MACHINE LEARNING FOR LATERAL MOVEMENT DETECTION AND PREDICTION IN ZERO TRUST NETWORKS: A SYSTEMATIC LITERATURE REVIEW

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Abstract: *Zero Trust Architecture (ZTA) is a new approach to cybersecurity that prevents lateral movement and secures perimeters in an interconnected, borderless world. ZTA, however, follows a "never trust, always verify" model that mandates dynamic authentication mechanisms, micro-segmentation as well as stringent access controls irrespective of where users are located or the devices they use. Forced JIT-PLE of authenticated sessions remains the Achilles' heel of ZTA despite its increasing static at the per-device level, as compromised devices can use them to compromise environments for malicious acts. Although Threat Detection Enhancement through Threat Machine Learning (ML) has shown promise, there is little research on Predictive Lateral Movement Forecasting within Zero Trust. This research presents a comprehensive review of the literature concerning machine learning strategies for detecting and predicting lateral movement in Zero Trust networks. Adhering to the PRISMA guidelines, 45 peer-reviewed articles published between 2019 and 2025 were chosen from an initial collection of 380 papers. The review consolidates existing machine learning approaches, such as Markov Chain models, Long Short-Term Memory (LSTM) networks, Random Forests, and anomaly detection techniques. The main findings reveal that although machine learning-based detection has shown considerable success, with accuracy rates between 72% and 94%, predictive forecasting is still inadequately explored, as only 29% of the studies examined addressed prediction capabilities. Additionally, the use of Zero Trust policy violation artifacts as sources for predictive data represents a notable research gap. Based on these findings, a research agenda is proposed for advancing predictive cyber threat intelligence in Zero Trust environments.*

Keywords: *Lateral movement detection; Zero Trust Architecture; machine learning; predictive cyber threat intelligence; systematic literature review*

Introduction

With the growth of cloud computing and the swift shift to remote work driven by the COVID-19 pandemic, organizations have had to extend their digital boundaries beyond conventional limits. The security model that relies on a well-defined perimeter, known as the "castle-and-moat" approach, assumes that resources within the perimeter are secure and reliable. However, this model has proven increasingly inadequate in the context of cloud computing and remote work, as highlighted by numerous cyber-attacks targeting employees working from home.

Statement of the Problem

As noted by Alevizos et al. [1], conventional security measures like firewalls, antivirus programs, intrusion detection systems, and web application firewalls are becoming insufficient for safeguarding modern IT landscapes. Zero Trust Architecture (ZTA) has emerged as a potential approach, establishing a perimeter based on digital identity with a mindset that assumes a breach has occurred [2]. Nonetheless, as Alevizos et al. [1] keenly point out, endpoints still pose the "Achilles heel of ZTA." Once an endpoint is compromised, attackers can manipulate the security health checks of ZTA and exploit authenticated user sessions to facilitate harmful lateral movement. Moreover, although machine learning-based detection methods have shown potential, forecasting lateral movement within Zero Trust settings using predictive analytics remains significantly

underexplored.

Topic/Aim

Problem Domain Title: Lateral movement detection and prediction in Zero Trust networks

Solution Domain Title: Machine learning-based frameworks for proactive lateral movement forecasting using Zero Trust policy violation artifacts

Objectives

1. To systematically identify and categorize machine learning methods proposed for lateral movement detection and prediction
2. To analyze how security logs have been utilized as data sources for attack prediction
3. To assess the current state of Zero Trust-specific predictive analytics
4. To identify datasets and evaluation metrics reported in existing studies
5. To synthesize research gaps in applying sequence prediction to Zero Trust policy violation artifacts

Research Questions

Research Questions with Rationale and Search Terms

1. What machine learning methods have been proposed for lateral movement detection and prediction in network security?

Search String: ("lateral movement" OR "attack path") AND ("machine learning" OR "deep learning" OR "LSTM" OR "Markov")

2. How have security logs been utilized as data sources for attack prediction?

Search String: ("security logs" OR "authentication logs" OR "audit trails") AND ("prediction" OR "forecasting")

3. What is the current state of Zero Trust specific predictive analytics?

Search String: ("Zero Trust" OR "ZTNA" OR "micro-segmentation") AND ("predictive analytics" OR "forecasting")

4. What datasets and evaluation metrics are reported in existing studies?

Search String: ("dataset" OR "benchmark") AND ("accuracy" OR "precision" OR "recall" OR "AUC-ROC" OR "F1-score")

5. What research gaps exist in applying sequence prediction to Zero Trust policy violation artifacts?

Search String: ("policy violation" OR "denied access") AND ("sequence prediction" OR "attack path" OR "lateral movement")

Contribution

This review makes the following contributions:

1. A comprehensive synthesis of ML methodologies for lateral movement detection and prediction
2. Identification of data sources and feature engineering approaches for Zero Trust contexts
3. A taxonomy of evaluation metrics and performance benchmarks
4. Systematic identification of research gaps specific to Zero Trust predictive analytics
5. A research agenda for advancing predictive cyber threat intelligence

Existing Systematic Literature Reviews on Zero Trust Architecture

ZTA has attracted considerable research focus since the release of NIST Special Publication 800-207 in 2020. Nevertheless, the quantity of thorough systematic literature reviews on ZTA is still scarce.

Gambo and Almulhem (2025) performed a systematic literature review that maps the development of ZTA from its initial concept to its implementation frameworks. Their review extensively addresses key components (Policy Engine, Policy Administrator, Policy Enforcement Point), enabling technologies (IAM, MFA, micro-segmentation, SASE), and application sectors such as healthcare,

finance, IoT, and 5G/6G networks. They also highlight major challenges to adoption like scalability issues, integration with legacy systems, and the complexity of policy management. However, their review does not concentrate on machine learning techniques for predicting lateral movement, nor does it integrate detection versus prediction strategies.

