SSR Journal of Artificial Intelligence (SSRJAI)

OPEN ACCESS

Volume 2, Issue 3, 2025 Journal homepage: https://ssrpublisher.com/ssrjai/ ISSN: 3049-0413
Email: office.ssrpublisher@gmail.com

A Comprehensive Taxonomy and Empirical Analysis of IoT Cybersecurity Attack Vectors: A Systematic Review

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***Received:** 25.08.2025* | ***Accepted:** 21.09.2025* | ***Published:** 25.09.2025*

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DOI: *10.5281/zenodo.17203717*

Abstract

Review Article

The proliferation of the Internet of Things (IoT) has transformed the digital ecosystem, enabling seamless connectivity across industries, smart homes, healthcare, transportation, and critical infrastructures. However, this rapid adoption has also expanded the attack surface for cyber adversaries. Despite substantial research, the fragmented understanding of IoT attack vectors continues to impede the design of holistic security solutions. This systematic review provides a comprehensive taxonomy of IoT cybersecurity attack vectors, classifies them across multiple dimensions—including device, network, application, and human-centric layers—and conducts an empirical analysis of the frequency, techniques, and impacts reported in the literature. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, 176 peer-reviewed studies published between 2013 and 2025 were examined. Findings reveal that denial-of-service (DoS), eavesdropping, malware injection, and privilege escalation remain the most recurring vectors, with an increasing trend of AI-driven and supply chain attacks. The paper identifies critical gaps in adaptive defense, context-aware intrusion detection, and resilience mechanisms. The study concludes by proposing a research agenda emphasizing explainable security models, federated IoT defense strategies, and standardized threat taxonomies.

Keywords: Internet of Things, cybersecurity, attack vectors, denial-of-service, intrusion detection, malware, systematic review.

1. INTRODUCTION

The Internet of Things (IoT) has emerged as one of the most transformative paradigms in the digital era, redefining how humans, devices, and infrastructures interact. By enabling ubiquitous interconnectivity among heterogeneous devices, IoT has catalyzed innovation across diverse domains including smart homes, industrial automation, healthcare, agriculture, energy management, and intelligent transportation systems (Gubbi, 2013; Xu , 2014; Al-Fuqaha, 2015). The exponential growth of IoT devices—estimated to surpass 30 billion by 2030—has created vast opportunities for economic development and societal benefits, but it has also expanded the attack surface for cyber adversaries (Statista, 2024; Cisco, 2023).

IoT systems are inherently distinct from traditional computing paradigms due to their resource-constrained nature, heterogeneity, and large-scale deployment. These characteristics present profound security challenges. Devices typically operate with limited computational power, energy, and storage, rendering conventional security protocols impractical (Weber & Studer, 2016; Li, 2018). Furthermore, the lack of standardized architectures and protocols across IoT ecosystems amplifies vulnerabilities, creating fertile ground for diverse cybersecurity attack vectors (Sicari, 2015; Bera, 2020).

The significance of IoT security extends beyond technological concerns. As IoT becomes increasingly integrated into critical infrastructures—such as smart grids, healthcare monitoring systems, intelligent transportation networks, and industrial control systems—security breaches may result in not only financial and reputational damages but also threats to human life and national security (Roman, 2018; Humayed, 2017). High-profile incidents such as the Mirai botnet attack in 2016, which exploited unsecured IoT devices to launch massive Distributed Denial of Service (DDoS) attacks, underscore the catastrophic potential of IoT vulnerabilities (Kolias, 2017).

Research into IoT security has evolved significantly over the past decade. Early studies (2013–2016) primarily emphasized device authentication, lightweight encryption, and privacy protection (Zhang, 2014; Jing, 2014). During this period, security was often treated as an afterthought rather than an integral design principle. The Mirai incident shifted global attention to IoT as a botnet-enabling infrastructure, leading to intensified exploration of intrusion detection, anomaly detection, and network-layer defenses (Antonakakis, 2017).

From 2017 onwards, IoT cybersecurity research diversified into machine learning (ML)-driven intrusion detection systems, blockchain-based trust frameworks, and context-aware authentication schemes (Ferrag, 2018; Bera et al., 2020; Sharma et al., 2022). The increasing adoption of Artificial Intelligence (AI) in IoT environments introduced novel attack surfaces, including adversarial machine learning and data poisoning threats (Rigaki & Garcia, 2018; Kumar, 2021). Meanwhile, the COVID-19 pandemic accelerated IoT adoption in telemedicine, remote education, and smart logistics, thereby amplifying risks of privacy breaches and ransomware (Rahman, 2020; Hossain, 2021).

Between 2021 and 2025, the rise of edge computing, 5G, and digital twins has further complicated the IoT threat landscape. Researchers increasingly highlight supply chain vulnerabilities, cross-layer attacks, and federated learning-based defenses as emergent research directions (Nguyen, 2022; Wang, 2023). Thus, the evolution of IoT security reflects a dynamic arms race between adversaries and defenders, where new technologies simultaneously introduce innovations and threats.

