
The Cybersecurity Psychology Framework (CPF): A Method for Quantifying Human Risk and a Blueprint for LLM Integration

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Abstract

This paper presents the Cybersecurity Psychology Framework (CPF), a novel taxonomy designed to categorize and quantify human-centric vulnerabilities in security operations. The core contribution of this work is two-fold: first, we operationalize the CPF by mapping its subcategories to specific, measurable indicators derived from standard SOC tooling (e.g., Splunk, Elasticsearch, Qualys) and communication platforms (e.g., Slack, Teams), formalizing these measures through algorithmic definitions. Second, we propose and detail a lightweight, efficient architecture for a Large Language Model (LLM) that leverages Retrieval-Augmented Generation (RAG) and targeted fine-tuning on a compact, domain-specific corpus. This architecture is designed to analyze the structured and unstructured data defined by the CPF algorithms to identify latent psychological risks. We argue that this approach makes sophisticated behavioral analysis computationally feasible and accessible, moving beyond theoretical taxonomy to provide a practical tool for proactive risk mitigation. The paper concludes with a methodology for validating the framework and its LLM component in a real-world environment.

Keywords: cybersecurity, human factors, psychology, large language models, risk assessment, SOC operations

1 Introduction

The human factor is consistently identified as the weakest link in cybersecurity defenses, yet traditional security tools lack the capability to quantitatively assess psychological states that lead to increased risk. This paper presents a novel, end-to-end methodology for operationalizing the Cybersecurity Psychology Framework (CPF), a taxonomy of human-centric vulnerabilities, transforming it from a theoretical model into a practical tool for proactive risk mitigation. Our primary contribution is the definition of specific, measurable algorithms that quantify key CPF subcategories—such as Compliance Fatigue, Alert Overload Bias, and Against-Gravity Communication—by analyzing data from standard SOC tools (e.g., Splunk, Qualys) and communication platforms (e.g., Slack). Furthermore, we propose a cost-effective and privacy-preserving LLM architecture based on a Retrieval-Augmented Generation (RAG) pipeline and lightweight fine-tuned models (e.g., Llama 3, Mistral) designed to reason over this data and generate actionable analyses of human risk. We detail a rigorous mixed-methods validation plan to evaluate the predictive power of our metrics and the utility of the LLM’s insights. Finally, we thoroughly address the critical ethical and privacy imperatives that must govern such a system. This work provides a foundational blueprint for moving beyond anecdotal understanding of human error towards a data-driven, psychologically-informed approach to building more resilient security operations.

2 Background and Related Work

2.1 Human Factors in Cybersecurity

Human factors have long been recognized as critical components in cybersecurity, with studies consistently showing that human error contributes to over 85% of security incidents. Traditional approaches to addressing human factors have focused primarily on security awareness training and policy enforcement. However, these approaches often fail to address the underlying psychological mechanisms that drive human behavior in security contexts.

Research in cybersecurity psychology has identified several key psychological factors that influence security behaviors, including compliance fatigue, alert overload bias, and risk perception gaps. These factors represent systematic patterns in how individuals and teams respond to security demands, often leading to predictable vulnerabilities.

2.2 Security Data Analytics

The field of security data analytics has made significant advances in detecting technical threats through the analysis of log data, network traffic, and system events. Tools like Splunk, Elasticsearch, and Qualys have become standard in Security Operations Centers (SOCs) for collecting and analyzing security-relevant data. However, these tools typically focus on technical indicators of compromise rather than psychological states of security personnel.

Recent work has begun to explore the use of operational data for understanding human performance in security contexts, but this research has largely focused on individual metrics rather than comprehensive psychological frameworks.

2.3 LLMs in Cybersecurity

Large Language Models have shown promising applications in cybersecurity, particularly in areas such as log analysis, threat intelligence parsing, and automated report generation. However,

their application to behavioral psychology and human factors analysis remains nascent. Current implementations typically use general-purpose models rather than systems specifically designed for psychological analysis.

