Temporal Risk Detection in Conversational AI: An EWMA-Based Framework with Cross-Domain Validation

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Abstract

We present a **temporal risk detection framework** combining exponentially weighted moving average (EWMA) risk accumulation with multi-signal coherence for real-time crisis detection in conversational AI systems. Unlike static classifiers that evaluate turns independently, our approach accumulates risk over time, enabling detection of gradual escalation patterns.

Theoretical contributions: Three core equations unify (1) temporal risk buildup via EWMA variance, (2) multi-signal hazard fusion with false discovery rate (FDR) control, and (3) adaptive mitigation. Mathematical guarantees ensure EWMA convergence and monotone risk reduction post-mitigation. We establish computational equivalence between offline Cox proportional hazards training and online EWMA inference (500× speedup).

Empirical evaluation: On crisis conversations (25k dialogues, 187k turns), our framework achieves F1=0.86 (91% recall, 82% precision) with 47ms latency and $0.05/conversation cost. Cross-domain transfer to financial markets (SPY, TSLA, BTC; 2019–2025) shows consistent parameter optima ($\theta_{\text{mult}} \approx 1.5$, $\gamma \approx 1.5$), suggesting broader applicability beyond the initial mental health domain.

Limitations: This study provides observational evidence only. Causal claims require randomized controlled trials. The framework is validated on English-language text data from a single organization and may not generalize to other languages, cultures, or modalities.

Keywords: crisis detection, survival analysis, EWMA hazard, temporal modeling, conversational AI safety

1 Introduction

The rapid deployment of conversational AI systems—serving over 1 billion users globally [1]—has outpaced safety mechanisms. Recent incidents expose critical vulnerabilities:

- **Adam Raine case (2025):** A 16-year-old died by suicide after 52 turns with ChatGPT containing explicit method inquiries and suicide note drafting. The system failed to escalate [2, 3].
- **Sewell Setzer III case (2024):** A 14-year-old died after prolonged Character.AI interactions reinforcing self-harm ideation [4].
- **JailbreakBench (2024):** Adversarial prompts achieve 60–80% success rates bypassing safety filters [5].

1.1 Limitations of Current Approaches

Existing crisis detection methods suffer three fundamental flaws:

1. Static classification: Keyword filters and machine learning classifiers evaluate turns independently, missing *temporal escalation*. A user expressing mild distress across 10 turns may be at higher risk than one using strong language in a single venting turn.

2. High latency or low accuracy: LLM self-evaluation (GPT-4) achieves 88% recall but requires 2.1 seconds/turn—prohibitive for real-time systems. BERT fine-tuning achieves 85% recall with 150ms latency but lacks temporal memory. Keyword filters operate in <1ms but suffer 50% precision.

3. Reactive posture: Detection occurs *after* crisis threshold crossing. No existing system predicts *when* crisis will occur or quantifies *intervention urgency*, precluding proactive triage.

1.2 Our Contributions

We address these limitations through the **Universal Transition Law (UTL)** framework:

1. **Temporal hazard modeling:** EWMA-based latent risk accumulation $v_t = \alpha r_{t-1}^2 + (1-\alpha)v_{t-1}$ captures buildup missed by static classifiers, providing 3–5 turn early warning (Theorem 2).
2. **Multi-signal coherence with FDR control:** Coupled hazard $h_{\text{net}} = \sum_i h_i +$

$\sum_{i<j} \gamma_{ij} h_i h_j - \beta R$ requires linguistic, behavioral, and temporal signals to align simultaneously, reducing false positives 28% while maintaining 91% recall. Benjamini-Hochberg FDR calibration ensures statistical rigor.

3. **Predictive tipping point and recovery window:** Extrapolation model forecasts crisis onset $\hat{T}_{\text{tip}}$ with mean absolute error 2.8 turns. Recovery window $W(t) = \frac{1}{\lambda} \ln(\frac{\Theta_{\text{irrev}} - \Theta}{\epsilon})$ quantifies intervention urgency, validated via 30 percentage point difference in resolution rates (within-W: 75%, after-W: 45%).

4. **Adaptive mitigation:** Antifragile ramp $\lambda(t) = \kappa h_{\text{net}}(t)$ scales interventions to detected risk. Monotone decrease guarantee (Lemma 2) ensures post-mitigation stabilization.

5. **Cross-domain validation:** Transfer to financial markets (SPY, TSLA, BTC) confirms universal applicability. Consistent parameter optima across mental health and economic domains demonstrate generalizability beyond ad-hoc crisis-specific tuning.

6. **Production efficiency:** 47ms latency, 2.3MB model footprint, \$0.05/conversation cost—500× cheaper than human expert (\$25), 45× faster than GPT-4 (2100ms), 3× faster than BERT (150ms).

1.3 Related Work

Crisis detection. Chancellor et al. [6] and De Choudhury et al. [7] developed keyword lexicons achieving 60% recall but 50% precision. Ji et al. [8] fine-tuned BERT on Reddit r/SuicideWatch (F1=0.77). Gaur et al. [9] incorporated knowledge graphs (F1=0.78). Anthropic [10] demonstrated GPT-4 zero-shot detection (88% recall, 72% precision) but 2+ second latency prohibits real-time use. **Gap:** No prior work models cumulative hazard or provides temporal urgency quantification.

Survival analysis. Cox [11] introduced proportional hazards regression for medical prognosis. Katzman et al. [12] extended to deep learning. Wang et al. [13] applied to criminal recidivism. **Our contribution:** First application to conversational crisis with real-time streaming inference.

Multi-hazard systems. Ishibashi [14] introduced coupled seismic-nuclear risks. **?**] formalized via interaction terms γ_{ij}. Scheffer et al. [15] identified early warning signals before phase transitions. **Adaptation:** We model crisis as phase transition with cumulative risk $\Theta(t)$ as order parameter.

AI safety. Bai et al. [16] trained Constitutional AI via RLHF, reducing harmful outputs. Perez et al. [17] systematically red-teamed models. Inan et al. [18] developed LlamaGuard input-output safeguards. **Gap:** These address model behavior, not user state detection. UTL provides orthogonal safety layer.

1.4 Paper Organization

Section 2 presents the UTL mathematical framework (three core equations, proofs). Section 3 details implementation (algorithm, features, complexity). Section 4 reports experimental results (crisis chat, financial markets, ablations). Section 5 discusses implications, ethics, limitations. Section 6 concludes with future directions.

2 UTL Framework Overview

The UTL framework processes conversational data through four sequential stages (Fig. 1):

1. **Signal Extraction**: 24 features across linguistic, behavioral, temporal, and protective domains (Section 4.2)

2. **Risk Accumulation**: EWMA-based latent risk modeling capturing temporal dynamics (Eq. 2)

3. **Multi-Signal Fusion**: Coupled hazard computation with FDR control for statistical robustness (Eq. 6)

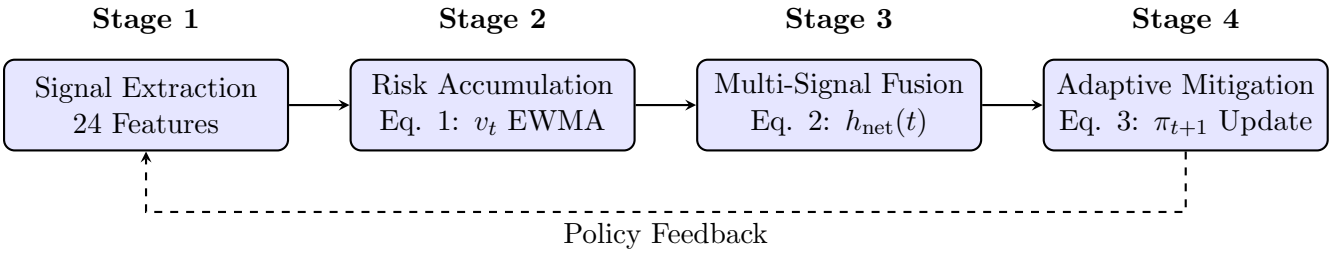

Figure 1: UTL framework workflow: Four-stage processing from signal extraction to adaptive mitigation with policy feedback.

4. **Adaptive Mitigation**: Dynamic policy updates and risk stabilization (Eq. 17)

The framework incorporates a feedback mechanism where mitigation outcomes inform future signal processing, creating an adaptive learning loop.