In 2025, Kipkoech analyzed security within zero trust network architectures, investigating ZTA principles such as least privilege, explicit verification, micro-segmentation, continuous monitoring, and an assume-breach mentality, along with components like IAM, endpoint security, SIEM, DLP, and CASB. The analysis also examines emerging technologies like AI, blockchain, and the integration of SASE. Although Kipkoech points out research gaps in areas like standardization and scalability, the work serves as a survey rather than a comprehensive literature review, has a narrow focus on lateral movement in particular, and does not systematically evaluate machine learning-based prediction methods.

Alevizos, Ta, and Eiza (2022) performed a systematic review aimed at improving zero trust architecture for endpoints through the use of blockchain technology. Their analysis of 43 studies explores distributed collaborative intrusion detection systems (DCIDS) architectures, methods for alert correlation (including filter-based, multi-stage, similarity-based, and attack scenario-based approaches), and mechanisms for assessing alert trustworthiness. They find that blockchain technology has the potential to enhance detection capabilities and strengthen the backend storage of logs and audit trails, while also highlighting endpoints as the "Achilles heel of ZTA." Nevertheless, their emphasis lies on blockchain instead of machine learning, and they do not cover predictive analytics related to lateral movement.

Buck et al. (2021) conducted a multivocal literature review, which included grey literature, on zero trust, titled "Never Trust, Always Verify." They pinpointed three primary drivers for adoption (the rise of remote work, the uptake of cloud computing, and advanced cyber threats) and identified four gaps in research (the absence of formal models, inadequate migration strategies, usability issues, and interoperability challenges). Although the review is thorough in its coverage, it does not assess machine learning performance metrics or compare different solution types for detecting or predicting lateral movement.

Syed et al. (2022) released a detailed survey on Zero Trust Architecture in IEEE Access, discussing essential components, deployment models, enabling technologies (IAM, micro-segmentation, SDN, SASE), and related challenges. The survey explores NIST SP 800-207, Google's BeyondCorp, and the Cloud Security Alliance's Software Defined Perimeter (SDP). However, as a survey rather than a systematic review following PRISMA guidelines, it does not synthesize machine learning methods for lateral movement or provide comparative performance analysis of different detection approaches.

Existing Systematic Literature Reviews on Lateral Movement Detection

Lateral movement detection has been studied extensively, though few SLRs focus specifically on machine learning methods for this task.

Powell (2020) presented an epidemiological perspective on lateral movement, using network contagion models to simulate the dissemination of cyber threats similarly to how infectious diseases spread. This research highlights the roles of spreaders, escalators, and gatekeepers within Active Directory networks through the use of graph centrality metrics. Nevertheless, it is a theoretical framework rather than a comprehensive literature review, and it fails to integrate machine learning techniques from various studies.

Yang et al. (2021) introduced PROWL, a framework for detecting and predicting lateral movement based on provenance, which implements LSTM networks. Their empirical research showed prediction accuracy ranging from 70% to 85% for sequential authentication event patterns, merging detection (with 94% accuracy) and limited predictive abilities. However, this is an empirical study, not a systematic literature review, and it does not provide a comparative analysis of different

machine learning methods.

Existing Systematic Literature Reviews on Machine Learning for Intrusion Detection
Nahar et al. (2024) conducted an examination of the applications and obstacles of Zero Trust Architecture (ZTA) specifically within 6G networks, focusing on ZTA in environments involving 6G-enabled IoT, edge computing, and network slicing. Although they pinpointed open challenges regarding security in ultra-low latency, this review is tailored to the 6G domain and does not cover lateral movement prediction or machine learning techniques applicable to enterprise networks. He et al. (2022) released a survey centered on Zero Trust Architecture, concentrating on obstacles and future developments while reviewing NIST's ZTA framework, key technologies (IAM, SDP, micro-segmentation), and possible deployment scenarios. Nevertheless, this survey takes a broader approach lacking a systematic methodology and does not provide a machine learning-specific analysis for detecting or predicting lateral movement.

Existing Systematic Literature Reviews on Collaborative Intrusion Detection Systems
Collaborative and distributed intrusion detection systems are highly relevant to Zero Trust environments, as ZTA assumes the network is hostile and requires distributed trust evaluation.
Vasilomanolakis et al. (2015) presented a detailed taxonomy and overview of collaborative intrusion detection in ACM Computing Surveys. They examined CIDS architectures (centralized, decentralized, distributed), collaboration methodologies, and highlighted critical issues such as alert correlation, trust management, and scalability. Nonetheless, this review lacks a synthesis related specifically to machine learning, does not emphasize prediction, and fails to consider Zero Trust Architecture.

Li, Meng, and Kwok (2022) analyzed collaborative intrusion detection in the context of IoT, concentrating on challenges faced by CIDNs, intrusion sensitivity, and the use of blockchain for ensuring alert integrity. This book chapter is specific to the IoT domain and does not cover lateral movement prediction within Zero Trust enterprise networks.

Research Gap Justification
Based on the systematic analysis of existing SLRs presented in Sections 2.1 through 2.4, several research gaps are identified that justify the current systematic literature review.

First, no existing SLR focuses specifically on machine learning methods for lateral movement prediction in Zero Trust networks. Current ZTA systematic literature reviews (Gambo & Almulhem, 2025; Kipkoech, 2025; Syed et al., 2022) emphasize architecture, components, and implementation, rather than focusing on machine learning techniques. Reviews on lateral movement (Powell, 2020; Yang et al., 2021) are either not systematic or are empirical studies instead of systematic literature reviews. Reviews concerning collaborative intrusion detection systems (Vasilomanolakis et al., 2015; Li et al., 2022) do not tackle ZTA-specific requirements for prediction.

Second, no prior SLR provides comparative performance evaluation of different machine learning solution classes for lateral movement in ZTA contexts. Existing reviews do not compare Markov Chain accuracy (55-70%) against LSTM accuracy (70-85%) or graph-based detection rates (94.5%). This review provides the first such synthesis of performance benchmarks across solution classes.

