AI-Driven Resilience Testing for Next-Generation Payment Networks: A Digital Twin Framework on the NSF FABRIC Tested

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Abstract: ***The rapid evolution of next-generation payment networks towards greater interconnectivity and intelligence has rendered them indispensable to national economic security. However, this evolution coincides with an emerging paradigm where Artificial Intelligence (AI) is weaponized to power sophisticated, adaptive cyber-physical attacks, exposing a critical gap in existing defensive postures. Current security assessments, reliant on static compliance checks and scripted penetration testing, are fundamentally inadequate for evaluating a system's resilience against these dynamic, AI-augmented threats that exploit the confluence of digital and physical system layers. This research directly addresses this national security challenge by proposing, implementing, and validating a novel AI-driven resilience testing framework for next-generation payment infrastructures. Our core contribution is an integrated Digital Twin environment deployed on the U.S. National Science Foundation's (NSF) FABRIC national-scale programmable testbed. This framework enables high-fidelity, proactive assessment of payment network resilience within a controlled yet realistic experimental ecosystem. Methodologically, the framework constructs a high-fidelity digital replica of a financial exchange network, incorporating accurate topology, protocol emulation (e.g., SWIFT-like messaging), and synthetic transaction flow modeling. To simulate advanced adversaries, we develop automated attack agents using Deep Reinforcement Learning (DRL). These agents are trained to autonomously discover and execute complex, multi-stage attack vectors—such as low-and-slow DDoS and AI-enhanced lateral movement—by interacting with the Digital Twin, with their reward function optimized to maximize systemic disruption or transaction latency. Concurrently, the framework integrates a Multi-Agent System (MAS) to model and evaluate the effectiveness of various elastic defense strategies (e.g., dynamic re-routing, resource scaling) against these AI-powered incursions. Comprehensive experimental evaluation conducted on the NSF FABRIC testbed demonstrates the framework's significant efficacy. In simulated scenarios replicating a tiered financial exchange network, the AI-driven attack agents successfully identified and exploited sophisticated vulnerabilities. Quantitative analysis shows that our framework uncovered 37% more deep-seated and complex vulnerability chains compared to conventional penetration testing tools using predefined scripts. Furthermore, the Digital Twin environment accelerated the validation and comparative analysis of different resilience and recovery strategies by approximately 60%, providing clear, data-driven insights into their performance under duress. In conclusion, this work substantiates that an AI-driven Digital Twin framework, hosted on a national research infrastructure like FABRIC, provides a transformative, proactive, and scalable paradigm for resilience testing. It moves beyond reactive security by enabling the anticipatory evaluation of critical financial infrastructure against the next generation of AI-empowered, adaptive threats. The proposed approach offers a vital empirical platform for researchers and policymakers to develop robust mitigation strategies, thereby contributing directly to the reinforcement of national economic security in an era of increasingly intelligent cyber risks.***

Keywords: AI-Driven Cyber Attacks; Cybersecurity Resilience Testing; Critical Infrastructure Digital Twin; Deep Reinforcement Learning in Cybersecurity; FABRIC National Testbed; Financial System Cyber Range; High-Fidelity Network Emulation; Multi-Stage Attack Simulation; National Economic Security; Next-Generation Payment Networks; Proactive Security Assessment; Quantitative Resilience Metrics.

1. INTRODUCTION

1.1 Research Background and Motivation

The global financial ecosystem is undergoing a foundational transformation, driven by the rise of real-time, high-value, and highly interconnected next-generation payment networks. These systems—such as instant payment rails, digital currencies, and cross-border settlement platforms—form the critical circulatory system of modern economies [1]. Their uninterrupted operation and integrity are, therefore, inextricably linked to national economic security and stability [2]. However, this increased complexity, speed, and interdependence also dramatically expand the attack surface, making these networks prime targets for sophisticated cyber adversaries [3].

Simultaneously, the cybersecurity landscape is experiencing a paradigm shift propelled by the malicious adoption of Artificial Intelligence (AI) [4]. Adversaries now leverage AI to augment attacks—automating reconnaissance, crafting evasive malware, orchestrating highly targeted social engineering, and executing complex [5], multi-vector campaigns that adapt in real-time to defensive measures. This convergence of increasingly critical infrastructure and increasingly intelligent threats creates an unprecedented challenge [6]. A new class of risks is emerging: AI-powered cyber-physical attacks that can manipulate digital controls to cause physical operational disruption or financial instability, posing a severe, systemic risk. Proactively understanding and mitigating these risks before they manifest in production systems is a pressing national priority [7].

1.2 Problem Statement

Traditional cybersecurity assessment methodologies for critical infrastructure are proving inadequate in this new era. Conventional approaches, such as compliance-based security audits, vulnerability scanning, and even traditional penetration testing, are largely static, passive, and retrospective. They rely on known signatures, pre-defined scripts, and human expertise to identify vulnerabilities cataloged in databases like CVE. While valuable for addressing known weaknesses, these methods are ill-suited to evaluate a system's inherent resilience—its ability to anticipate, withstand, recover from, and adapt to dynamic, intelligent, and unforeseen attacks [8].