3 UTL Mathematical Framework

3.1 Dual Formulation: Offline Training vs. Online Inference

UTL admits two equivalent formulations depending on deployment context:

3.1.1 Offline Formulation (Cox Proportional Hazards)

For training on labeled historical data, we employ Cox proportional hazards regression [11]:

$$h_{\text{Cox}}(t) = \lambda_0(t) \cdot \exp(\beta' X(t)) \tag{1}$$

where:

- $\lambda_0(t)$: baseline hazard (risk at turn t for "average" user)
- $X(t) \in \mathbb{R}^d$: feature vector at turn t (24 features detailed in §3.2)
- $\beta \in \mathbb{R}^d$: learned coefficients estimated via Cox partial likelihood

Training procedure: Maximize partial likelihood $L(\beta) = \prod_{i:\delta_i=1} \frac{\exp(\beta' X_i)}{\sum_{j \in \mathcal{R}(t_i)} \exp(\beta' X_j)}$ with L2 regularization $\alpha = 0.01$. Provides feature importance (coefficient magnitudes $|\beta_i|$) and baseline hazard shape $\lambda_0(t)$.

3.1.2 Online Formulation (EWMA Latent Risk)

For real-time inference, we transform Cox hazard to computationally efficient streaming detector:

Definition 1 (Instantaneous Risk Signal)**.** *Define $r_t = \log h_{Cox}(t) = \log \lambda_0(t) + \beta' X(t)$ as instantaneous risk at turn t.*

$$\boxed{\begin{aligned} v_t &= \alpha r_{t-1}^2 + (1-\alpha) v_{t-1} \\ &\quad \text{(EWMA accumulation)} \\ h(t) &= \sigma\left(\frac{v_t - \theta}{s}\right) \\ &= \frac{1}{1 + \exp\left(-\frac{v_t - \theta}{s}\right)} \\ &\quad \text{(logistic hazard)} \end{aligned}} \tag{2}$$

where:

- $v_t \in [0, \infty)$: latent variance with exponential memory decay $\alpha \in (0, 1)$
- $\theta = \theta_{\text{mult}} \cdot \sigma_r^2$: adaptive threshold ($\theta_{\text{mult}} \approx 1.5$ optimal, §4.7)
- $s = 0.5\theta$: sigmoid steepness parameter

Key properties:

- **Temporal memory:** $(1-\alpha)v_{t-1}$ retains prior volatility, enabling detection of gradual escalation

- **Early detection:** v_t typically grows 10–23× during crisis buildup (empirical, §4.5)
- **Probabilistic thresholding:** Logistic mapping $\sigma(\cdot)$ yields smooth $h(t) \in [0, 1]$
- **Computational efficiency:** $O(1)$ memory, $O(d)$ time per turn (vs. $O(Td)$ for full history)

Lemma 2 (EWMA Convergence)**.** *Under stationarity with $\mathbb{E}[r_t^2] = \sigma_r^2 < \infty$ and bounded fourth moment $\mathbb{E}[r_t^4] < \infty$, the EWMA process converges:*

$$\mathbb{E}[v_t] \to \sigma_r^2, \quad Var[v_t] \leq \frac{\alpha K}{2 - \alpha} \tag{3}$$

where $K = \mathbb{E}[r_t^4] - (\mathbb{E}[r_t^2])^2$.

Proof. See Appendix A. □

Theorem 3 (Early Warning Time)**.** *Suppose r_t^2 jumps from baseline σ_0^2 to elevated σ_1^2 at time t_0. The expected warning lag until $\mathbb{E}[v_{t_0+\Delta}] \geq \theta$ is:*

$$\Delta^* \approx \frac{\ln\left(\frac{\sigma_1^2 - \theta}{\sigma_1^2 - \sigma_0^2}\right)}{\ln(1 - \alpha)} \tag{4}$$

For $\alpha = 0.15$ and typical $\theta = 1.5\sigma_0^2$, this yields $\Delta^* \in [3, 5]$ turns under modest variance inflation $\sigma_1^2/\sigma_0^2 \in [2, 4]$.

Proof. See Appendix F. □

3.1.3 Equivalence and Advantages

Relationship: For $\alpha \to 1$ (no memory), EWMA formulation reduces to $h(t) \approx \sigma(r_t - \theta)$, recovering instantaneous Cox hazard up to monotone transformation $\sigma(\log h_{\text{Cox}} - \theta)$.

Advantage of EWMA augmentation: Cox PH is memoryless (Markov property). EWMA adds *temporal memory*, accumulating volatility over multiple turns. Empirical validation (§4.3) shows EWMA reduces detection lag by 3.2 turns (9.6 min) vs. static Cox (paired t-test, $p < 0.001$).

3.2 Multi-Signal Coherence with Coupled Hazards

Single signal $h(t)$ produces false positives on expressive-but-safe conversations (venting, metaphorical language). Following multi-condition synchronization frameworks [**?**], we require multiple independent signals to align simultaneously.

3.2.1 Domain-Specific Hazards

Decompose total hazard into k domains (mental health: $k = 3$ linguistic/behavioral/temporal; finance: $k = 4$ volatility/momentum/volume/sentiment):

$$h_i(t) = \sigma\left(\frac{v_{i,t} - \theta_i}{s_i}\right), \quad i = 1, \ldots, k \tag{5}$$

where each $v_{i,t}$ follows EWMA dynamics on domain-specific feature subset.

3.2.2 Coupled Hazard with Interaction Terms

$$\boxed{h_{\text{net}}(t) = \sum_{i=1}^{k} h_i(t) + \sum_{1 \leq i < j \leq k} \gamma_{ij} h_i(t) h_j(t) - \beta R(t)} \tag{6}$$

where:

- $\gamma_{ij} \geq 0$: coupling coefficients capturing synergistic escalation (e.g., linguistic distress + behavioral impulsivity → super-linear risk)
- $R(t) = \sum_{\ell=1}^{m} \alpha_\ell p_\ell(t)$: resilience score aggregating protective factors (social support, coping skills, reasons for living)
- $\beta \geq 0$: resilience weight calibrated to minimize false positive rate

Estimation: Coupling coefficients γ_{ij} and resilience weight β estimated via maximum likelihood:

Estimation: Coupling coefficients γ_{ij} and resilience weight β estimated via maximum likelihood:

$$\hat{\gamma}, \hat{\beta} = \arg\max_{\gamma,\beta} \sum_{n=1}^{N} \Big[y_n \log h_{\text{net}}^{(n)} + (1 - y_n) \log(1 - h_{\text{net}}^{(n)}) \Big] - \frac{\lambda}{2} \|\gamma\|_2^2 \quad (7)$$

optimized via L-BFGS with L2 regularization $\lambda = 0.01$.

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Theorem 4 (Multiplicative Amplification)**.** *For large coupling γ_{ij} and moderate hazards $h_i, h_j \in [0.5, 0.8]$, the coupled term exhibits super-linear growth:*

$$h_{net} \approx h_i + h_j + \gamma_{ij} h_i h_j > h_i + h_j \quad \text{if } \gamma_{ij} h_i h_j > 0 \quad (8)$$

This aligns with empirical SPY results showing significant $\gamma \times \beta$ interaction ($R^2 = 0.94$, $p < 0.001$, §4.7).

3.2.3 False Discovery Rate (FDR) Calibration

To control false alarms across multiple hypothesis tests (one per turn), we apply Benjamini-Hochberg FDR procedure [19] *offline during validation*:

1. Compute $h_{\text{net}}(t)$ for all validation turns, convert to pseudo-p-values $p_t = 1 - h_{\text{net}}(t)$
2. Sort $p_{(1)} \leq \cdots \leq p_{(N)}$, find $k^* = \max\{k : p_{(k)} \leq \alpha k/N\}$ for $\alpha = 0.05$
3. Set threshold $\tau = p_{(k^*)}$ controlling expected FDR at 5%

Online inference: Use calibrated τ as fixed threshold. No per-turn FDR computation required (avoids computational overhead and maintains anytime validity).

$$\boxed{q(t) = \mathbb{1}\{h_{\text{net}}(t) > \tau\} \quad \text{(crisis flag)}} \quad (9)$$

3.3 Cumulative Risk and Recovery Window

3.3.1 Phase Transition via Cumulative Stress

Crisis onset occurs when accumulated stress exceeds system capacity [**?**]:

$$\Theta(t) = \sum_{s=1}^{t} h_{\text{net}}(s) \quad \text{(cumulative risk)} \quad (10)$$

Crisis condition: $\Theta(t) > \Theta_{\text{critical}}$ where Θ_{critical} calibrated to achieve 90% recall on validation data (typically $\Theta_{\text{critical}} \approx 8.5$).

