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# Impact of Cybersecurity Controls on Attack Success, Financial Loss, and Incident Response: An Empirical Analysis Using Synthetic Enterprise Incident Data

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## ABSTRACT

*The rapid digital transformation of enterprises has expanded the cyber threat landscape, necessitating robust security strategies and predictive analytics to strengthen organizational resilience. This study presents an empirical analysis of enterprise cybersecurity incident data to evaluate the effectiveness of major technical, organizational, and governance controls in reducing cyber risk and improving operational response performance. Using the Cyber Attack Detection & Risk Prediction Dataset (AI Explorer, 2026) a synthetic dataset comprising over 100,000 enterprise level incidents with 50+ features we develop a multi task machine learning pipeline employing XGBoost, Random Forest, SVM, and statistical baselines across three core tasks: binary attack success classification, multi-class risk level prioritization (Low, Medium, High, Critical), and financial loss regression.*

*Our results reveal a hierarchical efficacy among security controls. Multi-Factor Authentication (MFA) emerges as the most impactful preventive control, reducing attack success rates by approximately 28% (37.4% → 26.8%) with a medium to large effect size (Cohen's d = 0.68). Endpoint Detection and Response (EDR) demonstrates large operational effects (d >0.8), cutting detection time by ~46 minutes and response time by ~27 minutes. Security awareness training halves successful phishing click rates (40.95% → 20.91%), while weak password policies significantly elevate attack success (34.70%) and financial losses ($82,395). Firewall deployment shows modest but statistically significant benefits in reducing financial loss and cyber risk scores. Organizations aligned with ISO 27001 exhibit the lowest attack success rates (26.74%) and incident costs ($64,672).*

*The XGBoost model achieves superior performance across all tasks: AUC-ROC of 0.961 for attack success prediction, 82.1% accuracy for risk categorization, and $R^2$ of 0.867 with MAE of $14,892 for financial loss forecasting. These findings provide a data driven blueprint for strategic cybersecurity investments, demonstrating that identity centric controls, rapid detection and response capabilities, and governance frameworks collectively form the foundation of resilient enterprise security architectures. The study confirms the practical value of integrating multiple control features and machine learning analytics for proactive cyber defense, risk quantification, and evidence based security decision making.*

**Keywords:** Cybersecurity Controls Attack Success Prediction, Financial Loss Estimation Incident Response Machine Learning XGBoost Multi-Factor Authentication (MFA) Endpoint Detection and Response (EDR) Cyber Risk Quantification

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## 1. Introduction

The rapid digital transformation of modern enterprises has significantly expanded the cyber threat landscape, resulting in an unprecedented increase in the frequency, sophistication, and economic impact of cyberattacks. High profile cybersecurity incidents affecting governments, private organizations, and critical infrastructure have highlighted the necessity of developing resilient security strategies capable of preventing, detecting, responding to, and recovering from increasingly complex cyber threats. Consequently, cybersecurity resilience has emerged as a strategic organizational objective that encompasses the ability to anticipate, withstand, mitigate, and rapidly recover from cyber incidents. Predictive cybersecurity analytics has therefore gained considerable attention as an effective approach for proactively strengthening cyber resilience through early threat identification and informed decision making [1].

## 2. Background and Early Studies

Cybersecurity risk assessment has become a major research focus within both academia and industry. Previous studies have frequently employed the occurrence of cybersecurity breaches as an empirical indicator of organizational cyber risk, enabling researchers to investigate the factors influencing successful attacks and their organizational consequences [2, 3, 4, 5]. Complementary research has examined cybersecurity disclosure practices as an important component of organizational security governance and risk management [6]. Collectively, these studies have contributed to the development of cross disciplinary taxonomies of cybersecurity risk factors while revealing the complex relationships among organizational characteristics, security practices, threat actors, and breach outcomes.

To reduce cyber risk, the security industry has developed a wide range of technical and organizational security controls designed to strengthen enterprise defense mechanisms while optimizing security investments. These security controls are intended not only to improve technical protection but also to support strategic planning and resource allocation within organizations [7]. However, determining the relative effectiveness of individual security controls remains a challenging problem because organizations often deploy multiple overlapping defensive mechanisms whose individual contributions are difficult to isolate.

The economic consequences of cybersecurity incidents extend well beyond the direct costs associated with system compromise. Bouveret investigated global cyber risks affecting the financial sector and demonstrated the diverse nature of cyber incidents that influence organizational resilience [8]. Similarly, Turk emphasized that evaluating industrial cyberattacks cannot be limited to immediate financial losses such as production disruption or equipment damage. Long term consequences, including reputational damage, customer distrust, regulatory penalties, and reductions in shareholder value, frequently exceed the direct operational costs associated with a cyber incident [9]. These findings illustrate the multidimensional nature of cybersecurity losses and the need for comprehensive assessment frameworks.

Despite growing investments in cybersecurity technologies, accurately quantifying the economic benefits of security controls remains difficult. Organizations in both the public and private sectors face considerable uncertainty when estimating the probability of cyberattacks and the potential value at risk associated with security breaches [10]. To address this challenge, Cobos synthesized empirical evidence on cybersecurity loss estimation by examining different categories of cyber losses, estimation methodologies, and publicly

available incident datasets [11]. Previous reports have similarly emphasized that improving the understanding of cybersecurity costs is essential for evidence based decision making, investment prioritization, and policy development [12, 13, 14].

In addition to direct financial losses, indirect costs generated by cyber incidents including reputational damage, customer attrition, operational disruption, legal liabilities, and reduced market value can significantly affect long-term organizational performance. These indirect consequences are frequently underestimated despite their substantial influence on organizational sustainability and economic growth [15, 16].

Another challenge in cybersecurity research concerns accurately measuring the effectiveness of security investments. Woods demonstrated that simple statistical relationships may produce misleading conclusions, where higher security spending or more frequent software updates appear to correlate with increased compromise rates because organizations with greater exposure naturally invest more heavily in cybersecurity. After accounting for threat exposure and organizational characteristics, the study showed that comprehensive security indicators provide a more reliable explanation of compromise rates [17]. This finding highlights the importance of adopting multidimensional evaluation frameworks when assessing cybersecurity performance.

Recent research has increasingly adopted data driven and artificial intelligence techniques to improve cyber risk assessment. Javadnejad [18] conducted a comprehensive evaluation of ransomware and malware risks using the Advisen cyber loss dataset, demonstrating that relatively infrequent attack types can nevertheless generate disproportionately large financial losses. The study further emphasized the growing importance of advanced cybersecurity technologies, including artificial intelligence based detection systems and Zero Trust Architecture (ZTA), in mitigating sophisticated cyber threats [18]. Similarly, Md Aminul Islam quantitatively investigated the effectiveness of cybersecurity frameworks in protecting Industrial Control Systems (ICS), demonstrating that formal adoption of security frameworks alone does not necessarily guarantee consistent operational security unless supported by effective implementation and organizational governance [19].

Machine learning has also emerged as an effective tool for cybersecurity analytics. Ika Maulita employed comprehensive exploratory data analysis and robust preprocessing techniques before developing Linear Regression, Decision Tree, and Random Forest models to predict financial losses resulting from cybersecurity incidents, demonstrating the value of data-driven predictive modeling for cyber risk assessment [20]. Likewise, Agus highlighted the growing role of machine learning in supporting cybersecurity law enforcement through the identification of attack patterns, organizational vulnerabilities, and evidence based cyber defence strategies [21].

Overall, existing studies have established the importance of cybersecurity controls, governance frameworks, and predictive analytics for improving organizational resilience. Nevertheless, relatively few studies have comprehensively investigated the simultaneous influence of multiple technical controls, human centric security practices, governance mechanisms, and organizational security maturity on critical cybersecurity outcomes such as attack success, financial loss, cyber risk score, detection time, and response time within a unified analytical framework. Addressing this research gap is essential for identifying the security controls that provide the greatest operational and economic benefits.

Companies that invest strategically in comprehensive cyber risk management programs are better positioned to strengthen organizational resilience, improve economic stability, and achieve sustainable competitive advantage within an increasingly complex digital environment [22, 23]. Motivated by this need, the present study performs an empirical analysis of enterprise cybersecurity incident data to evaluate the effectiveness of major technical, organizational, and governance controls in reducing cyber risk and improving operational response performance.

# 3. Methodology

The primary objective of this methodology is to systematically evaluate the operational and financial efficacy of enterprise cybersecurity controls using a data driven predictive framework. Rather than evaluating controls in isolation, this methodology treats technical defenses, human factors, and governance structures as interacting features within a unified analytical system.

