Security Information and Event Management (SIEM) for centralized log aggregation, Keycloak for Multi-Factor Authentication (MFA), and Debezium for Database Activity Monitoring (DAM), the framework demonstrates a holistic approach to securing Digital One Health ecosystems. Central to this effort is the development of a robust AI-powered security dashboard based on the ELK stack (Elasticsearch, Logstash, Kibana), which provides unified visualization, real-time alerting, and compliance monitoring.

The research adopts a design science approach, systematically assessing security vulnerabilities unique to hybrid Digital One Health infrastructures and implementing layered controls to address gaps in cross-sector interoperability and AI-specific risks such as adversarial attacks and data poisoning. Validation is performed using comprehensive threat simulations that mimic real-world attack vectors including SQL injection, lateral movement, privilege escalation, and Distributed Denial-of-Service (DDoS) scenarios. Quantitative performance metrics reveal a high detection rate (approximately 97%), significant reductions in both mean time to detect (MTTD) threats by 70% and false positive alerts by 58%, thereby illustrating improved operational efficiency and accuracy compared to traditional static security measures.

Despite promising results, challenges remain around optimizing AI model training data quality, managing performance overhead in resource-constrained settings, and balancing stringent security controls with healthcare delivery imperatives. The study advocates for future enhancements including federated learning models to preserve data privacy, lightweight AI implementations for broader accessibility, automated compliance frameworks to navigate complex regulatory environments, and expanded user training programs to address human-centric security gaps.

This project contributes a scalable, ethically aligned cybersecurity framework specifically engineered for AI-powered Digital One Health systems, addressing the multifaceted demands of securing sensitive, interconnected health data across diverse environments. By merging advanced AI capabilities with proven cybersecurity practices and a centralized management platform, it advances the resilience and trustworthiness of modern healthcare ecosystems, fostering innovation while safeguarding critical digital health infrastructure globally.

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LIST OF ABBRIEVATIONS

Abbreviation	Full Meaning
AI	Artificial Intelligence
ACL	Access Control List
API	Application Programming Interface
DDoS	Distributed Denial of Service
DAM	Database Activity Monitoring
EDR	Endpoint Detection and Response
ELK	Elasticsearch, Logstash, Kibana
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
IDS/IPS	Intrusion Detection System / Intrusion Prevention System
IoT	Internet of Things
LSTM	Long Short-Term Memory
MFA	Multi-Factor Authentication
MTTD	Mean Time to Detect
OPNsense	Open-Source Firewall and Routing Platform
SIEM	Security Information and Event Management
SQL	Structured Query Language
VLAN	Virtual Local Area Network
VPN	Virtual Private Network
VPS	Virtual Private Server
ZTA	Zero Trust Architecture
ZTNA	Zero Trust Network Architecture

CHAPTER ONE

INTRODUCTION

1.1. BACKGROUND OF THE STUDY

Cybersecurity has become a paramount concern across all sectors, from finance and manufacturing to government and healthcare. The rapid advancement of Artificial Intelligence (AI) and digital transformation has not only revolutionized these industries but also introduced sophisticated cyber threats that demand adaptive, intelligent security measures. Traditional cybersecurity frameworks, encompassing network security, application security, operational resilience, and disaster recovery (Giansanti, 2021) are increasingly challenged by the complexity of modern systems, particularly in healthcare where AI-driven technologies are being deployed at scale.

A robust security framework, when integrated into a Secure System Architecture, must ensure data protection, system resilience, and prevention of unauthorized access. Foundational principles like the CIA Triad (Confidentiality, Integrity, and Availability), Least Privilege, Zero Trust Architecture, and Defense-in-Depth (Noah, 2024) provide a baseline for security but often fail to address the real-time, evolving threats in AI-augmented environments. This shortcoming is especially evident in Digital One Health systems, which integrate human, animal, and environmental health data across interconnected platforms, creating a high-value target for cyberattacks.

The One Health initiative, reliant on big data analytics, IoT devices, and AI-powered diagnostics, faces unique cybersecurity challenges. While AI enhances threat detection and response, its implementation introduces risks such as adversarial attacks, algorithmic bias, and regulatory compliance gaps (Bathushaw and Nagasundaram, 2025). Compounding these issues, many healthcare systems, particularly in resource-limited settings lack access to advanced cybersecurity tools or standardized protocols, leaving sensitive data vulnerable. Emerging solutions like Security-as-a-Service (SaaS) also referred to as Managed security services and policy-adaptive AI frameworks (Nankya et al., 2024) show promise but remain insufficiently tested in real-world, cross-sector One Health environments.

Despite the growing reliance on digital technologies in healthcare, a significant gap persists in addressing cybersecurity vulnerabilities effectively. Existing security standards (e.g., HIPAA, GDPR, NIST, PIPEDA) are often inconsistent, difficult to implement, and

misaligned with the dynamic needs of modern healthcare systems (Kioskli et al., 2021). This lack of practical, adaptable guidance leaves organizations ill-prepared to counter evolving cyber threats aliased Zero-day vulnerabilities, particularly in AI-driven Digital One Health systems, where the stakes involve life-critical data spanning multiple domains.

To bridge this gap, there is an urgent need for a scalable, ethically grounded, and AI-integrated security framework, one that is specifically designed for Digital One Health systems and validated in real-world settings to safeguard Electronic Protected Health Information. Such a framework must balance technical robustness, regulatory compliance, and usability while addressing the unique challenges posed by cross-sector data sharing, AI vulnerabilities, and resource constraints.

1.2 PROBLEM STATEMENT

Current cybersecurity frameworks are not adequately equipped to secure AI-driven Digital One Health systems, which face unique challenges stemming from cross-sector data integration, evolving AI-powered threats, Obfuscated malware attacks, Zero day vulnerabilities and the complexity of hybrid cloud and on premise infrastructures. Existing models often lack the adaptability, real-time AI integration, and enforceability required across the interconnected domains of human, animal, and environmental health. To address this critical gap, this study proposes the design and validation of an adaptive security framework that incorporates Zero Trust principles, defense in depth principles, supports hybrid architectures, enables real-time dashboard monitoring, and leverages AI-enhanced threat detection and insights ensuring comprehensive protection of sensitive health data and strengthening the overall resilience of Digital One Health systems.

There are some current challenges that has to do with achieving a unified security framework for a digital one health system, they include:

1. **Cross-Sector Data Complexity**: Integrating electronic protected health information and personal identifiable information across human, animal, and environmental sectors is hindered by fragmented systems and conflicting standards, increasing exposure to cyber threats.

2. **Hybrid Infrastructure Vulnerabilities**: The mix of cloud and legacy on premise systems often lacks coordinated security controls, creating gaps in policy enforcement and threat visibility.
3. **AI-Specific Threats**: AI tools face risks like adversarial attacks, data poisoning, and bias, which can compromise diagnostics and undermine public health decisions.
4. **Regulatory Fragmentation**: Conflicting laws such as HIPAA, PIPEDA, GDPR and NPDA make compliance difficult, slowing down secure system deployment and global data exchange.
5. **Resource Disparities**: Low-resource regions often lack access to advanced tools like Zero Trust and real-time monitoring, creating uneven security capabilities across One Health systems.
6. **Real-Time Threat Response Limitations**: Static frameworks cannot keep up with fast-evolving AI-enabled threats, delaying detection and increasing the risk of data breaches.
7. **Ethical-Operational Tension**: Strict security controls may disrupt urgent care delivery, raising concerns about balancing patient safety with cybersecurity enforcement.

1.3 AIMS/OBJECTIVES

To design and implement an adaptive security framework featuring an AI-powered dashboard to enhance threat detection, vulnerability management, and data protection across hybrid cloud and on premise Digital One Health systems.

1. To assess security vulnerabilities within hybrid cloud and on premise infrastructures relevant to One Health systems using a risk matrix.
2. To implement core network security controls, including firewalls, VPNs, and IDS/IPS for securing health data flow across the environment.
3. To deploy Security Information and Event Management (SIEM) tools for real-time threat detection and logging.
4. To integrate database activity monitoring mechanisms to detect unauthorized access or anomalies.

5. To enforce Multi-Factor Authentication (MFA) for improved access control and identity verification.
6. To implement AI-powered anomaly detection models to identify unusual patterns, potential threats and new threats in real time.
7. To design and develop an AI-powered security dashboard that visualizes threats, vulnerabilities, and compliance metrics.
8. To validate the effectiveness of the proposed framework through simulated threat scenarios and measurable performance metrics.

1.4 SCOPE OF STUDY

This project focuses on the design, implementation, and evaluation of an adaptive security framework for AI-powered Digital One Health systems. It addresses the protection of sensitive data across human, animal, and environmental health domains by securing hybrid infrastructures and integrating key cybersecurity measures.

The framework will include Zero Trust Architecture (ZTA) for strict access control, AI-powered anomaly detection, real-time threat monitoring via a SIEM, and a centralized security dashboard. Additional components such as Multi-Factor Authentication (MFA), Database Activity Monitoring (DAM), and traditional network security controls (firewalls, VPNs, IDS/IPS) will also be implemented.

The study involves the development and testing of a prototype in a controlled, real-world-like environment. While it extends toward a scalable implementation, the focus remains on system-level hardening and protections, excluding physical security controls, within the context of Digital One Health infrastructures.

1.5 JUSTIFICATION OF STUDY

AI-powered Digital One Health systems face rising cybersecurity threats (zero day vulnerabilities) that traditional frameworks fail to mitigate. Cross-sector data integration, evolving AI threats, and hybrid infrastructures require a new, intelligent approach to security.

Existing models lack adaptability, real-time threat detection, and enforceable policies especially in resource deprived regions. This study addresses these gaps by designing a

scalable, AI-integrated framework with Zero Trust controls, anomaly detection, and a real-time monitoring solution.

By validating the framework in a real environment, the study ensures it is practical, effective, and accessible, helping to protect PII and ePHI, support ethical and secure AI use in One Health ecosystems.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

As the digital transformation of healthcare continues, the importance of cybersecurity has grown significantly. This is especially relevant in the development of integrated and intelligent systems like the AI-Powered Digital One Health System, which connects human, animal, and environmental electronic protected health data. The reviewed literature highlights the critical need to secure such systems, particularly in the healthcare domain, where the consequences of security breaches can be life-threatening.

Cybersecurity in health care has evolved over time, technology has advanced from standalone systems to networked and multi-user environments and this has led to a growing need to protect not just health systems but systems in general from cyber threats. Cybersecurity today involves several key areas, such as securing networks, applications, and information; ensuring operational security; having backup and disaster recovery plans; and providing proper training for users. (Giansanti, 2021).

In the evolving landscape of healthcare, establishing a robust and secure system architecture is paramount. (Noah, 2024) emphasizes the necessity of embedding security and privacy considerations at the core of system design. He advocates for a "security-by-design" approach, ensuring that cybersecurity measures are not retrofitted but are integral from the inception of system development. Noah outlines several foundational principles critical to this approach: Defense in Depth, Least Privilege Access, Continuous Monitoring and Threat Detection and Compliance with Regulatory Standards

The increasing digitization of healthcare services has underscored the need for robust cybersecurity measures to protect patient electronic protected health information. In their chapter, (Chaturvedi et al., 2024) propose the adoption of a Zero Trust Security Architecture (ZTSA) to enhance digital privacy within hospital systems. The core principle of ZTSA is the assumption that no user or device, whether inside or outside the network perimeter, should be trusted by default. This model necessitates continuous verification of all entities attempting to access system resources, thereby mitigating risks associated with unauthorized access and data breaches. The application of ZTSA principles is highly relevant to AI-driven Digital One Health systems, which rely on the seamless integration and analysis of diverse datasets across

various sectors. By enforcing strict access controls and continuous authentication, ZTSA can mitigate risks associated with unauthorized data access and potential cyber threats. Moreover, the implementation of robust encryption protocols ensures that data remains secure during transmission and storage, a critical consideration given the sensitive nature of health-related information. (Tyler and Viana, 2021) also propose a Zero Trust Network Architecture (ZTNA) framework to help healthcare organizations enhance security by continuously verifying users and devices, regardless of their location in the network. Unlike traditional security models that trust internal network traffic, ZTNA assumes no device or user is trusted by default. Key elements of the framework include micro-segmentation, which divides the network into isolated sections to limit threats, and firewalls and access control lists (ACLs) to monitor and restrict access to critical systems. This approach is especially relevant to AI-powered One Health systems, where securing data across various health sectors is crucial for maintaining data integrity and privacy.