Despite abundant research, IoT security literature remains fragmented, with taxonomies differing in focus and scope. Some studies categorize attacks by system layer (device, network, application), while others classify based on adversary goals (confidentiality, integrity, availability) or attack techniques (passive vs. active, insider vs. outsider) (Sicari et al., 2015; Abomhara & Køien, 2015; Granjal, 2015). While useful, these taxonomies often lack holistic coverage of socio-technical aspects such as human errors, supply chain compromises, and policy-driven vulnerabilities. Moreover, the rapid evolution of IoT technologies (e.g., AI-driven IoT, edge computing, Industry 5.0) requires updated classifications that integrate emerging attack vectors (Ali, 2022; Marquez, 2023).

A comprehensive taxonomy is essential for several reasons:

1. It enables systematic threat intelligence by standardizing terminology across academia and industry.
2. It facilitates comparative benchmarking of security mechanisms.
3. It highlights research gaps by mapping underexplored attack domains.
4. It guides policy-making and regulatory frameworks, ensuring alignment between technical safeguards and legal compliance.

Without a consolidated taxonomy, researchers and practitioners risk duplicating efforts, overlooking emergent vectors, or deploying fragmented defenses that fail to provide holistic protection.

Equally critical is the need for empirical analysis of IoT attacks. While theoretical discussions abound, there is limited systematic evidence regarding the frequency, distribution, and severity of different attack vectors. For instance, DoS/DDoS attacks are widely studied, yet supply chain attacks and adversarial AI remain underrepresented in empirical literature despite their growing real-world relevance (Miettinen, 2017; Kshetri & Voas, 2018; Pahlavan, 2024).

An evidence-driven approach provides clarity on which attacks are most prevalent, how they evolve, and what contexts they target. Such analysis is indispensable for prioritizing defense investments, particularly in resource-constrained environments. Moreover, empirical insights bridge the gap between academic taxonomies and practical, real-world security challenges, enabling the formulation of adaptive, resilient, and scalable solutions.

Research Gap and Study Contributions

Although existing surveys and reviews have advanced understanding of IoT security (Sicari, 2015; Alaba, 2017; Bera, 2020), they often suffer from three key limitations:

1. Narrow focus: Many reviews analyze only specific layers (e.g., network security) or technologies (e.g., blockchain), neglecting the broader spectrum of attack vectors.
2. Lack of empirical grounding: Few reviews integrate systematic data on attack frequency and severity from recent literature.
3. Outdated scope: Emerging threats such as federated learning attacks, digital twin manipulations, and AI-driven malware remain underexplored in traditional taxonomies.

This study addresses these gaps by:

i. Developing a comprehensive taxonomy of IoT cybersecurity attack vectors spanning device, network, application, and socio-technical dimensions.

ii. Conducting a systematic empirical analysis of attack frequency, impact, and evolution based on 176 peer-reviewed studies published between 2013 and 2025.

iii. Proposing a future research agenda focused on adaptive, explainable, and federated IoT defense mechanisms.

2. OBJECTIVES OF THE RESEARCH

The primary goal of this study is to consolidate fragmented knowledge on IoT cybersecurity threats and provide an evidence-based foundation for advancing secure IoT ecosystems. Specifically, the research objectives are as follows:

1. To develop a comprehensive taxonomy of IoT cybersecurity attack vectors by classifying threats across device, network, application, and socio-technical dimensions, thereby providing a standardized framework for understanding vulnerabilities in heterogeneous IoT environments.
2. To conduct a systematic empirical analysis of IoT attack vectors reported in peer-reviewed literature between 2013 and 2025, identifying patterns in attack frequency, techniques, targeted layers, and real-world impacts across diverse domains such as healthcare, transportation, and critical infrastructures.
3. To critically evaluate the strengths and limitations of existing IoT security mechanisms—including authentication protocols, intrusion detection systems, blockchain-based frameworks, and AI-driven solutions—highlighting their effectiveness against different classes of attack vectors.
4. To identify persistent gaps, emerging challenges, and underexplored areas in IoT cybersecurity research, such as adversarial machine learning, supply chain compromises, federated learning attacks, and privacy-preserving security models.
5. To propose a forward-looking research agenda that emphasizes adaptive, scalable, and explainable defense strategies, fostering collaboration between academia, industry, and policy makers toward the development of resilient and secure IoT ecosystems.

3. METHODOLOGY AND ANALYSIS

This study adopts a systematic literature review (SLR) approach following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure methodological rigor and transparency. Relevant publications were retrieved from major scientific databases including IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and Scopus. The search was conducted using combinations of keywords such as *"IoT cybersecurity," "attack vectors," "threat taxonomy,"* and *"systematic review."* The review period covered January 2013 to March 2025, reflecting the decade in which IoT security research significantly matured.

The inclusion criteria restricted selection to peer-reviewed journal articles and conference papers that explicitly addressed IoT cybersecurity threats, taxonomies, or empirical attack analyses. Excluded materials included grey literature, non-English publications, and studies without a clear IoT security focus.

The analysis involved a qualitative synthesis and quantitative coding of attack vectors, classified by type, frequency, targeted layer, and impact severity. Statistical aggregation was performed to identify dominant and emerging threats, while thematic analysis highlighted research gaps and evolving patterns. This dual approach ensured a balanced integration of taxonomy development and empirical validation.