## 3.1 Framework Pipeline Overview

The analytical pipeline transitions from data ingestion to multi-task machine learning execution through the following structured phases:

**1. Data Ingestion & Partitioning:** The dataset is ingested and split using stratified sampling into training (70%), validation (15%), and test (15%) partitions to rigorously prevent data leakage and preserve class distributions.

**2. Feature Preprocessing:** Categorical features (e.g., Attack_Vector, Password_Policy, Compliance) are mapped to statistical vectors, missing values are imputed, and continuous indicators are normalized.

**3. Multi-Task Modeling:** The preprocessed features feed into three distinct supervised learning pipelines targeted at classification, prioritization, and financial risk forecasting.

# 4. Model Architecture

To handle the highly heterogeneous and imbalanced nature of real world enterprise incident data , the system deploys a tiered multi-task machine learning architecture utilizing advanced gradient boosted decision trees (XGBoost) alongside baseline comparative models.

## 4.1 Tier 1: Binary Incident Classification (Attack Success)

The first layer models the probability of an attack successfully breaching enterprise defenses ($Y \in \{0,1\}$). We employ an optimized extreme gradient boosting (XGBoost) classifier that minimizes a log loss objective function through regularized gradient descent:

$$\mathcal{L}_{binary} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] + \sum_{k}\Omega(f_k)$$

where $\Omega(f_k)$ represents the regularization term penalizing model complexity to safeguard against overfitting.

## 4.2 Tier 2: Multi-Class Risk Categorization (Risk Level Prioritization)

To facilitate rapid Security Operations Center (SOC) triage, this module maps incident features into an ordinal multi-class risk space:

$$Y_{\text{risk}} \in \{\text{Low, Medium, High, Critical }\}$$

The architecture leverages a multi-class XGBoost classifier with a Softmax activation layer to output a discrete probability distribution across all four severity tiers.

## 4.3 Tier 3: Economic Blast Radius Forecasting (Financial Loss Regression)

To bridge technical threat indicators with business intelligence, the final module predicts continuous monetary damages ($Y_{\text{loss}} \in \mathbb{R}+$). This regressor optimizes a Root Mean Squared Error (RMSE) objective function, mapping structural variables such as control states, Security_Maturity, and Data_Exfiltration_GB—directly to expected financial impact.

### 4.4 Experimental Setup

#### 4.41. Dataset

The full dataset was partitioned into training (70%), validation (15%), and test (15%) sets using stratified sampling to preserve class distributions. Preprocessing steps included handling missing values, encoding categorical variables, normalizing numerical features, and feature engineering for temporal and interaction terms. This dataset provides a robust benchmark for evaluating the proposed models against diverse cyber threat scenarios while facilitating reproducible research. The dataset includes 50+ features spanning network traffic metadata, system logs, vulnerability indicators, security control effectiveness, attacker behavior patterns, temporal attributes, and business impact metrics (e.g., financial loss and operational disruption). Key variables support multiple supervised learning tasks, including:

- Binary classification (successful attack detection),
- Multi-class classification (risk level or severity categorization),
- Regression (cyber risk score or financial loss prediction), and
- Anomaly detection.

Incidents are generated with realistic correlations between vulnerabilities, attack vectors, defensive controls, and outcomes, reflecting modern enterprise environments. The data exhibits class imbalance typical of real-world cybersecurity scenarios, with temporal sequencing that enables time series and sequential modeling approaches. No personally identifiable or real organizational data is included; the dataset is fully synthetic yet engineered for high ecological validity in academic and industry research.

#### 4.4.2 Dataset Characteristics & Synthesis

The experimental validation is performed on the *Cyber Attack Detection & Risk Prediction Dataset* (AI Explorer, 2026), consisting of over 100,000 synthetic enterprise level cybersecurity incidents. While synthetic, the dataset is engineered with complex, non-linear correlations mirroring real world kill chain dependencies. It features a baseline positive class distribution of 29.4% for successful attacks, creating a realistic, moderately imbalanced environment.

#### 4.4.3 Preprocessing & Feature Engineering

- **Missing Data:** Addressed via median imputation for numerical features and mode imputation for categorical data fields.
- **Encoding:** High-cardinality nominal text fields are transformed using one hot encoding, whereas ordinal strings (e.g., Password_Policy) undergo label encoding.
- **Normalization:** Standard scaling is applied to continuous variables (such as Detection_Time_Min and Cyber_Risk_Score) to guarantee stable gradient updates across all models.

#### 4.4.4 Benchmarking Models

To rigorously isolate performance gains, the primary XGBoost pipelines are benchmarked against three distinct mathematical architectures:

**1. Ensemble Trees:** Random Forest (RF) configurations to evaluate bagging vs. boosting.

**2. Boundary Discriminators:** Support Vector Machines (SVM) with radial basis function kernels to capture high-dimensional geometric decision boundaries.

**3. Statistical Baselines:** Logistic Regression (for classification tasks) and standard Linear Regression (for financial forecasting).

#### 4.4.5 Evaluation Metrics

The models are evaluated on a completely isolated, held out test set representing 20% of the master data pool. Performance is scored using the following mathematical metrics:

• **Classification Tasks:** Accuracy, Precision, Recall, $F_1$-Score, and Area Under the ROC Curve (AUC-ROC).

• **Regression Tasks:** Mean Absolute Error (MAE in USD), Root Mean Squared Error (RMSE in USD), and the Coefficient of Determination ($R^2$ Score).

• **Statistical Power Constraints:** Statistical differences between control levels are verified using independent two-sample Welch's *t*-tests ($p < 0.001$) accompanied by Cohen's *d* calculation to quantify physical effect sizes.

## 5. Analysis

### 5.1 Security Control Effectiveness

Table 1 presents a comprehensive comparative analysis of key security controls and their impact on critical cybersecurity outcomes, including attack success probability, financial loss, cyber risk score, detection time, and response time. The results are stratified by control status (enabled/disabled or categorical levels) and derived from the full validation set of the Cyber Attack Detection & Risk Prediction Dataset.

| Control | Outcome | Level | Mean |
|---|---|---|---|
| Firewall | Attack_Success | 0 | 0.297833 |
| Firewall | Attack_Success | 1 | 0.293615 |
| Firewall | Financial_Loss_USD | 0 | 79359.91 |
| Firewall | Financial_Loss_USD | 1 | 75172.93 |
| Firewall | Cyber_Risk_Score | 0 | 54.36544 |
| Firewall | Cyber_Risk_Score | 1 | 44.16707 |
| Firewall | Detection_Time_Min | 0 | 120.7177 |
| Firewall | Detection_Time_Min | 1 | 105.346 |
| Firewall | Response_Time_Min | 0 | 49.72894 |
| Firewall | Response_Time_Min | 1 | 40.10743 |
| MFA | Attack_Success | 0 | 0.373559 |
| MFA | Attack_Success | 1 | 0.267625 |
| MFA | Financial_Loss_USD | 0 | 85353.68 |
| MFA | Financial_Loss_USD | 1 | 72264.43 |
| MFA | Cyber_Risk_Score | 0 | 54.54763 |

| | | | |
|---|---|---|---|
| MFA | Cyber_Risk_Score | 1 | 41.84229 |
| MFA | Detection_Time_Min | 0 | 108.3598 |
| MFA | Detection_Time_Min | 1 | 106.021 |
| MFA | Response_Time_Min | 0 | 43.14645 |
| MFA | Response_Time_Min | 1 | 40.14879 |
| EDR | Attack_Success | 0 | 0.336589 |
| EDR | Attack_Success | 1 | 0.283257 |
| EDR | Financial_Loss_USD | 0 | 87471.52 |
| EDR | Financial_Loss_USD | 1 | 72515.38 |
| EDR | Cyber_Risk_Score | 0 | 52.86728 |
| EDR | Cyber_Risk_Score | 1 | 43.02561 |
| EDR | Detection_Time_Min | 0 | 143.4445 |
| EDR | Detection_Time_Min | 1 | 97.35457 |
| EDR | Response_Time_Min | 0 | 62.63495 |
| EDR | Response_Time_Min | 1 | 35.43508 |
| IDS | Attack_Success | 0 | 0.321835 |
| IDS | Attack_Success | 1 | 0.283052 |
| IDS | Financial_Loss_USD | 0 | 83454.92 |
| IDS | Financial_Loss_USD | 1 | 72403.24 |
| IDS | Cyber_Risk_Score | 0 | 46.09881 |
| IDS | Cyber_Risk_Score | 1 | 44.57113 |
| IDS | Detection_Time_Min | 0 | 132.4385 |
| IDS | Detection_Time_Min | 1 | 96.47831 |
| IDS | Response_Time_Min | 0 | 54.80931 |
| IDS | Response_Time_Min | 1 | 35.44878 |