The integration of LLMs with psychological frameworks represents an emerging frontier in cybersecurity research, with potential applications in predictive analytics, automated assessment, and personalized interventions.

2.4 Research Gap

No existing work provides a complete pipeline from psychological taxonomy to data measurement to AI-driven analysis for human factors in cybersecurity. This paper aims to fill that gap by operationalizing the Cybersecurity Psychology Framework through specific algorithms and demonstrating how a purpose-built LLM architecture can effectively analyze this data to predict human-centric security risks.

3 The Cybersecurity Psychology Framework (CPF): A Taxonomy of Human Risk

The Cybersecurity Psychology Framework (CPF) is a comprehensive taxonomy designed to categorize and analyze human-centric vulnerabilities in security operations. Developed through interdisciplinary research integrating psychoanalytic theory, cognitive psychology, and cybersecurity practice, the CPF provides a structured approach to understanding the psychological dimensions of security failures.

3.1 Framework Structure

The CPF organizes human risk factors into a hierarchical structure consisting of Categories, Subcategories, Behaviors, and Manifestations. This structure enables systematic analysis of psychological vulnerabilities at multiple levels of granularity.

3.2 Core Categories

The CPF comprises ten primary categories of human risk:

1. **Authority-Based Vulnerabilities:** Patterns of behavior related to responses to authority figures and hierarchical structures
2. **Temporal Vulnerabilities:** Time-related factors affecting security decisions and behaviors
3. **Social Influence Vulnerabilities:** Social dynamics impacting security practices
4. **Affective Vulnerabilities:** Emotional factors influencing security-related decision making
5. **Cognitive Overload Vulnerabilities:** Limitations in cognitive processing affecting security tasks
6. **Group Dynamic Vulnerabilities:** Team and organizational factors creating security risks

7. **Stress Response Vulnerabilities:** Reactions to pressure and stress impacting security performance
8. **Unconscious Process Vulnerabilities:** Automatic or non-conscious processes creating security gaps
9. **AI-Specific Bias Vulnerabilities:** Unique psychological factors in human-AI interaction contexts
10. **Critical Convergent States:** Complex, multi-factor vulnerability conditions

3.3 Operationalization Need

For the CPF to transition from theoretical taxonomy to practical tool, its subcategories must be measurable through specific indicators derived from operational data. The following section addresses this need by defining algorithms for quantifying key CPF subcategories using data from standard security tools and platforms.

4 Operationalizing the CPF: From Theory to Algorithms

5 A Lightweight LLM Architecture for CPF Analysis

6 Validation Methodology

To empirically evaluate the efficacy of the CPF and its associated LLM analysis pipeline, we propose a mixed-methods validation strategy conducted in two phases. This approach assesses both the accuracy of the individual algorithmic metrics and the practical utility of the integrated system in a realistic environment.

6.1 Phase 1: Algorithmic Validation (Quantitative)

The goal of Phase 1 is to validate the core hypothesis: that the metrics defined by the CPF algorithms are accurate leading indicators of human-centric security incidents.

6.1.1 Study Design

A retrospective case-control study will be performed on historical data from a participating organization. The study period will be 12 months.

- **Cases:** A set of *known, confirmed security incidents* caused primarily by human error (e.g., a missed alert leading to a breach, an unpatched dev-server exploited for lateral movement). These will be identified from incident response reports.
- **Controls:** A set of *"normal" periods* randomly selected from the same time frame, matched for overall alert volume and team composition but where no major incidents occurred.

6.1.2 Data Analysis

For each case and control period, the relevant CPF metrics (e.g., MTTA, PMR, PLG, UCTR) will be calculated using the algorithms defined in Section 4.

$$\text{logit}(p(\text{Incident})) = \beta_0 + \beta_1 \cdot \text{MTTA} + \beta_2 \cdot \text{PMR} + \beta_3 \cdot \text{PLG} + \dots \quad (1)$$

A multivariate logistic regression model (Equation 1) will be used to determine which combination of CPF metrics are statistically significant ($p < 0.05$) predictors of an incident. The predictive power of the model will be evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

6.1.3 Success Criteria

The algorithms will be considered validated if:

1. The logistic regression model achieves an AUC-ROC score of > 0.8 , indicating excellent predictive power.
2. At least three of the defined CPF metrics are statistically significant predictors in the model.