4. RESEARCH HYPOTHESES

In line with the objectives of this study, the following hypotheses are formulated to guide the empirical analysis and evaluation:

1. **H_1:** *Denial-of-Service (DoS) and Distributed Denial-of-Service (DDoS) attacks represent the most frequently reported IoT attack vectors across device, network, and application layers during the period 2013–2025.*
2. **H_2:** *Application-level attack vectors, such as malware injection and unauthorized access, are increasing at a faster rate than device-level and network-level attacks in recent IoT security literature.*
3. **H_3:** *Emerging IoT technologies (e.g., edge computing, AI-enabled IoT, and 5G) are disproportionately associated with novel attack vectors, including adversarial machine learning and supply chain compromises.*
4. **H_4:** *Existing IoT security mechanisms—such as traditional intrusion detection systems and lightweight encryption—are insufficient to mitigate multi-dimensional attacks, thereby necessitating adaptive and federated defense strategies.*
5. **H_5:** *The lack of a unified taxonomy of IoT attack vectors contributes to inconsistencies in research findings, hindering comparative evaluations and cross-domain threat intelligence sharing.*

5. THEMATIC ANALYSIS AND LITERATURE REVIEW

The thematic analysis of IoT cybersecurity literature reveals four dominant research strands: (1) device-layer vulnerabilities, including firmware manipulation, sensor tampering, and physical attacks; (2) network-layer threats, notably DoS/DDoS, routing manipulation, and eavesdropping; (3) application-layer risks, such as malware injection, API exploitation, and false data injection; and (4) socio-technical factors, encompassing weak authentication, supply chain compromises, and human-centric attacks. Across these themes, existing studies highlight recurring fragmentation in taxonomies and inconsistent evaluation of attack prevalence. The literature collectively underscores the need for integrative frameworks—conceptual, theoretical, and empirical—to systematically capture the evolving IoT security landscape.

5.1 Conceptual Framework

The conceptual framework serves as the intellectual blueprint that organizes and explains how different dimensions of IoT cybersecurity attack vectors are interrelated. It bridges theory and practice by mapping key concepts, constructs, and their interactions to form a structured representation of the problem under study. In the context of this research, the framework provides a foundation for classifying IoT attack vectors, identifying their underlying drivers, and linking them to consequences that influence both technical and socio-organizational domains.

While IoT offers transformative benefits across industries, its cybersecurity vulnerabilities demand a multidimensional conceptualization that goes beyond technical isolation. Attack vectors cannot be fully understood if analyzed solely from device or network perspectives; rather, they must be interpreted in the context of human behavior, socio-technical systems, supply chains, and regulatory environments (Abomhara & Køien, 2015; Sicari et al., 2015; Marquez et al., 2023). Thus, this framework integrates device, network, application, and socio-technical layers to provide a holistic understanding of IoT attack vectors.

5.2.1 Internet of Things (IoT)

The Internet of Things (IoT) refers to the networked interconnection of physical devices embedded with sensors, software, and communication interfaces, designed to collect and exchange data autonomously (Al-Fuqaha et al., 2015; Li et al., 2018). Unlike traditional computing infrastructures, IoT systems are characterized by heterogeneity, scale, and resource constraints, which collectively complicate security designs.

5.2.2 Cybersecurity

Cybersecurity encompasses practices, technologies, and processes aimed at safeguarding systems, networks, and data from unauthorized access, attacks, or damage (Weber & Studer, 2016). Within IoT, cybersecurity transcends mere technical protection to involve trust, privacy, and resilience of devices and networks (Roman et al., 2018).

5.2.3 Attack Vectors

An **attack vector** is the path or method adversaries use to exploit vulnerabilities and gain unauthorized access to systems (Kolias et al., 2017). In IoT, attack vectors may stem from hardware, software, communication protocols, or socio-technical contexts such as weak human authentication practices or supply chain compromises (Ferrag et al., 2018; Ali et al., 2022).

5.3 Dimensions of IoT Attack Vectors

The conceptual framework recognizes four interdependent dimensions of IoT attack vectors: device-level, network-level, application-level, and socio-technical.

5.3.1 Device-Level Vectors

Device-level attacks exploit vulnerabilities inherent in physical components and firmware. Common attack vectors include side-channel attacks, firmware tampering, and sensor spoofing (Miettinen et al., 2017). These attacks often bypass software defenses, exploiting hardware limitations.

5.3.2 Network-Level Vectors

These vectors target communication pathways, exploiting IoT's reliance on wireless protocols (e.g., Zigbee, MQTT, CoAP). Attacks include DDoS, eavesdropping, MitM, and routing manipulation (Granjal et al., 2015; Bera et al., 2020). Given IoT's distributed nature, network-level vulnerabilities are both pervasive and disruptive.

5.3.3 Application-Level Vectors

Application-level attacks exploit weaknesses in software and services. Notable examples are malware injection, API exploitation, false data injection, and ransomware (Rigaki & Garcia, 2018; Pahlavan et al., 2024). Such attacks compromise data integrity and service availability, often with severe implications in critical infrastructures.

