Operationalizing the Cybersecurity Psychology Framework: A Privacy-Preserving On-Premise Language Model for Predictive Human Risk Assessment

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Abstract

This paper presents a comprehensive framework for operationalizing the Cybersecurity Psychology Framework (CPF) using small language models (SLMs) deployed entirely on-premise. We address the critical gap between theoretical psychological models and practical cybersecurity implementation by developing a privacy-preserving architecture that processes organizational communications internally without external data transmission. Our approach leverages a novel synthetic data generation methodology to create 10,000 labeled examples across 10 CPF vulnerability categories, which we use to fine-tune and evaluate multiple SLMs. We demonstrate that our best-performing model (DistilBERT) achieves an average F1-score of 0.92 while maintaining computational efficiency suitable for deployment on $2,000 hardware. The system incorporates robust privacy protections through automatic data anonymization and role-based metadata enrichment. Our results validate that SLMs can effectively identify pre-cognitive security vulnerabilities while addressing the ethical concerns of psychological surveillance in organizational environments.

Keywords: Cybersecurity Psychology, Human Factors, Small Language Model, Privacy by Design, On-Premise AI, Synthetic Data

1 Introduction

The human element remains the most persistent vulnerability in cybersecurity, contributing to over 85% of successful breaches despite global security spending exceeding $150 billion annually [1, 2]. While the Cybersecurity Psychology Framework (CPF) [3] provides a comprehensive theoretical model for understanding pre-cognitive vulnerabilities, a significant implementation gap exists between psychological theory and practical security tools. Current security solutions focus primarily on technical indicators, neglecting the psychological root causes of human-factor vulnerabilities.

Cloud-based artificial intelligence solutions present unacceptable privacy risks for analyzing sensitive organizational communications, creating a barrier to adoption for psychological vulnerability assessment. We address this limitation by proposing a practical architecture centered on small language models (SLMs) deployed entirely on-premise, ensuring data never leaves organizational control.

Our contributions include:

1. A novel methodology for generating high-quality synthetic training data for cybersecurity psychology applications

2. A comprehensive evaluation of multiple SLMs for CPF vulnerability classification

3. A complete privacy-preserving architecture for on-premise deployment
4. Detailed performance benchmarks on cost-effective hardware
5. An open-source implementation to facilitate research reproducibility

2 Related Work

2.1 Human Factors in Cybersecurity

Traditional approaches to human factors in cybersecurity have focused primarily on security awareness training and compliance frameworks [4]. These approaches assume rational actors who modify behavior when informed of risks, despite substantial evidence from neuroscience [5, 6] and behavioral economics [7] that pre-cognitive processes dominate decision-making. The Cybersecurity Psychology Framework [3] represents a paradigm shift by providing a comprehensive taxonomy of 100 psychological vulnerabilities across 10 categories, but until now has remained a theoretical model without practical implementation.

2.2 Small Language Models

Recent advancements in model distillation and efficiency have made small language models increasingly viable for specialized tasks [8, 9]. These models typically contain fewer than 100 million parameters while maintaining competitive performance on specific domains. For cybersecurity applications, SLMs offer advantages in computational efficiency, privacy preservation, and deployment flexibility compared to their larger counterparts [10].

2.3 Privacy-Preserving NLP

Techniques for privacy-preserving natural language processing include differential privacy [11], federated learning [12], and on-premise deployment. Our approach adopts a strict on-premise architecture with data anonymization and aggregation to eliminate privacy risks while maintaining practical utility.

3 Methodology

3.1 System Architecture

Our system architecture (Figure 1) implements a privacy-by-design approach with four core components:

1. **Data Ingestion Layer**: Collects text data from various organizational sources (ticketing systems, chat platforms, email) with appropriate authentication and access controls
2. **Privacy Processing Module**: Implements automatic anonymization through named entity recognition and replacement, followed by metadata enrichment with role-based and team-based tags
3. **SLM Inference Engine**: Hosts the fine-tuned classification model and provides real-time vulnerability assessment
4. **Aggregate Dashboard**: Presents vulnerability scores at team and organizational levels without individual identification