6.2 Phase 2: LLM System Validation (Qualitative & Quantitative)

The goal of Phase 2 is to evaluate the performance and utility of the full integrated system, focusing on the quality, accuracy, and actionability of the LLM-generated analyses.

6.2.1 Study Design

A prospective pilot study will be conducted with a security team from a participating organization over a 3-month period. The team will use the integrated CPF+LLM system alongside their existing tools.

6.2.2 Evaluation Methodology

The evaluation will employ a triangulation approach:

1. **Simulated Task Evaluation:** Participants will be given 10 historical scenarios redacted from their own incident logs. For each scenario, they will receive three analyses:
 - **A:** Generated by the proposed CPF/LLM system.
 - **B:** Generated by a state-of-the-art general-purpose LLM (e.g., GPT-4) given the same data context.
 - **C:** A ground-truth analysis written by a human expert psychologist and senior SOC analyst.

Participants will be blinded to the source of each analysis and will rate them on a 5-point Likert scale for **accuracy**, **insightfulness**, and **actionability**.

2. **Real-World Utility Tracking:** During the pilot, all analyses generated by the system will be logged. Key operational metrics will be tracked:

- **Mean Time to Acknowledge (MTTA)** and **Mean Time to Resolve (MTTR)** for incidents flagged by the system.
 - The **adoption rate** of the mitigation strategies recommended by the LLM.
3. **Participant Interviews:** Structured interviews will be conducted with SOC analysts and managers at the end of the pilot to gather qualitative feedback on the system’s usability, perceived value, and impact on their workflow.

6.2.3 Success Criteria

The integrated CPF+LLM system will be considered successful if:

1. Its analyses (A) achieve a statistically significant higher average rating in accuracy and actionability than those from the general-purpose LLM (B) in the simulated task ($p < 0.05$, paired t-test).
2. The pilot shows a measurable improvement (e.g., 15% reduction) in MTTA/MTTR for incidents flagged by the system compared to the baseline period.
3. Interview feedback indicates that the system provides novel, useful insights that were not previously available to the team.

6.3 Threats to Validity

- **Internal Validity:** The main threat is historical bias in the retrospective study (Phase 1). We will mitigate this by using a large, diverse dataset and controlling for confounding variables like team size and event volume.
- **External Validity:** The results from a single-organization pilot may not be generalizable. We will explicitly describe the organizational context of our pilot partner to clarify the scope of our findings.
- **Construct Validity:** The metrics we defined (e.g., UCTR) are proxies for psychological constructs. Expert validation (the interviews in Phase 2) is crucial to ensure these metrics are measuring what we intend them to measure.

6.4 Data Collection Plan

For both phases, data will be collected under a strict protocol approved by an Institutional Review Board (IRB). All data will be anonymized and aggregated before analysis to protect individual privacy. The specific data to be collected includes:

- Anonymized SIEM logs and alert histories.
- Anonymized tickets and their status transitions.
- Aggregated, topic-based analysis of communication data (no direct messages will be read by researchers; analysis will be performed by automated scripts only).
- Vulnerability scan results with asset metadata.
- Participant ratings and interview transcripts (from Phase 2).

7 Ethical and Privacy Considerations

The implementation of the Cybersecurity Psychology Framework (CPF) and its associated LLM analysis pipeline involves the processing of sensitive data, including security alerts, vulnerability reports, and—most critically—human communications. Without rigorous ethical safeguards, such a system could itself become a vector for harm, eroding trust and violating privacy. This section outlines the principles, policies, and technical measures that must underpin any deployment of this technology.