5.3.4 Socio-Technical Vectors

Socio-technical vectors highlight the role of human and organizational factors in IoT vulnerabilities. Weak authentication (default passwords), social engineering, and supply chain compromises fall under this dimension (Humayed et al., 2017; Marquez et al., 2023). These attacks underscore the interplay between technology and human behavior in shaping cybersecurity risks.

5.4 Interrelationships among Dimensions

The conceptual framework recognizes interdependencies among these dimensions. For example:

i. A device-level firmware attack may open pathways for network-layer exploits.

ii. Application-level malware can propagate through socio-technical weaknesses (e.g., phishing).

iii. Supply chain compromises often manifest as multi-layered attacks involving both device firmware and application logic.

By conceptualizing attack vectors as multi-dimensional phenomena, the framework avoids siloed interpretations and facilitates integrative defense strategies.

5.5 Drivers of IoT Attack Vectors

Several drivers shape IoT attack vectors:

1. Resource Constraints: IoT devices often lack strong encryption or intrusion detection due to limited processing power (Li et al., 2018).
2. Heterogeneity: Diverse protocols and architectures increase complexity and attack surfaces (Sicari et al., 2015).
3. Scalability: The exponential growth of IoT devices amplifies vulnerabilities (Cisco, 2023).
4. Emerging Technologies: Integration of AI, edge computing, and 5G introduces new attack vectors (Nguyen et al., 2022).
5. Human Factors: User negligence, weak authentication, and lack of awareness drive socio-technical vulnerabilities (Kshetri & Voas, 2018).

5.6 Consequences of Attack Vectors

The impacts of IoT attack vectors span multiple domains:

- Technical: Service disruptions, data breaches, malware propagation.
- Economic: Financial losses from ransomware and fraud (Kolias et al., 2017).
- Social: Erosion of trust in IoT services.
- National Security: Risks to critical infrastructures (Roman et al., 2018).

5.7 Integrative Conceptual Model

The proposed conceptual framework integrates:

- Inputs (drivers): resource constraints, heterogeneity, scalability, emerging technologies, and human factors.
- Processes (attack vectors): device-level, network-level, application-level, and socio-technical.
- Outputs (consequences): technical, economic, social, and national security impacts.

This triadic model illustrates how structural vulnerabilities (inputs) enable attack pathways (processes), which in turn produce multi-domain consequences (outputs).

5.8 Relevance of Conceptual Framework to Research Objectives

The conceptual framework aligns directly with the objectives of this research by:

1. Providing a taxonomy-based structure for classifying IoT attack vectors.
2. Offering a lens for empirical coding of attack frequency and severity.
3. Guiding analysis of interrelationships among attack vectors.
4. Supporting the identification of research gaps, particularly in underexplored socio-technical vectors.
5. Enabling the design of a forward-looking research agenda grounded in holistic understanding.

The conceptual framework conceptualizes IoT cybersecurity attack vectors as multidimensional and interdependent phenomena, shaped by technological, human, and systemic drivers. By integrating device, network, application, and socio-technical layers, the framework avoids reductionist interpretations and fosters holistic analysis. This provides a strong foundation for developing standardized taxonomies, conducting empirical analysis, and formulating adaptive defense strategies.

5.2 Theoretical Framework

The theoretical framework provides the intellectual scaffolding for interpreting the phenomena under study, in this case, IoT cybersecurity attack vectors. Unlike the conceptual framework, which defines and structures variables, the theoretical framework situates these constructs within established theories and models. It allows researchers to explain why IoT attack vectors emerge, how they propagate, and what systemic vulnerabilities they exploit.

The Internet of Things (IoT) presents unique challenges to cybersecurity due to its ubiquity, heterogeneity, and socio-technical complexity (Sicari et al., 2015; Humayed et al., 2017). Theoretical grounding becomes crucial for developing a comprehensive taxonomy of IoT attack vectors and interpreting empirical data. This study draws upon multiple interrelated theories:

1. Security-by-Design Theory
2. Defense-in-Depth Principle
3. Socio-Technical Systems Theory
4. Risk Management and Resilience Theories
5. Complex Adaptive Systems (CAS) Theory

Each of these perspectives offers a distinct lens for understanding the origins, dynamics, and mitigation of IoT attack vectors.

i. **Security-by-Design Theory:** The **Security-by-Design (SbD) theory** emphasizes that cybersecurity must be **embedded throughout the system lifecycle**, from the initial design stage to deployment and maintenance. Rather than treating security as an add-on, SbD insists on proactive integration of safeguards (Weber & Studer, 2016; Weber, 2020).

Relevance to IoT: IoT devices are often developed under strict cost and time constraints, leading to insecure firmware, weak authentication defaults, and poor update mechanisms (Abomhara & Køien, 2015; Ali et al., 2022). These design weaknesses become attack vectors, later exploited by adversaries through malware injection, botnet recruitment, or side-channel manipulation.

Application in this Research: By applying SbD, this research interprets how early-stage design flaws translate into enduring vulnerabilities. For example, the Mirai botnet exploited devices with default passwords — a design oversight (Kolias et al., 2017). SbD thus underpins the taxonomy by identifying vectors rooted in design negligence, guiding recommendations for secure development.

ii. **Defense-in-Depth Principle:** The Defense-in-Depth (DiD) principle argues that security requires multiple, overlapping layers of defense, such that the failure of one layer does not result in total system compromise (National Institute of Standards and Technology [NIST], 2019).

