Bayesian Cross-Indicator Inference for Cybersecurity Psychology Assessment: Integrating SOC Machine Data with Human Auditing

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Abstract

The human factor remains the primary attack vector in cybersecurity, with 82% of breaches involving human elements (Verizon DBIR 2023). Traditional vulnerability assessments focus on technical controls while neglecting psychological and organizational factors that enable social engineering, phishing, and insider threats. We present the Cybersecurity Psychology Framework (CPF), a structured methodology combining automated Security Operations Center (SOC) monitoring with expert human auditing across 100 psychological vulnerability indicators spanning 10 categories: Authority, Temporal, Social, Affective, Cognitive, Group Dynamics, Stress, Unconscious Bias, AI Manipulation, and Convergent Risks.

Our contribution introduces a Bayesian cross-indicator inference engine that: (1) merges SOC machine data with Field Kit human assessments using weighted confidence intervals, (2) models inter-category dependencies (e.g., high Authority compliance increases Social risk by 30%), and (3) generates prioritized remediation recommendations based on risk propagation analysis. Validation on 8 synthetic organizations with 30-day assessment histories demonstrates 94% convergence between automated and human evaluations, with trend detection accuracy exceeding 89% for deteriorating risk patterns.

The framework addresses the critical gap between technical vulnerability scanning and organizational psychology, providing security teams with actionable insights into human-centric attack surfaces. Our open-source implementation enables real-time risk monitoring, historical trend analysis, and evidence-based security awareness training prioritization.

Keywords: Cybersecurity Psychology, Human Factors, Bayesian

Inference, SOC Integration, Social Engineering, Vulnerability Assessment

1 Introduction

1.1 The Human Factor in Cybersecurity

Despite significant advances in technical security controls, human vulnerabilities remain the dominant attack vector. Recent industry reports highlight alarming statistics:

- 82% of data breaches involve human elements (Verizon DBIR 2023)
- Phishing attacks increased 61% year-over-year (2022-2023)
- Average cost of insider threats: $15.38M per incident (Ponemon 2023)
- Social engineering success rate: 68% against untrained users

Traditional vulnerability assessment frameworks (CVSS, OWASP, NIST) excel at quantifying technical risks but lack systematic approaches to psychological vulnerabilities. Security awareness training often relies on generic content without organizational context, leading to poor effectiveness (average retention rate: 35% after 30 days).

1.2 Research Gap

Current limitations include:

1. **Fragmented Assessment**: Technical scans (SIEM, EDR, vulnerability scanners) and human evaluations (phishing simulations, surveys) operate independently without integration
2. **Qualitative Bias**: Manual audits rely on subjective scoring with limited reproducibility
3. **Static Analysis**: Point-in-time assessments fail to capture temporal dynamics and emerging risks
4. **Missing Dependencies**: Psychological vulnerabilities interact (authority compliance enables phishing), but existing tools treat indicators independently
5. **No Prioritization**: Organizations receive laundry lists of issues without guidance on optimal remediation sequencing

1.3 Contribution

We address these gaps through:

- **Unified Framework**: 100 indicators across 10 CPF categories with standardized scoring (0-1 scale)
- **Bayesian Inference Engine**: Merges SOC automated data with human expert assessments using confidence-weighted averaging
- **Cross-Indicator Dependencies**: Explicit modeling of psychological risk propagation (e.g., Temporal Pressure $\rightarrow$ Stress $\rightarrow$ Cognitive Errors)
- **Prioritization Matrix**: Risk $\times$ Weight $\times$ Downstream Impact scoring for optimal remediation sequencing
- **Convergence Analysis**: Detects divergence between machine and human assessments for targeted review
- **Trend Detection**: 30-day historical analysis with improving/stable/deteriorating classification

The framework is implemented as an open-source client-side dashboard with zero backend dependencies, enabling deployment in air-gapped environments.

2 Methodology

2.1 CPF Taxonomy

The framework organizes psychological vulnerabilities into 10 categories with 10 indicators each (100 total):

Category weights reflect empirical attack prevalence and remediation difficulty based on literature review and industry data.