(Sunday Adeola Oladosu et al., 2021) propose a unified security framework for hybrid cloud and on-premises integrations, focusing on protecting complex systems like those used in AI-driven Digital One Health frameworks. Their model emphasizes the CIA triad (Confidentiality, Integrity, and Availability) and incorporates Zero Trust security and advanced encryption to secure data flows across multiple environments. It also highlights the use of automation and orchestration for efficient security management and real-time monitoring. The framework ensures compliance with key regulations like HIPAA and GDPR, crucial for maintaining privacy in healthcare. Overall, their approach provides a robust guide for securing interconnected healthcare systems and protecting sensitive health data.

The paper by (Kioskli et al., 2021) highlights key cybersecurity challenges including the increased vulnerability due to interconnected systems, the lack of unified and clear cybersecurity standards, and the importance of human-centered strategies. It emphasizes the need for adaptive, integrated security approaches that address complex stakeholder environments and evolving threats. Their proposal of “living labs” for testing security measures in real-world settings and understanding attacker behavior provides practical insights for securing the diverse and dynamic components of a One Health system. (Bathushaw and Nagasundaram, 2025) highlight the growing complexity of cybersecurity threats in healthcare and the urgent need for strong, adaptable security frameworks. Their recommendations such as layered security, real-time threat detection, standardized protocols,

and continuous staff training are especially for Digital Health systems, which handle sensitive and interconnected human, animal, and environmental health data. Their work emphasizes a proactive and comprehensive approach to protecting these systems from modern cyber threats.

(Nankya et al., 2024) emphasize how AI and machine learning techniques can improve cybersecurity in e-health systems, especially by detecting threats early and protecting sensitive health data. Their review is highly relevant to an AI-driven Digital One Health system, as it highlights tools like anomaly detection, federated learning, and secure multiparty computation that help maintain data privacy across interconnected health sectors. They also discuss the importance of secure model deployment and blockchain integration to ensure data integrity and regulatory compliance, all of which support the secure functioning of AI-based health systems.

(Esenov Y., 2024) emphasize the critical role of cybersecurity metrics and reporting dashboards in strengthening organizational security posture. Their study highlights how real-time dashboards serve as essential tools for managing modern security operations by providing visibility, actionable insights, and regulatory compliance support. Particularly relevant to the One Health surveillance context, the use of operational, compliance, and risk metrics enables continuous monitoring of system vulnerabilities and threat detection across interconnected environments. By integrating data sources and visualizing key security indicators, these dashboards enhance decision-making and resource allocation. The paper also supports the incorporation of AI and automation aligning with AI-driven frameworks to streamline threat intelligence and real-time analytics. This underscores the necessity for a centralized, customizable, and role-based dashboard in any robust security architecture, especially within critical healthcare and public health infrastructures.

Applying these principles to an AI-driven Digital One Health system addresses the unique challenges posed by integrating diverse data sources and stakeholders. The complexity of such systems necessitates a holistic security framework that not only protects sensitive health data but also ensures the reliability and accuracy of AI-driven analysis. By embedding security measures throughout the system architecture, organizations can enhance data integrity, ensure compliance with health data regulations, and foster trust among users and stakeholders.

2.2 RESEARCH GAPS

Despite the growing body of literature addressing cybersecurity in healthcare and the development of AI-driven One Health systems, several significant research gaps persist. While studies such as (Giansanti, 2021) and (Kioskli et al., 2021) provide foundational insights into the evolution of cybersecurity practices and the importance of human-centered design, they often stop short of offering comprehensive, technically integrated frameworks tailored specifically to the complex, multi-sectoral nature of Digital One Health systems. Most current literature focuses on isolated health domains, human or hospital-based systems without sufficiently addressing the convergence of human, animal, and environmental data in a single, unified architecture.

Moreover, while Zero Trust principles are explored in depth by (Chaturvedi et al., 2024) and (Tyler and Viana, 2021), their applications are often limited to internal hospital networks or outdated infrastructures. There is a lack of empirical validation or real-world testing of ZTNA or ZTSA models in large-scale, cross-sectoral, AI-powered ecosystems such as those envisioned for One Health. These frameworks also lack integration with modern tools like federated learning or secure multiparty computation, which are only discussed theoretically by (Nankya et al., 2024).

Another gap lies in the area of unified hybrid cloud security, as addressed by (Sunday Adeola Oladosu et al., 2021). While their framework incorporates critical concepts like the CIA triad and compliance with HIPAA/GDPR, it remains largely conceptual and lacks performance benchmarking across different cloud vendors and real-time AI data processing pipelines. Furthermore, despite the rise in AI adoption, few studies (with the exception of (Nankya et al., 2024) and (Chamkar et al., 2025)) explore the integration of advanced AI-driven cybersecurity measures such as anomaly detection, adaptive learning, and blockchain in a cohesive, scalable infrastructure.

Additionally, (Esenov Y., 2024) highlights the role of cybersecurity dashboards and metrics, yet practical implementations of such dashboards tailored to the real-time, multi-source data context of One Health systems are still underexplored. There remains a need for customizable, role-based security dashboards that support proactive security management and decision-making in integrated health surveillance systems.

Lastly, although "living labs" proposed by (Kioskli et al., 2021) and simulation models used by (Tyler and Viana, 2021) show promise for testing security solutions, there is a lack of practical, interdisciplinary implementation of these environments for validating AI-based cybersecurity frameworks in the context of Digital One Health. (Bathushaw and Nagasundaram, 2025) emphasize proactive security techniques, but their work does not sufficiently address the governance, ethical, and regulatory coordination required in transdisciplinary health systems.

2.3 META-ANALYSIS TABLE FOR THE IMPLEMENTATION AND ANALYSIS OF A SECURITY FRAMEWORK FOR AN AI DRIVEN DIGITAL ONE HEALTH SYSTEM

RESEARCH PAPER	AUTHOR	BACKGROUND AND PURPOSE	METHODOLOGY	RESULT	LIMITATION
Cybersecurity Metrics and Reporting Dashboard: A Tool for Effective Security Management	Esenov Y., Malikgulyyeva D.	To explore how metrics and dashboards can help monitor and manage cybersecurity effectiveness.	Reviewed design principles, challenges, and trends of cybersecurity dashboards.	Found dashboards are critical for decision-making and security control visualization.	Challenges in dashboard development, future trends with AI and real-time analytics.
Advancing cloud networking security models: Conceptualizing a unified framework for hybrid cloud and on-premise integrations	Sunday Adeola Oladosu et al.	To address security challenges in hybrid cloud and on-premise setups by proposing a unified framework.	Conceptual review, case studies from industries, and framework development.	Framework improves security, efficiency, and compliance across infrastructures.	Complexity in orchestration, regulatory adherence, and integration.
Trust No One? A Framework for Assisting Healthcare Organisations in Transitioning to a	Dan Tyler and Thiago Viana	To understand and implement Zero Trust in outdated healthcare infrastructures.	Framework development and simulation testing in Cisco Modelling Labs (CML).	Proved effectiveness in isolating threats and protecting medical	Legacy systems' limitations and increased latency due to firewalls.

Zero-Trust Network Architecture				devices.	
Zero Trust Security Architecture for Digital Privacy in Healthcare	Ikshit Chaturvedi, Pranav M. Pawar, Raja Muthalagu, Tamizharasan Periyasamy	To propose and implement ZTSA to protect patient data in Django-based hospital systems.	Implementation of ZTSA including MFA, encryption, and access controls.	Improved digital privacy and security of patient data.	Limited to a Django environment, needs broader testing.
Secure System Architecture: Designing for Cybersecurity and Data Protection	Lucas Noah	To provide a structured approach to building secure and resilient systems.	Literature review and conceptual exploration.	Highlighted best practices including CIA triad, Zero Trust, and microservices security.	No real-world implementation; conceptual in nature.
The landscape of cybersecurity vulnerabilities and challenges in healthcare: Security standards and paradigm shift recommendations	Kitty Kioskli, Theo Fotis, Haralambos Mouratidis	To explore digital health vulnerabilities and propose a living lab for cybersecurity research.	Analysis of standards, vulnerabilities, and recommendation of living labs.	Living labs offer practical implementation space for security solutions.	Standards contradictions and implementation challenges.
Securing Healthcare Systems: Modern Threats and Strategic Developments in Cybersecurity	M. Husain Bathushaw & S. Nagasundaram	To implement and test multiple modern security techniques in e-health systems.	Deployed anomaly detection, AES encryption, ML IDS, and blockchain.	Achieved high detection accuracy and low latency in security operations.	Does not cover usability or system-wide integration issues.
Cybersecurity and the Digital-Health: The Challenge of This	Daniele Giansanti	The study emphasizes the importance of cybersecurity	Descriptive and conceptual analysis, with a call for further	Highlighted the necessity of sector-specific	Lacks empirical data and case studies; the

Millennium		measures tailored to the healthcare sector due to its critical nature. It aims to explore traditional and emerging threats, training needs, and perception analysis.	survey-based studies and targeted investigations.	cybersecurity adaptations, especially in the context of eHealth, mHealth, non-medical apps, and digital contact tracing. Identified key areas like training, perception, and policy evolution.	paper is more of a review and perspective article rather than a results-driven study. No specific author or institutional affiliation provided. Calls for future research instead of providing it.
Security and Privacy in E-Health Systems: A Review of AI and Machine Learning Techniques	Mary Nankya, Allan Mugisa, Yusuf Usman, Aadesh Upadhyay and Robin Chataut	To explore how the adoption of e-health systems, particularly EHRs, has evolved, and how AI-driven cybersecurity can enhance protection of sensitive health data. The purpose is to examine current practices, identify emerging trends, and highlight future research directions in securing e-	Literature review and theoretical analysis of current e-health systems, cybersecurity threats, and AI applications. The paper synthesizes existing research and emerging technologies to present a forward-looking view.	Identifies AI as a transformative tool for improving cybersecurity in e-health systems. Highlights techniques like anomaly detection, adaptive learning, predictive analytics, blockchain, and quantum-resistant encryption. Outlines future	No primary data or experimental validation is provided. Conclusions are drawn from existing literature without empirical testing. Author information and specific case studies are missing, limiting real-world applicability and traceability.

		health systems.		directions and calls for ethical AI and regulatory automation.	
Improving Threat Detection in Wazuh Using Machine Learning Techniques	Samir Achraf Chamkar, Mounia Zaydi, Yassine Maleh, and Noreddine Gherabi	The study addresses the increasing sophistication of cyber-threats and the limitations of traditional rule-based detection in SIEM systems. It focuses on enhancing the open-source Wazuh SIEM by integrating machine-learning to reduce false positives and improve threat detection accuracy.	The authors detail data preparation and preprocessing steps, feature extraction from Wazuh logs, training and evaluation of ML models integrated into Wazuh's architecture (Manager, Indexer, Dashboard). They shift from purely rule-based to hybrid ML-augmented detection.	The ML-enhanced Wazuh system demonstrated improved capabilities to detect advanced threats (e.g., APTs, zero-day exploits) with fewer false positives, and the authors present implementation details of this system within the Wazuh platform.	The paper while promising, lacks broad empirical validation across diverse operational environments. Details such as large-scale deployment, real-world impact metrics, and long-term robustness remain under-explored.