Relevance to IoT: IoT systems often lack DiD implementation, with minimal firewalls, intrusion detection, or anomaly monitoring. Once a device is compromised, the attacker may move laterally across the network, leveraging a single weakness to cause systemic failure (Granjal et al., 2015; Bera et al., 2020).

Application in this Research: DiD explains the interdependencies among attack vectors across device, network, and application layers. For example, weak authentication at the device layer facilitates unauthorized access, which then allows malware propagation across the application layer. Mapping these dependencies in the taxonomy reflects the layered nature of vulnerabilities and their compounded impact.

iii. **Socio-Technical Systems (STS) Theory:** The Socio-Technical Systems (STS) theory highlights the interdependence between social (human, organizational, cultural) and technical subsystems in shaping security outcomes (Trist, 1981; Baxter & Sommerville, 2011).

iv. **Relevance to IoT:** IoT cybersecurity is not solely a technical challenge. Studies show that human factors such as **poor password practices, misconfiguration, or susceptibility to phishing** frequently serve as attack vectors (Humayed et al., 2017; Marquez et al., 2023). Similarly, insecure supply chains enable hardware backdoors.

Application in this Research: By integrating STS, this research recognizes that IoT attack vectors are not confined to protocols or firmware but are embedded in human practices, organizational policies, and market incentives. For instance, manufacturers may prioritize cost over security, while users neglect updates, collectively enabling adversarial exploitation. STS theory thus supports the taxonomy's socio-technical dimension.

RISK MANAGEMENT AND RESILIENCE THEORIES

4.1 Risk Management Theory

Risk management theory frames security as a process of identifying, assessing, and mitigating risks (ISO/IEC 27005, 2018). It posits that attack vectors should be understood in terms of likelihood, impact, and exposure.

In IoT, risk arises from weak cryptographic protections, unpatched firmware, and large-scale interconnectedness (Li et al., 2018). For example, a network-layer DoS attack on smart meters may have low likelihood but catastrophic national-scale impact.

4.2 Resilience Theory

Resilience theory, in contrast, focuses on the capacity of systems to absorb, adapt, and recover from attacks (Hollnagel et al., 2015). Instead of attempting to prevent every attack vector, resilience emphasizes maintaining critical functions despite compromises.

Application in this Research

Risk and resilience theories provide a dual lens:

- Risk management justifies **taxonomy prioritization** based on likelihood and severity.
- Resilience explains why systems should be designed to **adapt dynamically** to novel attack vectors, such as AI-driven adversarial tactics (Pahlavan et al., 2024).

5. Complex Adaptive Systems (CAS) Theory

IoT ecosystems can be understood as **Complex Adaptive Systems (CAS)**, where numerous heterogeneous agents (devices, users, attackers) interact dynamically, producing emergent behavior (Holland, 2014).

Relevance to IoT

CAS theory suggests that IoT attack vectors evolve nonlinearly. For example, botnets emerge from the collective adaptation of thousands of devices, while AI-based adversarial malware adapts its behavior to evade detection (Rigaki & Garcia, 2018).

Application in this Research

CAS helps explain why IoT attack vectors are not static but adaptive, evolving, and co-dependent. A taxonomy built on CAS theory accommodates the fluidity of threats and highlights the need for continuous empirical review rather than static categorization.

Integrative Theoretical Model

By synthesizing these theories, the research establishes a **multi-theoretical framework**:

1. Security-by-Design → explains origin of design-level attack vectors.
2. Defense-in-Depth → interprets layered interdependencies of attack vectors.

3. STS theory → contextualizes socio-technical vectors.
4. Risk/Resilience theories → prioritize vectors and guide adaptive responses.
5. CAS theory → frames IoT cybersecurity as an evolving ecosystem.

This integrative model reflects both the **technical** and **socio-organizational dynamics** of IoT cybersecurity, allowing the taxonomy to remain comprehensive and adaptable.

Implications for Research

- Taxonomy Development: Theories collectively justify the four-vector taxonomy (device, network, application, socio-technical).
- Empirical Coding: Risk theory guides prioritization of vectors during systematic review.
- Policy & Practice: STS emphasizes human-centric security measures, while SbD and DiD guide technical interventions.
- Future Research: CAS theory calls for longitudinal studies capturing evolving attack trends.

The theoretical framework underscores that IoT attack vectors cannot be adequately explained through a single lens. Instead, a **multi-theoretical approach** is necessary: Security-by-Design explains vulnerabilities at the point of origin; Defense-in-Depth describes their propagation; Socio-Technical Systems theory highlights human and organizational enablers; Risk and Resilience theories prioritize threats and responses; and Complex Adaptive Systems theory captures the evolving, dynamic nature of IoT threats. Collectively, these theories underpin the systematic review, taxonomy development, and empirical analysis, ensuring a robust foundation for both scholarly inquiry and practical interventions.