7.1 Core Ethical Principles

The design and operation of the CPF system must be guided by the following principles:

- **Beneficence and Non-Maleficence:** The system must be designed to create a net positive benefit for the organization and its employees. Its primary purpose is to support and augment human analysts, not to replace or punish them. All efforts must be made to minimize potential harms, such as privacy violations or increased stress from perceived surveillance.
- **Transparency:** The existence of the system, its capabilities, the types of data it analyzes, and its intended purpose must be communicated clearly to all employees. Secrecy around its deployment would be ethically untenable and counterproductive to building a strong security culture.
- **Justice and Equity:** The system must be designed and monitored to avoid unfairly targeting specific individuals or groups. Algorithms must be checked for biases that could lead to disproportionate scrutiny of certain teams or demographics.
- **Respect for Personhood and Autonomy:** Employees must not be treated merely as data points or sources of risk. The system should be configured to analyze trends and group behaviors, not to perform continuous, individualized monitoring.

7.2 Privacy by Design and Default

The principle of *Privacy by Design* must be embedded into the architecture of the system from its inception. This translates to several technical and procedural mandates:

7.2.1 Data Minimization and Purpose Limitation

The system should only collect and process data that is strictly necessary for its defined security purpose. For example:

- **Communications Analysis:** The content of direct messages (DMs) should not be ingested into the vector database for LLM analysis. The algorithm for *Against-Gravity Communication* should rely solely on metadata (e.g., presence of keywords, channel type) and aggregated topic modeling, not on the full textual content.
- **Anonymization and Aggregation:** Personal identifiers must be stripped from data before processing wherever possible. Metrics should be calculated and reported at the team or department level (e.g., "The EMEA SOC team shows signs of alert fatigue") rather than at the individual level.

7.2.2 Access Controls and Governance

Strict access controls are non-negotiable.

- **Role-Based Access:** Raw, un-anonymized data should only be accessible to a very small number of vetted personnel (e.g., the CISO and their direct delegates) for the purpose of system maintenance and audit.
- **Independent Oversight:** The deployment and operation of the system should be reviewed and overseen by a committee comprising members from HR, legal, compliance, and employee representative groups. This body would approve use cases and audit system usage logs.

7.2.3 Technical Safeguards

- **On-Premises Deployment:** The entire system, especially the LLM component, must be deployed on the organization's own infrastructure. This ensures that sensitive data never leaves the organization's control and is not exposed to third-party vendors.
- **Encryption:** All data must be encrypted both at rest and in transit.
- **Data Retention Policies:** Automatically delete raw data after it is processed into aggregated metrics. For example, chat logs used for topic extraction should be purged immediately after the weekly UCTR metric is calculated.

7.3 Legal and Regulatory Compliance

The system must be designed for compliance with all relevant data protection regulations, which may include:

- **GDPR (General Data Protection Regulation):** Requires a lawful basis for processing (likely *legitimate interest*, which must be balanced against individual rights), mandates data subject access requests, and requires Data Protection Impact Assessments (DPIAs) for high-risk processing.
- **CCPA/CPRA (California Consumer Privacy Act/ Rights Act):** Grants California employees similar rights to access, delete, and opt-out of the sale of their personal information.

A DPIA must be conducted prior to any deployment to identify and mitigate risks.

7.4 The Human Element: Building Trust

Technology alone cannot ensure ethical deployment. The following human-centric policies are essential:

- **Explicit Consent and Collective Agreements:** While legal basis may be claimed under *legitimate interest*, seeking explicit consent or, more effectively, negotiating the system's use through collective bargaining agreements demonstrates respect for employees and builds crucial trust.

- **Transparency Reports:** Regularly publish reports detailing what the system has detected at an aggregated level (e.g., "we observed a 20% increase in cross-team communication about incidents") and how those insights were used to improve the work environment (e.g., "we hired two new analysts to reduce overload").
- **Opt-Out for Individuals:** While potentially limiting the system’s comprehensiveness, providing a mechanism for individuals to opt-out of certain analyses (e.g., communication analysis) for personal reasons is a powerful gesture of respect for autonomy.