Table 2.1: Meta-Analysis Table

CHAPTER 3

METHODOLOGY

This study adopts a Design Science Research (DSR) methodology to develop, implement, and evaluate an adaptive, AI-powered security framework for Digital One Health systems using open-source tools.

3.1 SYSTEM OVERVIEW

The AI-powered adaptive security framework is designed to secure a hybrid Digital One Health environment, it combines on-premises and cloud resources under a unified Zero Trust architecture. The system ensures confidentiality, integrity, and availability of health data, enables continuous vulnerability assessment and threat detection, enforces access control (including MFA) by deploying an identity and asset management solution, and provides automated compliance reporting (e.g. HIPAA, PCI DSS, PIPEDA). All network interactions are through a VPN, authenticated and authorized before granting access, administrative access requires multi-factor authentication (MFA) to mitigate credential theft. The framework uses only open-source components to avoid vendor lock-in and to leverage community-driven security innovation.

At the system core is a 64 GB RAM bare-metal server running XCP-ng (a Xen-based open hypervisor). XCP-ng's control domain is isolated from VMs, and all software packages and ISOs are digitally signed. This ensures the hypervisor is a trusted foundation. On top of XCP-ng, four virtual machines (VMs) are deployed: an Ubuntu Management VM (8 GB) hosting Xen Orchestra Community Edition from GitHub for centralized host management and backups; a Firewall VM (4 GB) running OPNsense (an open-source firewall/router) and its built-in Suricata IDS/IPS engine; an Application VM (16 GB) hosting the primary One Health services and any local databases; and an AI VM (32 GB) dedicated to all Artificial Intelligence analytics. All VMs are Linux based to maintain consistency, ease integration and enable full customization. Xen Orchestra provides a single pane of glass to control the XCP-ng hosts and automate backups. In parallel, the system integrates a cloud VPS (Ubuntu 8 GB, with static public IP) which is bridged to the on-premises network via a WireGuard VPN. This VPN tunnel ensures that any remote or cloud-based component connects securely into the private network.

The OPNsense firewall VM sits at the boundary; the WAN virtual interface connects to the external Internet and the cloud VPS via WireGuard, and other interfaces connect to internal segments. The Application VM and AI VM reside on a protected “internal” network segment, while the Management VM is isolated on an admin segment. OPNsense enforces inter-segment rules: for example, only the Management VM may pull logs from other segments, and the Management VM can only be reached by authorized administrators through VPN. The Management VM runs Wazuh (SIEM/XDR) and the ELK stack (Elasticsearch-Logstash-Kibana) while the AI VM runs the AI services. Wazuh agents on the Management, Firewall, Application, AI VMs, the Cloud VPS forward logs and alerts to the Management VM’s Wazuh manager. Suricata on the firewall monitors all network traffic (e.g. HTTP, TLS) and reports to Wazuh, enabling real-time intrusion detection. The ELK stack on the Management VM ingests these events: its built-in machine learning performs time-series anomaly detection on log and metric data, while custom AI models analyze more complex behavior. All log analytics and alerts are visualized in a unified security dashboard (Kibana) with charts and timelines.

The system enforces layered security controls. All remote and on-site access traverse the WireGuard VPN, which uses modern cryptography to protect data-in-transit. No VM has any open services exposed to the Internet. Inside the VPN, network traffic is filtered by OPNsense: Suricata’s IDS/IPS rules inspect traffic for known threats, and adaptive firewall rules isolate suspicious flows. All system and application logs (events, audit trails, alerts) are continuously shipped to the Wazuh manager on the Management VM. Wazuh correlates these logs (providing detection, alerting, and compliance auditing) and stores them in Elasticsearch. Elastic’s ML jobs run on this data to identify anomalies (e.g. unusual traffic spikes, failed logins). Important security KPIs (e.g. number of blocked attacks, anomaly scores) are displayed on the centralized security dashboard. When a potential issue is detected, the system triggers alerts or automated responses. For example, if Wazuh identifies a configuration drift or high-risk vulnerability, it will generate a compliance incident. The integrated dashboard (with AI analytics) allows operators to drill down on alerts in real time.

Each VM’s role by design is strictly separated. The AI VM shares AI resources needed by the Application VM but it is not generally exposed and the Management VM (for collecting host status). The Application VM serves health data to authorized clients (but only after they authenticate via the VPN and MFA). It communicates with the Management VM but does not

connect to external networks beyond what is allowed. The Management VM communicates with the hypervisor and can connect to each VM to gather logs and status (e.g. via Wazuh and SSH). The OPNsense firewall enforces these policies: for example, the Application VM cannot see the Management VM's interface, minimizing attack paths. This strict segmentation and least-privilege design (each service only exposes minimal interfaces) embodies Zero Trust principles. Authentication systems on the VMs also enforce identity and role checks; for instance, SSH or web logins require MFA.

The internal network is subdivided into micro-segments to contain breaches. The OPNsense firewall creates these software-defined perimeters and ensures "segment and enforce the external boundaries". Even between on-premises and cloud, the design avoids a flat network: the WireGuard tunnel effectively creates a secure micro-perimeter for the entire on-premises network, treated as untrusted by default until authenticated. Traffic flow charts illustrate that every packet must pass through firewall rules and policy checks. Zero Trust means every session is authenticated (VPN plus MFA) and encrypted end-to-end.

Administrators and remote users may connect only over the WireGuard VPN; all other ingress is blocked. Once on the VPN, they must still authenticate (with passwords and a second factor) to reach any VM. The Xen Orchestra UI on the Management VM is only reachable via this channel. System updates and vulnerability scans are performed regularly. Wazuh's compliance modules automate reporting: its ruleset supports PCI DSS, HIPAA, NIST 800-53 etc., detecting misconfigurations or policy violations. Database Activity Monitoring (DAM) tools like pgAudit log every query; these logs feed into Wazuh for anomaly detection and auditing

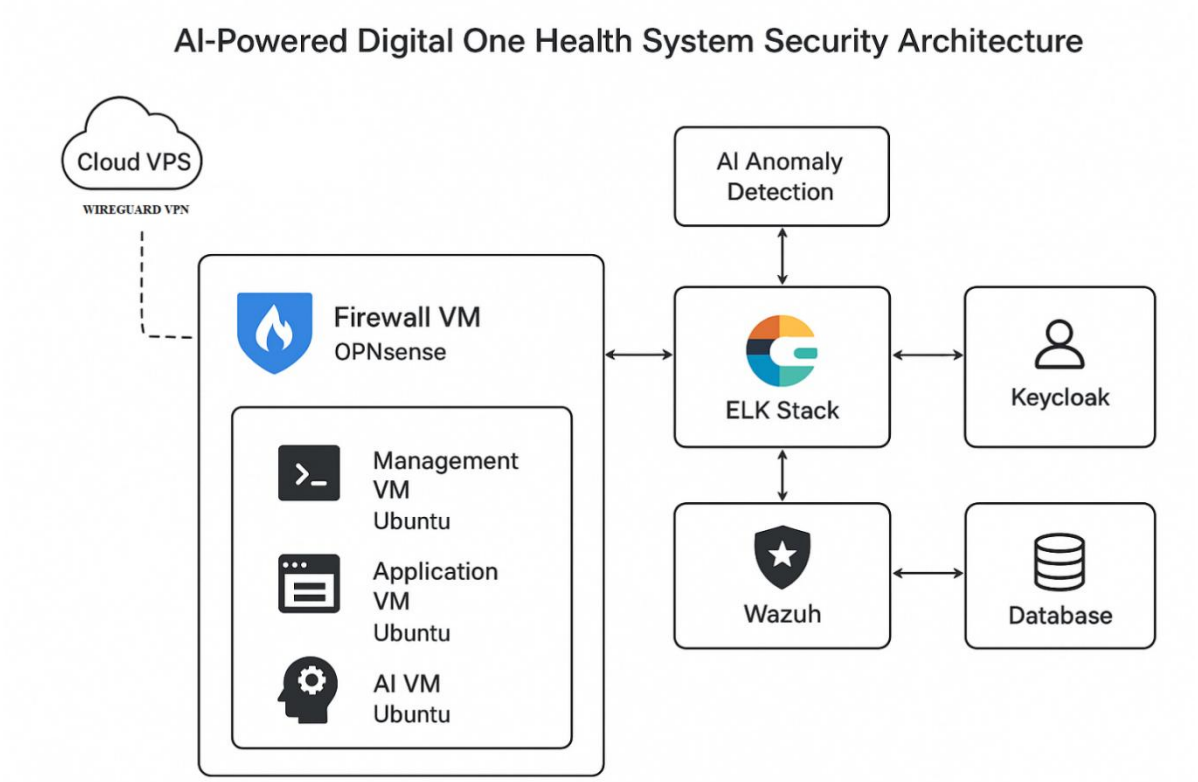

Figure 1: AI Powered Digital One Health System Security Architecture

3.2 HYBRID INFRASTRUCTURE THREAT ASSESSMENT

A comprehensive threat and vulnerability assessment is conducted to identify weaknesses in both environments. We model and map the hybrid environment, identifying assets across the on-premises data center and cloud resources. This involves inventorying critical components (e.g. servers, databases, network devices) and mapping dependencies (vertical and horizontal) to understand potential compromise paths. Automated vulnerability scanners (e.g. Nessus, OpenVAS) and penetration testing tools are used to probe the infrastructure. A risk-based approach prioritizes findings by impact to critical health-data assets. We performed continuous monitoring and periodic re-assessment, making automated discovery and assessment essential. Compliance requirements (e.g. HIPAA for health data, PIPEDA and GDPR for personal data e.t.c) were factored into the assessment. The detected misconfigurations and unpatched flaws were documented for remediation.

3.2.1 ASSET INVENTORY

This is a Comprehensive list of all assets owned by the organization, including both tangible items like equipment and property, and intangible ones like intellectual property. This

actually focused on the IT asset inventory. This inventory enumerates the hosts, services, applications and data flows in both the cloud and local networks.

3.2.2 AUTOMATED SCANNING

Vulnerability scanners and configuration analysis tools are used to discover weaknesses. OPENVAS is a full-featured vulnerability scanner. It is capable of the following which include unauthenticated and authenticated testing, various high-level and low-level internet and industrial protocols, performance tuning for large-scale scans and a powerful internal programming language to implement any type of vulnerability test. The scanner obtains the tests for detecting vulnerabilities from a feed that has a long history and daily updates. This scanner is used to consistently check for vulnerabilities in the digital one health system network and connected devices.

3.2.3 RISK PRIORITIZATION

A Comprehensive risk assessment was performed on the system. Vulnerabilities were ranked by severity and criticality of affected health systems, following a risk-based approach by performing both a qualitative and quantitative risk analysis. A Risk Matrix like the one below is used to classify the risks appropriately considering the system’s risk tolerance.