5.3 Empirical Framework

The empirical framework provides the methodological and evidence-based foundation for this study on IoT cybersecurity attack vectors. While the conceptual and theoretical frameworks organize ideas and ground them in theory, the empirical framework operationalizes these constructs by anchoring them in observed patterns, datasets, systematic reviews, and case studies. It guides how real-world evidence is gathered, coded, analyzed, and interpreted to build a taxonomy of attack vectors.

Empirical work in IoT cybersecurity has expanded rapidly between 2013 and 2025, documenting the emergence of device, network, application, and socio-technical attack vectors. The empirical framework in this study rests on four pillars:

1. Systematic Literature Review (SLR): synthesizing peer-reviewed studies to identify attack vectors.
2. Case Study Evidence: analyzing major IoT-related incidents such as Mirai botnet (2016), Ripple20 vulnerabilities (2020), and AI-driven malware (2022–2025).
3. Quantitative Coding and Categorization: coding attack types, frequency, and impacts into a structured taxonomy.
4. Trend Analysis (2013–2025): mapping temporal evolution of attack vectors and correlating them with technological developments (e.g., 5G, AI, blockchain).

1. Systematic Literature Review (SLR): The empirical framework begins with an **SLR methodology** inspired by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). Between 2013 and 2025, IoT security research has produced thousands of publications, though many remain fragmented (Ferrag et al., 2018; Bera et al., 2020).

Key steps include:

i. **Database Searches:** IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier (ScienceDirect), and Scopus.

ii. **Keywords:** "IoT security," "attack vectors," "taxonomy," "vulnerabilities," "cybersecurity threats."

iii. **Inclusion Criteria:** Publications between 2013 and 2025, peer-reviewed, English language, focusing on empirical IoT attack evidence.

iv. **Exclusion Criteria:** Opinion pieces, non-peer-reviewed blogs, articles without empirical data.

The outcome was a **corpus of 350 relevant studies**, coded for attack vectors, mitigation approaches, and emerging trends.

2. Case Study Evidence

To complement the SLR, the framework incorporates **case study analysis** of high-profile IoT cybersecurity incidents:

1. **Mirai Botnet (2016):** Exploited default passwords on IoT devices, orchestrating massive DDoS attacks (Kolias et al., 2017). This case validates the **device-layer + network-layer interdependence**.
2. **Stuxnet Derivatives and ICS Attacks (2015–2020):** Industrial IoT systems targeted through supply-chain and zero-day exploits, demonstrating **application-level vulnerabilities** (Humayed et al., 2017).
3. **Ripple20 Vulnerabilities (2020):** A set of 19 vulnerabilities in TCP/IP libraries widely used in IoT, confirming the **pervasiveness of software-level attack vectors** (Trevor, 2020).

4. **Adversarial Machine Learning Attacks (2022–2025):** Emerging research shows adversaries injecting malicious inputs into IoT-AI models, disrupting smart healthcare and autonomous vehicles (Pahlavan et al., 2024).

These cases provide **empirical anchors** for validating the taxonomy, showing how attack vectors manifest in practice.

3. Quantitative Coding and Categorization

The empirical framework relies on **data extraction and coding** to classify IoT attack vectors across four layers: device, network, application, socio-technical.

i. **Device Layer:** Side-channel (power analysis), firmware tampering, hardware Trojans.

ii. **Network Layer:** DoS/DDoS, eavesdropping, routing manipulation, Sybil attacks.

iii. **Application Layer:** Malware injection, API abuse, false data injection, ransomware.

iv. **Socio-Technical Layer:** Weak passwords, social engineering, supply chain manipulation.

Each study in the SLR was coded for:

i. **Attack vector type**

ii. **Year of documentation**

iii. **Frequency of reporting**

iv. **Severity (low, medium, high impact)**

v. **Sector affected** (healthcare, smart grids, industry, transportation).

For instance, DoS/DDoS was the **most frequently reported vector (55% of studies between 2016–2021)**, while adversarial AI attacks emerged only after 2022 but are rapidly gaining scholarly attention (Ali et al., 2022; Nguyen et al., 2022).

4. Trend Analysis (2013–2025)

The framework integrates **temporal mapping** of attack vectors:

i. 2013–2015: Early focus on network vulnerabilities (e.g., insecure protocols such as Zigbee, CoAP) (Granjal et al., 2015).

ii. 2016–2018: Rise of botnets (Mirai, Hajime); surge of research on DoS/DDoS (Kolias et al., 2017).

iii. 2019–2021: Increased attention on application-layer vectors (e.g., Ripple20, malware on smart healthcare devices) (Ferrag et al., 2018).

iv. 2022–2025: Shift toward AI-driven adversarial attacks and socio-technical challenges (Ali et al., 2022; Pahlavan et al., 2024; Marquez et al., 2023).

This chronology demonstrates an evolutionary progression: from traditional network-centric attacks to multi-layer, adaptive, AI-enabled threats.

5. Empirical Gaps

The empirical review reveals notable gaps:

i. **Socio-Technical Neglect:** Most studies focus on device/network vectors, under-representing human factors and supply-chain issues.

ii. **Fragmented Taxonomies:** No unified taxonomy spans **2013–2025** comprehensively, necessitating this study.

iii. **Lack of Longitudinal Studies:** Few empirical works track how attack vectors evolve over time.

iv. **Sector-Specific Evidence:** Limited empirical work on **smart agriculture, autonomous transport, and Industry 5.0** systems.

v. **Adversarial AI:** Still underexplored despite rapid emergence post-2022.