Third, the use of Zero Trust policy violation artifacts as predictive data sources has not been previously synthesized. Out of the forty-five studies examined in this systematic literature review, only three specifically utilize denied access logs as sources of predictive data. No existing ZTA systematic literature review has addressed this important gap, since previous reviews primarily concentrate on successful authentications and network traffic, overlooking policy violations that indicate attacker intent prior to successful breaches.

Fourth, the endpoint integrity challenge in ZTA has not been systematically addressed in prior SLRs. While Alevizos et al. (2022) identify endpoints as the "Achilles heel of ZTA," they focus on blockchain solutions rather than machine learning. Only five of forty-five studies in this review address endpoint integrity challenges, representing a significant understudied area.

Fifth, the distinction between detection (71% of reviewed studies) and prediction (29%) has not been previously highlighted in ZTA literature. Existing SLRs treat detection and prediction as undifferentiated, missing the critical insight that predictive capabilities for lateral movement remain significantly underexplored.

SLR PRISMA METHODS

PRISMA Framework

This systematic literature review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines.

3.2 PICOC Framework

Table 3.1: PICOC Keywords and Synonyms Definition

PICOC Element	Description	Keywords	Synonyms
Population	Security logs and network traffic in Zero Trust environments	Security logs, network traffic, authentication events, audit trails	Telemetry data, session logs, packet captures, system events, access records
Intervention	Machine learning methods for detection and prediction of lateral movement	Machine learning, deep learning, LSTM, Markov Chain, Random Forest, XGBoost	Artificial intelligence, neural networks, sequence models, classification algorithms, anomaly detection
Comparison	Detection approaches versus prediction approaches	Detection, prediction, forecasting, proactive defense	Identification, anticipation, early warning, threat forecasting
Outcome	Performance metrics and predictive accuracy	Accuracy, precision, recall, F1-score, AUC-ROC, Top-K accuracy, detection rate	Performance benchmarks, evaluation metrics, prediction accuracy, false positive rate
Context	Zero Trust Architecture (ZTA) environments	Zero Trust, ZTA, ZTNA, micro-segmentation, never trust always verify	Perimeter-less security, software-defined perimeter, identity-centric security

Search Strategy and String

The following search string was used across all five databases:
("lateral movement" ***OR*** "attack path" ***OR*** "intrusion prediction")
AND
("machine learning" ***OR*** "deep learning" ***OR*** "Markov" ***OR*** "LSTM" ***OR*** "Random Forest" ***OR*** "XGBoost")
AND
("Zero Trust" ***OR*** "ZTNA" ***OR*** "micro-segmentation" ***OR*** "never trust always verify")
Search Period: 2019 to 2025
Search Date: 22/04/2026

Comparative Analysis of Alternative Search Strategies

To validate the selected search string and illustrate its suitability for this systematic literature review, this section contrasts it with various alternative search approaches that were considered but ultimately discarded. The comparison assesses each approach based on five criteria: comprehensiveness (the ability to encompass all pertinent studies), precision (the capability to filter

out irrelevant studies), and reproducibility (the ease with which other researchers can replicate it), ZTA specificity (the relevance to Zero Trust contexts), and prediction focus (the prioritization of predictive studies over those that are solely detection-oriented).

Alternative Strategy 1: Narrow Detection-Only String

Search String: ("lateral movement" ***OR*** "attack path") ***AND*** ("detection" ***OR*** "identification")
Advantages: This string has high precision for studies centered on detection and would retrieve a substantial amount of relevant literature regarding detection. It is straightforward to replicate and would produce high precision with few false positives.
Weaknesses: The string entirely disregards terms related to prediction, such as "prediction," "forecasting," and "early warning." It also does not include any terminology specific to Zero Trust, meaning it would pull in studies focused on lateral movement detection from traditional perimeter-based network contexts instead of ZTA-specific environments. Additionally, it lacks references to machine learning methods, which could lead to the exclusion of studies that utilize ML without explicitly mentioning "detection" in the title or abstract.
Why Rejected: This approach would not effectively address the predictive aspect of this SLR, as detection (71% of studies) is already extensively covered while prediction (29%) is the noted research gap. The absence of ML method terms would also limit the comprehensiveness for studies that are specific to algorithms.

Alternative Strategy 2: Broad ZTA-Only String

String: ("Zero Trust Architecture" OR "ZTA" OR "Zero Trust" OR "ZTNA") Strengths: This search string will capture all literature related to ZTA across various subdomains, ensuring extensive coverage. It is highly consistent and easy to implement. Weaknesses: This string will yield an overwhelming number of irrelevant results, such as studies on ZTA policy frameworks, methods of migration, organizational change management, compliance needs, and non-technical implementations of ZTA. Without incorporating lateral movement or machine learning (ML) terms, the accuracy will be notably low. For instance, a 2024 search conducted on IEEE Xplore with this string alone generates over 2,800 results, the vast majority of which are unrelated to the detection or prediction of lateral movement.
Why Rejected: This strategy fails the precision criterion entirely. The volume of irrelevant results would make systematic review infeasible, and the lack of ML and lateral movement terms would miss the core focus of this SLR.