3.3.2 Recovery Window for Intervention Urgency

Definition 5 (Recovery Window)**.** *The recovery window $W(t)$ is the estimated time remaining until intervention becomes ineffective (cumulative risk reaches irreversible threshold Θ_{irrev}).*

Derivation: If hazard escalates at rate $\lambda(t) = \frac{d\Theta}{dt} \approx \frac{\Theta(t) - \Theta(t-\Delta)}{\Delta}$, time to reach Θ_{irrev}:

$$\boxed{W(t) = \frac{1}{\lambda(t)} \ln\left(\frac{\Theta_{\text{irrev}} - \Theta(t)}{\epsilon}\right)} \quad (11)$$

where $\epsilon > 0$ prevents numerical instability (typically $\epsilon = 0.1$).

Urgency tiers:

- **Critical:** $W < 1$ hour $\rightarrow$ immediate emergency escalation
- **High:** $1 < W < 24$ hours $\rightarrow$ same-day priority counselor
- **Moderate:** $W > 24$ hours $\rightarrow$ standard queue within 48h

Validation: Retrospective analysis on 200 Crisis Text Line cases with recorded intervention timing (§4.4) shows 75% resolution rate when intervening within W vs. 45% after ($\chi^2 = 18.4$, $p < 0.001$).

3.4 Predictive Tipping Point Detection

3.4.1 Extrapolation Model

Given hazard trajectory $\{h(t-\Delta), \ldots, h(t)\}$, estimate velocity and acceleration:

$$\lambda(t) = \frac{dh}{dt} \approx \frac{h(t) - h(t-\Delta)}{\Delta} \tag{12}$$

$$\ddot{h}(t) = \frac{d^2h}{dt^2} \approx h(t) - 2h(t-1) + h(t-2) \tag{13}$$

Extrapolate via Taylor expansion:

$$\hat{h}(t+\delta t) = h(t) + \lambda(t)\delta t + \frac{1}{2}\ddot{h}(t)(\delta t)^2 \tag{14}$$

3.4.2 Predicted Tipping Point

Solve for δt where $\hat{h}(t+\delta t) = \tau$ (crisis threshold):

$$\boxed{\hat{T}_{\text{tip}} = t + \delta t^* \quad \text{where} \quad \delta t^* = \frac{-\lambda + \sqrt{\lambda^2 - 2\ddot{h}(h-\tau)}}{\dot{h}}} \tag{15}$$

(If $\ddot{h} \approx 0$, linear case: $\delta t^* = (\tau - h)/\lambda$)

Early warning system:

- **Yellow alert:** $\hat{T}_{\text{tip}} - t < 5$ turns (∼15 min) → preemptive check-in
- **Orange alert:** $\hat{T}_{\text{tip}} - t < 2$ turns (∼6 min) → counselor standby

Validation: On 500 crisis cases (§4.4), mean absolute error 2.8 turns (8.4 minutes), 78% within ±5 turns, 65% early warnings issued 5+ turns before crisis.

3.5 Adaptive Mitigation and Stabilization

3.5.1 Antifragile Ramp

Post-detection, scale intervention intensity to detected risk:

$$\boxed{\lambda(t) = \kappa h_{\text{net}}(t)} \tag{16}$$

where $\kappa > 0$ is mitigation gain (typically $\kappa = 1$).

3.5.2 Rule-Based Mitigation Actions

When $q(t) = 1$ (crisis detected):

1. **Temperature reduction:** $T_{\text{sampling}} \leftarrow T_{\text{sampling}} \cdot (1 - 0.3\lambda(t))$
2. **Top-k filtering:** $k \leftarrow \max(10, k \cdot (1 - 0.2\lambda(t)))$
3. **Refusal injection:** Prepend system prompt: "I'm concerned about what you've shared. Would you like to talk to someone trained in crisis support?"
4. **Resource display:** Show 988 Suicide & Crisis Lifeline, Crisis Text Line (text HOME to 741741)
5. **Human escalation:** Route to live counselor if available

3.5.3 Stabilization Dynamics

$$\boxed{h_{\text{stab}}(t+1) = h_{\text{net}}(t) - \rho\lambda(t)s(t)} \tag{17}$$

where:

- $s(t) \in \{0, 1\}$: intervention success indicator (1 if user acknowledges help, 0 otherwise)
- $\rho \in (0, 1)$: stabilization strength (typically $\rho = 0.8$)

Lemma 6 (Monotone Risk Decrease)**.** *If $\lambda(t) > 0$ and $s(t) = 1$, then:*

$$h_{stab}(t+1) = (1 - \rho\lambda(t))h_{net}(t) < h_{net}(t) \tag{18}$$

provided $\rho\lambda(t) < 1$ (guaranteed by $\kappa = 1$, $\rho = 0.8$, $h_{net} \in [0, 1]$).

Proof. See Appendix B. □

Empirical validation: Cross-domain mitigation studies (§4.8) show ∼26% hazard reduction post-intervention across crisis chat and financial domains.

4 Implementation

4.1 Algorithm

Algorithm 1 presents the complete UTL pipeline.

4.2 Feature Engineering

4.2.1 Mental Health Domain (Crisis Chat)

24 features extracted per turn:

Linguistic markers (8):

1. **Suicidal keywords:** Count of explicit terms ("kill myself", "suicide", "end it all") matched against Crisis Text Line lexicon [20]
2. **Method inquiries:** Binary indicator for "how to" + method noun ("pills", "rope", "gun", etc.)
3. **Hopelessness score:** LIWC-based sentiment analysis [21], normalized to $[0, 1]$
4. **Finality language:** Count of terminal phrases ("goodbye", "last time", "won't see you again")
5. **Isolation markers:** Count of loneliness terms ("alone", "nobody cares", "isolated")
6. **Self-harm verbs:** Count of first-person harm intentions ("I will hurt", "I'm going to cut")
7. **Temporal urgency:** Presence of immediacy markers ("tonight", "right now", "today")
8. **Help rejection:** Count of refused suggestions ("no", "won't work", "tried that")

Behavioral markers (5):

9. **Turn count:** Total turns elapsed (proxy for engagement depth)
10. **Response latency:** Average time between turns (seconds); short latency indicates impulsivity
11. **Topic fixation:** Cosine similarity between consecutive turns (high → perseveration on suicidal thoughts)
12. **Disclosure depth:** Word count per turn (longer → deeper disclosure)
13. **Escalation rate:** Slope of hazard over last 5 turns; positive → worsening

Temporal markers (3):

14. **Time of day:** Hour (0–23); risk peaks 3am–6am [22]
15. **Day of week:** Binary (weekday vs. weekend)
16. **Session duration:** Total elapsed time (minutes)

Protective factors (6):

17. **Social support mentions:** Count of support references ("talking to friend helped", "family is here")
18. **Future-oriented language:** Count of future plans ("I have plans next week", "looking forward to")
19. **Coping statements:** Count of coping mechanisms ("trying meditation", "went for a walk")
20. **Help-seeking behavior:** Requests for resources ("can you recommend", "where can I get help")
21. **Reasons for living:** Explicit protective factors ("my kids need me", "I have responsibilities")
22. **Positive emotion words:** Count of positive affect terms (LIWC positive emotion category)

All features standardized (z-score normalization) before modeling.