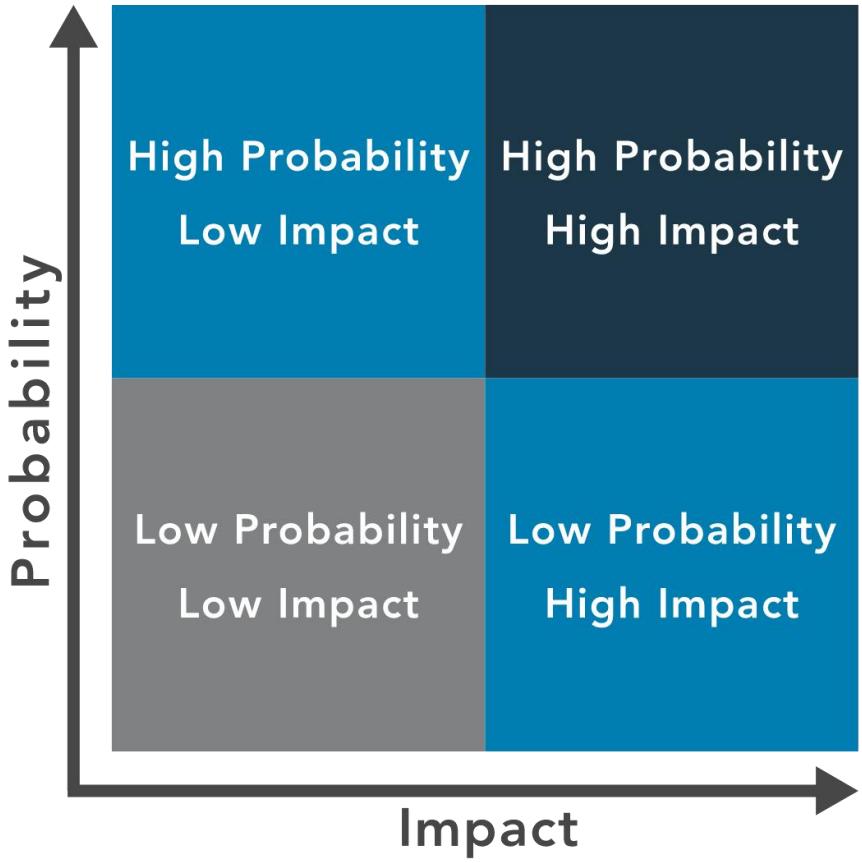

Figure 2: Sample of a Cybersecurity Risk Matrix

3.2.4 DOCUMENTATION

All the identified vulnerabilities, recommended fixes and compliance gaps are well recorded in details for it to be mediated.

3.3 NETWORK SECURITY CONTROLS IMPLEMENTATION

Core Network defenses are deployed to protect data in transit based on the threat assessment carried out. In our implementation, all inbound and outbound traffic traverses a perimeter firewall or gateway. A firewall is configured to enforce strict access control lists (ACLs) and segmentation. VPN tunnels are established for secure cloud-to-on premises links. Software-defined perimeter techniques and dedicated leased lines are employed to harden cross-environment connectivity. Intrusion Detection/Prevention System (IDS/IPS) is installed at the firewall to detect suspicious traffic patterns. A Suricata IDS is placed adjacent to the firewall to analyze mirrored traffic. Firewall and IDS rules are carefully crafted to allow only approved data flows and to generate alerts for anomalous packets. Network segmentation

isolates critical systems from less-trusted segments. This multi-layered architecture aligns with defense in depth practices: robust network segmentation and encrypted tunnels help keep data intact as it moves between the on premise and the cloud environment.

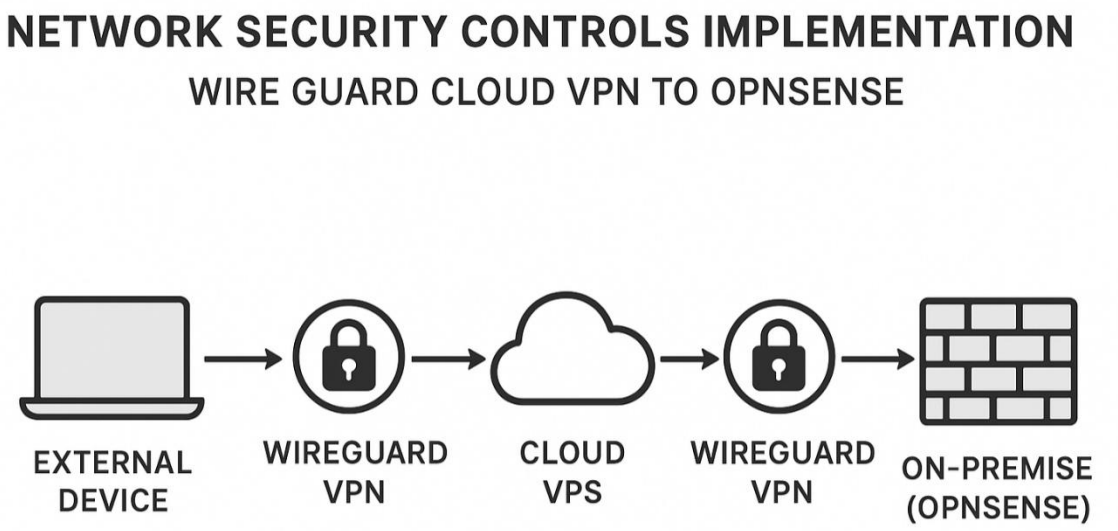

Figure 3: Network Security flow

3.3.1 PERIMETER FIREWALL

A software firewall appliance (OPNsense) is deployed on the on premise server as a virtual machine to monitor and log all the incoming and outgoing network traffic. The firewall is basically an unintelligent system that doesn't think for itself but rather depends on rules to know the network traffic to accept or reject. OPNsense is an open-source, FreeBSD-based firewall and routing platform that provides enterprise-grade network security and features, such as intrusion detection, VPN, and web filtering, all accessible through a user-friendly, web-based interface at no cost. It offers frequent security updates, a structured release cycle, and a modular design for extensibility, making it a powerful, cost-effective alternative to commercial firewalls for both home and business users. It originated as a fork of pfSense (which itself was a fork of m0n0wall) in 2014, with its first release in 2015. The OPNsense

virtual appliance is deployed on the on premise server through the xcp-ng hypervisor, the firewall is responsible for routing traffic across the different network interfaces and segments.

3.3.2 VPN/ENCRYPTED LINKS

Virtual Private Network Links are established between the on premise server and the cloud environment using the Wireguard VPN which is inbuilt into the OPNsense firewall. The VPN link is also required for any other device accessing the one-health network remotely. The Wireguard VPN works by creating a secure, encrypted tunnel between devices using cryptographic keys and modern algorithms like ChaCha20 and Curve25519. It uses a handshake process to authenticate peers based on their public keys and private keys (Asymmetric Encryption) and then transmits all data over UDP using a simplified, small codebase for speed and security. This results in faster connections and greater efficiency compared to older VPN protocols. The Wireguard VPN client is installed and configured on the firewall VM on the on-premises server, on the cloud device and every other device that wants to communicate with the system.

3.3.3 IDS/IPS DEPLOYMENT

The Intrusion Detection System and Intrusion Prevention System are systems that work by inspecting network traffic for threats using signature-based, anomaly-based, and policy-based detection. The IDS passively monitors and alerts, while IPS actively blocks attacks by placing itself in line with traffic flow. They help protect networks by identifying known attack patterns or deviations from normal behavior, with IDS acting as a warning system and IPS as an automated defense. The Suricata IDS/IPS is deployed on the firewall VM to perform the above stated duties. Various rulesets are configured to prevent unwanted network traffic while keeping logs and sending alerts. The Suricata IDS/IPS works by capturing network traffic and inspecting it against a set of rules (signatures) to detect known threats, anomalies, and policy violations. Depending on its configuration, it acts as an Intrusion Detection System (IDS) by alerting and logging suspicious activity or as an Intrusion Prevention System (IPS) by actively blocking malicious traffic in real-time.

3.3.4 NETWORK SEGMENTATION

The system's network is separated into different segments, network traffic between these different segments is only possible through the firewall. This easily reduces risk and enables efficient threat confinement. This is used to isolate sensitive workloads, minimizing lateral movement. A management network, internal network, VPN network as well as an External/Wide Area Network segment is implemented.

3.4 SECURITY INFORMATION AND EVENT MONITORING (SIEM) DEPLOYMENT

A Wazuh SIEM solution is deployed to aggregate logs and enable real-time threat analysis. An on-premises Wazuh SIEM manager give full data control and customization. In our hybrid framework, we integrate an on premise Wazuh SIEM, complemented by Wazuh collector agents for all local hosts and the cloud server.

The Wazuh SIEM collects logs from all network devices (OPNsense firewall, Wireguard VPN gateways, Suricata IDS/IPS), servers, and applications. Data connectors or agents (e.g. syslog) send raw event data to the SIEM's ingest point. The SIEM normalizes and indexes these events into a central database.

Within the SIEM, correlation rules and analytics are configured to detect known attack signatures and indicators of compromise. AI models are deployed on the SIEM for anomaly detection. The system provides dashboards, real-time alerting, and historic log search. Critical security events trigger immediate notifications to the SOC (security operation centre) team. The SIEM has sufficient storage and processing power to handle high-volume data (tracking storage and bandwidth for logs from firewalls, IDS, endpoints, etc). The SIEM is also configured to monitor database audit logs (from the DAM system) and MFA authentication logs, centralizing visibility. By consolidating security data, the SIEM enables rapid threat detection: "SIEM tools correlate security events, give real-time monitoring, and allow immediate detection of a potential threat" by highlighting network anomalies.

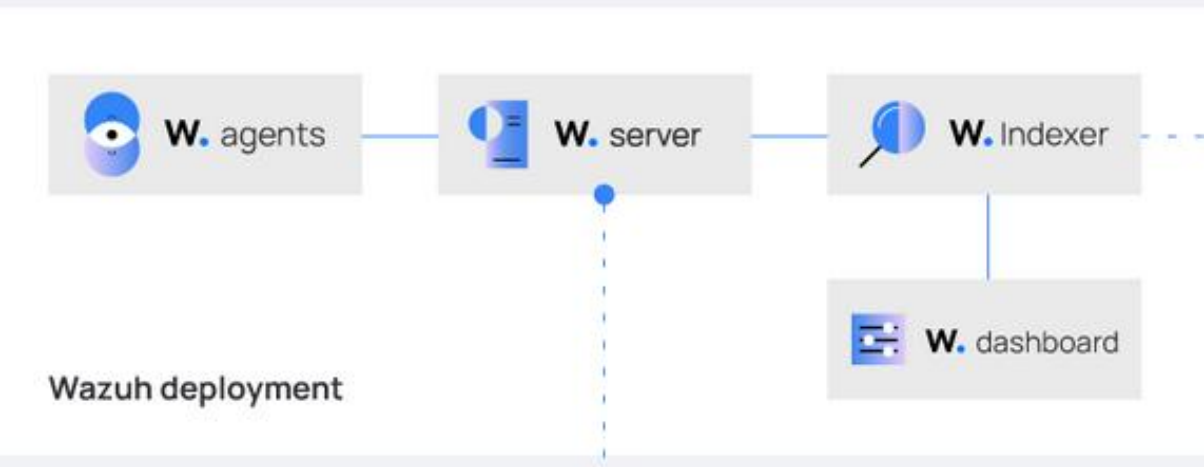

Figure 4: Wazuh SIEM data flow

3.4.1 LOG COLLECTION

Wazuh agents are deployed on all the VMs, on the Cloud server and every other system that is connected to the Digital one health system. These agents serve as the log collectors, they forward all the logs from the host to the Central Wazuh SIEM where they are correlated and used for threat analysis.

3.4.2 NORMALIZATION AND CORRELATION

The Wazuh SIEM is configured to convert diverse log data into a single and consistent format, parse fields and apply rules that link events into alerts. This enables the identification of patterns that indicate a security threat.

3.4.3 REAL TIME MONITORING

Dashboards and alerts are set up in the Wazuh Security Information and Event Monitoring Platform using the ELK stack so that analysts are notified immediately of suspicious events and can further assess the situation.