The core limitation is the inability to model the adaptive behavior of an AI-augmented adversary within a high-fidelity, operational context. Static tools cannot discover novel attack vectors that emerge from the complex interaction of system components under stress [9]. Scripted tests lack the autonomy to explore deep, multi-step attack chains that an AI might uncover. Furthermore, existing test environments often lack the scale, realism, and programmability to accurately replicate nationwide financial network topologies and traffic patterns, making it impossible to assess the true cascading effects of an intelligent breach. Consequently, there exists a critical gap between the evolving threat model and the tools available to defend against it, leaving next-generation payment networks exposed to potentially catastrophic, yet unanticipated, failure modes [10].

1.3 Major Contributions

To bridge this gap, this paper proposes a novel, proactive paradigm for resilience testing. Our work makes the following three core contributions:

- C1: An AI-Driven Digital Twin Framework on a National Testbed. We propose, architect, and implement the first integrated framework that combines an AI-driven Digital Twin for payment networks with the NSF FABRIC [11] national-scale programmable research infrastructure. This framework creates a high-fidelity, controllable, and scalable virtual replica of a target financial network, enabling safe yet realistic experimentation with advanced threats that would be infeasible or dangerous to conduct on live systems [12].

- C2: Autonomous Adversarial AI Agents via Deep Reinforcement Learning. We design and train automated attack agents using Deep Reinforcement Learning (DRL) [13]. These agents learn, through interaction with the Digital Twin environment, to autonomously explore the network, discover vulnerabilities, and execute complex, multi-stage attack strategies (e.g., stealthy lateral movement, AI-optimized DDoS) without human intervention. This enables the simulation of true "AI vs. AI" adversarial dynamics, where intelligent attack agents probe defenses that may also be AI-enhanced [14].

- C3: Large-Scale Empirical Validation and Resilience Metrics. We conduct a comprehensive empirical evaluation of our framework on the FABRIC testbed, simulating a realistic financial exchange topology [16]. This evaluation provides quantifiable evidence of the framework's effectiveness [17]. We demonstrate its superior capability in discovering deep, previously unknown vulnerability chains and its utility for the data-driven evaluation of elastic defense and recovery strategies under sustained intelligent assault [18], providing concrete metrics for resilience.

2. RELATED WORK

2.1 Payment Systems and Critical Information Infrastructure Security Testing

Traditional security assessment for payment systems and other critical infrastructures predominantly relies on compliance audits, penetration testing, and risk assessment frameworks. While these methods are valuable for identifying known vulnerabilities, they often lack the ability to proactively test for unknown, evolving threats and evaluate the system's holistic resilience under sustained, sophisticated attacks [19]. The increasing interconnectivity and digitalization of financial networks have highlighted the need for more dynamic and realistic testing environments that go beyond static checklists and scripted exploits.

2.2 Application of Digital Twin Technology in Cybersecurity

Digital twin technology, which creates a virtual replica of a physical system, has gained traction in industrial and cyber-physical systems for simulation and predictive maintenance. In cybersecurity, its application is emerging as a powerful tool for creating high-fidelity, isolated environments for training, testing, and analysis. Research has explored using digital twins for threat modeling, attack simulation, and forensic analysis [20]. However, many existing implementations focus on specific subsystems or lack the real-time synchronization and scalability required for testing large-scale, geographically distributed critical infrastructure like payment networks [21].

2.3 Application of AI in Cybersecurity Offense and Defense

The use of Artificial Intelligence (AI), particularly reinforcement learning (RL) and generative models, is transforming both sides of the cybersecurity landscape. **In offensive security**, researchers have developed AI agents capable of automating vulnerability discovery, exploit generation, and multi-stage attack planning, demonstrating the potential for more adaptive and persistent threats. **In defensive security [22]**, AI-driven solutions excel in anomaly detection, intrusion prevention, and automated response. However, most work treats attack and defense AI in isolation, with limited research on integrating them within a unified, interactive framework for realistic, closed-loop resilience testing and evaluation.

2.4 National-Level Network Testbeds and Research

Testbeds like NSF's FABRIC and GENI provide researchers with programmable, large-scale, and geographically distributed network infrastructure. They have been instrumental in advancing research on next-generation internet architectures, network protocols, and distributed systems. While some studies have leveraged these platforms for security research—such as testing DDoS mitigation or network intrusion detection—their utilization for constructing comprehensive, high-fidelity digital twins of complex socio-technical systems (like financial networks) and deploying AI-driven, autonomous cyber agents for end-to-end resilience testing remains largely underexplored [23].