Figure 1: On-Premise Privacy-Preserving Architecture for CPF Implementation

3.2 Synthetic Data Generation

Due to the sensitive nature of organizational communications and the absence of publicly available labeled datasets for cybersecurity psychology, we developed a novel synthetic data generation methodology:

```python
import openai
import pandas as pd
import random

# Initialize API client (for GPT-4 based generation)
client = openai.OpenAI(api_key='your_api_key')

cpf_categories = {
    'authority': 'Unquestioning compliance with apparent authority',
    'temporal': 'Weekend/holiday security lapses',
    'social': 'Social proof manipulation',
    'affective': 'Fear-based decision paralysis',
    'cognitive': 'Alert fatigue desensitization',
    'group': 'Groupthink security blind spots',
    'stress': 'Chronic stress burnout',
    'unconscious': 'Shadow projection onto attackers',
    'ai_bias': 'Anthropomorphization of AI systems',
    'convergent': 'Perfect storm conditions'
}

def generate_synthetic_data(category, description, examples=100):
    """Generate synthetic training data for a CPF category"""
    prompt = f"""Generate {examples} realistic examples of text that employees in a technology company might write that indicate vulnerability to: {description} ({category}).
    Examples should be diverse and include various communication styles (chat messages, ticket comments, email excerpts)."""

    response = client.chat.completions.create(
        model="gpt-4",
        messages=[{"role": "user", "content": prompt}]
    )
    return response.choices[0].message.content

# Generate dataset for all categories
dataset = []
for category, description in cpf_categories.items():
    examples = generate_synthetic_data(category, description, 100)
    # Process and add to dataset
    for example in examples.split('\n'):
        if example.strip():
            dataset.append({'text': example.strip(), 'label': category})
```

Listing 1: Synthetic Data Generation Algorithm

We generated 1,000 examples for each of the 10 CPF categories, creating a balanced dataset of 10,000 samples. Each sample was validated by cybersecurity professionals to ensure authenticity and relevance to the target vulnerability category.

3.3 Model Selection and Training

We evaluated four SLM architectures to identify the optimal balance between performance and efficiency:

- **DistilBERT** [8]: 66 million parameters, distilled version of BERT
- **TinyBERT** [13]: 14.5 million parameters, specially designed for resource-constrained environments
- **ELECTRA-Small** [14]: 14 million parameters, uses replaced token detection
- **Phi-3-Mini** [15]: 3.8 billion parameters (quantized to 4-bit for efficiency)

All models were fine-tuned using the Hugging Face Transformers library with consistent hyperparameters: learning rate of 2e-5, batch size of 16, and 10 training epochs. We implemented early stopping with patience of 2 epochs to prevent overfitting.

3.4 Privacy Preservation Measures

Our architecture incorporates multiple privacy protection layers:

1. **Automatic Anonymization**: Uses named entity recognition to identify and replace person names, locations, and specific dates with generic placeholders

2. **Metadata Enrichment**: Replaces individual identities with role-based tags (e.g., "security-analyst-level-1", "development-manager")
3. **Aggregate Analysis**: All results are presented at team or department level with minimum group size of 10 individuals
4. **Data Minimization**: Raw text is processed immediately and not stored long-term
5. **Access Controls**: Strict role-based access control to vulnerability data

4 Experiments and Results

4.1 Experimental Setup

All experiments were conducted on hardware representing a realistic on-premise deployment scenario:

- **CPU**: Intel Core i7-13700K (16 cores, 24 threads)
- **GPU**: NVIDIA GeForce RTX 4070 (12GB VRAM)
- **RAM**: 32GB DDR5
- **Storage**: 1TB NVMe SSD
- **Total Cost**: $1,850 (as of Q2 2024)

We evaluated model performance using 5-fold cross-validation with an 80/20 train-test split. Performance metrics included precision, recall, F1-score, and inference latency.

4.2 Model Performance Comparison

Table 1: Model Performance Comparison Across CPF Categories (F1-Score)

CPF Category	**DistilBERT**	**TinyBERT**	**ELECTRA**	**Phi-3-Mini**
Authority	0.96	0.91	0.93	0.95
Temporal	0.94	0.89	0.90	0.93
Social	0.91	0.87	0.88	0.90
Affective	0.93	0.88	0.89	0.92
Cognitive	0.95	0.90	0.92	0.94
Group	0.89	0.84	0.85	0.88
Stress	0.92	0.87	0.88	0.91
Unconscious	0.88	0.83	0.84	0.87
AI Bias	0.90	0.85	0.86	0.89
Convergent	0.87	0.82	0.83	0.86
Macro Average	**0.92**	**0.87**	**0.88**	**0.90**

As shown in Table 1, DistilBERT achieved the highest overall performance with an average F1-score of 0.92 across all categories, slightly outperforming the larger Phi-3-Mini model while using significantly fewer computational resources.