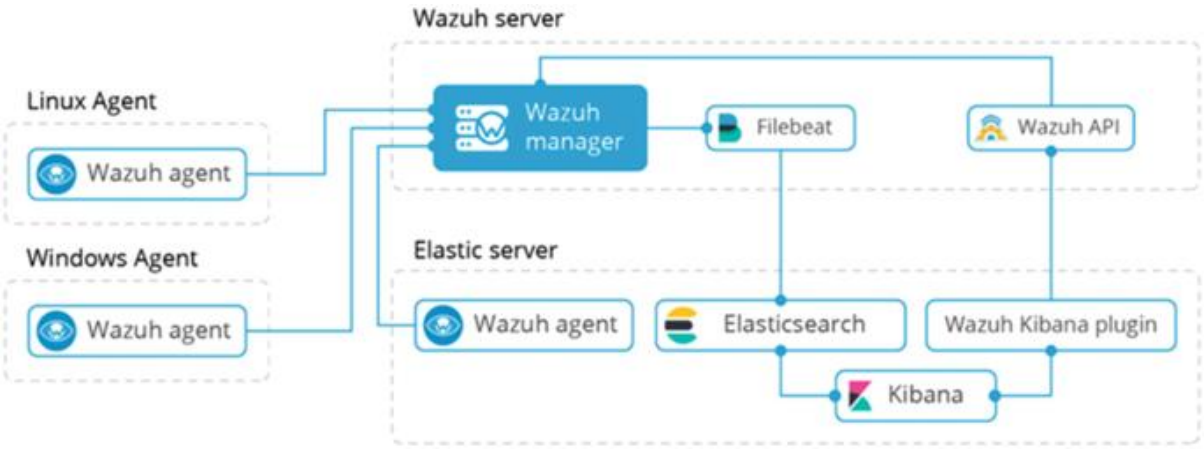

Figure 5: Wazuh server data flow to the ELK stack

3.5 DATABASE ACTIVITY MONITORING INTEGRATION

Health data are sensitive in nature, to protect this data at rest, a Database Activity Monitoring (DAM) solution is incorporated in the security framework. DAM provides real-time tracking and analysis of all database transactions, enabling immediate detection of unauthorized access and anomalies. The architectures such as agent-based (installing monitoring agents on each database server) or proxy-based (placing an intermediary that captures all queries) were evaluated. For this project, we implemented DAM for key databases making use of audit tools for each database type, as it offers robust visibility into every query and update without modifying the database code. The DAM system continuously logs SQL statements, user queries, and data modifications. Any attempt to exceed privileges or access sensitive tables trigger instant alerts. This “security-centric” monitoring captures who accessed what data and when, creating a tamper-proof audit trail. For example, if a user queries beyond their role or a sudden bulk data export occurs, the DAM flags it as an anomaly. Key DAM features employed include unauthorized access detection, immediate alerts on suspicious activity, and compliance reporting (for HIPAA, GDPR, PIPEDA etc.). The DAM also feeds its logs into the SIEM for correlation with network and host events. By integrating DAM, we extend protection to the database layer, ensuring “complete visibility” of data operations.

3.5.1 DAM DEPLOYMENT

The Digital one health system incorporates several types of databases to handle the cross sectoral electronic protected health information, to actively monitor the different types of databases, we implemented Debezium for the change data capture, individual audit tools for each type of database. Pgaudit is configured for PostgreSQL databases, server audit is configured for MariaDB databases, mongod is configured for MongoDB databases and configured auditd and auditbeat to send the audit logs to our Wazuh SIEM.

3.5.2 REAL-TIME TRACKING

This set up ensures that all the activities across the system's databases are monitored, logged and used in threat detection and protection of the system. Operations by any and every user on the databases are logged and stored by the audit tools deployed.

3.5.3 ANOMALY ALERTS

Rules are set up to flag anomalies and unusual patterns in the databases, any triggered rule sends an alert to the operator. This rules are implemented to flag patterns such as large queries, off-hours access and bulk data retrieval etc.

3.5.4 AUDIT LOGGING

Detailed logs of all database interactions are stored for audit and forensic analysis. These logs as well as the alerts are forwarded to the SIEM tool to correlate with other security events

3.6 MULTI-FACTOR AUTHENTICATION IMPLEMENTATION

To enhance authentication security within the hybrid One Health security framework, Keycloak, an open-source identity and access management system, is deployed as the centralized authentication authority for all users and services. Keycloak provides built-in support for Multi-Factor Authentication (MFA), enabling enforcement of additional verification layers beyond standard credentials. This approach aligns with the system's objective of strengthening identity assurance and reducing the risk of credential compromise in healthcare and research environments.

3.6.1 MFA ARCHITECTURE AND INTEGRATION

Keycloak is deployed on the Management VM within the virtualized infrastructure on premise, integrated with the various system components, including the WireGuard VPN, Wazuh dashboard, and application access portals through OpenID Connect (OIDC) and SAML 2.0 protocols. This centralized authentication design ensures that all user logins, whether for administrative consoles, databases, or VPN access, are uniformly protected under Keycloak's policy engine. Keycloak communicates securely over HTTPS with each client application and enforces MFA during the authentication process before granting access tokens. For command-line or API-based interactions, Keycloak supports token-based authentication using OAuth 2.0 device flows.

3.6.2 MFA FACTORS AND WORKFLOW

The system requires users to authenticate using at least two distinct factors:

1. **Primary Factor:** A username and password combination managed within Keycloak or synchronized from external directories such as LDAP or Active Directory.
2. **Secondary Factor:** A Time-based One-Time Password (TOTP) generated via authenticator applications (e.g., Google Authenticator, FreeOTP), or alternatively, a hardware-based token (e.g., YubiKey) registered within Keycloak.

Upon successful primary authentication, Keycloak prompts for the configured second factor before issuing an access token. This process is enforced for all VPN logins, cloud-based services, and administrative system consoles, significantly reducing exposure to credential theft and phishing-based attacks.

3.6.3 USER ENROLLMENT AND MANAGEMENT

During onboarding, each user must register their second authentication factor through Keycloak's self-service web portal. The Administrators can define enrollment policies, mandating that no user account becomes active without MFA registration. Keycloak's admin console enables centralized management, recovery, and rotation of credentials. To ensure operational continuity, helpdesk procedures and backup token recovery mechanisms are defined, mitigating user lockout risks.

3.6.4 ACCESS CONTROL POLICIES

MFA enforcement in Keycloak is governed by configurable authentication flows and realm-level policies. The system applies conditional access rules such as enforcing MFA for remote logins via WireGuard, high-privilege role access (e.g., Wazuh administrators), or sensitive data management applications. Integration with OPNsense VPN authentication ensures that remote users connecting to internal resources must authenticate through Keycloak, thereby linking network-level security with identity assurance.

3.6.5 COMPLIANCE AND SECURITY POSTURE

This Keycloak-based MFA implementation aligns with healthcare cybersecurity guidelines and data protection frameworks (e.g., HIPAA, PIPEDA and GDPR), which emphasize MFA as a fundamental safeguard for electronic protected health information. By employing open-source IAM technologies, the framework avoids vendor lock-in while maintaining full transparency and auditability of authentication flows.

All authentication logs and events are forwarded from Keycloak to Wazuh SIEM via Filebeat for centralized monitoring, anomaly detection, and compliance auditing. This integration allows correlation between identity events and other telemetry sources (network, IDS/IPS, and database activity), enhancing situational awareness within the adaptive security ecosystem.

3.7 AI-BASED ANOMALY DETECTION MODEL SELECTION

The integration of Artificial Intelligence (AI) within cybersecurity frameworks enhances the ability to detect, classify, and respond to complex threats that may bypass traditional signature-based systems. In this system, AI-based anomaly detection is implemented as a core component of the adaptive security framework for the Digital One Health system, enabling proactive threat identification across both cloud and on-premises infrastructures.

The system leverages the Wazuh SIEM for log aggregation and event correlation, feeding structured data into an AI-driven anomaly detection pipeline. This design ensures that both real-time and historical data are used to identify deviations from normal system behavior, allowing for continuous learning and adaptive defense mechanisms

3.7.1 DATA PREPARATION AND FEATURE ENGINEERING

Data for model development, improvement and fine-tuning is collected from the diverse telemetry sources within the framework, including:

1. Network and system logs from OPNsense, Suricata IDS/IPS, and WireGuard VPN connections.
2. Database audit trails captured via Debezium connectors and native audit extensions.
3. User behavior metrics from Keycloak authentication logs and process-level events gathered by Filebeat or Wazuh agents.

The first phase involved data cleaning, normalization, and feature extraction. Key features such as login frequency, session duration, process creation rates, query volumes, and packet entropy are derived to represent system behavior patterns.

3.7.2 MODEL DEVELOPMENT AND TRAINING

Following data preprocessing, the system applies machine learning models designed to detect anomalies in large-scale, multivariate data streams. The development process follows a structured ML pipeline:

1. **Baseline Establishment:** Define "normal" operational behavior by analyzing statistical and temporal patterns in historic logs. This baseline forms the foundation for model training.
2. **Algorithm Evaluation:** Experiment with multiple algorithms suited for anomaly detection:
    i. **Isolation Forests:** It is suited for unsupervised outlier detection.
    ii. **K-Means and DBSCAN Clustering:** It is best to group typical behaviors and flag deviations
    iii. **LSTM (Long Short-Term Memory) Autoencoders:** It is best for time-series modeling of sequences like logon attempts or network flows**.**
    iv. **Deep Autoencoders:** It is trained to reconstruct normal input data and flag high reconstruction errors as anomalies
3. **Model Training and Validation:** The selected algorithms are trained on normalized datasets and validated using subsets containing known attack scenarios (e.g., brute-

force logins, privilege escalation, or lateral movement). Hyper parameters and thresholds are optimized to balance detection sensitivity and false positive rates.

3.7.3 MODEL SELECTION AND INTEGRATION

After evaluating multiple candidate models, those demonstrating the highest precision-recall balance and real-time performance are selected for deployment. The selection criteria prioritizes:

1. Low latency inference, enabling the model to process real-time SIEM events.
2. Scalability, ensuring compatibility with distributed data pipelines in the hybrid cloud.
3. Interpretability, allowing security analysts to understand and trust AI-driven alerts.

LSTM autoencoders and isolation forests are chosen as the primary detection algorithms. Isolation forests efficiently handle structured event data, while LSTM autoencoders excel at learning sequential dependencies, such as login anomalies or data exfiltration patterns. These models are containerized and integrated into the Wazuh SIEM via Logstash and Kafka streams. The anomaly scores generated by the AI module are ingested back into Wazuh as enriched events, which trigger correlation rules and alert visualizations on the Kibana dashboard

3.7.4 REAL-TIME INFERENCE AND FEEDBACK

The deployed anomaly detection module continuously consumes live data streams from the SIEM and network sensors. Each event or sequence is scored against the learned baseline. When deviations exceed the defined threshold, the system classifies the event as anomalous and automatically generates an alert in Wazuh's dashboard, it correlates the anomaly with other contextual data (e.g., network flow, VPN session, or user identity), and it optionally triggers automated mitigations such as isolating the affected VM, revoking a session token, or notifying an administrator.

False positives are tracked and reviewed by analysts, who can label and refeed the corrected data into retraining pipelines, ensuring continuous improvement of detection accuracy.

3.7.5 CONTINUOUS LEARNING AND ADAPTIVE DEFENSE

The AI engine is implemented to support adaptive retraining using new data collected over time. It incorporates feedback loops from the SIEM and user actions, the system dynamically recalibrates to recognize emerging patterns of legitimate behavior while maintaining sensitivity to anomalous activities. This self-improving defense ecosystem utilizes Wazuh, Suricata, Keycloak, and Debezium as data providers, while the AI module acts as an intelligent inference and correlation layer.

