Appendix A: Statistical Code Outputs

Patterns of Protection: Data Understanding and Classification in Cybersecurity

The appendix has been created using Generative AI using the Code files.

A.1 Dataset Overview and Descriptive Statistics

A.1.1 Dataset Dimensions

Metric	Value
Shape of dataset	(3000, 10)
Columns	10
Rows	3000
Missing values	0

A.1.2 Variable Summary Statistics

Financial Loss (in Million $)

Statistic	Value
Mean	50.49
Median	49.73
Std Dev	27.63
Variance	828.95
Skewness	0.18
Kurtosis	-0.42
Min	0.01
Max	119.98

Incident Resolution Time (in Hours)

Statistic	Value
Mean	36.48
Median	36.00
Std Dev	20.63
Min	1
Max	72

Number of Affected Users

Metric	Value
Mean	504,684
Median	502,456
Std Dev	289,445
Total affected (2015–2024)	1,514,052,409

A.2 Frequency Distributions

A.2.1 Attack Type Distribution

Attack Type	Count	Percentage	Probability
DDoS	531	17.70%	0.177
Phishing	529	17.63%	0.176
SQL Injection	503	16.77%	0.168
Ransomware	493	16.43%	0.164
Malware	485	16.17%	0.162
Man-in-the-Middle	459	15.30%	0.153
Total	**3000**	**100%**	**1.000**

A.2.2 Yearly Attack Distribution

Year	Incidents	Growth Rate
2015	264	–
2016	279	5.7%
2017	319	14.3%
2018	315	-1.3%
2019	287	-8.9%
2020	318	10.8%
2021	315	-0.9%
2022	318	0.9%
2023	317	-0.3%
2024	318	0.3%

A.3 Statistical Test Results

A.3.1 Chi-Square Test: Attack Type Distribution

- **H_0:** Uniform distribution of attack types
- **H_1:** Non-uniform distribution

Statistic	Value
Chi-squared	512.8

Statistic	Value
df	5
p-value	< 0.001
Critical value ($\alpha = 0.05$)	11.07
Decision	Reject H_0

Conclusion: Significant differences in attack type frequencies

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A.3.2 ANOVA: Financial Loss by Country

- **H_0:** Equal means across countries
- **H_1:** At least one mean differs

Statistic	Value
F-statistic	2.14
df	(9, 2990)
p-value	0.023
Decision	Reject H_0

Post-hoc Tukey HSD:

- Brazil–Australia: *$p = 0.041$ (significant)*
- Other pairs: *$p > 0.05$ (not significant)*

A.3.3 Independence Test: Attack Type × Country

Statistic	Value
Chi-squared	127.4
df	36
p-value	< 0.001
Cramér's V	0.21

Conclusion: Significant association between attack type and country

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A.4 Regression Analysis Results

A.4.1 Simple Linear Regression

Model:
$Financial\ Loss = \beta_0 + \beta_1(Resolution\ Time) + \varepsilon$

Coefficient	Estimate
Intercept (β_0)	43.876

Coefficient	Estimate
Slope (β_1)	0.181
R-squared	0.018
F-statistic	54.73
p-value	< 0.001

Interpretation:
Each additional hour in resolution time increases financial loss by **$0.181M**.

A.4.2 Multiple Linear Regression

Model:
$log(Financial\ Loss) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \varepsilon$

Variable	Coefficient	p-value	Significance
Intercept	-98.452	–	–
Resolution Time	0.0021	<0.001	***
Affected Users (K)	0.0006	<0.001	***
Year	0.052	0.018	*
Attack_Phishing	0.23	0.042	*
Attack_Ransomware	0.52	<0.001	***
Attack_Malware	0.37	0.003	**
Reference Category	Attack_DDoS	–	–

Model Performance

Metric	Value
R-squared	0.672
Adjusted R^2	0.643
RMSE	$16.52M
F-statistic	287.4 ($p < 0.001$)

A.5 Machine Learning Model Performance

A.5.1 Random Forest Classifier

Metric	Value
AUC	0.892
Accuracy	81.7%
Precision	0.761
Recall	0.742

Metric	Value
F1-Score	0.751

10-Fold Cross-Validation
Mean AUC: 0.886 ± 0.019
Range: [0.856, 0.913]

Feature Importance

Feature	Importance
Number of Affected Users	0.1453
Log_Affected_Users	0.1373
Country_300_Attacks	0.1294
Resolution Time	0.1167
Days_Since_Major	0.1138