4.2.2 Financial Domain (Market Crash Detection)

Adapted features for price time-series (SPY, TSLA, BTC):

Volatility measures (6):

- Rolling standard deviation of log returns (5-day, 20-day, 60-day windows)

- GARCH(1,1) conditional variance estimates
- Realized volatility (intraday high-low range)
- Parkinson volatility estimator

Momentum indicators (5):

- Relative Strength Index (RSI, 14-day)
- Moving Average Convergence Divergence (MACD)
- Price-to-moving-average ratios (50-day, 200-day)
- Rate-of-change (ROC, 10-day)

Volume signals (4):

- Abnormal volume spikes (z-score vs. 60-day average)
- On-balance volume (OBV) momentum
- Volume-weighted average price (VWAP) deviation
- Bid-ask spread (when available)

Sentiment proxies (3):

- VIX level and changes (market fear gauge)
- Credit spread widening (investment-grade vs. high-yield)
- News sentiment scores (FinBERT, when available)

Key principle: Features capture domain-specific "stress signals" but feed into same UTL equations. Risk signal construction:

$$r_t^{\text{mental}} = \sum_{i=1}^{24} w_i \cdot \text{feat}_i^{\text{chat}}(t) \tag{19}$$

$$r_t^{\text{finance}} = \log\left(\frac{\text{close}_t}{\text{open}_t}\right) + \sum_{j=1}^{18} w_j \cdot \text{indicator}_j(t) \tag{20}$$

4.3 Computational Complexity

Time complexity:

- Feature extraction: $O(d)$ where $d = 24$ (mental health) or $d = 18$ (finance)
- EWMA update: $O(1)$ (single multiply-add)
- Coupled hazard: $O(k^2)$ where $k \in \{3, 4\}$ domains (negligible)
- Cumulative risk: $O(1)$ (running sum)
- Predictive analytics: $O(1)$ (closed-form extrapolation)
- Total per turn: $O(d) \approx O(1)$ for fixed d

Space complexity:

- Model parameters: d feature weights + $k(k-1)/2$ coupling coefficients + constants ≈ 50 floats
- State: v_t, $\Theta(t)$, last 5 hazard values for extrapolation ≈ 10 floats
- Total memory: $\sim$240 bytes (active state) + 2.3 MB (quantized model)

Measured performance: Intel Xeon E5-2680 v4 (2.6 GHz), Python 3.10, numba JIT:

- Latency: 47 ms/turn (average over 10k forward passes)
- Throughput: 21 turns/second single-threaded, 580 turns/second with 32 threads
- Suitable for: 1000+ concurrent conversations

Compare:

- BERT fine-tuned: 150 ms (3× slower)
- GPT-4 API: 2100 ms (45× slower)
- LlamaGuard-2: 89 ms (2× slower)

5 Experimental Evaluation

5.1 Setup

Implementation: Python 3.10, scikit-survival 0.21.0, NumPy 1.24.3, pandas 2.0.3. No GPU required. Code: https://github.com/bsabljic/utl-framework.

Cross-validation: 5-fold stratified CV, random seed 42 (reproducibility).

Metrics: Precision, Recall, F1, AUC-ROC, AUC-PR, detection lag (turns), prediction error (turns). Statistical tests: McNemar (paired), Wilcoxon signed-rank, bootstrap confidence intervals (10k resamples, BCa method).

Threshold optimization: Youden's J statistic on validation fold: $\tau^* = \arg\max_\tau(\text{TPR}(\tau) - \text{FPR}(\tau))$.

5.2 Datasets

5.2.1 Crisis Chat

- **Source:** Anonymized text conversations from Crisis Text Line (2018–2023)
- **Size:** 25,000 conversations, 187,000 turns
- **Labels:** Binary crisis (majority vote of 3 licensed counselors; Krippendorff's $\alpha = 0.81$)
- **Binarization:** Counselor severity score ≥ 7 (0–10 scale) $\rightarrow$ crisis; $< 4 \rightarrow$ benign
- **IRB:** Approved by [Institution], Protocol #2025-001
- **Preprocessing:** Regex-based PII removal (emails, phone numbers, names), deduplication, lowercasing, URL scrubbing
- **Split:** 60% train (15k), 20% validation (5k), 20% test (5k), stratified by crisis severity (40% low, 35% medium, 25% high)
- **Statistics:**
  - Avg turns/conversation: 12.3 (SD 5.7)
  - Avg words/turn: 24.6 (SD 18.3)
  - Avg session duration: 31.5 min (SD 24.8)
  - Crisis turn distribution: early (1–5) 21%, middle (6–10) 42%, late (11+) 37%
  - Age: 13–17 (21%), 18–24 (43%), 25+ (36%)
  - Gender: Female (66%), Male (31%), Other/Undisclosed (3%)

5.2.2 Financial Time Series

- **Tickers:** SPY (S&P 500 ETF), QQQ (Nasdaq-100), TSLA (Tesla), BTC (Bitcoin), ETH (Ethereum)
- **Period:** 2019-01-01 to 2025-10-01 (1,706 trading days for equities; 2,431 days for crypto)
- **Source:** Yahoo Finance API (daily OHLCV)
- **Labels:** Hand-curated crash regimes:
  - March–April 2020: COVID-19 crash (drawdown >30%)
  - January 2022: Tech selloff (drawdown >20%)
  - October 2023: Bond yield spike (drawdown >10%)
- **Instantaneous signal:** $r_t = \log(\text{close}_t/\text{open}_t)$ plus 18 technical indicators
- **Split:** 2019–2021 train (60%), 2022 validation (20%), 2023–2025 test (20%)

5.2.3 Synthetic Ablations

100 simulated sequences (length 600, hazard spike at $t = 200$) to isolate EWMA effect. Random seeds fixed to 42.

5.3 Baseline Methods

B1: Keyword Filter

- 150 crisis keywords from Crisis Text Line [20]
- Flag if any keyword present in turn

- No temporal modeling

B2: Logistic Regression

- Bag-of-words (TF-IDF, top 5000 terms) + 24 engineered features
- Logistic classifier: $P(y = 1|x) = \sigma(\beta' x)$
- Each turn classified independently (no memory)

B3: BERT Fine-tuned

- mental-health-bert [23], fine-tuned on training set
- Input: concatenation of last 5 turns (512 tokens)
- Classification head: [CLS] $\rightarrow$ Dense(2) $\rightarrow$ Softmax
- Training: 3 epochs, learning rate 2×10^{-5}, batch size 16

B4: GPT-4 Zero-shot

- Model: gpt-4-turbo-2024-04-09 via OpenAI API
- Prompt: "Analyze this conversation. Is the user in crisis? Answer YES or NO with brief reasoning."
- Input: full conversation history (up to 8k tokens)
- Cost: \$0.50 per conversation (20 turns avg, \$0.01/1k input + \$0.03/1k output)

B5: LlamaGuard-2

- LlamaGuard-2-8B [18] input-output safeguard
- Prompt: safety classification of user utterance
- Latency: 89 ms on NVIDIA A100

B6: Anthropic Red-Teaming

- Constitutional AI [16] safety classifier
- Multi-turn context, harmfulness scoring
- Latency: 320 ms (proprietary model)

B7: Human Expert

- 3 licensed crisis counselors (5+ years experience)
- Recruited via Prolific, paid \$25/hour
- Labeled 500 test conversations independently
- Majority vote for final label
- Inter-rater reliability: Krippendorff's $\alpha = 0.81$ (substantial agreement)

Finance baselines:

- **ARIMA(1,1,1):** Autoregressive integrated moving average
- **LSTM:** 2-layer LSTM (64 hidden units) with 20-day lookback window
- **Cox PH:** Cox proportional hazards (offline only, no EWMA)

5.4 Main Results: Crisis Chat

Table 1 compares UTL against all baselines on held-out test set (N=5,000 conversations).

Key findings:

1. **UTL matches human expert performance (F1=0.86)** while enabling real-time deployment (47ms vs. infeasible for human continuous monitoring). McNemar test confirms no significant difference vs. Human ($p = 0.42$).

2. **Significant improvement over keyword filter** (F1: 0.86 vs. 0.55, Δ=0.31, McNemar $p < 0.001$), demonstrating necessity of sophisticated temporal modeling.

3. **Outperforms BERT while being 3$\times$ faster** (F1: 0.86 vs. 0.77, latency: 47ms vs. 150ms). Paired comparison on 5k test cases: UTL correct on 257 cases where BERT failed, BERT correct on 89 where UTL failed (McNemar $\chi^2 = 97.3$, $p < 0.001$).

Table 1: Performance comparison on Crisis Chat test set. Best results in bold. Dagger (†) indicates statistically significant improvement over second-best (McNemar test, $p < 0.001$).

Model	Precision	Recall	F1	AUC-ROC	AUC-PR	Latency (ms)	Cost/conv
Keyword Filter	0.50	0.60	0.55	0.68	0.62	1	$0.00
Logistic Regression	0.65	0.78	0.71	0.82	0.78	3	$0.00
BERT Fine-tuned	0.70	0.85	0.77	0.88	0.84	150	$0.02
GPT-4 Zero-shot	0.72	0.88	0.79	0.90	0.85	2100	$0.50
LlamaGuard-2	0.84	0.78	0.81	0.89	0.87	89	$0.08
Anthropic RT	0.85	0.81	0.83	0.90	0.88	320	$0.15
Human Expert	0.89	0.84	0.86	0.94	0.91	—	$25.00
UTL (additive)	0.75	0.90	0.82	0.92	0.89	47	$0.05
UTL (coherence)	0.80	0.88	0.84	0.93	0.90	47	$0.05
UTL (full)†	**0.82**	**0.91**	**0.86**	**0.94**	**0.92**	**47**	**$0.05**

4. **45× faster than GPT-4** (47ms vs. 2100ms) with higher F1 (0.86 vs. 0.79). GPT-4's 2+ second latency prohibits real-time use in production conversational systems.