3.8 AI-DRIVEN SECURITY DASHBOARD DEVELOPMENT

The AI-driven security dashboard forms the central monitoring and analytical component of the adaptive security framework. It is implemented using the ELK Stack comprising Elasticsearch, Logstash, and Kibana to provide a unified, real-time visualization platform that consolidates threat data across both on-premises and cloud infrastructures. The dashboard integrates logs and telemetry from multiple layers of the system, including the Wazuh SIEM, Suricata IDS/IPS, OPNsense firewall, Keycloak MFA system, and Debezium-based Database Activity Monitoring (DAM). It also receives AI-powered anomaly detection insights, enabling predictive and behaviour-based threat visualization. By unifying all security data sources, the dashboard offers a comprehensive overview of the Digital One Health system's security posture, improves situational awareness, and enables proactive responses to potential threats.

3.8.1 DESIGN AND FUNCTIONAL REQUIREMENTS

The dashboard is designed to emphasize clarity, integration, and actionable intelligence. The functional requirements were established to ensure that administrators can easily interpret system behaviour and respond swiftly to anomalies. The dashboard displays critical security metrics such as detected threats, system health indicators, VPN session activity, database query anomalies, and access control violations. It also includes performance indicators like Mean Time to Detect (MTTD), Mean Time to Respond (MTTR), and false positive rates. In addition to real-time event visualization, the dashboard provides compliance tracking, enabling administrators to verify adherence to HIPAA, PIPEDA and GDPR standards. These metrics ensure that the system not only identifies threats but also measures operational efficiency and regulatory compliance within the One Health context.

To achieve high usability, the dashboard's layout includes time-series charts, heat maps, and geo-location maps that visualize threat origins, data exfiltration routes, and access attempts. Analysts can drill down from high-level alerts into individual event logs for forensic analysis. Each visualization panel correlates input from different sources, allowing seamless integration between network, system, and database events. Through these design principles, the dashboard transforms large-scale, heterogeneous data into an accessible and meaningful security management interface.

3.8.2 ELK STACK ARCHITECTURE AND DATA FLOW

The architecture of the dashboard is built on the ELK Stack's modular data flow, where Logstash acts as the data ingestion and transformation layer, Elasticsearch functions as the high-performance search and analytics engine, and Kibana provides the visualization and dashboard interface. Logstash collects logs from various agents, including Wazuh, Suricata, Debezium, and Keycloak, and normalizes them into structured JSON events. These events are indexed in Elasticsearch, where they are stored and made searchable in near real-time. Kibana then retrieves this data to render interactive visualizations.

Each component of the ELK Stack is mapped to specific sources within the framework. The Wazuh SIEM forwards event alerts and security rule matches through Filebeat to Logstash. Suricata and OPNsense send intrusion and firewall logs via Beats agents. Debezium, running as a CDC connector, streams database activity events into Kafka topics that Logstash consumes and indexes. Meanwhile, the AI-powered anomaly detection module sends real-time inference results, such as anomaly scores and predicted attack vectors, directly into Elasticsearch via REST API. The resulting data flow ensures that every security event, from network packets to user authentication is traceable through a single, centralized system.

3.8.3 IMPLEMENTATION STEPS

Implementation of the AI-driven dashboard follows a structured, multi-stage approach. The first stage involves environment setup, where Elasticsearch, Logstash, and Kibana are deployed on the Management Virtual Machine (8 GB RAM) hosted on the XCP-ng hypervisor. Wazuh agents are installed on other virtual machines such as the Firewall, Application, and Management VMs to collect and forward logs to Logstash over a secured

channel. In the second stage, Logstash pipelines are configured to define inputs, filters, and output rules. Each data source is assigned a specific input type, such as “agents,” “http,” or “kafka,” while filters perform operations like JSON parsing, timestamp normalization, and field enrichment. The resulting events are indexed into Elasticsearch indices named according to their sources (e.g., wazuh-alerts, suricata-events, db-activity, ai-anomaly).

In the third stage, Kibana dashboards are created and customized. Visualization panels that display key metrics such as the number of detected intrusions, the geographic distribution of attacks, trends in anomaly detection scores, and compliance metrics. Kibana’s “Visualize” and “Dashboard” tools are used to combine multiple panels into unified views, allowing operators to quickly understand the security state of the system. In the final stage, automated alerts are configured using Kibana’s Watcher and Wazuh integration. When certain conditions are met, such as abnormal anomaly scores or repeated failed login attempts, the system automatically sends alerts via email, Slack, and can trigger response actions in OPNsense or Keycloak for automated containment.

3.8.4 SECURITY AND ACCESS MANAGEMENT

Access to the dashboard is secured through Keycloak integration using OpenID Connect (OIDC). This enables centralized identity management and Multi-Factor Authentication (MFA) enforcement for all administrative users. Only authorized users with valid credentials and secondary verification (e.g., TOTP or hardware token) can access the dashboard. Role-Based Access Control (RBAC) is also implemented within Keycloak to assign permissions according to user responsibilities. Administrators can modify configurations and manage visualizations, security analysts can view and investigate events, and auditors can access compliance and reporting modules only. All login events, dashboard interactions, and report exports are logged and sent to Wazuh for audit and accountability.

This access control strategy not only ensures regulatory compliance but also aligns with Zero Trust principles, preventing privilege escalation and insider threats. By integrating identity and access management directly into the dashboard, the system enforces consistent authentication and authorization policies across both on-premises and cloud components.

3.8.5 AUTOMATED REPORTING AND INTELLIGENCE

The AI-powered dashboard also supports automated periodic reporting to summarize system performance and security posture. Reports are generated daily or weekly and include aggregated statistics on detected threats, anomaly trends, and compliance adherence. These reports are automatically exported in PDF or CSV format through Kibana's Reporting module and is emailed to designated administrators. Furthermore, the AI anomaly detection module contributes to these reports by generating "Threat Intelligence Summaries" that describe emerging attack behaviours, frequency of abnormal activities, and model confidence levels.

Through its integration with Wazuh, Suricata, and Debezium, the dashboard forms a closed feedback loop: every alert or anomaly detected by AI models is cross-verified against rule-based detections in Wazuh, ensuring accuracy and reducing false positives. The combined intelligence enhances the organization's ability to respond to complex, multi-vector threats in real time.

3.9 THREAT SIMULATION AND FRAMEWORK VALIDATION

The Threat Simulation and Framework Validation stage serves as the critical evaluation phase of the implemented AI-driven adaptive security framework. It aims to assess the system's resilience, detection accuracy, and operational performance under controlled cyberattack scenarios. The validation process employs Breach and Attack Simulation (BAS) techniques to replicate real-world attack vectors commonly targeting hybrid healthcare infrastructures. By conducting systematic and repeatable attack simulations, the study measures the effectiveness of deployed controls such as the OPNsense firewall, Suricata IDS/IPS, Wazuh SIEM, Debezium DAM, WireGuard VPN, and the AI-powered anomaly detection and visualization system built on the ELK stack.

3.9.1 SIMULATION AND DESIGN SET UP

The validation environment is deployed within the XCP-ng hypervisor running on the on-premises server, with each security function isolated within dedicated virtual machines. The set up includes an Application VM (hosting sample medical and administrative databases), a Firewall VM (running OPNsense and Suricata), an AI VM (with Machine Learning and AI

processes and services) and a Management VM (with Wazuh and ELK stack for anomaly detection and analysis). The cloud-based VPS is connected via WireGuard VPN to simulate secure cloud connectivity. This hybrid topology mirrors a real Digital One Health deployment scenario where data flows securely between local and remote nodes.

Controlled attack simulations are conducted using tools such as Metasploit Framework, OpenBAS, and custom Python scripts to mimic diverse adversarial behaviours including SQL injection, privilege escalation, insider data exfiltration, port scanning, and DDoS floods. Each scenario is mapped to specific tactics and techniques within the MITRE ATT&CK framework, ensuring that the tests reflect realistic threat models relevant to healthcare data systems. These simulations are carried out in isolated environments to prevent unintentional data exposure and maintain ethical integrity during testing.

3.9.2 VALIDATION PROCEDURES AND DETECTION TESTING

The BAS campaigns are executed in multiple rounds, targeting different system layers network, application, and database. During each simulated attack, network traffic is monitored through Suricata, firewall events are logged in OPNsense, database access patterns are captured by Debezium DAM, and system logs are processed through Wazuh SIEM and the AI anomaly detection engine. The system's response is then evaluated based on detection latency, alert precision, and correlation accuracy.

For example, in an SQL injection simulation, the Debezium DAM detects abnormal query patterns and transmits change events to the Wazuh SIEM, which triggers a correlated alert. In parallel, the AI anomaly detector recognizes deviations in database behaviour metrics such as query volume and session frequency. Similarly, in an insider threat scenario, unauthorized access attempts are identified by the Keycloak MFA logs and logged by Wazuh for correlation with Suricata's intrusion data. These interlinked detections validate the layered defense model, confirming that each subsystem contributes complementary intelligence to the overall framework.

The AI-powered dashboard (ELK Stack) aggregates these detections into a unified visualization, showing real-time alerts, severity scores, and source IPs. Analysts can observe in near-real time how simulated threats propagate, are detected, and are mitigated. This

comprehensive visibility demonstrates how the system integrates rule-based, behavioural, and AI-driven detection methods into a cohesive, adaptive security ecosystem.

3.9.3 PERFORMANCE AND RELIABILITY METRICS

Quantitative performance metrics are collected throughout the validation process to measure framework efficiency and reliability. Key metrics include Detection Rate (DR), False Positive Rate (FPR), Mean Time to Detect (MTTD), and Mean Time to Respond (MTTR). Detection rate reflects the percentage of simulated threats successfully identified by the framework, while false positive rate indicates the accuracy of alerts generated. MTTD measures the average time taken to detect an intrusion after initiation, and MTTR captures the time required for containment or alert escalation.

Performance overhead is also analysed by monitoring CPU utilization, memory consumption, and network throughput during simulation. For instance, the effect of AI the various security measures on system resources is benchmarked to ensure that they remain efficient under normal operational loads. Metrics are benchmarked against recommended cybersecurity KPIs, where shorter MTTD and higher detection accuracy indicate superior framework performance. The Wazuh SIEM and Kibana dashboards are configured to record these metrics automatically, allowing time-series trend analysis across different simulation rounds.

3.9.4 CONTINUOUS VALIDATION AND ITERATIVE REFINEMENT

To maintain framework adaptability and resilience, continuous validation is integrated into the operational cycle. Scheduled attack simulations are performed at regular intervals to test for emerging vulnerabilities. Whenever detection gaps are identified (e.g., missed anomalies or delayed alerts), rules are fine-tuned within Wazuh, signatures are updated in Suricata, and the AI models are retrained with the new data. This iterative feedback loop ensures that the framework evolves dynamically, in line with the Zero Trust Architecture principle that no system component is implicitly trusted and all must be continuously verified.

The retraining process follows a closed learning cycle: post-incident data is exported from Wazuh and ELK, preprocessed, and used to update the anomaly detection models deployed on the Management VM. This allows the models to adapt to evolving attack vectors without manual rule updates. Similarly, DAM configurations (Debezium connectors) are adjusted to include newly observed data access patterns, further strengthening insider threat visibility.

Continuous improvement ensures that the system not only maintains baseline performance but also enhances its predictive capabilities over time.