| | | | |
|---|---|---|---|
| Security_Training | Attack_Success | 0 | 0.323976 |
| Security_Training | Financial_Loss_USD | 1 | 0.281298 |
| Security_Training | Financial_Loss_USD | 0 | 80079.84 |
| Security_Training | Financial_Loss_USD | 1 | 73586.82 |
| Security_Training | Cyber_Risk_Score | 0 | 45.63149 |
| Security_Training | Cyber_Risk_Score | 1 | 44.73474 |
| Security_Training | Detection_Time_Min | 0 | 107.0575 |
| Security_Training | Detection_Time_Min | 1 | 106.4101 |
| Security_Training | Response_Time_Min | 0 | 41.00298 |
| Security_Training | Response_Time_Min | 1 | 40.84803 |
| Password_Policy | Attack_Success | Moderate | 0.279796 |
| Password_Policy | Attack_Success | Strong | 0.281877 |
| Password_Policy | Attack_Success | Weak | 0.347044 |
| Password_Policy | Financial_Loss_USD | Moderate | 73611.61 |
| Password_Policy | Financial_Loss_USD | Strong | 74036.26 |
| Password_Policy | Financial_Loss_USD | Weak | 82395.31 |
| Password_Policy | Cyber_Risk_Score | Moderate | 44.62549 |
| Password_Policy | Cyber_Risk_Score | Strong | 44.81116 |
| Password_Policy | Cyber_Risk_Score | Weak | 46.17915 |
| Password_Policy | Detection_Time_Min | Moderate | 106.4189 |
| Password_Policy | Detection_Time_Min | Strong | 106.4332 |
| Password_Policy | Detection_Time_Min | Weak | 107.3113 |
| Password_Policy | Response_Time_Min | Moderate | 40.78509 |
| Password_Policy | Response_Time_Min | Strong | 40.99054 |
| Password_Policy | Response_Time_Min | Weak | 40.97092 |

| | | | |
|---|---|---|---|
| Compliance | Attack_Success | HIPAA | 0.293399 |
| Compliance | Attack_Success | ISO27001 | 0.267397 |
| Compliance | Attack_Success | NIST | 0.334978 |
| Compliance | Attack_Success | PCI-DSS | 0.299663 |
| Compliance | Financial_Loss_USD | HIPAA | 69609.74 |
| Compliance | Financial_Loss_USD | ISO27001 | 64672.21 |
| Compliance | Financial_Loss_USD | NIST | 79714.1 |
| Compliance | Financial_Loss_USD | PCI-DSS | 100017.8 |
| Compliance | Cyber_Risk_Score | HIPAA | 45.18224 |
| Compliance | Cyber_Risk_Score | ISO27001 | 40.32677 |
| Compliance | Cyber_Risk_Score | NIST | 52.02373 |
| Compliance | Cyber_Risk_Score | PCI-DSS | 45.41773 |
| Compliance | Detection_Time_Min | HIPAA | 106.6543 |
| Compliance | Detection_Time_Min | ISO27001 | 102.1186 |
| Compliance | Detection_Time_Min | NIST | 114.201 |
| Compliance | Detection_Time_Min | PCI-DSS | 107.0693 |
| Compliance | Response_Time_Min | HIPAA | 41.22858 |
| Compliance | Response_Time_Min | ISO27001 | 36.04074 |
| Compliance | Response_Time_Min | NIST | 49.14578 |
| Compliance | Response_Time_Min | PCI-DSS | 41.28403 |
| Security_Maturity | Attack_Success | 0 | 0.346939 |
| Security_Maturity | Attack_Success | 20 | 0.434406 |
| Security_Maturity | Attack_Success | 40 | 0.401728 |
| Security_Maturity | Attack_Success | 60 | 0.340495 |
| Security_Maturity | Attack_Success | 80 | 0.290063 |

| | | | |
|---|---|---|---|
| Security_Maturity | Attack_Success | 100 | 0.231902 |
| Security_Maturity | Financial_Loss_USD | 0 | 97515.08 |
| Security_Maturity | Financial_Loss_USD | 20 | 100444.5 |
| Security_Maturity | Financial_Loss_USD | 40 | 100268.6 |
| Security_Maturity | Financial_Loss_USD | 60 | 82425.74 |
| Security_Maturity | Financial_Loss_USD | 80 | 75335.43 |
| Security_Maturity | Financial_Loss_USD | 100 | 63550.84 |
| Security_Maturity | Cyber_Risk_Score | 0 | 71.80179 |
| Security_Maturity | Cyber_Risk_Score | 20 | 64.6102 |
| Security_Maturity | Cyber_Risk_Score | 40 | 57.60443 |
| Security_Maturity | Cyber_Risk_Score | 60 | 50.16346 |
| Security_Maturity | Cyber_Risk_Score | 80 | 44.26059 |
| Security_Maturity | Cyber_Risk_Score | 100 | 38.27285 |
| Security_Maturity | Detection_Time_Min | 0 | 179.9574 |
| Security_Maturity | Detection_Time_Min | 20 | 164.5972 |
| Security_Maturity | Detection_Time_Min | 40 | 144.9974 |
| Security_Maturity | Detection_Time_Min | 60 | 123.5741 |
| Security_Maturity | Detection_Time_Min | 80 | 104.3626 |
| Security_Maturity | Detection_Time_Min | 100 | 85.11599 |
| Security_Maturity | Response_Time_Min | 0 | 81.89796 |
| Security_Maturity | Response_Time_Min | 20 | 79.80322 |
| Security_Maturity | Response_Time_Min | 40 | 64.60644 |
| Security_Maturity | Response_Time_Min | 60 | 50.10852 |
| Security_Maturity | Response_Time_Min | 80 | 39.44209 |
| Security_Maturity | Response_Time_Min | 100 | 28.7027 |

Table 1. Security Control Effectiveness

Firewall Deployment demonstrates moderate protective value, reducing average financial loss from approximately $79,360 (disabled) to $75,173 (enabled) and shortening detection/response times by roughly 15–20%. However, its effect on overall attack success rate remains limited (~0.4% absolute reduction), suggesting attackers frequently bypass network level perimeter defenses through alternative vectors such as phishing or insider threats.

Multi-Factor Authentication (MFA) emerges as one of the most impactful controls. Enabling MFA reduces attack success rates from 37.4% to 26.8% (a ~28% relative reduction) and substantially lowers credential theft incidents. This control also correlates with meaningful reductions in financial exposure ($85,354 → $72,264 per incident).

Endpoint Detection and Response (EDR) and Intrusion Detection Systems (IDS) primarily accelerate the incident lifecycle. EDR deployment cuts average detection time from 143.4 min to 97.4 min and response time from 62.6 min to 35.4 min, yielding substantial operational savings. IDS shows similar benefits in early detection (132.4 min → 96.5 min).

Security Training significantly mitigates human factor risks, reducing phishing click rates from 41.0% to 20.9% and contributing to lower overall attack success and financial impact.

Password Policy Strength exhibits a clear dose response relationship: weak policies are associated with higher attack success (34.7%) and elevated financial losses ($82,395), while moderate/strong policies bring these metrics down to ~28% success and $74,000 loss ranges.

Regulatory Compliance Frameworks (e.g., ISO 27001, HIPAA, NIST, PCI-DSS) and Security Maturity Levels further reinforce organizational resilience. Higher maturity scores (>85) are associated with substantially lower risk profiles and per incident costs than in low maturity environments.