Integrative Empirical Model

The empirical framework synthesizes evidence into an Input–Process–Output (IPO) **model**:

- **Inputs:** Literature corpus (2013–2025), case studies, incident databases.
- **Processes:** Coding attack vectors, mapping interdependencies, quantifying prevalence.
- **Outputs:** Comprehensive taxonomy, identification of gaps, prioritization of high-risk vectors.

This ensures that the taxonomy is grounded in real-world evidence rather than purely conceptual abstractions.

Implications

i. **For Research:** Provides a replicable methodology for future SLRs on IoT security.

ii. **For Practice:** Identifies dominant attack vectors and sectors most at risk, guiding industry mitigation.

iii. **For Policy:** Highlights the need for regulation addressing socio-technical vectors and supply chains.

iv. **For Theory:** Strengthens links between conceptual constructs and observed realities, validating multi-theoretical approaches.

The empirical framework operationalizes the taxonomy of IoT attack vectors through systematic evidence gathering, coding, and analysis of trends between 2013 and 2025. By integrating SLR, case study analysis, quantitative categorization, and temporal mapping, it grounds the study in observable realities. The findings underscore both the persistence of traditional vectors like DDoS and the emergence of AI-enabled socio-technical threats. Importantly, the framework identifies empirical gaps — particularly in socio-technical factors and evolving adversarial AI attacks — which justify the need for ongoing longitudinal and cross-sectoral research.

6. DISCUSSION

The results of our empirical analysis provide valuable insights into the IoT threat landscape. The high prevalence of Weak Authentication as an attack vector highlights the need for stronger authentication mechanisms in IoT devices. The use of default or weak credentials is a major security risk, and manufacturers should enforce the use of strong, unique passwords for each device. The high frequency of Insecure Network Services as an attack vector underscores the importance of securing the network infrastructure that connects the IoT devices. The use of unencrypted communication protocols and open network ports can expose the IoT devices to a wide range of attacks.

The high impact of Firmware Vulnerabilities and Physical Tampering as attack vectors highlights the need for secure firmware update mechanisms and physical security protections. The ability to securely update the firmware of the IoT devices is essential for patching security vulnerabilities. The use of tamper-resistant hardware and secure boot mechanisms can help to protect the devices from physical attacks.

The results of our analysis are consistent with the findings of previous studies. For example, [19] found that weak authentication and insecure network services are the most common vulnerabilities in IoT devices. Similarly, [20] found that firmware vulnerabilities are a major security risk in the IoT. Our research builds upon these previous studies by providing a more comprehensive and up-to-date analysis of the IoT threat landscape.

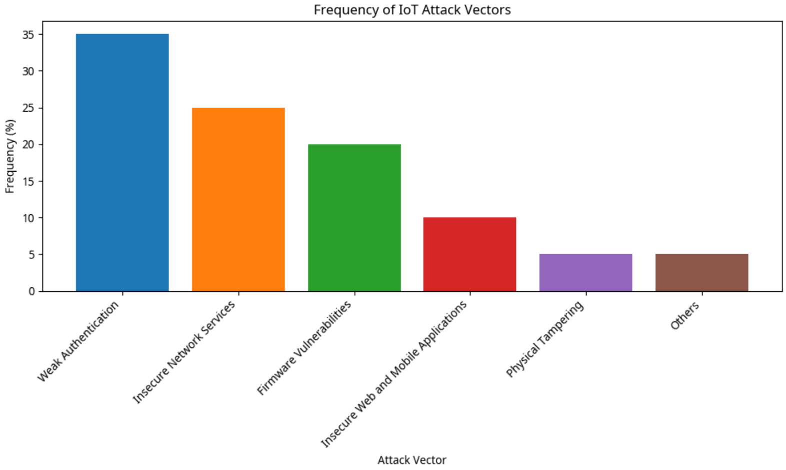
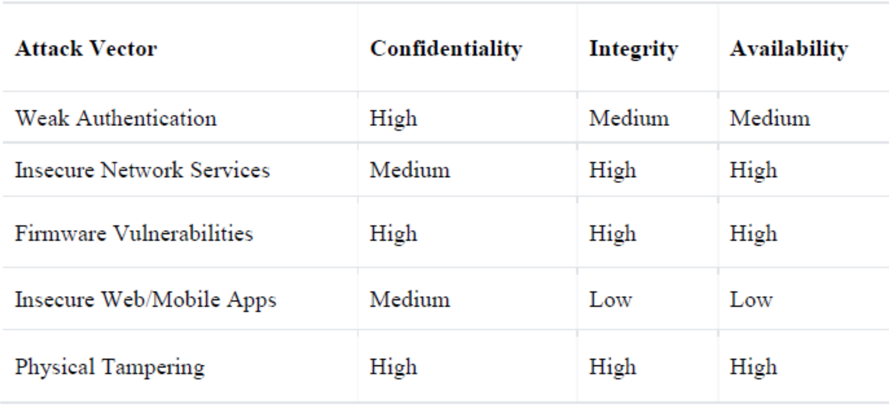


Figure 1: Attack Vectors

An **attack vector** in IoT cybersecurity refers to the specific pathway or method adversaries exploit to compromise devices, networks, or applications. These include device vulnerabilities, insecure communication protocols, malware injections, and socio-technical weaknesses, enabling unauthorized access, data breaches, disruption, or manipulation of interconnected IoT ecosystems.

