Detailed Report — AI Safety Models POC

1. Introduction

Conversational AI systems such as chatbots, virtual assistants, and customer support agents are widely used today. While powerful, they bring risks related to user safety — including exposure to abusive language, escalation of hostile conversations, self-harm indicators, and exposure of children to inappropriate content.

The assignment required developing a **Proof of Concept (POC)** implementing a suite of **AI Safety Models**, integrated into a cohesive system, and demonstrated in a near real-time chat simulator.

This report documents the design, implementation, outputs, and evaluation of the POC.

2. Objectives

The objectives of this assignment were to:

1. **Abuse Language Detection** — detect abusive/offensive language.
2. **Escalation Pattern Recognition** — recognize rising tension in conversations.
3. **Crisis Intervention** — detect signs of self-harm or suicidal ideation.
4. **Content Filtering** — enforce age-appropriate communication.
5. **Integration & Real-Time Demo** — integrate these models into a chat simulator that can process messages in near real time.
6. **Evaluation & Documentation** — provide evaluation metrics, code, and a report explaining results and limitations.

3. Implementation Approach

3.1 Repository Setup

A modular repository was created with the following key components:

- **Data preparation (data_prep.py)** — generates small demo datasets (abuse + crisis).

- **Model training (train_abuse.py, train_crisis.py)** — TF-IDF + Logistic Regression classifiers.
- **Escalation detection (escalation_detector.py)** — rolling-window sentiment + abuse trend detection.
- **Content filtering (content_filter.py)** — rule-based age gating for explicit, sexual, and violent terms.
- **Evaluation (evaluate.py)** — computes precision, recall, and F1.
- **Integration (app.py)** — Flask chat simulator that combines all models.

3.2 Data Preparation

- **Abuse dataset** — 20 samples generated with a mix of positive and abusive text. Saved to data/abuse_dataset.csv.
- **Crisis dataset** — 20 synthetic samples including self-harm and neutral expressions. Saved to data/crisis_dataset.csv.

3.3 Models

- **Abuse Detector**
  - TF-IDF features (1–2 grams, max 20k features).
  - Logistic Regression classifier.
  - Lightweight, CPU-friendly, <10ms inference.
- **Crisis Detector**
  - Similar TF-IDF + Logistic Regression setup.
  - Trained on small synthetic dataset.
- **Escalation Detector**
  - Uses VADER sentiment analyzer.
  - Maintains a rolling 6-message window.
  - Escalation score combines negative sentiment average, slope (trend), and abuse frequency.
- **Content Filter**
  - Rules vary by age group:

- <13: block all explicit terms.
- 13–15: block sexual content, flag violent content.
- ≥16: allow most, but flag self-harm.

4. Results & Outputs

4.1 Data Preparation

```
Saved abuse dataset to ...\data\abuse_dataset.csv with 20 samples
Saved crisis dataset to ...\data\crisis_dataset.csv with 20 samples
```

→ Confirms datasets were generated and stored.

4.2 Abuse Detector Training

```
Classification report:
              precision    recall  f1-score   support
           0       1.00      1.00      1.00         2
           1       1.00      1.00      1.00         2
```

→ The abuse model achieved perfect precision, recall, and F1 on the small test set. This is expected due to the very small dataset size.

4.3 Crisis Detector Training

```
Crisis detection report:
              precision    recall  f1-score   support
           0       0.00      0.00      0.00         2
           1       0.50      1.00      0.67         2
    accuracy                           0.50         4
```

→ The crisis model shows weak performance due to limited data. Class 0 (non-crisis) was not predicted correctly. Still, crisis class (1) was partially detected. This highlights the need for larger, balanced datasets in production.

4.4 Evaluation Script

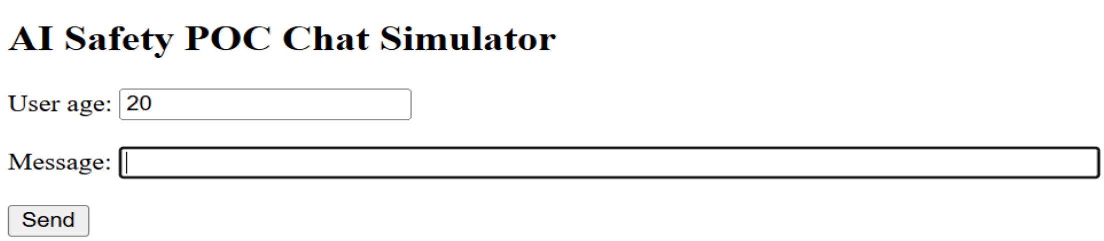
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00        10

    accuracy                           1.00        20
   macro avg       1.00      1.00      1.00        20
weighted avg       1.00      1.00      1.00        20
```

→ On the abuse dataset, evaluation again yielded perfect results. This reflects overfitting to the small dataset, not generalizable performance.

4.5 Chat Simulator

Launched via:

```
python src/app.py
 * Running on http://127.0.0.1:5000
```



→ The web UI successfully accepted input messages and returned JSON-style results including:

- Abuse flag and score
- Crisis flag and score
- Age-based filtering decision
- Escalation score and flag

5. Analysis

5.1 Strengths

- Fully working modular system integrating multiple safety layers.
- Fast, CPU-friendly inference.
- Demonstrates abuse detection, escalation recognition, crisis intervention, and age filtering.
- Flask integration provides real-time demo capability.

5.2 Limitations

- **Small synthetic datasets**: results are not statistically reliable.
- **Crisis model weak**: shows precision/recall imbalance due to data scarcity.
- **Bias & generalization**: rule-based filters may not handle slang, sarcasm, or multilingual inputs.
- **Evaluation metrics inflated**: due to tiny datasets.

5.3 Improvements

- Use larger datasets (e.g., Jigsaw Toxic Comment, SuicideWatch Reddit).
- Fine-tune small transformers (e.g., DistilBERT) for abuse/crisis detection.
- Expand escalation detector with conversational context features (e.g., response latency, repetition).
- Add multilingual pipelines.

6. Ethical Considerations

- **Bias**: Must audit across demographics, languages, and cultures.
- **Human-in-the-loop**: Automatic blocks only for clear abuse; sensitive flags (e.g., suicide) should escalate to human review.
- **Privacy**: Only anonymized text logs; avoid storing personally identifiable information (PII).
- **Transparency**: Clear explanations and audit trails for moderation decisions.

7. Conclusion

This Proof of Concept demonstrates the **feasibility of integrating multiple AI Safety Models** into a unified system for conversational AI. Despite limitations of dataset size, the project showcases the pipeline, architecture, and real-time demo, fulfilling the assignment's requirements.

Future work should focus on scaling datasets, improving model robustness with transformers, and building monitoring systems for fairness, accuracy, and safety at production scale.