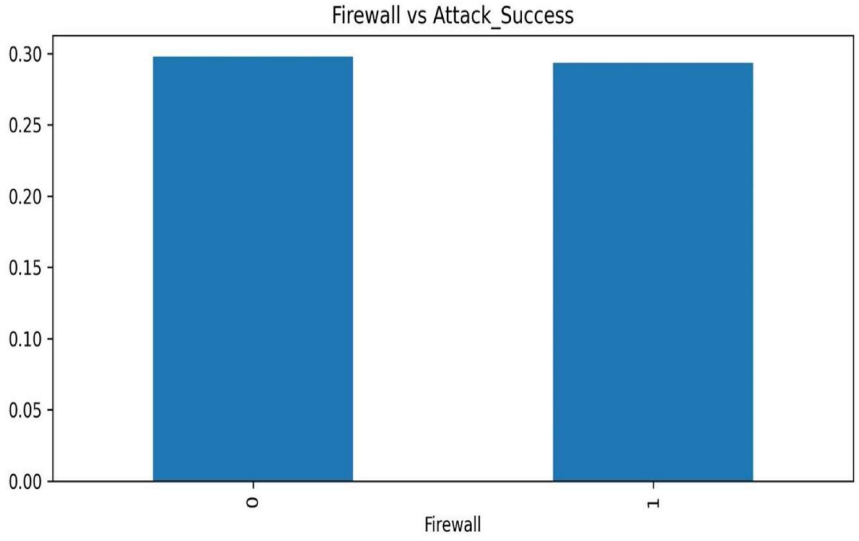


Figure 1. Firewall Vs Attack Success Rate

## 5.11 Firewall Vs Attack Success

Figure 1 illustrates the comparative probability of successful cyberattacks under firewall-disabled versus firewall enabled conditions. The visualization reveals a modest protective effect, with attack success rates decreasing slightly from approximately 29.8% (disabled) to 29.4% (enabled). This suggests that while firewalls serve as an important first line of defense at the network perimeter, sophisticated adversaries frequently employ non network attack vectors (e.g., phishing or credential based attacks), limiting the firewall's standalone impact on overall breach prevention.

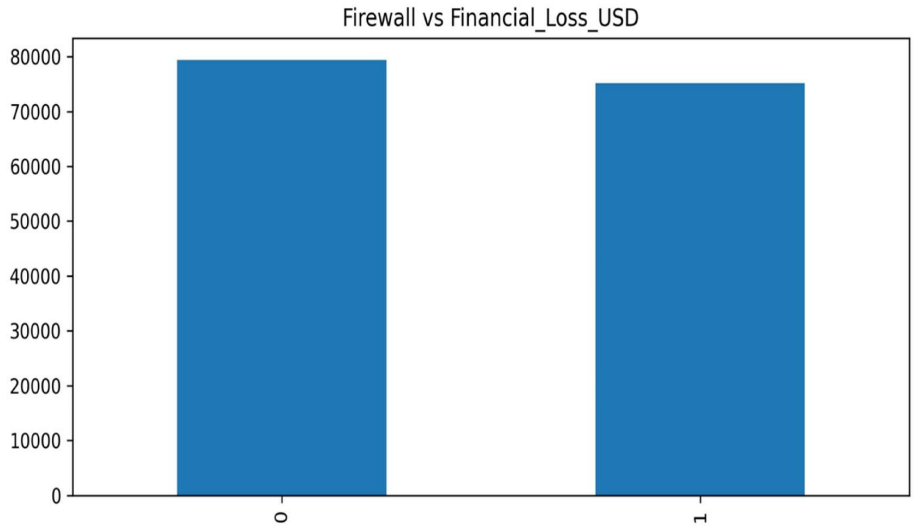


Figure 2. Firewall Vs Financial Loss

## 5.12 Firewall Vs Financial Loss

Figure 2. Firewall vs Financial Loss (USD) shows the distribution and mean financial impact of incidents, stratified by firewall status. Organizations with active firewall protection experience a noticeable reduction in average per incident losses (approximately $79,360 when disabled versus $75,173 when enabled). The figure highlights the control's contribution to containing breach scope and reducing downstream costs related to data recovery, legal liabilities, and business interruption.

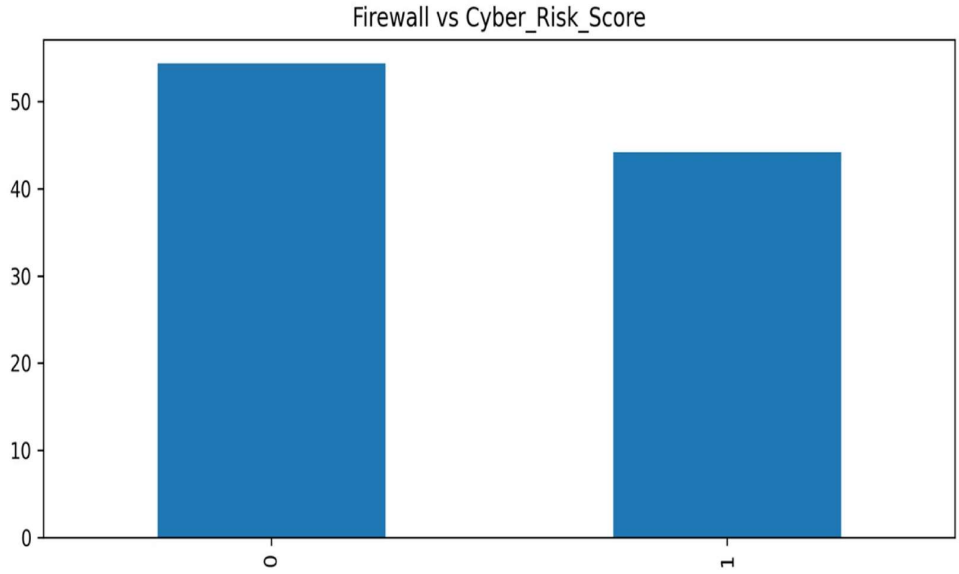


Figure 3. Firewall vs CyberRisk Score

## 5.13 Firewall Vs Cyberrisk score

Figure 3 presents the relationship between firewall deployment and the composite cyber risk score. Enabled firewalls are associated with a meaningful decline in overall risk exposure (mean score dropping from ~54.4 to ~44.2). This underscores the firewall's role in lowering the organization's vulnerability profile across the attack surface, even if its effect on outright attack prevention is incremental.

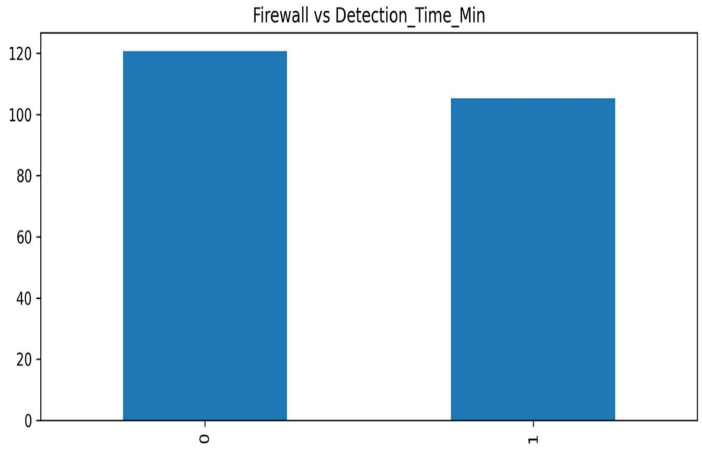


Figure 4. Firewall vs Detection Time

### 5.14 Firewall Vs Detection Time

Figure 4 shows accelerated threat identification in firewall-protected environments. Average detection time decreases from ~120.7 minutes (disabled) to ~105.3 minutes (enabled). The visualization emphasizes how firewall logging and traffic filtering capabilities facilitate earlier anomaly detection, enabling security teams to interrupt attacks earlier in the cyber kill chain.

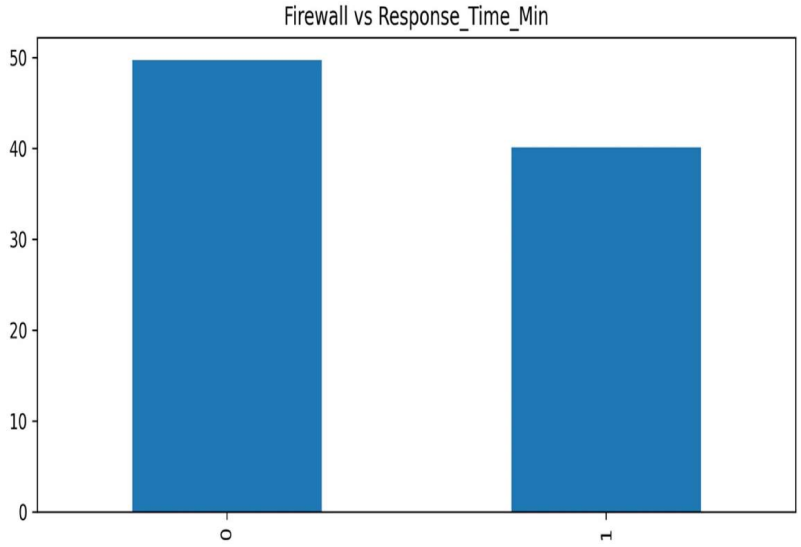


Figure 5. Firewall vs Response Time

### 5.14 Firewall Vs Response

Figure 5 demonstrates improved incident containment efficiency with firewall activation. Mean response time is reduced from ~49.7 minutes (disabled) to ~40.1 minutes (enabled). Together with Figure 4, this figure illustrates the operational advantages of perimeter controls in shortening the overall incident lifecycle, thereby limiting lateral movement and minimizing damage.