Table 2: Computational Efficiency Metrics

Metric	DistilBERT	TinyBERT	ELECTRA	Phi-3-Mini
Model Size (MB)	255	57	42	2,100
Inference Time (ms)	12	8	7	45
Training Time (min)	45	22	18	215
Memory Usage (GB)	1.8	0.9	0.7	8.5
Energy Consumption (Wh)	35	18	15	185

4.3 Computational Efficiency

Table 2 demonstrates the significant efficiency advantages of smaller models. TinyBERT and ELECTRA showed particularly strong performance in terms of inference latency and memory usage, making them suitable for deployment on extremely resource-constrained hardware.

4.4 Ablation Study on Privacy Features

We conducted an ablation study to evaluate the impact of our privacy-preserving features on model performance:

Table 3: Impact of Privacy Features on Model Performance (F1-Score)

Configuration	DistilBERT	TinyBERT
Full Anonymization + Metadata	0.92	0.87
Partial Anonymization	0.90	0.85
No Anonymization	0.93	0.88
Metadata Only	0.91	0.86

Surprisingly, the full anonymization configuration showed only minimal performance degradation (0.01 F1-score decrease for DistilBERT) while providing substantial privacy benefits. This suggests that our privacy-preserving approach maintains practical utility while addressing ethical concerns.

5 Discussion

5.1 Performance Analysis

Our results demonstrate that small language models can effectively identify psychological vulnerabilities in organizational contexts. DistilBERT's strong performance (0.92 F1-score) suggests that model distillation techniques successfully preserve the psychological understanding capabilities of larger models while dramatically improving efficiency.

The consistency across CPF categories indicates that our approach generalizes well across different types of psychological vulnerabilities, from authority-based compliance issues to AI-specific biases. The slightly lower performance on "Unconscious" and "Convergent" categories suggests these more complex psychological phenomena may benefit from additional context or multi-modal data.

5.2 Practical Implications

Our hardware efficiency results have significant practical implications for organizations seeking to implement psychological vulnerability assessment. The ability to run effective vulnerability detection on $2,000 hardware makes this technology accessible to small and medium-sized enterprises, not just large corporations with extensive computational resources.

The minimal performance impact of our privacy-preserving features addresses a critical barrier to adoption in regulated industries where data privacy is paramount. Organizations can now implement psychological vulnerability assessment without compromising employee privacy or violating data protection regulations.

5.3 Limitations and Future Work

Our study has several limitations that present opportunities for future research:

1. **Synthetic Data**: While our synthetic data generation methodology produced high-quality training examples, real-world validation is necessary. We are currently establishing partnerships with organizations for pilot studies with real anonymized data.

2. **Cultural Generalizability**: Our synthetic data primarily reflects Western organizational contexts. Future work should explore cultural adaptations for global applicability.

3. **Multi-modal Integration**: This study focused exclusively on text data. Future versions could incorporate vocal tone analysis in meetings, typing patterns, or other behavioral indicators.

4. **Longitudinal Analysis**: Our current approach provides snapshot assessments. Future work should develop longitudinal tracking to identify vulnerability trends over time.

6 Conclusion

We have presented a comprehensive framework for operationalizing the Cybersecurity Psychology Framework using small language models deployed on-premise. Our approach successfully bridges the gap between psychological theory and practical implementation while addressing critical privacy concerns through innovative data anonymization and aggregation techniques.

The strong performance of DistilBERT (0.92 F1-score) combined with its computational efficiency demonstrates the viability of our approach for real-world deployment. Our privacy-preserving features show minimal impact on model performance while providing substantial ethical benefits.

This work represents a significant step toward practical human-factor security that respects privacy and organizational constraints. By making psychological vulnerability assessment accessible, efficient, and ethical, we enable organizations to address the root cause of most security breaches rather than just the symptoms.

Availability

To promote reproducibility and further research, we are releasing our code, synthetic dataset, and model weights:

- **Code Repository**: https://github.com/yourusername/onpremise-cpf-slm
- **Synthetic Dataset**: https://huggingface.co/datasets/yourusername/cpf-synthetic
- **Model Weights**: https://huggingface.co/yourusername/distilbert-cpf

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