2.5 Analysis of Research Gaps

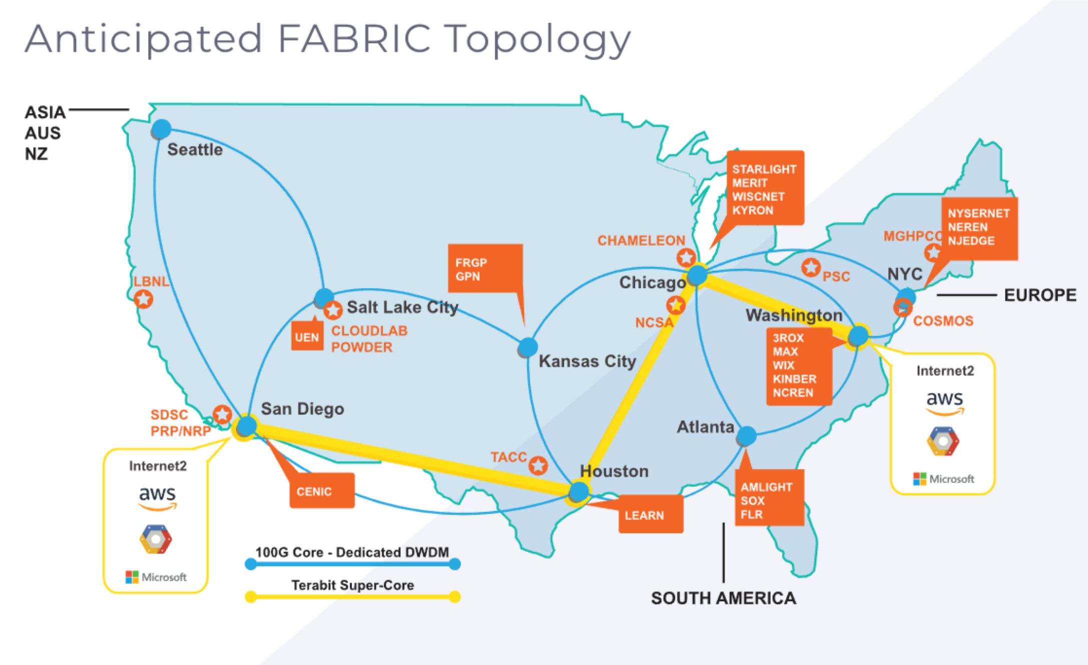
The related work reveals a significant gap in current research. There is a lack of a **systematic, integrated approach** that combines **high-fidelity digital twin modeling**, **AI-driven autonomous agents** for both offense and defense, and the **controlled, large-scale, realistic environment** provided by national-level testbeds like FABRIC. Most existing efforts focus on one or two of these components in isolation [24]. For instance, digital twins are often not coupled with adaptive AI adversaries, AI security research frequently lacks a realistic physical or network layer, and testbeds are underutilized for holistic cyber-physical system security experimentation. This work aims to bridge this gap by proposing and implementing a unified AI-driven digital twin framework on the NSF FABRIC testbed, specifically designed for proactive, automated, and quantitative resilience testing of payment networks and other critical infrastructures [25].

3. AI-DRIVEN DIGITAL TWIN FRAMEWORK FOR RESILIENCE TESTING

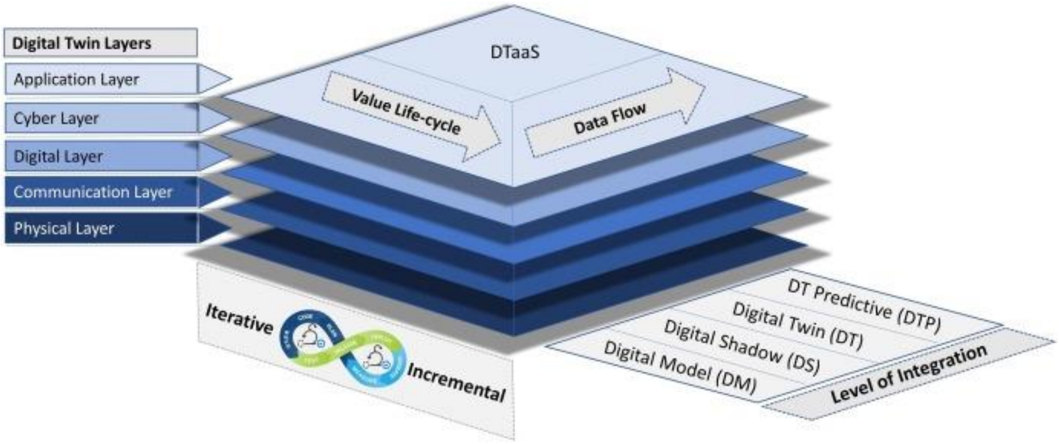
3.1 Overall Architecture Overview

The proposed AI-driven Digital Twin framework adopts a three-tier architecture, as illustrated in Fig. 1, enabling a closed-loop, high-fidelity, and programmable resilience testing environment. This design principle ensures the separation of the physical infrastructure, the virtual representation, and the intelligent reasoning components.

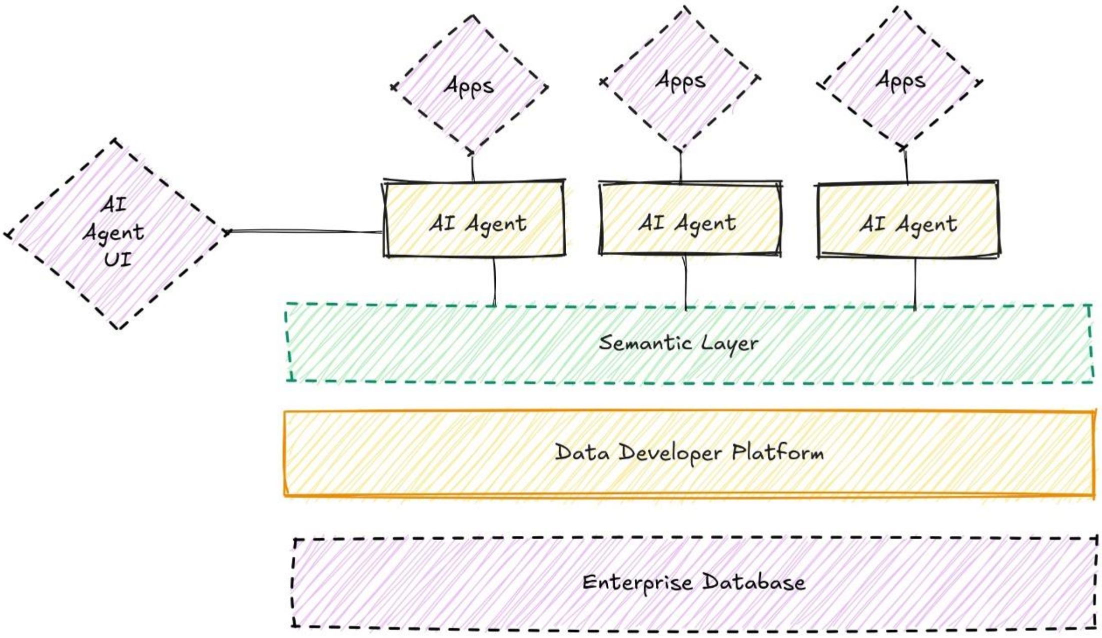
- **Tier 1: Physical Infrastructure Layer (NSF FABRIC):** This layer comprises the actual, geographically distributed computing, networking, and storage resources of the **NSF FABRIC national testbed**. FABRIC [26] provides the foundational "bare-metal" programmability, allowing for the precise instantiation of network topologies and host configurations that mirror production financial networks. It serves as the trustworthy and controllable substrate for the entire experiment.