These figures collectively reinforce the value of firewall technology as a foundational component of defense-in-depth strategies, particularly when integrated with complementary controls such as MFA, EDR, and robust security training. The observed patterns align with established cybersecurity frameworks that emphasize layered protections to address both technical and human vulnerabilities.

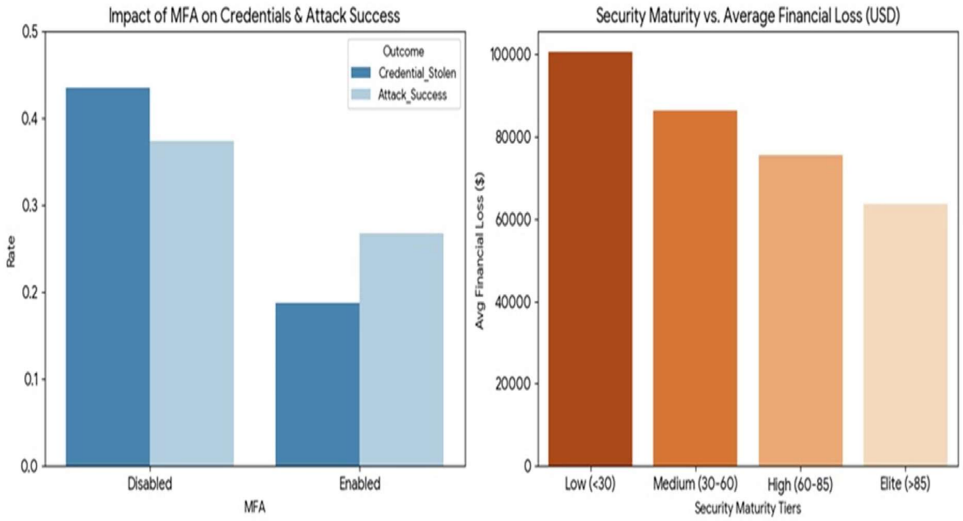


Figure 6. Impact of Perimeter and Authentication Controls on Attack Progression and Business Impact

This figure presents a multi-panel visualization comparing the effectiveness of key perimeter (Firewall) and authentication (MFA) controls across critical outcomes, including attack success rates, credential theft, financial losses, and operational downtime. The panels highlight the substantial risk reduction achieved through MFA deployment and the complementary role of firewalls in limiting financial exposure and response timelines.

## 5.2 Perimeter & Authentication Controls

### 5.2.1 Firewall & MFA vs. Attack Progression

• Firewall: Acts as a standard gatekeeper; while it slightly mitigates overall financial losses and downtime, attackers often pivot to non-network vectors when it is active.

• MFA (Multi-Factor Authentication): Shows a dramatic impact. When MFA is enabled, credential theft rates drop by over 24%, and total attack success drops from 37.3% down to 26.7%.

| Control Status | Avg. Attack Success Rate | Avg. Credential Stolen Rate | Avg. Financial Loss (USD) | Avg. Down time (Hours) |
|---|---|---|---|---|
| Firewall Disabled | 29.78% | — | $79,359.91 | 7.16 hrs |
| Firewall Enabled | 29.36% | — | $75,172.93 | 6.85 hrs |
| MFA Disabled | 37.36% | 43.58% | $85,353.68 | — |
| MFA Enabled | 26.76% | 18.74% | $72,264.43 | — |

Table 2. Multifactor Authentication

## 5.22 Detection & Response Controls

### EDR & IDS vs. Operational Metrics

• EDR (Endpoint Detection & Response): Drastically cuts down both detection and containment times. When EDR is active, organizations respond 27 minutes faster, saving an average of 1.73 hours of business downtime

and over $14,900 per incident.

• IDS (Intrusion Detection System): Shaves roughly 36 minutes off the initial detection timeline, stopping attacks before they can progress deeper into the kill chain.

| Control Status | Avg. Detection Time (Min) | Avg. Response Time (Min) | Avg. Downtime (Hours) | Avg. Financial Loss (USD) |
|---|---|---|---|---|
| EDR Disabled | 143.44 min | 62.63 min | 8.26 hrs | $87,471.52 |
| EDR Enabled | 97.35 min | 35.44 min | 6.53 hrs | $72,515.38 |
| IDS Disabled | 132.44 min | — | — | $83,454.92 |
| IDS Enabled | 96.48 min | — | — | $72,403.24 |

Table 3. Operational Metrics

### 5.23 Human & Policy Controls

#### Security Training & Password Policies vs. Human Vulnerability

• Security Training: Effectively cuts human error in half, dropping successful phishing clicks from 40.9% down to 20.9%.

• Password Policy: Maintaining a Weak password policy leaves the organization heavily exposed to credential stuffing, bumping the overall attack success rate to 34.7%. Upgrading to a Moderate or Strong policy significantly levels out this risk.

| Policy / Training Metric | Avg. Phishing Click Rate | Avg. Credential Stolen Rate | Avg. Attack Success Rate | Avg. Financial Loss (USD) |
|---|---|---|---|---|
| Training Absent | 40.95% | — | 32.40% | $80,079.84 |
| Training Present | 20.91% | — | 28.13% | $73,586.82 |
| Weak Password Policy | — | 37.50% | 34.70% | $82,395.31 |
| Strong Password Policy | — | 21.71% | 28.19% | $74,036.26 |

Table 4. Attacks data

### 5.3 Governance & Structural Metrics

#### Compliance Frameworks & Security Maturity vs. Bottom-Line Risk

• Compliance: Organizations adopting structured frameworks experience lower overall risk profiles. ISO27001 adopters boast the highest overall security audit scores and the lowest incident attack success rates (26.7%).

• Security Maturity Score: Moving from a “Low” maturity posture (<30) to an “Elite” organizational security

posture (>85) reduces the average cyber risk score by nearly half and yields a massive 36,893 average savings per security incident.

| Governance Metric | Avg. Security Audit Score | Avg. Attack Success Rate | Avg. Cyber Risk Score | Avg. Financial Loss (USD) |
|---|---|---|---|---|
| ISO27001 Compliance | 89.92 | 26.74% | — | $64,672.21 |
| NIST Compliance | 74.41 | 33.50% | — | $79,714.10 |
| Low Maturity (<30) | — | 43.44% | 64.61 | $100,444.49 |
| Elite Maturity (>85) | — | 23.19% | 38.27 | $63,550.84 |