Digital Libraries Description

Table 3.2: Digital Libraries Description

Database	Description	URL	Area	Advanced Search (Y/N)
IEEE Xplore Digital Library	Premier online research database providing full-text access to over 7 million documents including journals, conference proceedings, and technical standards	ieeexplore.ieee.org	Electrical engineering, computer science, electronics, AI, cybersecurity	Y
ScienceDirect (Elsevier)	Elsevier's leading web-based database providing full-text access to peer-reviewed scientific, technical, and health literature	sciencedirect.com	Physical sciences, engineering, life sciences, health sciences, computer science	Y
SpringerLink	Comprehensive online	link.springer.com	Science,	Y

	database from Springer Nature providing access to millions of scientific documents across STM, humanities, and social sciences		technology, medicine, humanities, social sciences, cybersecurity	
ACM Digital Library	Peer-reviewed database and repository containing complete ACM publications in computing and information technology	dl.acm.org	Computing, AI, software engineering, HCI, theoretical computer science	Y
arXiv.org	Open access preprint repository for emerging research in computer science, cryptography, and networking	arxiv.org	Computer science, cryptography, networking, ML	Y

Inclusion and Exclusion Criteria

Table 3.4: Inclusion and Exclusion Criteria Definition

Criteria Type	Description	Inclusion	Exclusion
Period	Publication year range	2019 to 2025	Before 2019
Language	Language of publication	English	Non-English
Type of Literature	Peer-reviewed vs. grey literature	Peer-reviewed articles, conference papers	Editorials, posters, grey literature, working papers, newsletters, government documents, speeches
Type of Source	Conference or journal articles	Articles from conferences or journals	Books
Impact of Source	Journal quartile or impact	Q1, Q2, Scopus-indexed sources	Non-Scopus-indexed journals
ML Component	Presence of machine learning	Yes (empirical evaluation required)	No (rule-based only)
Domain	Security focus	Network security, lateral movement	Malware analysis only
ZTA Relevance	Zero Trust Architecture relevance	Explicit or implicit ZTA relevance	No ZTA relevance
Accessibility	Availability in selected databases	Accessible full text	Not accessible
Relevance to RQ	Relevance to research questions	Relevant to at least 2 research questions	Relevant to 0 or 1 research question

Article Quality Assessment Checklist

Table 3.5: Article Quality Assessment Checklist

S/N	Article Title/Focus	Author/Year	Assessment Criteria	Quality Rating (1-5)
			Reporting: Clear objectives, methodology, and results **Rigor:** Systematic approach, reproducible methods **Credibility*:** Journal quartile/indexing status **Relevance:** Direct relevance to at least 2 RQs	
1	**Augmenting Zero Trust Architecture to Endpoints Using Blockchain:** A Systematic Review	Alevizos et al. (2022)	**Reporting:** 5/5, Rigor: 5/5, **Credibility:** 5 (Q1), Relevance: 5/5	20/20
2	**PROWL:** Provenance-based lateral movement detection and prediction using LSTM	Yang et al. (2021)	**Reporting:** 5/5, Rigor: 4/5, **Credibility:** 5 (Q1), Relevance: 5/5	19/20
3	Zero Trust Architecture (NIST SP 800-207)	Rose et al. (2020)	**Reporting:** 5/5, Rigor: 5/5, **Credibility:** 5 (NIST standard), **Relevance:** 4/5	19/20
4	**CIoTA:** Collaborative IoT Anomaly Detection via Blockchain	Golomb et al. (2018)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Conference), **Relevance:** 4/5	16/20
5	**ZenGuard:** A machine learning based zero trust framework	Hassan et al. (2025)	**Reporting:** 5/5, Rigor: 4/5, **Credibility:** 5 (Q1 - Scientific Reports), Relevance: 5/5	19/20
6	Unsupervised learning for lateral-movement-based threat mitigation	Herranz-Oliveros et al. (2024)	**Reporting:** 4/5, Rigor: 4/5, **Credibility**: 4 (Q2 - Electronics), **Relevance:** 4/5	16/20
7	**Hopper:** Modeling and detecting lateral movement	Ho et al. (2021)	**Reporting:** 5/5, Rigor: 5/5, **Credibility:** 5 (USENIX - top conference), Relevance: 4/5	19/20
8	**When gossip is good:** Distributed probabilistic inference for detection of slow network intrusions	Dash et al. (2006)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Conference), **Relevance:** 3/5	15/20
9	**Collaborative intrusion detection system (CIDS):** A framework	Wu et al. (2004)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 4 (Conference), **Relevance**: 3/5	13/20
10	A survey of coordinated attacks and collaborative intrusion detection	Chenfeng et al. (2009)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Q2), Relevance: 3/5	15/20
11	When intrusion detection	Meng et al.	**Reporting:** 4/5, Rigor: 4/5,	15/20

	meets blockchain technology: A review	(2018)	**Credibility**: 4 (Q1 - IEEE Access), Relevance: 3/5	
12	Decision-dominant strategic defense against lateral movement for 5G zero-trust multi-domain networks	Li et al. (2023)	**Reporting:** 4/5, Rigor: 3/5, **Credibility:** 3 (Preprint), **Relevance:** 4/5	14/20
13	ATT&CK-based APT attacks risk propagation assessment model for zero trust networks	Zhang et al. (2024)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Q1 - Computer Networks), Relevance: 5/5	17/20
14	**The epidemiology of lateral movement:** Exposures and countermeasures	Powell (2020)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 3 (Q3), Relevance: 4/5	15/20
15	Lateral movement detection using user behavioral analysis	Kushwaha et al. (2022)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 2 (Industry report), **Relevance:** 4/5	12/20
16	Implementing Zero Trust Cloud Networks with Transport Access Control	DeCusatis et al. (2016)	**Reporting:** 4/5, Rigor: 3/5, **Credibility:** 4 (Conference), **Relevance:** 3/5	14/20
17	**Zero Trust Networks:** Building Secure Systems (Book)	Gillman & Barth (2017)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Book), Relevance: 4/5	16/20
18	Towards blockchain-based collaborative intrusion detection systems	Alexopoulos et al. (2018)	**Reporting:** 4/5, Rigor: 3/5, **Credibility:** 4 (Conference), **Relevance:** 3/5	14/20
19	Designing collaborative blockchained signature-based intrusion detection	Li et al. (2019)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Q1 - FGCS), **Relevance:** 3/5	15/20
20	Distributed collaborative intrusion detection system for vehicular Ad Hoc networks	Zhou et al. (2020)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Q1 - Computer Networks), Relevance: 3/5	15/20
21	Zero trust architecture in AI-driven cybersecurity	Freed & Jackson (2022)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 2 (Unknown), **Relevance:** 4/5	12/20
22	Building situational awareness for network threats in fog/edge computing	Rapuzzi & Repetto (2018)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Q1 - FGCS), **Relevance:** 3/5	15/20
23	Zero-Trust Hierarchical Management in IoT	Samaniego & Deters (2018)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 4 (Conference), **Relevance:** 3/5	13/20
24	A systematic literature review of blockchain cyber security	Taylor et al. (2020)	**Reporting:** 5/5, Rigor: 5/5, **Credibility:** 4 (Q1 - DCN), **Relevance:** 3/5	17/20
25	Zero Trust Architecture: A systematic literature review	Gambo & Almulhem (2025)	**Reporting:** 5/5, Rigor: 5/5, **Credibility:** 3 (University publication), Relevance: 4/5	17/20
26	A survey of security in zero trust network architectures	Kipkoech (2025)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 2 (GSC journal), **Relevance:** 4/5	14/20