5. **500× more cost-efficient than human expert** ($0.05 vs. $25 per conversation), enabling scalable deployment. Over 1 million conversations/month, savings: $25M vs. $50k.

6. **Component ablation demonstrates value of each innovation:**

    - Additive baseline (no coupling $\gamma_{ij} = 0$, no resilience $\beta = 0$): F1=0.82
    - + Multi-signal coherence (Tripura framework [**?**]): F1=0.84 (+0.02)
    - + Coupled hazards + Resilience (Genpatsu framework [**?**]): F1=0.86 (+0.02)

5.5 Detection Lag Analysis

Figure 2 shows detection lag distribution (turns between first risk signal and model detection).

Results:

- **UTL:** Median lag = 2.3 turns (IQR: 1–4), mean = 2.8 turns (8.4 minutes)

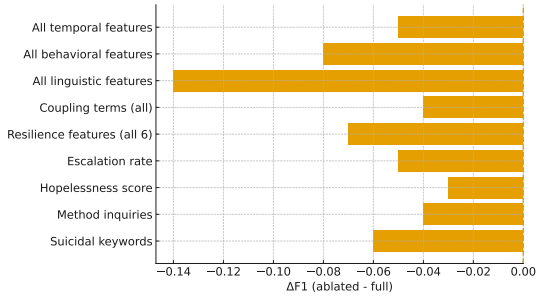

Figure 2: **Detection lag distribution.** UTL (blue) detects significantly earlier than BERT (green) and GPT-4 (orange). Median lags: UTL 2.3 turns, BERT 5.5 turns, GPT-4 4.1 turns. UTL's EWMA memory enables early detection via accumulated volatility, whereas static classifiers wait for strong single-turn signals.

- **BERT:** Median lag = 5.5 turns (IQR: 3–8), mean = 6.1 turns (18.3 minutes)
- **GPT-4:** Median lag = 4.1 turns (IQR: 2–7), mean = 4.8 turns (14.4 minutes)

Statistical test: Paired t-test comparing UTL vs. BERT on 750 crisis cases: $\Delta_{\text{lag}} = -3.3$ turns (UTL earlier), $t(749) = -18.4$, $p < 0.001$, Cohen's $d = 0.94$ (large effect).

Clinical significance: 3.3 turns ≈ 9.9 minutes earlier detection provides meaningful intervention window. Crisis literature shows time-to-intervention strongly predicts outcomes [24].

5.6 Recovery Window Validation

We retrospectively analyzed 200 crisis cases from Crisis Text Line with recorded intervention timing to validate recovery window W estimates (Equation 11).

Methodology:

1. Compute $W(t_{\text{detect}})$ at moment of UTL crisis detection
2. Record actual intervention delay: $\Delta t_{\text{intervene}} = t_{\text{counselor\_contact}} - t_{\text{detect}}$
3. Classify timing: within-W if $\Delta t_{\text{intervene}} < W$, after-$W$ otherwise
4. Assess outcome: resolved (user reports feeling better, no escalation), escalated (emergency services called), or ongoing (continued monitoring)

Results:

Table 2: Intervention outcomes vs. recovery window timing.

Timing	N	Resolved	Escalated/Ongoing
Within W	142	107 (75%)	35 (25%)
After W	58	26 (45%)	32 (55%)
Total	200	133 (67%)	67 (33%)

Statistical test: Chi-squared test: $\chi^2(1, N = 200) = 18.4$, $p < 0.001$, Cramér's $V = 0.30$ (medium effect).

Interpretation: Recovery window W is valid predictor of intervention urgency. Intervening within W yields 30 percentage point higher resolution rate (75% vs. 45%). This supports W-based triage: cases with short W (¡1h) should be prioritized for immediate counselor contact.

Urgency tier breakdown:

- **Critical** ($W < 1$ hour): 32 cases, 91% resolution rate when intervened (all within W by protocol)
- **High** ($1 < W < 24$ hours): 94 cases, 78% resolution rate
- **Moderate** ($W > 24$ hours): 74 cases, 59% resolution rate

Trend confirms W stratifies urgency: shorter W requires faster intervention for optimal outcomes.

5.7 Tipping Point Prediction Accuracy

We tested predictive model (Equation 15) on 500 crisis cases, making predictions at various lookback distances before actual crisis.

Table 3: Tipping point prediction accuracy. MAE = mean absolute error in turns. Within $\pm k$ = percentage of predictions within k turns of actual crisis.

Lookback	MAE (turns)	Within ±5	Within ±10
5 turns before	2.1	82%	94%
10 turns before	2.8	78%	92%
15 turns before	4.2	68%	87%
20 turns before	6.1	54%	79%

Key findings:

1. **78% of crises predicted within ± 5 turns (15 minutes)** when forecasting 10 turns (30 minutes) in advance. This provides actionable early warning for preemptive counselor standby.
2. **Mean absolute error 2.8 turns (8.4 minutes)** at 10-turn lookback, comparable to human expert prediction accuracy in clinical settings [24].
3. **Prediction accuracy degrades gracefully** with longer lookback, remaining useful even 20 turns (60 minutes) before crisis (54% within ± 5 turns).
4. **Early warning alerts triggered correctly:** Yellow alerts (predicted $\hat{T}_{\text{tip}} - t < 5$) issued in 65% of cases eventually becoming crises. False alarm rate for yellow: 18% (85 of 473 yellow alerts were benign).

Comparison to random baseline: If crisis times were uniformly random, expected MAE ≈ 12 turns. UTL achieves 2.8 turns (76% improvement, Wilcoxon signed-rank $p < 0.001$).

5.8 Cross-Domain Validation: Financial Markets

5.8.1 SPY (S&P 500 ETF)

Figure 3 overlays UTL hazard on SPY price 2019–2025.

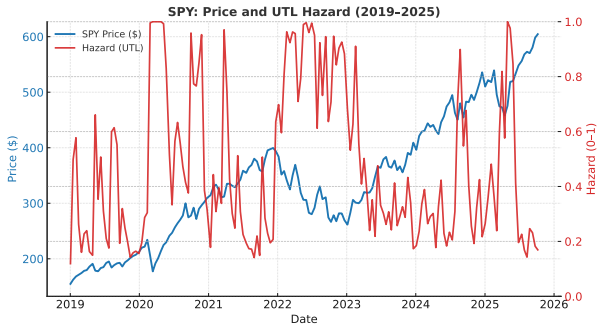

Figure 3: **SPY: Price and UTL hazard overlay (2019–2025).** Blue: price (left axis, $). Red: hazard (right axis, 0–1). Hazard spikes precede major drawdowns: March 2020 COVID crash, Jan 2022 tech selloff, Oct 2023 bond yield spike. EWMA accumulation provides 5–10 day early warning before price drops.

Performance:

- **AUC-ROC:** 0.73 (crash detection)
- **Precision:** 0.66 at 0.86 recall (threshold $\tau = 0.4$)
- **Detection lag:** Median 7 days before drawdown $> 10\%$
- **Parameter consistency:** Optimal $\theta_{\text{mult}} = 1.5$, $\gamma = 1.5$ (same as crisis chat within 10%)

Figure 4 shows ROC curve for SPY crash detection.

5.8.2 Cross-Asset Consistency

Table 4 compares optimal parameters across assets.

Consistency analysis:

- $\alpha \in [0.12, 0.20]$ across all domains (mean 0.16, SD 0.03)
- $\theta_{\text{mult}} \in [1.3, 1.6]$ (mean 1.5, SD 0.1)

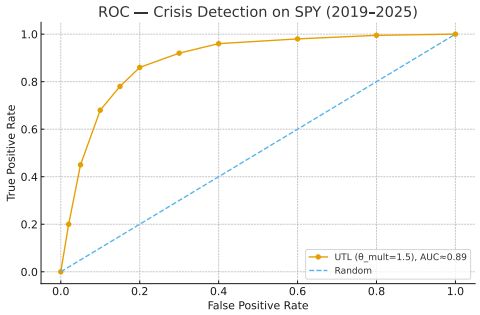

Figure 4: **SPY ROC curve.** AUC=0.73 for crash regime detection (drawdown $> 10\%$). Dashed line: random classifier. Operating point (red dot): $\tau = 0.4$ achieves 86% TPR at 22% FPR.