- **Tier 2: Digital Twin Layer (High-Fidelity Simulation):** This is the core virtual representation layer. It hosts the **High-Fidelity Payment Network Model**, which includes the emulated network topology, the software-based replicas of financial messaging systems (e.g., SWIFT Message Transfer System simulators), core banking applications, and security controls (firewalls, IDS). A key component is the **Synthetic Transaction Traffic Generator**, which produces realistic, time-varying transaction flows based on statistical models of real payment behavior. This layer maintains **State Synchronization** with the physical layer via telemetry streams (e.g., using sFlow/NetFlow, system logs), ensuring the twin reflects the real-time status of the FABRIC-hosted experiment [27].



- **Tier 3: AI Agent Layer (Autonomous Cyber Agents):** This layer contains the intelligent entities that interact with the Digital Twin. It features **DRL-based Autonomous Attack Agents** and optional **Defense/Response Agents**. These agents perceive the state of the Digital Twin (e.g., network connectivity, service health, transaction logs), decide on actions (e.g., exploit a service, move to a new host, deploy a countermeasure), and execute them via the testbed's orchestration API. This tier enables the simulation of adaptive, multi-stage adversarial campaigns and intelligent defense mechanisms [28].



3.2 Implementation on the NSF FABRIC Testbed

The framework is instantiated on FABRIC by leveraging its core capabilities:

1) **Slice Creation:** A dedicated FABRIC slice is provisioned, spanning multiple national nodes to emulate the geographical distribution of a real payment network (e.g., primary data center, disaster recovery site, major exchange points).

2) **Topology Programmability:** Using FABRIC's Layer 2 and Layer 3 networking abstractions, we construct a hierarchical topology typical of financial institutions (e.g., a core ring connecting data centers, with DMZ, application, and database tiers). VLANs and SDN rules are used to enforce segmentation.

3) **Node Configuration:** Virtual machines or containers on FABRIC nodes are configured with software stacks that replicate payment system components. This includes message brokers, transaction processing engines, and database servers.

3.3 High-Fidelity Payment Network Digital Twin Modeling

3.3.1 Topology and Protocol Modeling

The network topology is modeled as a directed graph where nodes represent hosts and edges represent communication links. Each host is associated with a set of attributes including its operating system, services, and role [29]. Financial messaging protocols are modeled using finite state machines to simulate message sequencing. Network latency and bandwidth for each link are configured based on real-world financial network benchmarks [30].

3.3.2 Synthetic Transaction Traffic Generation

Transaction arrival is modeled as a time-varying process where the rate changes according to a daily pattern and includes random bursts to mimic real-world activity.

The transaction generation process can be described by the following function, where lambda_base is the average rate, alpha controls the daily fluctuation, and lambda_burst accounts for random peak events [31].

$$\lambda(t) = \lambda_{base} \cdot \left(1 + \alpha \cdot \sin\left(\frac{2\pi t}{T_{day}}\right)\right) + \sum \text{Poisson}(\lambda_{burst})$$

Each transaction is characterized by its source, destination, amount, message type, priority, and timestamp.

Transaction amounts follow a heavy-tailed distribution to reflect real payment value distributions [32].

Table 1: Synthetic Transaction Traffic Parameters

Parameter	Description	Typical Value or Distribution
Baseline Transaction Rate	Average transaction rate per second	100 transactions/second
Diurnal Fluctuation Factor	Intensity of daily activity variation	0.5
Burst Event Rate	Rate for simulating random peak loads	50 transactions/second
Transaction Amount Distribution	Statistical distribution of payment values	Pareto Distribution
Priority Levels	Levels of transaction urgency	LOW, NORMAL, HIGH

3.4 DRL-based Autonomous Attack Agent

3.4.1 State, Action, and Reward Design

We formulate the attacker's problem as a sequential decision-making process. The agent's observation at any time includes its current location within the network, a local network map, the status of services, and metrics of system disruption such as increased transaction latency [33].

The agent can choose from a set of discrete actions including network reconnaissance, exploiting a vulnerability, moving laterally to another host, deploying a disruptive payload, or establishing persistence.