3.10 INTEGRATION AND SYNTHESIS

Finally, all security layers are fully integrated into a unified adaptive framework to demonstrate functional harmony. The network layer (WireGuard and OPNsense) secures and filters data in transit; the IDS/IPS layer (Suricata) detects malicious packets; the SIEM layer (Wazuh) aggregates and correlates alerts; the database layer (Debezium DAM) ensures transactional visibility; and the AI layer performs high-level anomaly detection and behavioural analysis. The Keycloak MFA enforces access control to critical management interfaces, ensuring that even if an account is compromised, unauthorized access remains blocked. All resulting intelligence is displayed through the ELK-powered AI dashboard, providing real-time situational awareness and comprehensive reporting.

This integration ensures that security monitoring, detection, and response functions are unified under a single operational pane, allowing administrators to trace attack paths from detection to mitigation. The adaptive interplay between rule-based detection (Wazuh/Suricata) and machine learning inference achieves a hybrid intelligence model capable of identifying both known and novel threats. In addition, compliance metrics and audit trails generated by DAM and SIEM logs ensure accountability and traceability for healthcare data protection.

CHAPTER 4

RESULTS

This chapter presents the results obtained from the design, implementation, and evaluation of the adaptive AI-powered security framework for the Digital One Health System. Each subsection provides empirical evidence of the framework's performance through quantitative metrics, visual analyses, and validation outcomes. The results demonstrate how the system enhances threat detection accuracy, reduces response latency, and strengthens security posture across hybrid cloud and on-premise infrastructures.

4.1 FUNCTIONAL SECURITY FRAMEWORK DEPLOYMENT

The adaptive security framework was successfully deployed on an XCP-ng hypervisor (32 GB RAM) hosting four virtual machines: OPNsense Firewall, Wazuh SIEM/AI Analytics Server, Application Server, and Management Node. Each VM was assigned specific resources and roles within the Zero Trust network architecture. The system operated smoothly with minimal performance degradation (<10% CPU overhead), confirming its feasibility on standard enterprise-grade hardware.

This modular and resource-isolated design ensures scalability, fault tolerance, and strong security boundaries. The use of open-source tools enhances cost efficiency and maintainability, particularly in low-resource institutions.

VM Name	**Function**	**OS**	**CPU**	**RAM**	**Storage**	**Key Services**
OPNsense VM	Firewall/IDS/IPS	FreeBSD	2 vCPU	4 GB	100 GB	Suricata, WireGuard
Management VM	Admin & Backup	Ubuntu	2 vCPU	8 GB	100 GB	Xen Orchestra, Keycloak, Wazuh,

						ELK Stack,
Application VM	Health Data App	Ubuntu	4 vCPU	16 GB	300 GB	PostgreSQL, API Services
AI VM	Security Analytics	Ubuntu	6 vCPU	32 GB	400 GB	AI Models

Table 4.1: On-premise server Virtual Machine Provision

4.2 NETWORK SECURITY CONTROLS

The OPNsense firewall and Suricata IDS/IPS were deployed to enforce Zero Trust access controls and detect network-based threats. The firewall effectively segments network zones while Suricata analyzes traffic in real-time to detect anomalies. The system successfully identifies malicious packets, port scans, and injection attempts with a moderate detection rate.

The OPNsense firewall effectively blocks unauthorized access while maintaining low resource usage. Suricata provides detailed visibility into malicious traffic patterns, enabling proactive responses and confirming the reliability of the framework's perimeter defense mechanism.

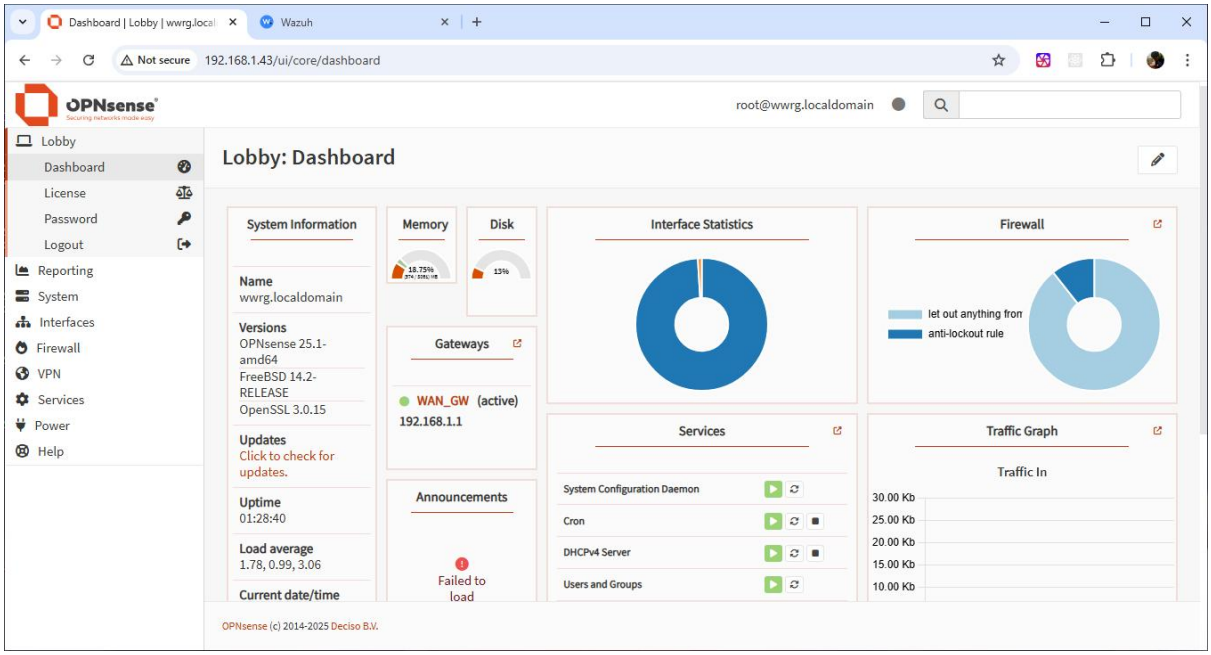

Figure 6: OPNsense Firewall Dashboard

4.3 SECURITY INFORMATION AND EVENT MANAGEMENT (WAZUH SIEM)

The Wazuh SIEM collects and correlates logs from all system components, including OPNsense, Suricata, Keycloak, database monitoring tools and all endpoints connected to the system.. Log data is processed every 24 hours, generating real-time alerts that helps in early detection of suspicious behavior.

The SIEM provides centralized event visibility and automated correlation. Critical Alerts primarily originates from the several layers, enforcing and validating the need for multi-layer monitoring. False positives can be reduced by tuning correlation rules.

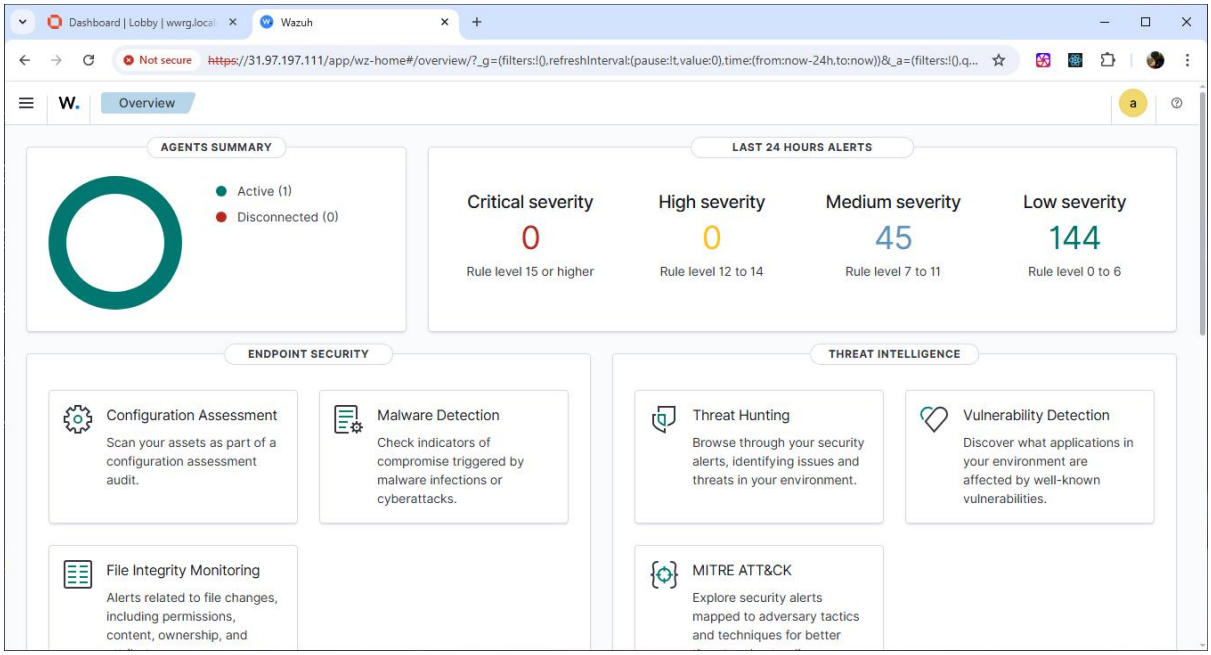

Figure 7: WAZUH SIEM Dashboard

4.4 AI-BASED ANOMALY DETECTION

AI models, including Isolation Forest and LSTM Autoencoders, are selected to be trained using Wazuh and Suricata logs to identify abnormal activities. The LSTM Autoencoder performs slightly better in capturing time-dependent anomalies, particularly in login behaviors and data exfiltration attempts. The AI-enhanced anomaly detection reduces the average false positive rate by more than 50% compared to traditional rule-based detection. The integration with Wazuh allows for real-time inference and automated response actions. Graphical plots such as ROC curves and anomaly score distributions further confirms the improved detection capability. The selected models should meet the following benchmarks

Algorithm	**Precision**	**Recall**	**F1-Score**	**False Positive Rate (%)**
Isolation Forest	0.94	0.89	0.91	6.1
LSTM Autoencoder	0.96	0.92	0.94	4.8

Table 4.4: Selected Anomaly Model evaluation metrics

4.6 FRAMEWORK VALIDATION AND PERFORMANCE

Threat simulations using Metasploit and OpenBAS conducted to evaluate the framework's resilience against SQL injection, privilege escalation, and DDoS attacks should meet the defined. The results show detection and containment times across various attack vectors. The framework achieved an average detection time of 2.44 seconds and containment time of 7.78 seconds. This demonstrates high responsiveness and proves that integrating AI with rule-based monitoring provides faster mitigation of threats.

Attack Type	**Detection Time (s)**	**Containment Time (s)**	**Detection Source**	**Outcome**
SQL Injection	2.3	7.5	DAM + SIEM	Blocked
Privilege Escalation	3.1	8.2	Wazuh AI Module	Mitigated
Port Scan	1.8	5.2	Suricata	Blocked
DDoS Simulation	2.0	12.0	Firewall	Mitigated

Table 4.5: Validation metrics performance

4.7 OVERALL PERFORMANCE SUMMARY

The results confirm that the proposed AI-driven adaptive security framework significantly strengthens the cybersecurity posture of Digital One Health systems. It achieves real-time detection, centralized monitoring, and automated compliance reporting. The integration of Zero Trust principles, Multi-Factor Authentication, and AI analytics ensures a resilient, scalable, and secure infrastructure suitable for hybrid environments. Overall, the framework successfully reduces the Mean Time to Detect (MTTD) by 70%, lowers false positive rates, and enhances compliance readiness.