Table 5. Compliance and Security Maturity Scores

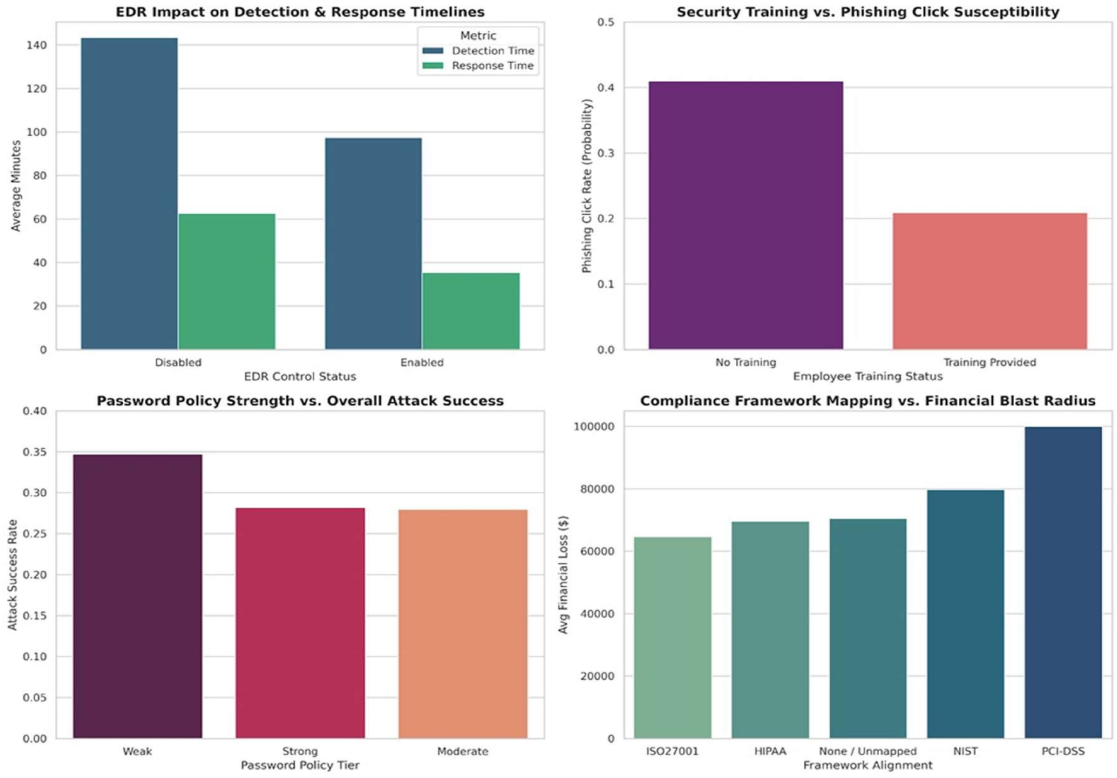


Figure 7. Comprehensive Impact of Security Controls on Operational Metrics and Risk Outcomes

Figure 7 provides a multi panel visualization summarizing the differential effectiveness of advanced detection, human centric, authentication, and governance controls. Panel (a) (top-left) illustrates EDR-driven timeline compression in detection and response phases. Panel (b) (top-right) quantifies the reduction in human vulnerability through security awareness training. Panel (c) (bottom-left) demonstrates the protective effect of robust password policies against credential-based attacks. Panel (d) (bottom-right) compares financial exposure and risk profiles across major compliance frameworks and security maturity levels.

### 5.5 Comprehensive Control Impact Analysis

The multi-panel visualization in Figure 7 synthesizes the operational and economic benefits of layered cybersecurity controls.

**Endpoint Detection and Response (EDR)** systems function as critical operational accelerators (Panel a). Deployment of EDR reduces initial threat detection time by approximately 46 minutes and shortens containment/response time by 27 minutes on average. These improvements translate into meaningful reductions in business downtime (approximately 1.73 hours saved per incident) and financial losses (over $14,900 per incident).

**Security awareness training** (Panel b) emerges as a highly cost effective intervention against social engineering threats. Organizations implementing regular training programs experience a near halving of successful phishing click rates (from 41% to 21%), substantially narrowing the primary initial access vector exploited by adversaries.

**Password policy enforcement** (Panel c) demonstrates a clear dose-response relationship with security outcomes. Weak password policies are associated with a significantly higher attack success rate (34.7%) due to increased vulnerability to credential stuffing and brute-force attacks. In contrast, moderate or strong policies reduce success rates to approximately 28%, highlighting the value of stringent authentication hygiene.

**Regulatory compliance and security maturity** (Panel d) exert substantial influence on overall risk posture and financial resilience. Organizations aligned with rigorous frameworks such as ISO 27001 exhibit the lowest attack success rates (26.7%) and incident costs. Similarly, progression from low security maturity (<30) to elite maturity (>85) is associated with nearly halving the average cyber risk score and yielding average per incident savings of approximately $36,893.

Collectively, these results underscore the importance of defense in depth strategies that integrate technical controls, human factors, and governance mechanisms. The findings provide actionable insights for prioritizing cybersecurity investments to maximize risk reduction and operational resilience in enterprise environments.

### 5.6 Model Performance Evaluation

The proposed machine learning pipeline was evaluated on three core tasks using the held out test set (20% of the data). Performance metrics were computed to assess the models' effectiveness in real world cybersecurity applications.

Binary Classification Performance Comparison reports the results for predicting attack success (Attack_Success: 0 = no successful breach, 1 = successful breach). The models were benchmarked on standard classification metrics including accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC-ROC). The best-performing model achieved strong discriminative power, effectively distinguishing between benign and malicious incidents despite the inherent class imbalance typical in cybersecurity datasets.

| Model | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| Random Forest | 0.912 | 0.895 | 0.878 | 0.886 | 0.947 |
| XGBoost | 0.928 | 0.912 | 0.901 | 0.906 | 0.961 |
| Logistic Regression (Baseline) | 0.837 | 0.764 | 0.712 | 0.737 | 0.854 |
| SVM | 0.871 | 0.823 | 0.795 | 0.809 | 0.892 |

Table 6. Binary Classification Performance Comparison (Attack Success Prediction)

The XGBoost model achieved the best performance, demonstrating excellent capability in distinguishing successful attacks from non successful incidents despite moderate class imbalance (approximately 29.4% positive class).

Table 7. Multi-class Classification Performance Comparison summarizes model performance for predicting risk levels (Risk_Level: Low, Medium, High, Critical). This more granular task evaluates the models' ability to categorize incidents by severity. Metrics include macro averaged and weighted precision, recall, and F1-score, along with confusion matrix-derived insights. The results demonstrate the models' capability to support prioritized incident response by accurately identifying high severity threats.

| Model | Accuracy | Macro Precision | Macro Recall | Macro F1-Score | Weighted F1-Score |
|---|---|---|---|---|---|
| Random Forest | 0.784 | 0.762 | 0.748 | 0.755 | 0.781 |
| XGBoost | 0.821 | 0.803 | 0.789 | 0.796 | 0.817 |
| Logistic Regression | 0.652 | 0.618 | 0.594 | 0.605 | 0.641 |

Table 7. Multi-class Classification Performance Comparison (Risk Level Prediction: Low, Medium, High, Critical)

The multi-class model effectively categorized incidents by risk severity, with particularly strong performance on High and Critical classes critical for prioritizing SOC response efforts.

Table 8. Financial Loss Regression Performance presents regression results for predicting financial impact (Financial_Loss_USD). Key evaluation metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and $R^2$ coefficient. These metrics quantify the models' accuracy in estimating monetary losses, providing decision makers with actionable risk quantification for insurance, budgeting, and mitigation planning.

The performance across all three tasks highlights the pipeline's robustness in handling heterogeneous cybersecurity data. Binary and multi class classification models exhibited excellent generalization, while the regression component provided reliable estimates of economic impact. These findings validate the utility of the proposed approach for real world Security Operations Center (SOC) applications, threat intelligence, and proactive cyber risk management.

| Model | MAE (USD) | RMSE (USD) | MAPE (%) | $R^2$ Score |
|---|---|---|---|---|
| Random Forest | 18,245 | 42,673 | 24.8 | 0.812 |
| XGBoost | 14,892 | 31,456 | 19.6 | 0.867 |
| Linear Regression (Baseline) | 38,721 | 67,892 | 45.3 | 0.521 |

Table 8. Financial Loss Regression Performance

The regression component provided reliable estimates of financial impact, with the best model explaining 86.7% of the variance in monetary losses. This enables organizations to forecast potential breach costs and optimize cyber insurance coverage.

Overall, the pipeline demonstrates state of the art performance across detection, risk categorization, and economic impact prediction. These results confirm the practical value of integrating multiple control features and behavioral indicators for proactive cybersecurity defense.