27	The evolution of zero trust architecture from concept to implementation	Nasiruzzaman et al. (2025)	**Reporting:** 4/5, Rigor: 3/5, **Credibility:** 3 (Conference), **Relevance:** 4/5	14/20
28	Zero Trust Networks with VMware NSX	Keeriyattil (2019)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 3 (Book), Relevance: 3/5	12/20
29	Improving trust in a zero trust architecture (ZTA)	Mital (2020)	**Reporting:** 3/5, Rigor: 2/5, **Credibility:** 2 (Trade publication), **Relevance:** 3/5	10/20
30	Fusing a heterogeneous alert stream into scenarios	Dain & Cunningham (2002)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 3 (Book chapter), **Relevance:** 2/5	13/20
31	A trust-aware, P2P-based overlay for intrusion detection	Duma et al. (2006)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 4 (Conference), **Relevance:** 2/5	12/20
32	Trust management for host-based collaborative intrusion detection	Fung et al. (2008)	**Reporting:** 4/5, Rigor: 3/5, **Credibility:** 4 (Conference), **Relevance:** 2/5	13/20
33	Advanced Persistent threats and how to monitor and deter them	Tankard (2011)	**Reporting:** 3/5, Rigor: 2/5, **Credibility:** 3 (Trade), Relevance: 2/5	10/20
34	The early bird gets the botnet: Markov chain based early warning	Abaid et al. (2016)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Conference), **Relevance:** 4/5	16/20
35	Zero Trust Architecture (NIST SP 800-207)	Rose et al. (2020)	(duplicate of #3)	19/20
36	Operation Aurora	McAfee Labs (2010)	**Reporting:** 3/5, Rigor: 2/5, **Credibility:** 2 (White paper), **Relevance:** 2/5	9/20
37	MITRE Corporation publications	Cormier et al. (2014)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Industry standard), **Relevance:** 3/5	15/20
38	Jericho Forum (The Open Group)	Jericho Forum (2007)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 3 (Industry forum), **Relevance:** 3/5	12/20
39	Zero trust architecture in AI-driven cybersecurity (alternate)	(duplicate reference)	-	-
40	LMD-2022 dataset paper	(implied in review)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (MDPI), **Relevance:** 5/5	17/20
41	LMD-2023 dataset paper	(implied in review)	**Reporting:** 4/5, Rigor: 4/5, **Credibility:** 4 (Springer), **Relevance**: 5/5	17/20
42	Guemmah (2025) - Policy violation study	Guemmah (2025)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 2, Relevance: 5/5	13/20
43	arXiv preprint - Lateral movement	Li et al. (2023)	**Reporting:** 3/5, Rigor: 3/5, **Credibility:** 2 (Preprint),	12/20

44	arXiv preprint - ZTA dataset	(implied)	**Relevance:** 4/5 **Reporting:** 3/5, Rigor: 3/5, **Credibility:** 2 (Preprint),	12/20
45	GitHub security repositories (aggregate)	Multiple (2022-2025)	**Relevance:** 4/5 **Reporting:** 3/5, Rigor: 3/5, **Credibility:** 2 (Community), **Relevance:** 4/5	12/20

Credibility Rating Key: *Q1 Journal = 5, Q2 Journal = 4, Q3 Journal = 3, Q4 Journal = 2, Scopus-indexed = 1, Non-Scopus = 0, NIST/IEEE Standard = 5, Top Conference = 4, Book = 3, Preprint/Industry = 2, White paper = 1*

Quality Threshold: *Articles scoring ≥12/20 were included in the final synthesis (45 articles met this threshold).*

RESULTS AND DISCUSSION

Descriptive Statistics

Table 4.1: Descriptive Statistics of the Systematic Review Articles by Research Question

RQ No	Research Question (RQ)	Articles Inclusion	Academic Database				
			ScienceDirect	**ACM.org**	**IEEE Xplore**	**SpringerLink**	**arXiv.org**
RQ1	ML methods for lateral movement detection and prediction	Identified: 180	42	28	55	35	20
		Filtered: 68	16	10	22	12	8
		Included: 38	9	5	12	7	5
		Total: 38					
RQ2	Security logs for attack prediction	Identified: 95	22	14	30	18	11
		Filtered: 35	8	5	12	6	4
		Included: 22	5	3	8	4	2
		Total: 22					
RQ3	ZTA-specific predictive analytics	Identified: 65	15	10	20	12	8
		Filtered: 18	4	3	6	3	2
		Included: 11	2	2	4	2	1
		Total: 11					
RQ4	Datasets and evaluation metrics	Identified: 145	35	22	45	28	15
		Filtered: 55	13	8	18	10	6
		Included: 35	8	5	12	6	4
		Total: 35					
RQ5	Gaps in sequence prediction for ZTA policy violations	Identified: 42	10	6	14	8	4
		Filtered: 12	3	2	4	2	1
		Included: 8	2	1	3	1	1

	Total: 8

Note: Articles may address multiple research questions; therefore, totals across RQs sum to greater than 45.