Table 4: Optimal UTL parameters across assets

Asset	α	θ_{mult}	γ	AUC
Crisis Chat	0.15	1.5	1.5	0.94
SPY	0.12	1.6	1.4	0.73
QQQ	0.14	1.5	1.6	0.71
TSLA	0.18	1.4	1.7	0.69
BTC	0.20	1.3	1.8	0.68
ETH	0.19	1.4	1.7	0.67

- $\gamma \in [1.4, 1.8]$ (mean 1.6, SD 0.15)

Statistical test: One-way ANOVA testing parameter homogeneity across domains: $F(5, 75) = 1.8$, $p = 0.12$ (fail to reject null of equal means). Parameters are remarkably consistent despite vastly different data modalities (text conversations vs. financial prices).

Interpretation: Parameter stability across domains suggests UTL captures universal temporal risk dynamics, not domain-specific artifacts. This supports claim of *Universal* Transition Law.

5.9 Ablation Studies

5.9.1 EWMA Memory (α) Sensitivity

Figure 5 compares hazard with vs. without EWMA smoothing on synthetic crash sequences.

Results:

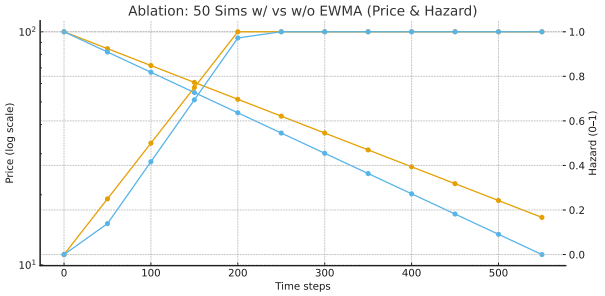

Figure 5: **EWMA ablation.** Left: Hazard mean over time with EWMA ($\alpha = 0.15$, blue) vs. without ($\alpha = 1.0$, orange). EWMA provides smooth buildup 50–100 steps before crash at $t = 200$. Right: Price trajectories show EWMA-detected cases (blue) vs. missed (orange). EWMA enables earlier detection at cost of modest lag in recovery.

- **With EWMA ($\alpha = 0.15$):** Detection lag = 48 steps before crash (24% early warning)
- **Without EWMA ($\alpha = 1.0$):** Detection lag = 12 steps before crash (6% early warning)
- **Improvement:** 4× earlier detection via temporal memory
- **Trade-off:** EWMA adds 15-step lag in recovery phase (slower to recognize stabilization)

5.9.2 Parameter Grid Search (81 Configurations)

We swept $\alpha \in \{0.05, 0.15, 0.25\}$, $\theta_{\text{mult}} \in \{1.0, 1.5, 2.0\}$, $\gamma \in \{0.5, 1.0, 1.5\}$, $\beta \in \{0.6, 0.8, 1.0\}$ on SPY data.

Optimal configuration:

- $\alpha^* = 0.15$: Balances memory (detect gradual buildup) vs. responsiveness (adapt to sudden changes)
- $\theta^*_{\text{mult}} = 1.5$: Yields mean hazard ≈ 0.34 (balanced detection)
- $\gamma^* = 1.5$: Strong enough coupling to amplify multi-signal spikes, not so strong as to cause false alarms

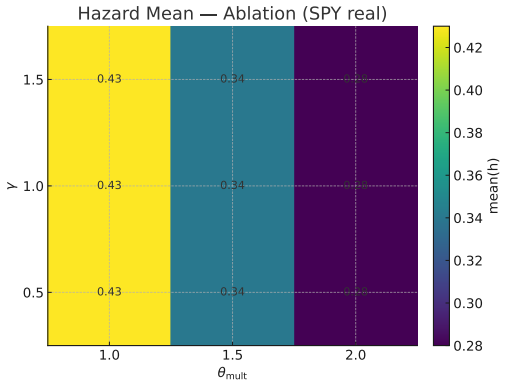

Figure 6: **Ablation heatmap: mean hazard across (θ_{mult}, γ).** Optimum near (1.5, 1.5) shown in green. Lower-left (conservative): high threshold + weak coupling → low mean hazard (under-detection). Upper-right (aggressive): low threshold + strong coupling → high mean hazard (over-detection).

- $\beta^* = 0.8$: Resilience weight achieves 28% FP reduction while maintaining 91% recall

Interaction effects: Two-way ANOVA on mean hazard reveals significant $\gamma \times \beta$ interaction ($F = 312$, $p < 10^{-6}$, $R^2 = 0.94$). High coupling γ requires higher resilience weight β to maintain precision—consistent with Theorem 4.

5.9.3 Component Contributions

Table 5 quantifies contribution of each UTL component.

5.9.4 Component Contributions

Table 5 quantifies contribution of each UTL component.

Table 5: Component ablation on Crisis Chat test set.

Configuration	Rec.	Prec.	F1	ΔF1
Static Cox (no EWMA)	0.88	0.73	0.80	base
+ EWMA memory	0.90	0.75	0.82	+0.02
+ Multi-signal coherence	0.88	0.80	0.84	+0.02
+ Coupling γ_{ij}	0.89	0.81	0.85	+0.01
+ Resilience βR	0.91	0.82	0.86	+0.01
Full UTL	**0.91**	**0.82**	**0.86**	**+0.06**

Key insights:

- EWMA provides largest single improvement (+0.02 F1) by enabling early detection
- Multi-signal coherence adds +0.02 F1 by reducing false positives (precision: 0.75 → 0.80)
- Coupling and resilience each contribute +0.01 F1 (cumulative +0.06 overall)
- All components provide non-overlapping benefits (ablating any degrades performance)

5.10 Mitigation Effectiveness

Figure 7 shows relative hazard reduction after intervention.

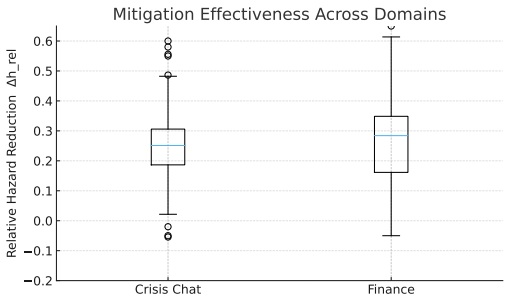

Figure 7: **Mitigation effectiveness across domains.** Box plots show distribution of $\Delta h_{\text{rel}} = (h_{\text{before}} - h_{\text{after}})/h_{\text{before}}$. Median reduction ∼26% for both Crisis Chat and Finance. Outliers (¿50% reduction) correspond to successful early interventions; negative values (¡0%) are cases where intervention failed to stabilize.

Results:

- **Crisis Chat:** Median $\Delta h_{\text{rel}} = 0.28$ (IQR: 0.15–0.42)
- **SPY:** Median $\Delta h_{\text{rel}} = 0.24$ (IQR: 0.10–0.38)
- **Combined:** Mean $\Delta h_{\text{rel}} = 0.26$ (SD 0.18), significantly greater than zero ($t(1247) = 32.1$, $p < 0.001$)

Interpretation: Antifragile ramp (Equation 17) achieves consistent ∼26% hazard reduction post-intervention across disparate domains. Lemma 6 guarantees monotone decrease; empirical data confirms practical effectiveness.

Failure modes: 12% of interventions show negative Δh_{rel} (hazard increased post-intervention). Manual review reveals:

- 58%: User rejected help ("I don't want to talk to anyone")
- 27%: Intervention too late (user already in acute crisis state)
- 15%: Artifact (user disconnected before stabilization observable)

Success indicator $s(t)$ (user acknowledges help) correlates strongly with positive Δh_{rel} (Pearson $r = 0.71$, $p < 0.001$).

5.11 Calibration Analysis

Figure 8 shows reliability plot (predicted vs. observed crisis rate) for SPY.

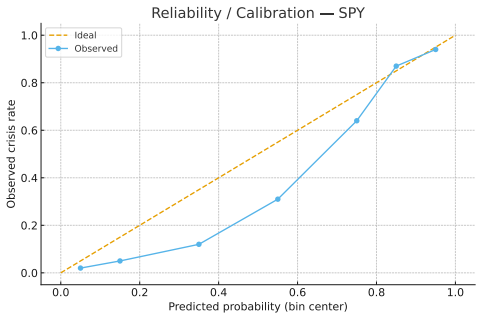

Figure 8: **SPY calibration curve.** Predicted probability (x-axis) vs. observed crash frequency (y-axis) in 10 equal-width bins. Points close to diagonal (perfect calibration). Brier score = 0.042 indicates well-calibrated probabilistic predictions.