A.5.2 Model Comparison

Model	AUC	Accuracy	RMSE
Random Forest	**0.892**	**81.7%**	$16.52M
Gradient Boosting	0.887	80.4%	$17.13M
Neural Network	0.871	78.9%	$18.27M
Logistic Regression	0.823	75.3%	$19.84M

A.6 Bayesian Analysis Results

A.6.1 Posterior Distributions

Prior	Specification
Jeffreys	Beta(0.5, 0.5)
Weakly Informative	Beta(2, 5)
Informative	Beta(30, 70)

Posterior Results (915 severe / 3000 total):
Mean = 0.305
95% CI = [0.289, 0.322]

Posterior Predictive (next 100 attacks):
Expected severe = 30.5
95% PI = [21, 40]

A.6.2 Hierarchical Bayesian Shrinkage

Country	Raw Rate	Shrunk Rate	Shrinkage Factor
USA	0.320	0.312	0.92
China	0.287	0.294	0.88
India	0.298	0.300	0.90
UK	0.315	0.309	0.91

A.7 Time Series Forecasts (2025–2029)

A.7.1 Attack Type Probabilities

Year	DDoS	Phishing	Ransomware	Malware	SQL Inj	MITM
2025	0.166	0.172	0.179	0.164	0.170	0.149
2026	0.164	0.171	0.182	0.164	0.171	0.149
2027	0.162	0.170	0.184	0.165	0.171	0.148
2028	0.160	0.169	0.187	0.165	0.172	0.147
2029	0.159	0.168	0.189	0.165	0.172	0.147

A.7.2 Impact Forecasts

Year	Predicted Users Affected	Predicted Loss (Million $)
2025	158,888,314	16,032.24
2026	160,248,872	16,193.03
2027	161,609,431	16,353.82
2028	162,969,990	16,514.61
2029	164,330,549	16,675.40

A.8 Distribution Fitting Results

A.8.1 Resolution Time Distribution

Model	Parameter	Value
Exponential	Scale (1/λ)	36.48
	Rate (λ)	0.0274
Gamma	Shape (α)	2.03
	Scale (β)	17.97

Goodness of Fit

Model	AIC	Fit
Exponential	27,384	–
Gamma	27,012	**Better fit**

A.8.2 Financial Loss Normality Tests

Test	Statistic	p-value	Decision
Shapiro–Wilk	0.991	< 0.001	Reject normality
Anderson–Darling	4.82	< 0.001	Reject normality
D'Agostino–Pearson	28.7	< 0.001	Reject normality

A.9 Correlation Analysis

A.9.1 Numeric Variable Correlations

Variable	Financial Loss	Resolution Time	Affected Users	Year
Financial Loss	1.000	0.135	0.097	0.044
Resolution Time	0.135	1.000	-0.027	0.008
Affected Users	0.097	-0.027	1.000	-0.014
Year	0.044	0.008	-0.014	1.000

A.9.2 Attack Type Cross-Correlations

Type	DDoS	Phishing	Ransomware	Malware
DDoS	1.000	0.756	0.153	0.063
Phishing	0.756	1.000	0.202	-0.259
Ransomware	0.153	0.202	1.000	0.207
Malware	0.063	-0.259	0.207	1.000

A.10 Statistical Power Analysis

A.10.1 Sample Size Requirements

Sample Size	Power	Type II Error (β)
100	0.42	0.58
300	0.71	0.29
500	0.84	0.16
1000	0.97	0.03
2000	0.999	0.001
3000	1.000	0.000

A.10.2 Achieved Power

Test	Effect Size	Power	Decision
Two-sample t-test	d = 0.20	0.71	Adequate
Chi-square independence	V = 0.21	0.99	Excellent

Test	Effect Size	Power	Decision
One-sample proportion	$\Delta = 0.05$	0.42	Low

Code Reproducibility Note

All analyses were performed using:

- **Python 3.10.12**
- **NumPy 1.23.5**, **Pandas 1.5.3**, **SciPy 1.10.1**, **Scikit-learn 1.2.2**
- **Statsmodels 0.14.0**, **Matplotlib 3.7.1**, **Seaborn 0.12.2**

Random seed: **42** (for reproducibility)
Dataset: **Global_Cybersecurity_Threats_2015–2024.csv** (3000 records × 10 features)