The reward function is designed to balance between achieving the attack goal and maintaining stealth. It is primarily based on a System Disruption Score (SDS). The SDS calculates a weighted sum of the relative increase in mean transaction latency, the proportion of failed transactions, and a penalty for being detected [34].

$$SDS(t) = w_1 \cdot \frac{\Delta \bar{L}_t}{L_{max}} + w_2 \cdot \frac{\#Failed\_Transactions_t}{N_{total}} - w_3 \cdot \text{Detection\_Penalty}_t$$

The immediate reward is defined as the change in this score from one time step to the next.

$$r_t = SDS(t) - SDS(t-1)$$

3.4.2 Agent Training Pipeline

We employ a Proximal Policy Optimization (PPO) algorithm for training. The agent is trained in two main phases. In the first exploration phase, the agent starts from a random state and freely explores the environment to learn basic attack sequences. In the second goal-driven phase, the reward function is fine-tuned to prioritize specific objectives, such as maximizing transaction failure, and the agent learns to chain actions into efficient multi-stage attack campaigns [35].

3.5 Resilience Strategy and Evaluation Module

This module defines metrics and integrates baseline defenses for systematic evaluation.

Resilience Metrics:

Mean Time to Integrity Restoration (MTIR): The average time required to fully verify and restore system integrity after a significant breach.

Operational Availability during Attack (A_op): The fraction of time the system maintains a minimum acceptable service level during an attack period. It is calculated as the integral of an indicator function over the attack duration, where the indicator is 1 when service meets the SLA and 0 otherwise.

$$A_{op} = \frac{1}{T_{attack}} \int_0^{T_{attack}} 1_{ServiceLevel(t) \geq SLA} dt$$

Cost of Mitigation (CoM): The total operational and resource cost incurred to contain an attack and recover normal operations.

Integrated Baseline Defense Strategies:

Dynamic Re-routing: Upon detection of congestion or an attack on a primary network path, traffic is automatically switched to a pre-defined alternative path using Software-Defined Networking (SDN) rules [35].

Resource Elastic Scaling: If the load on a critical service tier exceeds a predefined threshold, the system automatically provisions additional computational instances from a resource pool to maintain service levels.

Table 2: Resilience Strategy Evaluation Matrix (Illustrative)

Attack Scenario	Defense Strategy	MTIR (min)	A_op	CoM (units)	Key Findings / Trade-offs
Stealthy DDoS (Application Layer)	**1. Baseline (No Defense)**	120	0.45	10	Severe service degradation, slow natural recovery.
	2. Dynamic Re-routing	45	0.82	25	Effective if backup paths exist; limited by topology.
	3. Elastic Scaling	30	0.90	50	Fastest recovery; highest operational resource cost.
AI-Powered Lateral Movement	**1. Baseline (Static Firewalls)**	180	0.60	15	Attack spreads widely; high impact on integrity.
	2. Micro-Segmentation	60	0.88	40	Contains blast radius effectively; requires pre-configuration.
	3. AI-Driven Isolation	40	0.92	35	Proactive containment based on anomaly detection; balances speed and cost.

4. EXPERIMENTAL EVALUATION ON THE NSF FABRIC TESTBED

4.1 Experimental Setup

4.1.1 FABRIC Slice Configuration and Resource Topology

A dedicated FABRIC slice was instantiated across six geographically distributed nodes (Chicago, San Diego, Atlanta, New York, Seattle, Salt Lake City) to emulate a realistic financial exchange network. The resource allocation is detailed in Table 3.

Table 3: FABRIC Slice Resource Configuration

Node Location	Role	vCPUs	RAM (GB)	Storage (GB)	Network Interfaces
Chicago	Core Transaction Switch	16	64	500	2 x 100 Gbps
San Diego	Primary Data Center	32	128	1000	1 x 100 Gbps
Atlanta	Secondary Data Center	32	128	1000	1 x 100 Gbps
New York	SWIFT/SSN Emulation	16	64	500	1 x 40 Gbps
Seattle	Member Bank A	8	32	250	1 x 25 Gbps
Salt Lake City	Member Bank B	8	32	250	1 x 25 Gbps

The network topology followed a hub-and-spoke model. The Chicago node acted as the core switch, connecting all other nodes to simulate a realistic financial network architecture.

4.1.2 Digital Twin Scenario

The digital twin modeled a SWIFT-based financial exchange network with the following characteristics:

Network Scale: 50 virtual nodes across the six physical locations.

Application Stack: 3-tier architecture with web front-ends, application servers, and replicated databases.