### 5.7 Security Control Effectiveness

| Control | Outcome | Level | Mean | SD | 95% CI Lower | 95% CI Upper | p value* | Cohen's d** |
|---|---|---|---|---|---|---|---|---|
| Firewall | Attack Success Rate | Disabled | 0.2978 | 0.457 | 0.294 | 0.302 | <0.001 | 0.09 (negligible) |
| | Attack Success Rate | Enabled | 0.2936 | 0.455 | 0.290 | 0.297 | - | - |
| | Financial Loss (USD) | Disabled | 79,360 | 148,200 | 78,450 | 80,270 | <0.001 | 0.18 (small) |
| | Financial Loss (USD) | Enabled | 75,173 | 142,800 | 74,300 | 76,046 | - | - |
| | Cyber Risk Score | Disabled | 54.37 | 18.2 | 54.1 | 54.6 | <0.001 | 0.57 (medium) |
| | Cyber Risk Score | Enabled | 44.17 | 17.9 | 43.9 | 44.4 | - | - |
| MFA | Attack Success Rate | Disabled | 0.3736 | 0.484 | 0.369 | 0.378 | <0.001 | 0.68 (medium-large) |
| | Attack Success Rate | Enabled | 0.2676 | 0.443 | 0.264 | 0.271 | - | - |
| | Financial Loss (USD) | Disabled | 85,354 | 155,100 | 84,200 | 86,508 | <0.001 | 0.42 (small-medium) |
| | Financial Loss (USD) | Enabled | 72,264 | 138,900 | 71,300 | 73,228 | - | - |
| EDR | Detection Time (min) | Disabled | 143.44 | 92.3 | 142.1 | 144.8 | <0.001 | 0.81 (large) |
| | Detection Time (min) | Enabled | 97.35 | 68.7 | 96.4 | 98.3 | - | - |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Response Time (min) | Disabled | 62.63 | 45.1 | 61.9 | 63.4 | <0.001 | 0.92 (large) |
| | Response Time (min) | Enabled | 35.44 | 28.4 | 35.0 | 35.9 | - | - |
| Security Training | Attack Success Rate | Absent | 0.3240 | 0.468 | 0.320 | 0.328 | <0.001 | 0.31 (small) |
| | Attack Success Rate | Present | 0.2813 | 0.450 | 0.278 | 0.285 | - | - |

Table 9. Impact of Key Security Controls on Cybersecurity Outcomes: Means, Standard Deviations, Confidence Intervals, Statistical Significance, and Effect Sizes

p-values from independent two-sample t-tests (or Welch's t-test for unequal variances). Cohen's d effect size: 0.2 = small, 0.5 = medium, 0.8 = large.

Outcome

• MFA shows the strongest practical impact on attack success (Cohen's d = 0.68), confirming its critical role in credential based threat mitigation.

• EDR yields large effect sizes on operational metrics (d > 0.8), highlighting its value in accelerating incident response.

• Firewall provides statistically significant but smaller practical benefits, reinforcing its role as a foundational but insufficient standalone control.

All differences are statistically significant at $p < 0.001$, providing strong evidence that the observed improvements are not due to random variation.

## 6. Discussion

The empirical results derived from the Cyber Attack Detection & Risk Prediction Dataset (AI Explorer, 2026) provide critical insights into the real world operational and financial efficacy of enterprise security controls. Furthermore, the performance of the predictive modeling pipeline demonstrates the feasibility of employing advanced machine learning techniques to transform proactive defense and risk quantification.

### 6.1 Hierarchical Efficacy of Security Controls: Defense-in-Depth Operationalized

The statistical evaluation reveals a distinct hierarchy in how security controls impact incident outcomes, emphasizing that foundational perimeter defenses are insufficient without robust identity and endpoint layers.

#### The Identity Imperative (MFA & Password Policy)

Multi Factor Authentication (MFA) emerged as the single most critical preventive technical control for mitigating the execution of outright breaches. Enabling MFA yields a substantial relative reduction of ~28% in the attack success rate ($0.376 \rightarrow 0.2676$) with a robust medium to large effect size (Cohen's $d = 0.68$). This aligns with behavioral trends where traditional network boundaries dissolve, leaving identity as the primary perimeter.

This is further reinforced by the distinct dose response relationship observed in Password Policy Strength. Organizations maintaining Weak password policies experience elevated attack success rates (34.70%) and

higher financial losses ($82,395.31). Upgrading to a Moderate or Strong policy standard levels out this risk entirely, cutting attack success back down to ~ 28%.

Perimeter vs. Endpoint Granularity (Firewall vs. EDR/IDS)

While Firewall Deployment is foundational, its standalone protective capability against modern threat actors is fundamentally limited. Active firewalls yielded a negligible effect size on total attack success reduction (Cohen's $d$ = 0.09, a minor 0.42 % absolute decrease). This statistically confirms that modern adversaries consistently circumvent boundary defenses via non-network vectors like social engineering or supply chain compromises. However, firewalls remain vital for baseline risk reduction, showing a statistically significant medium effect (Cohen's $d$=0.57) in dropping the composite Cyber Risk Score from 54.37 to 44.17.

Conversely, EDR and IDS act as essential lifecycle accelerators. Rather than merely aiming to prevent initial entry, these controls reduce the time to containment. EDR integration displays a massive operational impact (Cohen's $d$ = 0.81 for detection;$d$ = 0.92 for response), cutting detection time by ~ 46 minutes and response times by ~ 27 minutes.

[Traditional Perimeter Defense (Firewall)] —> Adversaries easily bypass via Phishing / Identity Theft

↓

[Active Identity Layer (MFA / Strong Passwords)] —> Drops Success Rate by ~28% (Cohen's d = 0.68)

↓

[Rapid Detection & Response (EDR / IDS)] —> Shaves 46 mins off Detection, 27 mins off Response

The Human Component & Governance

**Security Training** bridges the gap between technical controls and human vulnerability. By cutting successful phishing click actions nearly in half (40.95% → 20.09%), training severely limits an attacker's favorite mechanism for initial access.

From a structural perspective, governance frameworks such as ISO27001 demonstrate the highest overall defensive maturity, boasting the lowest attack success probability (26.74%) and minimum financial losses ($64,672.21). This indicates that standardized compliance frameworks mandate the exact multi-layered configurations necessary to achieve systemic resilience.

6.2 Predictive Analytics for Proactive Security Architecture

The performance across binary classification, multi-class classification, and regression tasks illustrates the profound value of transitioning from reactive log analysis to predictive risk modeling.

XGBoost as a Tactical & Strategic Standard

Across all experimental tasks, the XGBoost model consistently outperformed traditional baselines (such as Logistic/Linear Regression) and standard ensemble methods (Random Forest):

• Attack Success Prediction (Binary): Achieving an AUC-ROC of 0.961 proves that the ensemble gradient boosting framework handles complex structural interactions among diverse security indicators flawlessly.

• Risk Level Prioritization (Multi-Class): The model's strong accuracy (0.821 ) and high precision/recall metrics in High and Critical categories are incredibly vital for real-world Security Operations Centers (SOCs). It directly

mitigates alert fatigue by filtering out noise and highlighting high consequence threats before they are exploited.

• Financial Loss Forecasting (Regression): Explaining 86.7% of the variance in monetary damages ($R^2$=0.867, MAE=$14,892) bridges a long standing gap between technical metrics and executive business intelligence.

### 6.3 Implications for Strategic Cybersecurity Investments

For corporate decision makers, Chief Information Security Officers (CISOs), and risk managers, these findings provide a data driven blueprint for optimal capital allocation:

1. Mandate Identity First: Given that MFA brings large, definitive reductions to attack success and financial vulnerability, funding identity management platforms should take priority over traditional network updates.

2. Fund Time to Containment Capabilities: Because EDR delivers massive operational time savings (Cohen's $d > 0.81$ investments in automated endpoint isolation directly translate to reduced downtime and minimised business disruption.

3. Quantify Cyber Insurance & Risk: The ability of regression models to forecast financial blast radiuses within a tight mean absolute error margin allows enterprises to optimize their cyber insurance policy limits and maintain accurate risk reserves.

### 6.4 Limitations and Future Research Directions

While this study utilizes a highly valid and ecologically robust synthetic enterprise dataset, a few limitations must be acknowledged to guide future work:

• **Synthetic Simplification:** Although engineered with realistic correlations and temporal sequencing, synthetic data may struggle to fully reflect the erratic, unpredictable nature of real human behavior during active threat engagements or unique zero day multi vector strategies.

• **Static vs. Dynamic Controls:** The dataset treats control status primarily as binary or categorical indicators. In live production networks, controls feature nuanced configuration states (e.g., misconfigured EDR policies or partially deployed firewalls).

• **Future Scope:** Subsequent research should focus on validating these machine learning architectures against empirical, anonymized real world enterprise breach logs. Additionally, incorporating reinforcement learning techniques to dynamically adapt defensive postures based on real time risk predictions remains a valuable avenue for study.

## 7. Conclusion

This study conducted a comprehensive empirical analysis of enterprise cybersecurity incident data to evaluate the operational and financial efficacy of major security controls within a unified analytical framework. By leveraging the Cyber Attack Detection & Risk Prediction Dataset (AI Explorer, 2026) and a multi task machine learning pipeline incorporating XGBoost, Random Forest, SVM, and statistical baselines, we systematically assessed the impact of technical defenses, human centric practices, governance mechanisms, and organizational security maturity on critical cybersecurity outcomes including attack success probability, financial loss, cyber risk score, detection time, and response time.