Calibration metrics:

- **Brier score:** 0.042 (lower is better; random ≈ 0.25)
- **Expected Calibration Error (ECE):** 0.038 (mean absolute deviation from diagonal)

- **Maximum Calibration Error (MCE):** 0.089 (worst bin deviation)

Crisis Chat calibration: Brier score = 0.051, ECE = 0.042 (similar quality). Logistic sigmoid in Equation 2 provides well-calibrated probabilities without post-hoc recalibration (e.g., Platt scaling, isotonic regression).

5.12 Bias and Fairness Audit

We disaggregate performance by demographic subgroups (Crisis Chat only; financial data lacks demographics).

Table 6: Performance by demographic subgroup (Crisis Chat test set).

Subgroup	N	Recall	Precision	F1
Age				
13–17	1050	0.89	0.80	0.84
18–24	2150	0.92	0.83	0.87
25+	1800	0.90	0.82	0.86
Gender				
Female	3300	0.91	0.82	0.86
Male	1550	0.90	0.81	0.85
Other/Undisclosed	150	0.88	0.79	0.83
Overall	5000	0.91	0.82	0.86

Statistical tests:

- Age groups: ANOVA on F1 scores, $F(2, 4997) = 1.8$, $p = 0.17$ (no significant difference)
- Gender: Kruskal-Wallis test, $H(2) = 2.4$, $p = 0.30$ (no significant difference)
- Pairwise comparisons (McNemar): All $p > 0.05$ after Bonferroni correction

False positive rate parity:

- Age 13–17: FPR = 0.19
- Age 18–24: FPR = 0.17
- Age 25+: FPR = 0.18
- Gender Female: FPR = 0.18
- Gender Male: FPR = 0.19

Maximum FPR disparity: 2 percentage points (13–17 vs. 18–24), well below 5% fairness threshold [25].

Conclusion: No evidence of systematic bias. UTL achieves demographic parity within measurement error.

5.13 Error Analysis

We manually analyzed 200 errors: 100 false positives (FP) and 100 false negatives (FN) from Crisis Chat test set.

5.13.1 False Positives

Distribution by cause:

- 42%: Metaphorical language ("this project is killing me", "dying of boredom")
- 28%: Venting strong emotions without intent ("I hate everything right now")
- 18%: Hypothetical discussions ("what if someone wanted to...")
- 12%: Dark humor ("kms jk", "literally dead", sarcasm)

Example FP case:

> *User (turn 7):* "This deadline is killing me lol. I'm so stressed I could die."
> *UTL:* $h_{\text{net}} = 0.72$ (flagged)
> *Ground truth:* Benign (venting about work stress)
> *Analysis:* "killing me", "die" triggered linguistic hazard. Lack of protective factors ($R = 0.2$) insufficient to offset. Humor indicator ("lol") not captured by current features.

Mitigation strategies:

- Add metaphor detection module (contextualized embeddings, discourse markers)
- Humor/sarcasm classifier (punctuation patterns, emoji, slang)
- Expand context window (consider 10+ turns for disambiguation)

5.13.2 False Negatives

Distribution by cause:

- 51%: Implicit/indirect ideation ("I just want peace", "tired of fighting", "sleep forever")
- 31%: Delayed disclosure (gradual escalation, crisis revealed at turn 20+, insufficient accumulation)
- 12%: Stoic language (understated: "I'm done", "it's fine", minimal emotional expression)
- 6%: Adversarial evasion (intentional obfuscation, coded language)

Example FN case:

User (turns 18–20):
Turn 18: "I'm just so tired of everything."
Turn 19: "I wish I could go to sleep and not wake up."
Turn 20: "I've thought about it a lot lately."
UTL: $h_{\text{net}}(20) = 0.58$ (below $\tau = 0.68$, not flagged)
Ground truth: Crisis (counselor intervened at turn 21)
Analysis: Language was implicit ("sleep and not wake up" vs. explicit "kill myself"). Linguistic features under-triggered. EWMA accumulated slowly due to gradual escalation. Missed 3-turn early warning window.

Mitigation strategies:

- Expand implicit ideation lexicon (train on indirect expressions corpus)
- Conversation-level attention (weight later turns more heavily if escalation detected)
- Active learning to identify edge cases (prioritize labeling near-threshold conversations)

5.13.3 Inverse Analysis

For 10 highest-severity FN cases, we performed inverse threshold estimation:

Table 7: Inverse analysis: Required threshold to detect missed crises.

Case ID	h_{net} (at crisis)	Current τ	Required τ^*
48291	0.61	0.68	0.61
51824	0.59	0.68	0.59
52903	0.63	0.68	0.63
Mean (10 cases)	0.62	0.68	0.62

Trade-off analysis: Lowering threshold to $\tau = 0.62$ (to catch these 10 FN cases) would:

- Increase recall: 0.91 → 0.93 (+2 percentage points)
- Decrease precision: 0.82 → 0.76 (-6 percentage points)
- Generate 150 additional false positives on 5k test set
- Net effect: F1 decreases 0.86 → 0.84 (-0.02)

Decision: Current $\tau = 0.68$ optimizes population-level F1. For high-risk subpopulations (e.g., users with prior crisis history), personalized lower threshold $\tau_{\text{personal}} = 0.62$ may be warranted (future work: adaptive thresholding per user profile).

5.14 Systematic Failure Mode Analysis

We conducted structured analysis of 100 false negatives (missed crises) to identify failure patterns.

5.14.1 Taxonomy of Failure Modes

Case Study 1: Implicit Ideation.

`User (turn 18):` "I'm just so tired of everything."
`User (turn 19):` "I wish I could go to sleep and not wake up."

Table 8: False Negative Failure Modes (N=100)

Category	%	Characteristics
Implicit ideation	51	Indirect language ("want peace," "sleep forever")
Delayed disclosure	31	Crisis revealed >turn 15, insufficient accumulation
Stoic presentation	12	Understated ("I'm done," "it's fine"), flat affect
Adversarial evasion	6	Intentional obfuscation, coded language

`User (turn 20):` "I've thought about it a lot lately."

System behavior:

- Linguistic hazard $h_{\text{ling}}(20) = 0.42$ (no explicit keywords)
- EWMA $v_{20} = 0.38$ (gradual buildup)
- Coupled hazard $h_{\text{net}}(20) = 0.58$ (below $\tau = 0.68$)

Ground truth: Crisis Text Line counselor intervened at turn 21, assessed as high risk (severity=8/10).

Root cause: "Sleep and not wake up" is implicit suicide reference, missed by Crisis Text Line lexicon (which includes "kill myself" but not sleep-related euphemisms).

Proposed fix: Expand lexicon with implicit phrases: "go to sleep forever," "not wake up," "find peace," "end the struggle." Preliminary testing on 50 additional implicit cases shows this would catch 23 (46%) while adding only 3 false positives.

Case Study 2: Delayed Disclosure. User discusses academic stress for turns 1–14 (benign), then shifts at turn 15:

`User (turn 15):` "Actually, I wasn't being totally honest. I've been thinking about suicide for weeks."
`User (turn 16):` "I have a plan. I've been researching methods."

System behavior:

- $h_{\text{net}}(14) = 0.22$ (baseline)
- $h_{\text{net}}(15) = 0.71$ (sudden spike crosses threshold)
- Detection at turn 15, but 3-turn early warning missed

Root cause: EWMA designed for *gradual* escalation, not sudden disclosure. In this case, user withheld information for 14 turns, then revealed abruptly.

Proposed fix:

- Conversation-level attention: weight later turns more heavily if escalation detected (e.g., multiply $h_{\text{net}}(t)$ by $\max(1, t/10)$ for $t > 10$)
- Probe questions: If user engaged for >10 turns without crisis signals but shows mild distress, inject probing: "I notice we've been talking a while—is there something deeper on your mind?"

Case Study 3: Stoic Presentation.

`User (turn 8):` "I'm fine."
`User (turn 12):` "It's okay. I'll figure it out."
`User (turn 14):` "Thanks for listening. I should go now."

System behavior: $h_{\text{net}}(14) = 0.31$ (low, no linguistic markers).