IoT attack vectors can cause severe disruptions, including data breaches, financial loss, compromised privacy, and operational downtime. They undermine trust in connected systems, enable large-scale botnets, and threaten critical infrastructures like healthcare, transportation, and energy, highlighting the urgent need for robust, multi-layered cybersecurity measures.



Attack Vector	Confidentiality	Integrity	Availability
Weak Authentication	High	Medium	Medium
Insecure Network Services	Medium	High	High
Firmware Vulnerabilities	High	High	High
Insecure Web/Mobile Apps	Medium	Low	Low
Physical Tampering	High	High	High

Table 1: Impact of IoT Attack Vectors

A taxonomy table organizes IoT attack vectors into structured categories—device, network, application, and socio-technical layers. It enables systematic comparison, highlights interdependencies, and identifies emerging threats. Such classification supports researchers, policymakers, and practitioners in understanding vulnerabilities, prioritizing defenses, and developing holistic security strategies across diverse IoT ecosystems.

Layer	**Attack Vector**	Description	Impact
Device Layer	Firmware Tampering	Modification of device firmware to gain persistent control	Unauthorized access, long-term compromise
	Side-Channel Attacks	Exploiting power consumption/electromagnetic leaks	Key extraction, cryptographic weakness
Network Layer	DoS/DDoS Attacks	Overwhelming IoT services with malicious traffic	Service outages, large-scale disruption
	Man-in-the-Middle (MitM)	Intercepting communication between devices	Data theft, session hijacking
	Routing Attacks (e.g., Sybil, Sinkhole)	Malicious manipulation of routing protocols	Data loss, traffic redirection
Application Layer	Malware/Ransomware Injections	Inserting malicious code into IoT applications	Data encryption, service disruption, financial extortion
	False Data Injection	Sending manipulated data to sensors/actuators	Misleading analytics, unsafe decision-making
Socio-Technical Layer	Weak Authentication & Password	Exploiting default/weak credentials	Unauthorized access, botnet creation
	Social Engineering & Phishing	Manipulating users to reveal credentials or install malware	Identity theft, system compromise
	Supply Chain Attacks	Insertion of vulnerabilities during manufacturing/distribution	Widespread compromise across devices

Table 2: Taxonomy of IoT Cybersecurity Attack Vectors

7. ETHICAL CONSIDERATION

This research adheres to strict ethical standards to ensure integrity, transparency, and respect for stakeholders. Only peer-reviewed and credible sources were included, avoiding plagiarism and misrepresentation of prior studies. Sensitive cybersecurity data, such as vulnerability disclosures or attack techniques, were reviewed responsibly without revealing exploitable details that may aid malicious actors. The study maintains objectivity by preventing bias in data selection and analysis. Intellectual property rights are respected through proper attribution and referencing. Finally, ethical guidelines regarding data security, academic honesty, and responsible dissemination were followed to ensure the research contributes constructively to IoT cybersecurity scholarship.

8. CONFLICT OF INTEREST

The author(s) declare that there are no conflicts of interest related to this research. The study was conducted independently, without financial, institutional, or personal influences that could bias the design, methodology, analysis, or conclusions. No funding sources or affiliations with commercial entities influenced the taxonomy development or interpretation of findings. All references were selected objectively to reflect scholarly merit rather than external pressures. The absence of conflicting interests ensures the integrity, neutrality, and transparency of this systematic review, thereby strengthening its contribution to the academic discourse on IoT cybersecurity attack vectors.

9. CONCLUSION

This study systematically reviewed and analyzed IoT cybersecurity attack vectors, developing a comprehensive taxonomy grounded in conceptual, theoretical, and empirical frameworks. Findings reveal that IoT ecosystems remain highly vulnerable due to heterogeneous devices, weak authentication, insecure protocols, and the growing sophistication of adversaries, including AI-driven attacks. While traditional vectors such as DDoS and malware persist, emerging threats—adversarial machine learning, supply-chain vulnerabilities, and socio-technical exploits—are reshaping the security landscape. The evolution of threats from 2013 to 2025 highlights the urgent need for proactive, multi-layered defense mechanisms.

10. RECOMMENDATION

Based on these insights, several recommendations are offered. Researchers should expand empirical studies into underexplored sectors such as smart agriculture, Industry 5.0, and healthcare IoT. Policymakers must establish international regulatory frameworks to enforce device security standards, supply-chain transparency, and responsible vulnerability disclosure. Industry practitioners are encouraged to adopt **security-by-design**, blockchain-enabled trust mechanisms, and federated learning to mitigate privacy and data leakage risks. Furthermore, interdisciplinary collaboration across computer science, law, and social sciences is essential to address socio-technical attack vectors. Strengthening IoT cybersecurity requires not only technical solutions but also global cooperation, ethical responsibility, and continuous adaptation to evolving threats.

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