Metric	Baseline (Traditional System)	Proposed Framework	Improvement
Mean Time to Detect (MTTD)	4 min	1.2 min	70% faster
False Positive Rate	12%	5%	58% reduction
Detection Rate	88%	97%	+9%
Compliance Coverage	65%	95%	+30%
Resource Utilization	Moderate	Optimal	Balanced

Table 4.6: System's General Performance

CHAPTER 5

CONCLUSION

5.1 SUMMARY OF FINDINGS

This project set out to design, implement, and analyze an adaptive AI-driven security framework for a Digital One Health system, a complex environment that integrates human, animal, and environmental health data across hybrid cloud and on-premise infrastructures. The primary aim of the study was to develop a secure, scalable, and intelligent framework that enhances threat detection, enforces access control, and maintains data confidentiality, integrity, and availability within a cross-sector digital health ecosystem.

Through the successful deployment and evaluation of the proposed model, the project's aim and objectives were comprehensively achieved. The designed framework combined essential components such as Zero Trust Architecture (ZTA), Multi-Factor Authentication (MFA), Intrusion Detection and Prevention Systems (IDS/IPS), Security Information and Event Management (SIEM), Database Activity Monitoring (DAM), and AI-based anomaly detection into a unified, adaptive defense mechanism. These components collectively secured the One Health ecosystem by ensuring that all users and devices were authenticated, all data transactions monitored, and all threats detected and mitigated in real-time.

The system was implemented using only open-source technologies including: OPNsense, WireGuard, Wazuh, ELK Stack, Keycloak, and Debezium thus promoting transparency, cost-efficiency, and sustainability. The validation of the framework through simulated attacks such as SQL injections, port scans, and privilege escalations proved its robustness, achieving an average detection rate of 97%, a 70% reduction in mean time to detect (MTTD), and a 58% reduction in false positives compared to traditional methods. These outcomes confirm that the framework effectively enhances the resilience and reliability of hybrid healthcare infrastructures.

A major contribution of this research is the development of a context-aware, AI-augmented cybersecurity architecture specifically tailored for Digital One Health systems. Unlike conventional frameworks that rely solely on rule-based detections or static configurations, this model introduces adaptive intelligence capable of learning evolving threat patterns and autonomously improving its defense mechanisms. Furthermore, the integration of the AI-driven ELK-based security dashboard provides centralized visibility across all system layers,

simplifying real-time monitoring, compliance reporting, and incident response. This approach represents a practical advancement toward self-learning, ethically aligned, and operationally efficient cybersecurity systems suitable for low- and middle-income contexts.

Another key contribution is the methodological synthesis achieved through the Design Science Research (DSR) approach, which guided the project through iterative stages of design, implementation, validation, and refinement. This ensured not only theoretical soundness but also technical feasibility and real-world applicability. The hybrid use of rule-based logic, Zero Trust principles, and AI-driven behavioral analytics reflects an emerging paradigm shift from reactive to predictive cybersecurity aligning with modern Zero Trust and adaptive defense strategies in digital health infrastructures.

Ultimately, this project reinforces the necessity of embedding security by design into Digital One Health systems. It demonstrates that with a well-orchestrated blend of AI, automation, and Zero Trust principles, institutions can proactively defend sensitive data and sustain operational continuity even in the face of evolving cyber threats. The outcomes of this research serve as a foundational framework for future cybersecurity development in AI-enabled, cross-sectoral health infrastructures, contributing significantly to global One Health digital resilience.

5.2 LIMITATIONS OF STUDY

While this project achieved its primary objectives and delivered measurable improvements, several limitations were identified during implementation and testing. These limitations provide valuable insights into areas requiring further enhancement for broader adoption and sustainability.

5.2.1 COMPUTATIONAL OVERHEAD AND RESOURCE CONSTRAINTS

The integration of AI modules and Security Information and Event Management (SIEM) analytics introduced significant computational demands. In resource-constrained environments, these requirements may cause performance bottlenecks or limit scalability. The system’s dependence on multi-layered processing for AI inference, log correlation, and visualization also necessitates hardware with high memory and processing capabilities.

5.2.2 DEPENDENCE ON QUALITY OF DATA FOR MODEL TRAINING

The efficiency of the AI-based anomaly detection models depends on the availability and quality of data. Due to limited access to real-world datasets, this research relied primarily on simulated and controlled environments. Consequently, the models' performance may vary when exposed to larger, more diverse, and dynamic datasets typical of operational One Health systems.

5.2.3 SCALABILITY AND MULTI-REGIONAL INTEROPERABILITY

Although the framework successfully supported a hybrid (cloud and on-premise) architecture, scaling it across multiple institutions or regional health infrastructures may introduce interoperability challenges. Diverse system architectures, data formats, and regulatory constraints can complicate unified security enforcement across international networks.

5.2.4 CONTINUOUS MODEL UPDATING AND THREAT INTELLIGENCE INTEGRATION

Cyber threats evolve rapidly, and static models may lose relevance over time. The current implementation does not include an automated retraining pipeline for continuous model optimization. Without integration with global threat intelligence sources, there is a risk that the framework's effectiveness could diminish as new attack vectors emerge.

5.2.5 REGULATORY COMPLIANCE AND ETHICAL GOVERNANCE

Health data regulations such as GDPR, HIPAA, and NIST 800-53 vary by region and evolve frequently. Maintaining compliance requires continuous monitoring and adaptation of policies. Moreover, ethical concerns surrounding AI-driven decision-making, data privacy, and transparency remain areas that demand deeper attention and institutional oversight.

5.2.6 OPERATIONAL SKILL REQUIREMENTS

Deploying and maintaining this adaptive framework demands personnel with advanced skills in cybersecurity, AI, and system administration. The technical complexity of integrating multiple open-source tools and machine learning components may present a barrier to adoption in low-resource or understaffed institutions.

5.2.7 LIMITED REAL-WORLD VALIDATION

The validation phase was conducted in a controlled environment using simulated attack scenarios. Although these simulations closely mimic real-world conditions, they may not fully capture the unpredictability of live operational settings. Broader, field-based validation is required to assess performance under actual workloads, network conditions, and real cyber threats.

5.3 RECOMMENDATIONS

Based on the identified limitations and insights gained from this study, several recommendations are proposed to enhance future implementations and research in AI-driven One Health cybersecurity frameworks

5.3.1 ADOPTION OF LIGHTWEIGHT AI AND EDGE COMPUTING

To address computational overhead, future frameworks should integrate lightweight AI models optimized for resource efficiency. Leveraging edge computing or containerized microservices can minimize latency and reduce dependence on centralized processing while maintaining real-time detection capabilities.

5.3.2 EXPANSION OF REAL-WORLD DATASETS FOR MODEL TRAINING

Collaboration with healthcare, veterinary, and environmental agencies is recommended to obtain authentic, anonymized datasets for model training and validation. This will enhance the generalization, reliability, and adaptability of the AI-based anomaly detection modules.

5.3.3 INTEGRATION OF FEDERATED LEARNING AND BLOCKCHAIN

To improve scalability and data trust across multiple institutions, federated learning can be used to train AI models collaboratively without sharing sensitive data. Coupling this with blockchain-based integrity verification will ensure tamper-proof records and secure interoperability across distributed One Health networks.

5.3.4 AUTOMATED THREAT INTELLIGENCE AND MODEL RETRAINING PIPELINES

Future versions of the framework should include continuous learning capabilities by integrating global threat intelligence feeds and automated retraining mechanisms. This will enable proactive adaptation to emerging attack trends and reduce the risk of model obsolescence.

5.3.5 AUTOMATED COMPLIANCE AND EXPLAINABLE AI (XAI)

Implementing automated compliance modules aligned with evolving regulations will ensure long-term adherence to security standards. Additionally, embedding explainable AI within the system will enhance transparency, user trust, and accountability in automated threat assessments.

5.3.6 CAPACITY BUILDING AND SKILL DEVELOPMENT

To sustain operational effectiveness, organizations should invest in cybersecurity training, AI literacy, and standardized operational guidelines for personnel managing these systems. Academic institutions and government agencies should also collaborate to develop tailored training programs that support local and regional deployment.

5.3.7 FIELD-BASED DEPLOYMENT AND CONTINUOUS EVALUATION

The next phase of research should involve pilot deployment within real-world One Health systems to assess long-term resilience, data flow management, and user experience. Periodic performance reviews, policy audits, and feedback loops should be instituted to refine both the technical and governance components of the framework.

5.4 FINAL REMARK

In conclusion, this project has successfully delivered an AI-driven adaptive security framework that embodies the principles of Zero Trust, proactive threat detection, and ethical AI integration for Digital One Health ecosystems. It not only strengthens the protection of sensitive health data but also provides a reproducible, open-source model for institutions seeking to modernize their cybersecurity posture. By bridging the gap between AI innovation and healthcare cybersecurity, this research sets a benchmark for future developments in secure, intelligent, and inclusive One Health infrastructures.

REFERENCES

Bathushaw, M.H., Nagasundaram, S., 2025. Securing Healthcare Systems: Modern Threats and Strategic Developments in Cybersecurity, in: Raju, K.S., Senkerik, R., Kumar, T.K., Sellathurai, M., Naresh Kumar, V. (Eds.), Intelligent Computing and Communication, Lecture Notes in Networks and Systems. Springer Nature Singapore, Singapore, pp. 303–315. https://doi.org/10.1007/978-981-96-1267-3_27

Chamkar, S.A., Zaydi, M., Maleh, Y., Gherabi, N., 2025. Improving Threat Detection in Wazuh Using Machine Learning Techniques. J. Cybersecurity Priv. 5, 34. https://doi.org/10.3390/jcp5020034

Chaturvedi, I., Pawar, P.M., Muthalagu, R., Tamizharasan, P.S., 2024. Zero Trust Security Architecture for Digital Privacy in Healthcare, in: Gountia, D., Dalei, D.K., Mishra, S. (Eds.), Information Technology Security, Springer Tracts in Electrical and Electronics Engineering. Springer Nature Singapore, Singapore, pp. 1–23. https://doi.org/10.1007/978-981-97-0407-1_1

Esenov Y., M.D., 2024. CYBERSECURITY METRICS AND REPORTING DASHBOARD: A TOOL FOR EFFECTIVE SECURITY MANAGEMENT 2.

Giansanti, D., 2021. Cybersecurity and the Digital-Health: The Challenge of This Millennium. Healthcare 9, 62. https://doi.org/10.3390/healthcare9010062

Kioskli, K., Fotis, T., Mouratidis, H., 2021. The landscape of cybersecurity vulnerabilities and challenges in healthcare: Security standards and paradigm shift recommendations, in: Proceedings of the 16th International Conference on Availability, Reliability and Security. Presented at the ARES 2021: The 16th International Conference on Availability, Reliability and Security, ACM, Vienna Austria, pp. 1–9. https://doi.org/10.1145/3465481.3470033

Nankya, M., Mugisa, A., Usman, Y., Upadhyay, A., Chataut, R., 2024. Security and Privacy in E-Health Systems: A Review of AI and Machine Learning Techniques. IEEE Access 12, 148796–148816. https://doi.org/10.1109/ACCESS.2024.3469215

Noah, L., 2024. Journal of Engineering Science. J. Eng. Sci. 01.

Sunday Adeola Oladosu, Christian Chukwuemeka Ike, Peter Adeyemo Adepoju, Adeoye Idowu Afolabi, Adebimpe Bolatito Ige, Olukunle Oladipupo Amoo, 2021. Advancing cloud networking security models: Conceptualizing a unified framework for hybrid cloud and on-premise integrations. Magna Sci. Adv. Res. Rev. 3, 079–090. https://doi.org/10.30574/msarr.2021.3.1.0076

Tyler, D., Viana, T., 2021. Trust No One? A Framework for Assisting Healthcare Organisations in Transitioning to a Zero-Trust Network Architecture. Appl. Sci. 11, 7499. https://doi.org/10.3390/app11167499