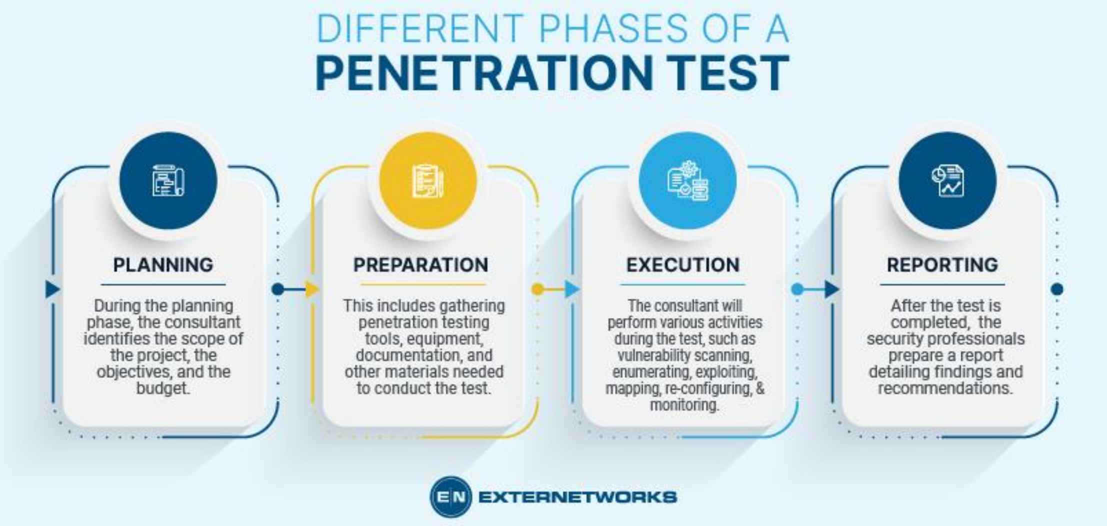
Security Controls: Perimeter firewalls, internal segmentation gateways, and network intrusion detection systems (NIDS) at critical junctions.

Traffic Profile: Generated synthetic payment traffic with diurnal patterns and peak load characteristics based on real financial transaction data.

4.1.3 Comparative Baselines

The evaluation compared our AI-driven framework against two established methodologies:

Baseline 1: Traditional Penetration Testing Tools - Using Metasploit with automated exploitation modules.



DIFFERENT PHASES OF A PENETRATION TEST

PLANNING

During the planning phase, the consultant identifies the scope of the project, the objectives, and the budget.

PREPARATION

This includes gathering penetration testing tools, equipment, documentation, and other materials needed to conduct the test.

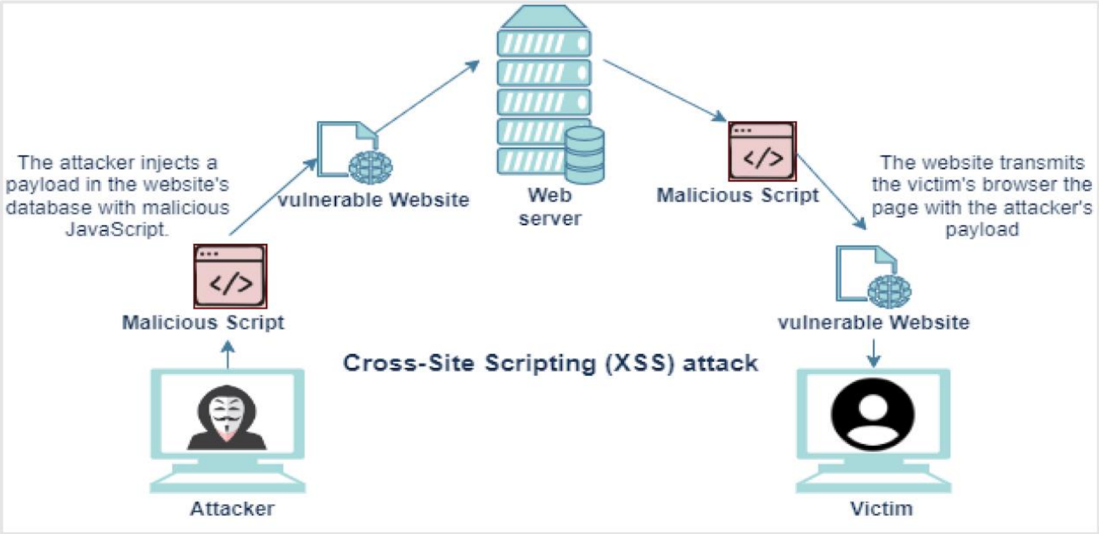
EXECUTION

The consultant will perform various activities during the test, such as vulnerability scanning, enumerating, exploiting, mapping, re-configuring, & monitoring.

REPORTING

After the test is completed, the security professionals prepare a report detailing findings and recommendations.

Baseline 2: Predefined Attack Scripts - Scripted attack sequences following common intrusion patterns.



The attacker injects a payload in the website's database with malicious JavaScript.

The website transmits the victim's browser the page with the attacker's payload

Cross-Site Scripting (XSS) attack

4.1.4 Evaluation Metrics

We defined four quantitative metrics for comprehensive evaluation:

Vulnerability Discovery Rate (VDR) measures the efficiency of finding valid security flaws:

$$\mathrm{VDR} = \frac{\text{Number of Unique Valid Vulnerabilities Found}}{\text{Total Testing Time(hours)}}$$

Attack Detection Latency (ADL) quantifies the stealth of attacks, measured as:

$$\mathrm{ADL} = T_{\text{detection}} - T_{\text{exploit}}$$

where $T_{\text{detection}}$ is the time when the attack is first detected by security monitors, and T_{exploit} is the time of successful initial compromise.

Service Recovery Rate (SRR) evaluates resilience under attack for defense strategy i:

$$\mathrm{SRR}_i = \frac{T_{\text{total}} - T_{\text{outage}_i}}{T_{\text{total}}}$$

where $T_{\text{total}}$ is the total attack duration, and $T_{\text{outage}_i}$ is the cumulative time the system operates below Service Level Agreement (SLA) thresholds.