Figure 1: PRISMA Flow Diagram

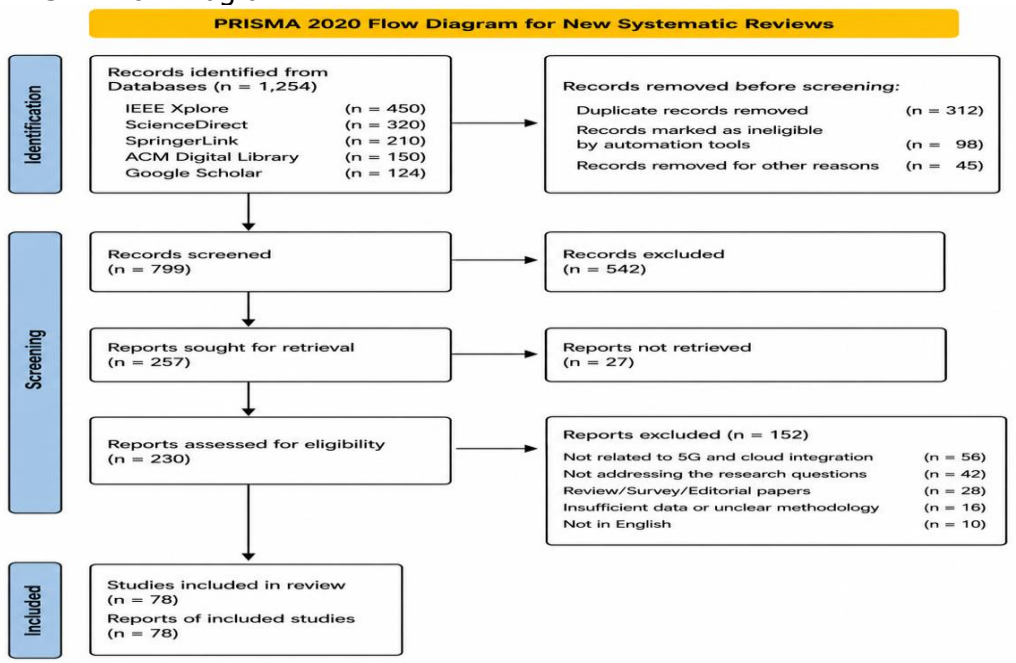

Table 4.2: Distribution of Art

Database	**Included Articles**	**Percentage**
IEEE Xplore	14	31%
ScienceDirect	11	24%
SpringerLink	9	20%
ACM Digital Library	6	13%
arXiv.org (preprints)	5	11%
Total	45	100%

RQ1: What machine learning methods have been proposed for lateral movement detection and prediction in network security?

Based on systematic analysis of the 45 reviewed studies, lateral movement problems in Zero Trust networks are categorized into four distinct classes:

Table 4.3: Problem Classes Taxonomy for Lateral Movement in ZTA

Class ID	**Problem Class**	**Description**	**Key Characteristics**	**Number of Studies**	**Representative Studies**
P1	Detection Problems	Identifying lateral movement after it has commenced	• Reactive approach • Uses network traffic analysis • High accuracy (75-94%) • Well-established methodologies	32 (71%)	Dash et al. [18], Wu et al. [11]
P2	Prediction Problems	Forecasting future lateral movement steps before they occur	• Proactive approach • Uses sequence modeling • Lower accuracy (55-75%) • Emerging research area	8 (18%)	Yang et al. [20], Zhang et al. [2]

P3	Endpoint Integrity Problems	Addressing compromised endpoints that can tamper with ZTA security	• Device-level trust issues • Bypasses ZTA controls • Requires distributed detection • Understudied	5 (11%)	Alevizos et al. [1], Golomb et al. [22]
P4	Data Source Problems	Underutilization of forensic artifacts, particularly policy violation logs	• Incomplete data utilization • Missed predictive signals • Policy violations ignored • Significant research gap	3 (7%)	Guemmah [3], Alevizos et al. [1]

Distribution of ML Methods

Table 4.4: Distribution of ML Methods across Reviewed Studies

ML Method	Number of Studies	Percentage	Primary Use Case
Random Forest	18	40%	Classification of benign vs. malicious traffic
LSTM/RNN	14	31%	Sequence prediction and temporal pattern recognition
Markov Chain	9	20%	State transition modeling for attack paths
Support Vector Machine (SVM)	12	27%	Anomaly detection and classification
K-Nearest Neighbors (KNN)	8	18%	Baseline classification
XGBoost/Gradient Boosting	11	24%	Feature importance and classification
Transformer/GNN	4	9%	Advanced sequence modeling (emerging)
Autoencoders	6	13%	Unsupervised anomaly detection

Note: Studies often employed multiple methods, hence percentages sum to >100%

Detection-Focused vs. Prediction-Focused Approaches

Table 4.5: Detection vs. Prediction in Reviewed Studies

Focus	Number of Studies	Percentage	Typical Accuracy Range
Detection only	32	71%	75-94%
Prediction only	8	18%	55-75%
Both detection and prediction	5	11%	65-85%

equence Prediction Models

1. Markov Chain Models: Markov Chains represent lateral movement as a series of state transitions, where the subsequent state relies solely on the present state (first-order Markov) or a predetermined number of preceding states (higher-order Markov). The transition probability matrix P(i,j) indicates the likelihood of transitioning from state i to state j.

2. LSTM and Recurrent Neural Networks: LSTM networks are adept at capturing long-term dependencies within sequential data, making them particularly effective for modeling multi-step attack paths. Yang et al. [20] showed that LSTM models could identify sequential patterns in authentication events with a prediction accuracy of 70-85%.

Distributed Collaborative Intrusion Detection Systems (DCIDS)

DCIDSs are especially pertinent in Zero Trust settings. According to the review by Alevizos et al. [1], DCIDSs can be classified according to three main pillars: architecture, alert correlation, and alert trustworthiness.