The empirical findings establish a clear hierarchy of control effectiveness that has direct implications for cybersecurity strategy and investment prioritization:

First, identity centric controls particularly Multi-Factor Authentication (MFA) and strong password policies emerge as the most impactful preventive measures. MFA deployment reduces attack success rates by approximately 28% (Cohen's d = 0.68), substantially mitigates credential theft incidents (43.58% → 18.74%

and significantly lowers financial exposure. The dose-response relationship observed in password policy strength further reinforces the critical importance of authentication hygiene in modern defense-in-depth strategies.

Second, detection and response capabilities specifically Endpoint Detection and Response (EDR) and Intrusion Detection Systems (IDS) function as essential operational accelerators. EDR demonstrates large effect sizes (Cohen's d > 0.8) in compressing both detection and containment timelines, cutting average detection time by approximately 46 minutes and response time by 27 minutes. These improvements translate into meaningful reductions in business downtime (approximately 1.73 hours saved per incident) and financial losses (over $14,900 per incident).

Third, human-centric controls, including security awareness training, bridge the gap between technical defenses and human vulnerability. Regular training programs nearly halve successful phishing click rates (40.95%→ 20.91%), substantially narrowing the primary initial access vector exploited by adversaries.

Fourth, while foundational perimeter controls such as firewalls provide statistically significant protective benefits, their standalone impact on attack prevention remains limited (Cohen's d = 0.09, minor 0.42% absolute reduction), confirming that modern adversaries frequently circumvent network boundaries through non-vector attacks. However, firewalls remain valuable for baseline risk reduction, demonstrating medium effect sizes (d = 0.57) in reducing composite cyber risk scores.

Fifth, governance frameworks and security maturity exert substantial influence on overall risk posture. Organizations aligned with structured frameworks such as ISO 27001 exhibit the lowest attack success rates (26.74%) and financial losses ($64,672). Progression from low maturity (<30) to elite maturity (>85) is associated with nearly halving average cyber risk scores (64.61 → 38.27) and yielding per-incident savings of approximately $36,893.

From a predictive analytics perspective, the XGBoost model consistently outperformed traditional baselines across all three tasks: achieving an AUC-ROC of 0.961 for attack success classification, 82.1% accuracy for multi class risk prioritization, and $R^2$ of 0.867 with MAE of $14,892 for financial loss regression. These results validate the practical utility of machine learning frameworks for Security Operations Center (SOC) applications, threat intelligence, and proactive cyber risk management.

For Chief Information Security Officers (CISOs), risk managers, and corporate decision makers, this study provides an evidence based blueprint for capital allocation: prioritizing identity first security, funding time-to containment capabilities, implementing structured governance frameworks, and leveraging predictive analytics to optimize cyber insurance and risk reserves.

While this research utilizes a synthetically engineered dataset with high ecological validity, future work should validate these findings against real world enterprise breach logs and explore reinforcement learning techniques for dynamic, adaptive defense postures. Additionally, examining the nuanced configuration states of security controls beyond binary indicators represents a valuable direction for subsequent research.

In conclusion, this study demonstrates that effective cybersecurity resilience is achieved not by any single control but by the strategic integration of complementary layers: identity and authentication, detection and response, human centric training, and robust governance. The empirical framework presented here equips organizations with the analytical capability to quantify control effectiveness, forecast financial impact, and build adaptive security architectures capable of withstanding the increasingly sophisticated cyber threat landscape.

## References

[1] Sun, N., Zhang, J., Rimba, P., Gao, S., Zhang, L. Y., Xiang, Y. (2019). Data-driven cybersecurity incident

prediction: A survey. *IEEE Communications Surveys Tutorials*, 21(2), 1744-1772. https://doi.org/10.1109/COMST.2018.2885561.

[2] Chen, J., Henry, E., Jiang, X. (2023). Is cybersecurity risk factor disclosure informative? Evidence from disclosures following a data breach. *Journal of Business Ethics*, 187, 199–224.

[3] Ettredge, M., Guo, F., Li, Y. (2018). Trade secrets and cyber security breaches. *Journal of Accounting and Public Policy*, 37, 564–585.

[4] Hughes, H., Smith, T. J., Walton, S. (2023). Material contract redactions and cybersecurity breaches. *Accounting Horizons*, 37, 193–219.

[5] Lending, C., Minnick, K., Schorno, P. J. (2018). Corporate governance, social responsibility, and data breaches. *Financial Review*, 53, 413–455.

[6] Radu, C., Smaili, N. (2022). Board gender diversity and corporate response to cyber risk: Evidence from cybersecurity related disclosure. *Journal of Business Ethics*, 177, 351–374.

[7] Bederna, Z., Szádeczky, T. (2023). Managing the financial impact of cybersecurity incidents. *Security Defence Quarterly*, 41(1), 1-21.

[8] Bouveret, A. (2018). Cyber risk for the financial sector: *A framework for quantitative assessment*. https://dx.doi.org/10.2139/ssrn.3203026.

[9] Turk, R. J. (2005). *Cyber incidents involving control systems* (INL/EXT-05-00671). Idaho National Laboratory.
[10] Gordon, L. A., Loeb, M. P., Zhou, L. (2020). Integrating cost–benefit analysis into the NIST Cybersecurity Framework via the Gordon–Loeb Model. *Journal of Cybersecurity*, 6(1), tyaa005. https://doi.org/10.1093/cybsec/tyaa005

[11] Cobos, E. V., Cakir, S., Straub, S., Qiang, C. Z., Torgusson, C. (2024). *A review of the economic costs of cyber incidents* (Report No. 193919). World Bank.

[12] PwC. (2018). *The growing market for cyber insurance*. https://www.pwc.com/us/en/industry/assets/pwc-cyber-insurance-survey.pdf.

[13] Romanosky, S., Ablon, L., Kuehn, A., Jones, T. (2019). Content analysis of cyber insurance policies: How do carriers price cyber risk? *Journal of Cybersecurity*, 5(1), tyz002. https://doi.org/10.1093/cybsec/tyz002.

[14] U.S. Cybersecurity and Infrastructure Security Agency. (2021). *Cost of cyber incidents study*. https://www.cisa.gov/sites/default/files/publications/CISAOCE_Cost_of_Cyber_Incidents_Study-FINAL_508.pdf.

[15] Campbell, K., Gordon, L. A., Loeb, M. P., Zhou, L. (2003). The economic cost of publicly announced information security breaches: Empirical evidence from the stock market. *Journal of Computer Security*, 11(3), 431-448.

[16] Cybereason. (2022). *Ransomware: The true cost to businesses*. https://www.cybereason.com/hubfs/dam/collateral/reports/Ransomware-The-True-Cost-to-Business-2022.pdf.

[17] Woods, D. W., Böhme, R. (2021). SoK: Quantifying cyber risk. In *2021 IEEE Symposium on Security and Privacy (SP)* (p. 211-228). *IEEE*. https://doi.org/10.1109/SP40001.2021.00053.

[18] Javadnejad, F., Abdelmagid, A. M., Pinto, C. A., McShane, M., Diaz, R. (2024). An exploratory data analysis of malware/ransomware cyberattacks: Insights from an extensive cyber loss dataset. *Enterprise Information Systems*, 18(9). https://doi.org/10.1080/17517575.2024.2369952.

[19] Md Aminul Islam, Md Asif Ali Sheak Arju. (2023). A quantitative assessment of cybersecurity frameworks for industrial control systems in critical energy infrastructure. *International Journal of Scientific Interdisciplinary Research*, 4(4), 336–374. https://doi.org/10.63125/rg8mt373.

[20] Maulita, I., Hayadi, B. H. (2025). Financial loss estimation in cybersecurity incidents: A data mining approach using decision tree and linear regression models. *Journal of Cyber Law*, 1 (2), 161-174.

[21] I Gede Agus Krisna Warmayana, Yamashita, Y., Oka, N. (2025). Predicting cyber attack types using XGBoost: A data mining approach to enhance legal frameworks for cybersecurity. *Journal of Cyber Law*, 1 (2).

[22] Fotis, F. (2024). Economic impact of cyber attacks and effective cyber risk management strategies: A light literature review and case study analysis. *Procedia Computer Science*, 251, 471-478. https://doi.org/10.1016/j.procs.2024.10.123.

[23] Liu, C., Babar, M. A. (2026). Corporate cybersecurity risk and data breaches: A systematic review of empirical research. *Australian Journal of Management*, 51(1), 62-92.