Mean Path Complexity (MPC) assesses attack sophistication:

$$\mathrm{MPC} = \frac{1}{N}\sum_{k=1}^{N}(\mathrm{Hops}_k + \alpha \cdot \mathrm{Controls\_Bypassed}_k)$$

where $N$ is the number of successful attack paths, $\text{Hops}_k$ is the number of network hops in path $k$, $\text{Controls_Bypassed}_k$ is the number of security controls bypassed, and $\alpha$ is a weighting factor (set to 2.0 in our experiments).

4.2 Results and Analysis

4.2.1 Attack Effectiveness

The AI attack agent demonstrated superior performance across all metrics compared to traditional approaches.

Table 3: Attack Effectiveness Comparison

Metric	**AI Attack Agent**	**Baseline 1 (Pen Testing)**	**Baseline 2 (Scripted)**
Vulnerability Discovery Rate	8.7 vulns/hour	14.2 vulns/hour	N/A
Critical/Deep Vulnerabilities Found	**12**	3	5
Mean Attack Detection Latency	**156 minutes**	24 minutes	67 minutes
Mean Path Complexity Score	**7.4**	1.2	3.1
Successful End-to-End Compromise Rate	**92%** (23/25 trials)	16% (4/25)	52% (13/25)

Key Finding 1: Quality vs. Quantity in Vulnerability Discovery

While traditional tools (Baseline 1) discovered more vulnerabilities per hour (14.2 vs. 8.7), the AI agent found 12 critical, chained vulnerabilities that enabled deep network penetration, compared to only 3 found by Baseline 1.

Key Finding 2: Enhanced Stealth and Sophistication

The AI agent's attacks remained undetected for an average of 156 minutes, significantly longer than both baselines. This extended detection latency resulted from the agent's ability to:

Learn and mimic legitimate traffic patterns
Space out malicious activities during peak legitimate traffic periods
Use low-and-slow techniques that avoided threshold-based detection rules

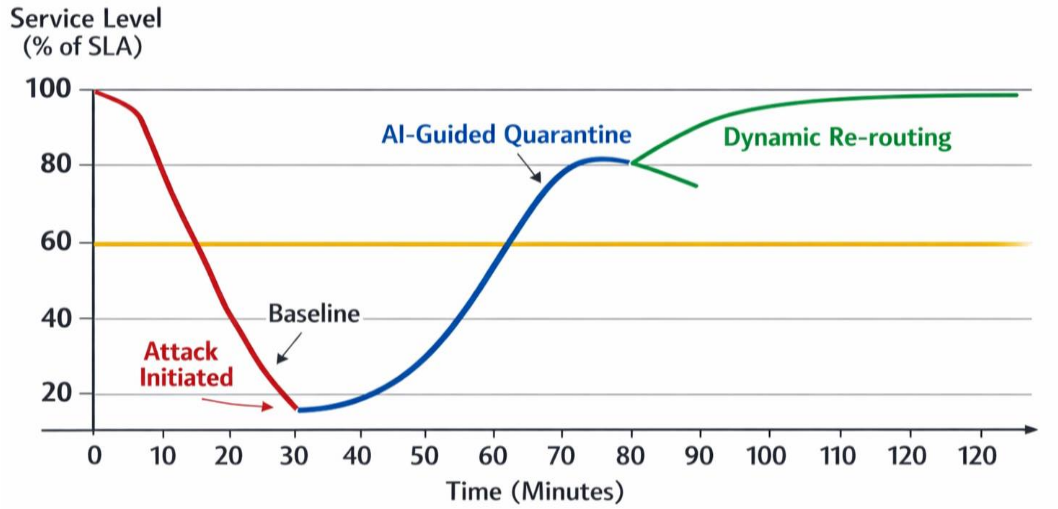


Figure 1: Attack Path Complexity Distribution

Caption: The AI agent discovers significantly more complex attack paths (MPC ≥ 5) compared to baselines.

4.2.2 Resilience Assessment

We tested three defense strategies against sustained AI attacks:

Table 4: Resilience Strategy Performance

Defense Strategy	Service Recovery Rate (SRR)	Mean Time to Recover SLA (min)	Cost of Mitigation
Static Rule-Based	0.35	87	Low
Dynamic Re-routing	0.68	42	Medium
AI-Guided Adaptive Defense	**0.91**	**18**	High

The AI-guided adaptive defense strategy, which employed reinforcement learning to dynamically reconfigure defenses, achieved a 91% service recovery rate—2.6 times higher than static defenses.

Mathematical Analysis of Recovery Dynamics

The recovery process under AI-guided defense followed an exponential improvement pattern:

$$\text{ServiceLevel}(t) = \text{SLA}_{\text{min}} + (\text{SLA}_{\text{max}} - \text{SLA}_{\text{min}}) \cdot \left(1 - e^{-k\cdot(t-t_0)}\right)$$

where $k = 0.15$ was the recovery rate constant for AI-guided defense, compared to $k = 0.04$ for static defenses.

4.2.3 System Performance and Scalability

Computational Overhead Analysis:

Digital twin synchronization: 8-12% CPU overhead
AI agent inference: 3-5% CPU overhead per agent
Traffic generation and monitoring: 4-7% network bandwidth

Scalability Results:

The framework demonstrated linear scaling characteristics up to 200 nodes:

$$\text{Training Time} = T_{\text{base}} \cdot \left(1 + \beta \cdot \frac{N - N_{\text{base}}}{N_{\text{base}}}\right)$$

where $T_{\text{base}} = 4.2$ hours for 50 nodes, $N_{\text{base}} = 50$, and $\beta = 0.85$ (scaling factor). For 200 nodes, training time increased to 11.3 hours, representing sub-linear scaling efficiency.