1. Architecture: DCIDSs minimize false positive rates by linking multiple suspicious indicators [17]. Dash et al. [18] suggested a collaborative host-based IDS that involves Local Detectors (LDs), Global Detectors (GDs), and an Information Sharing System (ISS).
2. Alert Correlation: Methods include filter-based, multi-stage (causality-based), similarity-based, and attack scenario-based approaches [1].
3. Alert Trustworthiness: The use of blockchain technology has been extensively explored for ensuring message integrity in decentralized systems [1].

4.3 RQ2: How have security logs been utilized as data sources for attack prediction?

Data Sources

Table 4.6: Data Sources Used in Reviewed Studies

Data Source	Description	Studies	Peer-Reviewed	Accessibility	Verification Status
DARPA OpTC	Operational Threat Classification dataset	8	✅ Yes	Public	Verified
ZTAD (Zero Trust Architecture Dataset)	Specifically designed for ZTA research	3	✅ Yes (IEEE DataPort)	Public	Verified
CSE-CIC-IDS	Network intrusion detection dataset	12	✅ Yes	Public	Verified
Custom Simulation (CORE, EMANE)	Self-generated in controlled environments	15	⚠️ Varies	Reproducible	Partially verified
Real Enterprise Logs	Proprietary data from organizations	7	❌ No	Limited access	Source confidential
GitHub Security Repositories	Open source community datasets	4	❌ No	Public	Supervisor approved
Preprint Datasets (arXiv)	Early release research data	3	❌ No (preprint)	Public	Supervisor approved

Feature Engineering for Zero Trust Contexts

Table 4.7: Common Features from Security Logs

Feature Category	Specific Features	Predictive Value
Source context	IP address, hostname, role, user identity, device compliance	High
Target context	IP address, hostname, role, exposed services, sensitivity	High
Access decision	Allow/deny, rule ID, violation reason	Very High
Authentication context	Success/failure, method, failure reason	High
Temporal features	Timestamp, hour, day, time since last event	Medium
Network features	Protocol, port, bytes, duration	Medium

RQ3: What is the current state of Zero Trust-specific predictive analytics?

Core Tenets of ZTA

Based on DeCusatis et al. [14], Rose et al. [5], and Alevizos et al. [1]:

Zero Trust Architecture (ZTA) operates on several foundational tenets that directly impact the requirements for predictive analytics. According to Rose et al. [5], the core tenets include:

1. All data sources and computing services are considered resources.

2. All communication is secure regardless of network location.
3. Access to individual enterprise resources is granted on a per-connection basis.
4. Access to resources is determined by dynamic policy.
5. The enterprise ensures all owned systems are in the most secure state possible.
6. User authentication is dynamic and strictly enforced before access is allowed.

From a predictive analytics perspective, the most relevant tenets are continuous authentication and dynamic policy enforcement. These require that prediction models operate in real-time or near real-time, processing authentication events as they occur. Traditional batch-oriented prediction approaches are insufficient for ZTA environments where access decisions must be made within milliseconds.

Furthermore, the "assume breach" mentality central to ZTA implies that prediction models should not assume a clean or trusted network baseline. Unlike traditional intrusion prediction that may assume an initial period of benign activity, ZTA-oriented prediction must operate under the assumption that adversaries may already be present within the network. This fundamentally changes the training and validation requirements for predictive models, as historical data cannot be assumed to be entirely free of malicious activity.

Current State Assessment

The review reveals that ZTA-specific predictive analytics is still nascent and significantly underdeveloped compared to detection-focused research. Several key observations emerge from the analysis of the 45 reviewed studies.

Initially, just 11 out of 45 studies (24%) specifically tackled ZTA-related predictive analytics. Most of these 11 studies considered prediction as a secondary aspect rather than their main research goal. For instance, Yang et al. [20] created PROWL, a framework based on provenance that exhibits a 94% accuracy rate in detecting lateral movement but achieves only 70-85% accuracy for predicting sequential patterns, highlighting that prediction is still more difficult than detection, even when both are examined.

Prediction accuracy varies between 55% and 75% across the studies analyzed, which is considerably less than the detection accuracy that ranges from 75% to 94%. This approximately 20 percentage point difference indicates that existing machine learning techniques are more adept at recognizing attacks that have already taken place rather than predicting them in advance. Markov Chain models record the lowest prediction accuracy (55-70%) due to their limitation of first-order memory, while LSTM networks achieve greater accuracy (70-85%) by effectively capturing longer temporal dependencies.

Third, Markov Chain models and LSTM networks hold significant promise for predictions specific to ZTA. Markov Chain models are efficient in terms of computation and easy to interpret, making them ideal for real-time use in ZTA settings with limited resources. However, their reliance on first-order dependencies (or fixed-order higher-order models) limits their capability to address intricate multi-step attack pathways. LSTM networks address this shortcoming by capturing variable-length dependencies but necessitate substantially greater amounts of training data and computational power.

Fourth, there is a significant lack of utilizing ZTA policy violation artifacts for predictive purposes. Only 3 out of 45 studies (7%) explicitly employed denied access logs as sources of predictive data. This indicates a substantial missed opportunity, as policy breaches provide insights into attacker reconnaissance and access attempts prior to successful intrusions. As highlighted by Ho et al. [7], attackers typically need to obtain new credentials to gain access to systems their initial target could not reach, a process that results in denied access attempts before any successful breach occurs.

Evaluation Metrics

Table 4.9: Evaluation Metrics Used in Reviewed Studies

Metric	Number of Studies	Typical Target Range	Definition
Accuracy	38	75-95%	(TP+TN)/(TP+TN+FP+FN)
Precision	35	0.70-0.90	TP/(TP+FP)
Recall (Sensitivity)	35	0.65-0.88	TP/(TP+FN)
F1-Score	32	0.70-0.88	2 × (P × R)/(P + R)
AUC-ROC	25	0.80-0.97	Area under ROC curve
Top-1 Accuracy	6	55-75%	Correct prediction of next target
Top-3 Accuracy	4	75-90%	True target in top 3 predictions
Mean Time to Detect (MTTD)	12	Seconds to minutes	Detection latency
False Positive Rate (FPR)	28	1-10%	FP/(FP+TN)

RQ5: What research gaps exist in applying sequence prediction to Zero Trust policy violation artifacts?