2.2 Indicator Scoring

Each indicator receives a risk score $r \in [0, 1]$:

- $r \in [0, 0.33]$: Low risk (green) - healthy security posture
- $r \in (0.33, 0.67]$: Medium risk (yellow) - review and improve
- $r \in (0.67, 1.0]$: High risk (red) - critical vulnerabilities

Category	Weight	Example Indicators
1. Authority	12%	Unquestioning compliance, hierarchy exploitation, credential trust
2. Temporal	10%	Deadline pressure, urgency manipulation, time-based decision errors
3. Social	11%	Peer pressure, FOMO, social proof exploitation
4. Affective	9%	Fear manipulation, greed exploitation, emotional hijacking
5. Cognitive	10%	Cognitive overload, confirmation bias, decision fatigue
6. Group	8%	Groupthink, diffusion of responsibility, in-group bias
7. Stress	11%	Burnout, chronic pressure, stress-induced errors
8. Unconscious	9%	Implicit bias, anchoring, availability heuristic
9. AI	12%	Deepfakes, synthetic media, AI-assisted phishing
10. Convergent	8%	Multi-vector attacks, compounding vulnerabilities

Table 1: CPF Category Taxonomy and Weighting

2.2.1 SOC Automated Assessment

SOC systems generate values $V_{soc} = \{v_1, v_2, ..., v_n\}$ with confidence scores $C_{soc} = \{c_1, c_2, ..., c_n\}$:

$$v_{soc,latest} = v_n, \quad c_{soc,latest} = c_n \tag{1}$$

Example SOC indicators:

- Failed authentication attempts (Authority 1.7)
- Suspicious email engagement (Temporal 2.4)
- Policy violation frequency (Social 3.2)

2.2.2 Field Kit Human Assessment

Human auditors complete structured interviews yielding:

$$V_{human} = \{v_1, v_2, ..., v_m\}, \quad w_{human} = 1.5 \tag{2}$$

Human assessments weighted 1.5× higher than SOC due to:

- Contextual understanding
- Qualitative nuance
- Organizational culture insight

Field Kit scoring formula:

$$S_{indicator} = 0.70 \times S_{quick} + 0.30 \times S_{redflags} \tag{3}$$

where S_{quick} aggregates rapid assessment questions and $S_{redflags}$ captures critical warning signs.

2.3 Bayesian Inference

2.3.1 Indicator-Level Merge

For indicator i, we merge SOC and human assessments:

$$r_i = \frac{\sum_{j \in SOC} v_j \cdot c_j + \sum_{k \in Human} v_k \cdot w_{human}}{\sum_{j \in SOC} c_j + \sum_{k \in Human} w_{human}} \tag{4}$$

Confidence of merged value:

$$conf_i = \min\left(\frac{\sum_{j \in SOC} c_j + m \cdot w_{human}}{2.5}, 1.0\right) \tag{5}$$

where m is the number of human assessments.

2.3.2 Cross-Category Dependencies

We model dependencies $D_{c_1 \to c_2} \in [0, 1]$ representing how risk in category c_1 amplifies risk in c_2:

Source	Target	Dependency	Mechanism
Authority	Social	0.30	Compliance enables peer pressure
Authority	Group	0.20	Hierarchy reinforces groupthink
Temporal	Stress	0.40	Urgency increases burnout
Temporal	Affective	0.25	Deadlines trigger fear
Social	Group	0.35	Social proof drives conformity
Stress	Cognitive	0.45	Burnout impairs reasoning
AI	Unconscious	0.30	Deepfakes exploit biases
Convergent	All	0.15	Multi-vector amplification

Table 2: Sample Cross-Category Dependencies (Full matrix: 28 edges)

Adjusted category risk R_c incorporates upstream influences:

$$R_c = \bar{r}_c + \sum_{c' \in Sources(c)} D_{c' \to c} \cdot R_{c'} \cdot (1 - \bar{r}_c) \tag{6}$$

where $\bar{r}_c$ is the average indicator risk in category c.

2.3.3 Overall Risk Aggregation

Organization-level risk:

$$R_{org} = \sum_{c=1}^{10} w_c \cdot R_c \cdot conf_c \tag{7}$$

where w_c are category weights (Table 1) and $conf_c$ is average confidence in category c.

2.4 Prioritization Algorithm

We rank categories for remediation using:

$$P_c = R_c \cdot w_c \cdot \left(1 + \sum_{c' \in Targets(c)} D_{c \to c'}\right) \tag{8}$$

The term $\sum D_{c \to c'}$ captures downstream impact: fixing category c reduces risk in all dependent categories c'.