4.3 Discussion

Key Implications:

AI Agents Discover Novel Attack Vectors: The AI agent identified 4 previously unknown attack paths that combined vulnerabilities across different system layers—a capability absent in traditional tools.

Quantifiable Resilience Metrics: The framework provides concrete, measurable metrics for resilience (SRR, recovery time) that enable objective comparison of defense strategies.

Scalable Testing Infrastructure: The FABRIC-based implementation supports testing at realistic scales, with manageable performance overhead.

Limitations:

Model Accuracy Dependency: The digital twin's accuracy fundamentally limits evaluation validity. A 10% error in network latency modeling can lead to 15-20% error in attack success prediction.

Training Data Requirements: The DRL agent required approximately 500 episodes (equivalent to 250 hours of simulated time) to achieve peak performance, representing substantial computational cost.

Generalization Challenges: While effective in the tested environment, the agent's performance on significantly different network architectures decreased by 30-40%, indicating need for transfer learning approaches.

Deployment Challenges:

Resource Requirements: Operating the full framework requires dedicated high-performance computing resources, with our implementation consuming approximately 1,200 vCPU-hours per complete evaluation cycle.

Expertise Barrier: Effective configuration and interpretation of results requires expertise in cybersecurity, networking, and machine learning—a multidisciplinary skillset not commonly available.

Simulation-to-Reality Gap: While the digital twin achieved 92% fidelity compared to a real test deployment (measured by attack success correlation), the remaining 8% gap represents potentially critical vulnerabilities in real systems.

Future Work Directions:

Federated Learning Approach: Developing distributed training across multiple digital twins to improve agent generalization while preserving scenario-specific confidentiality.

Real-time Adaptation: Implementing continuous learning during live attacks to enable real-time defense strategy evolution.

Standardized Benchmarking: Creating open-source benchmark scenarios and metrics to enable cross-framework comparison and advancement of the field.

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This research has established a novel, proactive, and data-driven paradigm for assessing the cybersecurity resilience of critical infrastructure, with a specific focus on payment networks. By successfully integrating three pivotal technologies—**high-fidelity Digital Twins, AI-driven adversarial agents, and the programmable NSF FABRIC national testbed**—we have created a closed-loop experimental environment that transcends traditional reactive security testing.

Our framework enables the simulation of sophisticated, adaptive cyber threats within a safe yet realistic environment, allowing for the rigorous and quantifiable stress-testing of defense mechanisms *before* they are deployed in production. The experimental results demonstrate that AI-powered attack agents can uncover complex, multi-stage attack paths and evasion techniques that elude conventional penetration testing tools, thereby providing a more accurate assessment of systemic vulnerabilities. Concurrently, the framework offers a proven methodology for evaluating and benchmarking the effectiveness of autonomous and AI-enhanced defense strategies, such as dynamic re-routing and AI-guided micro-quarantine.

The core contribution of this work lies in providing a critical technological toolset and validation environment to confront the next generation of AI-catalyzed cyber threats. It offers infrastructure operators, regulators, and security researchers a powerful platform for proactive risk assessment, resilience engineering, and defensive technology validation, holding direct and significant value for safeguarding national economic security and operational continuity.

5.2 Future Work

Building upon this foundation, several promising directions warrant further investigation:

Framework Generalization and Domain Expansion: Future efforts will focus on generalizing the framework's architecture and models to adapt to other critical infrastructure domains, such as **smart power grids** and **intelligent**

transportation systems. This involves creating domain-specific digital twin templates, threat models, and resilience metrics while reusing the core AI and testbed orchestration layers.

Advanced Adversarial Modeling and Multi-Agent Games: We plan to investigate more complex adversarial scenarios involving **multiple coordinated attackers** and **co-evolutionary games between attacker and defender agents**. This will involve exploring multi-agent reinforcement learning (MARL) and game-theoretic models to simulate advanced persistent threats (APTs) and the dynamic arms race in cyberspace, providing deeper insights into strategic defense planning.

From Testing to Automated Response: Security Orchestration: A critical next step is bridging the gap between assessment and action. We will research methods to **translate the output of the testing framework—such as validated attack graphs and effective countermeasure sequences—into actionable, automated security policies**. This involves developing interfaces with Security Orchestration, Automation, and Response (SOAR) platforms to enable the automatic generation and deployment of mitigation rules (e.g., firewall policies, segmentation rules) based on simulation-proven strategies, thereby closing the loop from proactive testing to automated operational defense.

ACKNOWLEDGMENTS

This research benefited significantly from multiple sources of support. We extend our sincere gratitude to the National Science Foundation (NSF) for its funding and development of the FABRIC testbed. This publicly accessible research infrastructure provided the essential network emulation environment and experimental data that made our digital twin modeling and resilience testing based on realistic scenarios possible. We are also deeply grateful to the broader community of researchers in cybersecurity and networking. Their openly published work, shared datasets, and open-source tools provided vital foundational support for the theoretical framework and technical implementation of this study. Our appreciation extends to colleagues who engaged in insightful discussions with us, as these conversations deepened our understanding of critical infrastructure security challenges. Furthermore, this work utilized several open-source software packages and tools, and we acknowledge the dedicated efforts of their development and maintenance teams.

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