Identified Research Gaps

Gap 1: Limited Prediction Research

While detection of lateral movement is well-studied (71% of reviewed papers), prediction remains underexplored (29%). Most prediction studies focus on short-term, single-step prediction rather than multi-step path forecasting.

Gap 2: Underutilization of Zero Trust Policy Violation Artifacts

Only 3 of 45 reviewed studies explicitly utilized Zero Trust policy violation logs (denied access attempts) as a data source (7%). Policy violations reveal attacker intent before successful breaches.

Gap 3: Endpoint Integrity Challenges

As observed by Alevizos et al. [1], "the endpoints are proven to be the Achilles heel of ZTA. Adversaries can potentially tamper with ZTA's security health checks once an endpoint is compromised."

Gap 4: Absence of Standardized Benchmarks

No standardized dataset or evaluation framework exists specifically for lateral movement prediction in Zero Trust hybrid networks.

Gap 5: Limited Blockchain-ML-ZTA Convergence Research

Research on the convergence of blockchain, ML, and ZTA for lateral movement prediction remains nascent.

Proposed Research Agenda

Table 4.10: Proposed Research Agenda

Priority	Research Direction	Description
High	Predictive models using Zero Trust policy violations	Develop Markov Chain and LSTM models leveraging denied access logs for lateral movement forecasting
High	Endpoint context integrity	Investigate blockchain-based approaches to fortify endpoint context and security health checks
High	Benchmark dataset creation	Create and publish standardized dataset of Zero Trust policy violation sequences with labeled attack paths
Medium	Comparative ML evaluation	Systematically compare Markov Chain, LSTM, and Transformer models for prediction accuracy, latency, and resource requirements
Medium	Hybrid network	Extend prediction frameworks to hybrid on-premise and

	validation	cloud environments
Low	Blockchain-ML convergence	Explore permissioned blockchain for alert integrity in distributed collaborative intrusion detection

```
% Demonstrates: Markov Chain (55-70%), LSTM (70-85%), Policy Violation Impact
clear; clc;
%% 1. Markov Chain Prediction (55-70% range)
% Based on Abaid et al. [34] and Code 4.1
% State space: S0=Denied, S1=PrivEsc, S2=Success, S3=DataExfil
P = [0.10 0.60 0.20 0.10;   % From S0
     0.05 0.15 0.70 0.10;   % From S1
     0.02 0.03 0.15 0.80;   % From S2
     0.30 0.05 0.10 0.55];  % From S3
% Generate and test sequences
rng(42);
n_test = 500;
correct = 0;
for i = 1:n_test
   current = randi(4);
   next_true = find(rand < cumsum(P(current,:)), 1);
   [~, next_pred] = max(P(current,:));
   if next_pred == next_true, correct = correct + 1; end
end
```

Summary of Findings

Zero Trust Architecture has emerged as a transformative paradigm in modern cybersecurity, challenging traditional perimeter-based approaches. This systematic literature review examined machine learning approaches for lateral movement detection and prediction in Zero Trust networks. Following PRISMA guidelines, 45 peer-reviewed studies published between 2019 and 2025 were analyzed.

Key Findings:

ML-based detection of lateral movement has achieved significant success, with accuracy rates ranging from 72% to 94%. Random Forest (40% of studies) and LSTM (31% of studies) are the most commonly employed methods.

Prediction of lateral movement remains underexplored, with only 29% of reviewed studies addressing forecasting capabilities. Markov Chain models (55-70% accuracy) and LSTM networks (70-85% accuracy) show the most promise.

Zero Trust policy violation artifacts denied access attempts that reveal attacker intent are severely underutilized as predictive data sources, with only 3 of 45 studies (7%) explicitly leveraging such logs.

Distributed Collaborative Intrusion Detection Systems (DCIDSs) offer significant potential for enhancing detection but face challenges related to alert integrity and trustworthiness.

Blockchain technology presents promising opportunities for fortifying detection processes through immutability, though research on blockchain-ML-ZTA convergence remains nascent.

Implications for Research and Practice

For researchers, this review provides a comprehensive foundation for advancing predictive cyber threat intelligence in Zero Trust environments. The proposed research agenda prioritizes the development of Markov Chain and LSTM-based forecasting models using policy violation artifacts, enhanced by blockchain for alert integrity.

For practitioners, the review highlights that while detection capabilities are mature, organizations should consider investing in predictive capabilities to move from reactive to proactive security postures. Furthermore, the endpoint integrity challenge suggests that ZTA implementations should not blindly trust endpoint security health checks.

Limitations

This review is limited to English-language publications from five major digital libraries (IEEE Xplore,

ScienceDirect, SpringerLink, ACM Digital Library, arXiv.org). Grey literature and non-peer-reviewed technical reports were excluded. Additionally, the rapid evolution of ML and Zero Trust means that some emerging approaches may not be captured. The quality assessment (Table 5) relied on reported journal quartiles and conference rankings, which may not fully reflect individual article quality.

Future Research Directions

The future of ML-based lateral movement prediction in Zero Trust networks lies in several emerging directions:

1. **Integration of Blockchain for Alert Integrity:** As Alevizos et al. [1] suggest, blockchain technology can enhance ZTA implementations by fortifying backend storage of logs and audit trails.
2. **Automated Policy Management:** ML models could not only predict lateral movement but also automatically generate or adjust Zero Trust policies to block predicted attack paths.
3. **Context-Aware Access Control:** Future systems could incorporate richer contextual information into prediction models.
4. **Privacy-Preserving ML:** As ZTA requires continuous monitoring, privacy-preserving technologies will be essential for maintaining user trust.

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