Algorithm 1 Prioritization Ranking

Input: Category risks $\{R_1, ..., R_{10}\}$, weights $\{w_1, ..., w_{10}\}$, dependency matrix D
Output: Ranked list of categories
for $c = 1$ to 10 **do**
  $downstream_c \leftarrow \sum_{c'} D_{c \to c'}$
  $priority_c \leftarrow R_c \cdot w_c \cdot (1 + downstream_c)$
end for
return sort($\{priority_1, ..., priority_{10}\}$, descending)

2.5 Convergence Analysis

We measure agreement between SOC and human assessments:

$$\Delta_i = |v_{soc,i} - v_{human,i}| \tag{9}$$

Classification:

- $\Delta_i \leq 0.15$: Close convergence (high confidence)
- $0.15 < \Delta_i \leq 0.35$: Moderate divergence (review recommended)
- $\Delta_i > 0.35$: Large divergence (manual investigation required)

Daily aggregation for timeline visualization:

$$\bar{v}_{soc}(t) = \frac{1}{N}\sum_{i=1}^{N} v_{soc,i}(t), \quad \bar{v}_{human}(t) = \frac{1}{M}\sum_{j=1}^{M} v_{human,j}(t) \tag{10}$$

2.6 Trend Detection

For 30-day rolling window, we compute linear regression slope β of $R_{org}(t)$:

$$\text{Trend} = \begin{cases} \text{Improving} & \text{if } \beta < -0.01 \\ \text{Stable} & \text{if } -0.01 \leq \beta \leq 0.01 \\ \text{Deteriorating} & \text{if } \beta > 0.01 \end{cases} \tag{11}$$

3 Implementation

3.1 Architecture

The system comprises:

1. **Field Kit Client** (JavaScript): Interactive assessment interface with 100 indicator questionnaires
2. **Bayesian Engine** (JavaScript): Client-side inference engine implementing Equations 4-9
3. **Dashboard** (HTML5/CSS3/Canvas): Multi-organization visualization with real-time updates
4. **Batch Importer** (Node.js): Automated ingestion of Field Kit exports
5. **Synthetic Generator** (Node.js): Realistic test data with industry profiles

Key design decisions:

- **Client-side only**: Zero backend (deployable in air-gapped environments)
- **JSON storage**: 6MB file for 8 orgs $\times$ 100 indicators $\times$ 30 days
- **No database**: Simplifies deployment, enables version control
- **Canvas rendering**: High-performance chart visualization

3.2 Data Flow

1. SOC systems export indicator values to `organizations.json`
2. Human auditors complete Field Kit assessments, export JSON files
3. Batch importer scans folder, merges human data into `organizations.json`
4. Bayesian engine recalculates all scores (Equations 4-9)
5. Dashboard loads updated JSON, renders visualizations

3.3 Field Kit Assessment Workflow

For each indicator (e.g., 1.3 - Authority/Credential Trust):

1. **Quick Assessment**: 7 rapid-fire questions (Yes/No/Partial) $\rightarrow$ 70% of score
2. **Red Flags**: Critical warning signs (multi-select) $\rightarrow$ 30% of score
3. **Deep Dive**: 14 follow-up questions for context (qualitative, not scored)
4. **Auto-calculation**: Score updates in real-time as responses entered
5. **Export**: JSON file with metadata (assessor, timestamp, organization)

Conversation completeness tracked separately (informational only, not part of vulnerability score).

4 Validation

4.1 Synthetic Dataset

We generated realistic test data for 8 organizations:

- **Industries**: Healthcare (2), Finance (2), Technology (2), Manufacturing (1), Retail (1)
- **Sizes**: Small (2), Medium (3), Enterprise (3)
- **Timeline**: 30 days with SOC assessments every 2 days, human audits weekly
- **Indicators**: All 100 per organization ($8 \times 100 = 800$ total)

Industry bias profiles:

- **Healthcare**: High authority (0.8), high stress (0.9), medium social (0.6)

- **Finance**: High authority (0.7), high temporal (0.8), low social (0.4)
- **Technology**: Low authority (0.4), high temporal (0.6), high stress (0.7)

Size bias: Enterprise +0.1 (complexity increases risk), Small -0.1 (simpler dynamics).

4.2 Convergence Metrics

Across 800 indicators with both SOC and human assessments:

Metric	**Value**	**Threshold**
Close Convergence ($\Delta \leq 0.15$)	94.2%	$> 90\%$
Moderate Divergence ($0.15 < \Delta \leq 0.35$)	4.8%	$< 8\%$
Large Divergence ($\Delta > 0.35$)	1.0%	$< 2\%$
Mean Absolute Error	0.089	< 0.10
Correlation (r)	0.96	> 0.90

Table 3: SOC vs Human Convergence (800 indicators)

Large divergence cases (1.0%) traced to:

- SOC false positives (misconfigured alerts)
- Human assessor calibration drift
- Genuine disagreement (organizational context vs machine data)

4.3 Trend Detection Accuracy

We manually labeled 30-day risk trajectories for 8 organizations:

True Trend	**Detected**	**Accuracy**	N
Improving	3/3	100%	3 orgs
Stable	2/2	100%	2 orgs
Deteriorating	3/3	100%	3 orgs
Overall	**8/8**	**100%**	**8 orgs**

Table 4: Trend Detection Performance

Perfect accuracy on synthetic data validates algorithm correctness. Real-world validation pending.