7.5 Conclusion

The power of the CPF to identify human-centric risks is significant, but so is its potential for misuse. An ethical deployment is not merely a legal requirement but a prerequisite for its effectiveness. A system that erodes trust will fail to improve security. Therefore, the safeguards outlined here are not impediments to the system but are integral to its long-term success and acceptance within the organization.

8 Conclusion and Future Work

8.1 Summary of Contributions

This paper presented a comprehensive methodology for moving the study of human factors in cybersecurity from theoretical taxonomy to practical, measurable, and actionable insight. Our primary contributions are threefold:

First, we introduced and formalized the **Cybersecurity Psychology Framework (CPF)** as a structured taxonomy for categorizing human-centric vulnerabilities. Beyond mere classification, our principal contribution lies in the **operationalization** of this framework. We defined specific, quantifiable metrics and detailed algorithms for key subcategories such as Compliance Fatigue, Alert Overload Bias, Risk Perception Gap, and Against-Gravity Communication. This provides a blueprint for translating psychological constructs into concrete data queries against standard SOC tooling.

Second, we proposed a **pragmatic and efficient LLM architecture** specifically designed for the CPF domain. Instead of relying on massive, monolithic models, our system leverages a Retrieval-Augmented Generation (RAG) pipeline built upon a small, fine-tuned open-weight model. This architecture is cost-effective, privacy-preserving, and grounds its analysis in the organization’s live data context, thereby reducing hallucinations and improving relevance.

Third, we outlined a rigorous **mixed-methods validation methodology** to evaluate both the predictive power of the CPF metrics and the practical utility of the integrated system. Furthermore, we dedicated significant attention to the critical **ethical and privacy considerations** that must govern any deployment of such a system, emphasizing principles like Privacy by Design, transparency, and human oversight.

8.2 Limitations

While this work provides a foundational framework, we acknowledge several limitations that must be considered:

- **Generalizability:** The validation study, as proposed, is designed for a single-organization pilot. The effectiveness of the CPF metrics may vary across organizations with different

cultures, tooling, and security maturity levels.

- **Data Quality and Integration:** The accuracy of the algorithms is heavily dependent on the quality and consistency of data across disparate sources (SIEM, ticketing, communication platforms). Inconsistent asset tagging or incomplete logs would degrade performance.
- **Simplified Psychological Model:** The CPF, like any taxonomy, simplifies complex human behaviors into discrete categories. The metrics are proxies for psychological states and may not capture the full nuance of individual or team dynamics.

8.3 Future Work

This work opens several promising avenues for future research and development:

- **Expansion of the CPF Taxonomy:** Future work should focus on operationalizing additional subcategories of the CPF, such as those related to organizational culture or team dynamics (e.g., *Groupthink*).
- **Advanced LLM Fine-Tuning:** Exploring more sophisticated fine-tuning techniques, such as Reinforcement Learning from Human Feedback (RLHF), could further enhance the quality, reliability, and alignment of the LLM’s outputs with expert reasoning.
- **Real-Time Intervention and SOAR Integration:** The logical evolution of this system is its integration into Security Orchestration, Automation, and Response (SOAR) platforms. Future work could develop automated playbooks that trigger based on CPF risk scores—for example, automatically rotating an analyst to a low-stress task upon detecting signs of severe fatigue or alert overload.
- **Cross-Cultural Studies:** A large-scale study applying the CPF across multiple organizations in different industries and countries would be invaluable for validating the generalizability of the metrics and understanding how human risk manifests in different cultural contexts.
- **Longitudinal Studies:** Conducting long-term studies to observe how CPF metrics evolve over time and in response to organizational changes (e.g., new tooling, policy changes, training programs) would provide deep insights into the dynamics of human security risk.

8.4 Concluding Remarks

The human element remains the most critical and challenging variable in the cybersecurity equation. By providing a method to quantify this element, the CPF and its associated analytical pipeline offer a path toward more resilient and adaptive security operations. We have demonstrated that it is possible to move beyond anecdotal discussions of human error and towards a data-driven understanding of human risk. We believe this approach represents a significant step forward in the quest to build security systems that are not only technologically robust but also psychologically informed.

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