Category	Risk	Weight	Downstream	Priority
7. Stress	0.78	0.11	0.45	**0.124** (1st)
1. Authority	0.71	0.12	0.65	**0.141** (2nd)
9. AI	0.52	0.12	0.30	0.081 (5th)
3. Social	0.48	0.11	0.35	0.071 (7th)

Table 5: Prioritization Example (Top/Bottom Ranked)

4.4 Prioritization Case Study

Organization: Healthcare Enterprise (high stress, high authority)

Recommendation: Address Stress first (burnout reduction), then Authority (reduce compliance exploitation). Fixing these two cascades to improve Social, Cognitive, and Group categories.

5 Results

5.1 Dashboard Analytics

The multi-organization dashboard provides:

1. **Overall Risk Heatmap**: 10 categories color-coded (green/yellow/red)
2. **Indicator Grid**: 100-tile matrix (10×10) with drill-down to SOC/Human details
3. **Convergence Timeline**: Daily SOC vs Human averages with divergence highlighting
4. **Prioritization Matrix**: Ranked categories with downstream impact visualization
5. **Trend Analysis**: 30-day trajectory with improving/stable/deteriorating classification

5.2 Auditing Progress Dashboard

Secondary dashboard tracks Field Kit assessment completion:

- **Per-organization**: 100-indicator grid showing completed (green) vs missing (gray)
- **Category breakdown**: 10 progress bars for category-level coverage
- **Missing list**: Explicit enumeration of incomplete indicators (e.g., "1.3, 2.7, 5.9")

- **Overall stats**: Total orgs, indicators completed, average coverage, average risk

Critical for managing 100-indicator audit workflows across multiple organizations.

5.3 Computational Performance

Operation	Time	Data Size
Load organizations.json	180 ms	6 MB (8 orgs)
Bayesian recalculation (all)	45 ms	800 indicators
Render dashboard	120 ms	Canvas + DOM
Field Kit auto-update	8 ms	Single indicator
Batch import (100 files)	1.2 s	Node.js

Table 6: Performance Benchmarks (MacBook Pro M1, Chrome 120)

Client-side JavaScript achieves real-time performance despite complex Bayesian calculations.

6 Discussion

6.1 Strengths

1. **Holistic Assessment**: First framework to systematically integrate psychological vulnerabilities with technical security
2. **Data Fusion**: Bayesian merging of SOC automation with human expertise leverages strengths of both
3. **Dependency Modeling**: Explicit cross-category influences enable cascade effect analysis
4. **Actionable Prioritization**: Downstream impact scoring optimizes remediation sequencing
5. **Deployment Simplicity**: Client-side architecture requires zero infrastructure

6.2 Limitations

1. **Dependency Matrix Validation**: Current dependencies based on literature review and expert judgment; requires empirical validation with real breach data

2. **Category Weight Calibration**: Fixed weights may need industry-specific tuning (finance vs retail)

3. **Synthetic Validation Only**: Real-world deployment needed to confirm trend detection accuracy

4. **Temporal Granularity**: 30-day windows may miss rapid attacks (credential stuffing campaigns)

5. **Human Assessor Variability**: Inter-rater reliability not yet quantified; calibration protocols needed

6. **Scalability**: 6MB JSON feasible for 8 orgs; 100+ organizations may require database

6.3 Comparison to Related Work

Framework	Human Factors	SOC Integration	Bayesian	Dependencies
CVSS	No	No	No	No
NIST CSF	Partial	Partial	No	No
FAIR (Risk)	No	Yes	No	No
Human Risk OS	Yes	Limited	No	No
CPF (Ours)	**Yes**	**Yes**	**Yes**	**Yes**

Table 7: Comparison to Existing Frameworks

CPF uniquely combines all four capabilities.

6.4 Future Work

1. **Real-World Deployment**: Partner with 10-15 organizations across industries for 6-month pilot

2. **Dependency Validation**: Correlate dependency predictions with actual breach propagation patterns

3. **Machine Learning**: Train neural networks on historical data to auto-adjust weights and dependencies

4. **Predictive Analytics**: Forecast future risk trajectories (30/60/90-day projections)

5. **Alert System**: Email/Slack notifications for deteriorating trends and divergence anomalies

6. **Benchmarking**: Industry-specific risk baselines (e.g., "Your healthcare org: 0.54, industry avg: 0.48")

7. **API Connectors**: Real-time SOC integrations (Splunk, QRadar, Sentinel APIs)
8. **Multi-Language Support**: Field Kit translation for global deployments
9. **Collaboration Features**: Multi-assessor workflows with consensus mechanisms
10. **Longitudinal Studies**: 12-month tracking to validate trend detection and measure training impact

7 Conclusion

We presented the Cybersecurity Psychology Framework (CPF), a comprehensive methodology for assessing human-centric cybersecurity vulnerabilities through integrated SOC machine data and expert human auditing. The Bayesian inference engine merges heterogeneous data sources with confidence weighting, models cross-category dependencies to capture psychological risk propagation, and generates prioritized remediation plans based on downstream impact analysis.

Validation on synthetic datasets demonstrates 94% convergence between automated and human evaluations, with 100% trend detection accuracy and actionable prioritization for remediation sequencing. The open-source client-side implementation enables immediate deployment without infrastructure requirements.

As organizations face increasingly sophisticated social engineering and AI-assisted attacks, CPF provides security teams with the missing layer between technical vulnerability scanning and organizational psychology. By quantifying human factors with the same rigor as technical controls, we enable evidence-based security awareness programs, risk-informed resource allocation, and proactive defense against the primary attack vector: human vulnerabilities.

The framework is publicly available at `https://github.com/[TODO]` under MIT license.

Acknowledgments

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A Full Dependency Matrix

From \ To	Auth	Temp	Soc	Aff	Cog	Grp	Str	Unc	AI	Conv
Authority	-	-	0.30	-	-	0.20	-	0.15	-	-
Temporal	-	-	-	0.25	0.20	-	0.40	-	-	-
Social	-	-	-	0.20	-	0.35	-	0.10	-	-
Affective	-	-	-	-	0.30	-	0.35	-	-	-
Cognitive	-	-	-	-	-	-	-	0.25	-	-
Group	-	-	0.25	-	-	-	-	0.20	-	-
Stress	-	-	-	0.40	0.45	-	-	-	-	-
Unconscious	-	-	0.15	-	0.20	-	-	-	-	-
AI	-	0.30	0.25	0.35	-	-	-	0.30	-	-
Convergent	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	-

Table 8: Complete Cross-Category Dependency Matrix (28 edges)

B Indicator Examples

Category 1: Authority-Based Vulnerabilities

- 1.1: Impersonation of supervisors/executives
- 1.3: Unquestioning trust in credentials (email domains, titles)
- 1.7: Failed authentication as authority test (SOC metric)

Category 7: Stress-Induced Vulnerabilities

- 7.2: Chronic overtime and burnout levels
- 7.5: Security shortcuts under pressure
- 7.9: Stress-related incident correlation (SOC metric)

Category 9: AI-Assisted Manipulation

- 9.1: Deepfake awareness and detection capability
- 9.4: Synthetic media verification protocols
- 9.7: AI-generated phishing detection rates (SOC metric)

C Field Kit Sample Assessment

Indicator 1.3: Authority - Credential Trust Exploitation

Quick Assessment (7 questions, 70% weight):

1. Do employees verify sender identity beyond email display name? (Yes/No/Partial)

2. Are there processes to confirm unusual requests from superiors? (Yes/No/Partial)
3. Is SPF/DKIM/DMARC email authentication enforced? (Yes/No/Partial)
4. Do employees question suspicious requests from authority figures? (Yes/No/Partial)
5. Are there public examples of authority impersonation incidents? (Yes/No/Partial)
6. Is there training on CEO fraud/BEC attacks? (Yes/No/Partial)
7. Do employees use out-of-band verification for sensitive requests? (Yes/No/Partial)

Red Flags (multi-select, 30% weight):

- Recent BEC/wire fraud incidents
- No email authentication (SPF/DKIM/DMARC)
- Culture of unquestioning obedience
- No verification protocols for financial requests
- Executives' emails frequently spoofed

Deep Dive (14 follow-up questions, informational):

- Describe last authority impersonation attempt and response...
- How do employees verify unusual wire transfer requests?...
- What percentage of employees can identify spoofed emails?...

11 more context questions

Scoring Example:

- Quick: 4/7 Yes (57%) $\rightarrow 0.57 \times 0.70 = 0.40$
- Red Flags: 2/5 selected $\rightarrow 0.40 \times 0.30 = 0.12$
- **Final Score**: $0.40 + 0.12 =$ **0.52** (Medium Risk)