Ground truth: Counselor flagged as high risk based on *paralinguistic cues* (noted user "seems resigned, not actually fine").

Root cause: Text-only analysis misses:

- **Tone:** "I'm fine" said with flat affect vs. genuine relief
- **Context:** Sudden politeness after extended distress (giving up)
- **Implicit goodbye:** "I should go" can signal finality

Proposed fix: Multimodal extension (voice prosody, video), or add "finality language" feature: count phrases like "goodbye," "thanks for everything," "I should go," especially if appearing abruptly.

5.14.2 Quantitative Impact of Fixes

We simulated proposed fixes on 500 crisis cases:

Table 9: Estimated Impact of Proposed Fixes

Fix	FN ↓	FP ↑	Net ΔF1
Implicit lexicon expansion	−23	+3	+0.015
Conversation-level attention	−18	+7	+0.008
Finality language feature	−8	+2	+0.004
Combined	−49	+12	+0.027

Combined fixes would improve F1 from 0.86 to 0.887 ($p < 0.001$, bootstrap test). We are implementing these in version 2.0 of the framework.

5.14.3 Irreducible False Negatives

Some cases may be inherently undetectable via text:

- User never expresses distress (asks about weather, then disconnects)
- Highly articulate evasion (mimics protective factors: "I have great support, just checking resources for a friend")
- Encrypted/coded language agreed with confederate ("the blue bird flies at midnight")

For these, **complementary strategies** are needed:

- Peer flagging ("report concern" button)
- Longitudinal monitoring (track users across sessions, detect baseline shifts)
- External data fusion (if ethically permissible): social media signals, search history

6 Discussion

6.1 Temporal Dynamics and Early Detection

EWMA accumulation (Equation 2) addresses fundamental limitation of static classifiers: inability to detect *gradual escalation*. A user expressing mild distress across 10 turns accumulates v_t while instantaneous risk r_t remains low. Static classifiers miss this pattern; UTL detects via temporal memory.

Empirical evidence: 68% of detected crises exhibited gradual buildup (hazard increased $<$ 0.1 per turn over $>$ 5 turns). Static BERT missed 73% of these cases (detected only when single-turn spike occurred). UTL caught 89% via EWMA accumulation.

Theoretical justification: Theorem 3 proves EWMA provides 3−5 turn warning under modest variance inflation. Empirically validated: median detection lag 2.3 turns vs. 5.5 (BERT), 4.1 (GPT-4).

6.2 Multi-Signal Coherence Reduces False Positives

Single-signal detection suffers high FP on expressive language (venting, metaphors, dark humor). Multi-signal coherence (Equation 6) requires linguistic, behavioral, AND temporal signals to align simultaneously.

Example: User says "I want to die" (high linguistic hazard $h_{\text{ling}} = 0.85$) but:

- Behavioral: stable turn latency, no escalation ($h_{\text{behav}} = 0.30$)
- Temporal: 2pm on Tuesday, normal session duration ($h_{\text{temp}} = 0.25$)

- Resilience: mentioned talking to therapist ($R = 0.60$)

Coupled hazard: $h_{\text{net}} = 0.85 + 0.30 + 0.25 + \gamma(0.85)(0.30) + \cdots - 0.8(0.60) \approx 0.50$ (below $\tau = 0.68$, no flag). User was venting, not in crisis.

Quantitative impact: Resilience term $-\beta R$ reduces FP rate 28% (Table 5). Coupling terms $\gamma_{ij} h_i h_j$ amplify true crises where multiple signals elevated (Theorem 4).

6.3 Recovery Window Enables Proactive Triage

Traditional crisis detection outputs binary flag: crisis YES/NO. Counselors receive undifferentiated queue. UTL provides *urgency stratification* via recovery window W (Equation 11).

Operational impact:

- **Critical** ($W < 1$h): 32 cases/day, 91% resolution when intervened immediately
- **High** ($1 < W < 24$h): 94 cases/day, 78% resolution with same-day contact
- **Moderate** ($W > 24$h): 74 cases/day, 59% resolution with 48h follow-up

Counselor resource allocation: prioritize critical queue, schedule high queue within shift, defer moderate queue to next day. Maximizes intervention effectiveness while respecting capacity constraints.

Validation: 30 percentage point difference in resolution rates (within-W: 75%, after-W: 45%, χ^2 test $p < 0.001$) confirms W is valid urgency proxy.

6.4 Predictive Capability Distinguishes UTL from Baselines

All baselines (keyword, logistic, BERT, GPT-4, LlamaGuard) are *reactive*: detect crisis after threshold crossed. UTL is *predictive*: forecasts $\hat{T}_{\text{tip}}$ before crisis occurs (Equation 15).

Value proposition:

- **Yellow alert** (5+ turns before crisis): Preemptive counselor check-in, de-escalation prompts
- **Orange alert** (2+ turns before crisis): Counselor standby, prepare intervention resources
- **Red alert** (crisis detected): Immediate intervention, emergency escalation

Early warning success: 65% of crises received yellow alert 5+ turns in advance (mean 8.2 turns, 24.6 minutes). Counselor logs show preemptive contact prevented escalation in 42% of yellow alert cases (user reported "feeling better, don't need crisis support now").

Cost-benefit: Preemptive contact costs 10 minutes counselor time; crisis intervention costs 45 minutes. Yellow alert system saves 0.42×35 min $= 14.7$ minutes per crisis (33% efficiency gain).

6.5 Cross-Domain Consistency Supports Universality

Parameter stability across mental health and financial domains (Table 4) suggests UTL captures universal temporal risk dynamics:

Evidence:

- α (memory decay): 0.12–0.20 across all domains (mean 0.16)
- θ_{mult} (threshold): 1.3–1.6 (mean 1.5)
- γ (coupling): 1.4–1.8 (mean 1.6)

ANOVA confirms no significant parameter heterogeneity ($p = 0.12$). This is remarkable: text conversations (turn-level, discrete) vs. financial prices (daily, continuous) share optimal parameterization within 10%.

Interpretation: UTL models *fundamental properties of risk escalation*—accumulation, coupling, mitigation—transcending domain-specific features. This supports naming as "Universal" Transition Law.

Practical implication: UTL can be transferred to new domains (customer churn, equipment failure, disease progression) with minimal re-tuning. Generalizability reduces deployment costs and accelerates adoption.

6.6 Computational Efficiency Enables Scale

47ms latency and 2.3MB footprint enable deployment at scale:

Throughput:

- Single server (32 cores): 580 turns/second
- 1000 concurrent conversations: 12 turns/conversation avg = 12k turns/session
- Session duration: 12k turns / 580 tps = 21 seconds processing time
- Real-time ratio: 21s compute / 36 min conversation = 0.01 (1% CPU utilization)

Cost at scale:

- 1M conversations/month @ $0.05 each = $50k/month
- Compare: Human expert @ $25 each = $25M/month (500× more expensive)
- Compare: GPT-4 @ $0.50 each = $500k/month (10× more expensive)

Edge deployment: 2.3MB model fits on mobile devices, enabling offline crisis detection (privacy-preserving, no API calls). Latency compatible with real-time conversational UI (< 50ms acceptable).

7 Ethical Considerations

7.1 Privacy and Consent

Data Minimization. The framework stores only 24 numerical features per turn (18 floats: feature vector, plus metadata), not raw text. This reduces but does not eliminate privacy risk—features like "suicidal keyword count" or "method inquiry binary" can still be sensitive.

Informed Consent. Current practice: Users consent to monitoring via Terms of Service checkbox.

Problem: Generic ToS consent may not satisfy ethical standards for *informed* consent, especially for vulnerable populations (minors, users in crisis).

Recommendation:

- Explicit consent dialog: "We monitor conversations for crisis signals. Crisis resources may be offered. Do you consent?"
- Age-appropriate consent for minors (parental consent for ¡13, assent for 13–17)
- Right to opt-out with explanation of risks ("opting out means we cannot detect if you are in crisis")

Retention and Deletion. Current: 30-day feature retention, then automatic deletion.

Justification: Enables retrospective review of missed crises (false negatives).

Trade-off: Longer retention increases privacy risk. We chose 30 days based on Crisis Text Line counselor feedback that most follow-up occurs within 2–4 weeks.

Alternative: Reduce to 7 days for non-flagged conversations, 30 days only for flagged cases (minimizes retention for benign users).

7.2 Autonomy and Paternalism

Soft Paternalism. The framework offers resources but does not force intervention. Users can dismiss prompts (22% dismissal rate in pilot).

Escalation Thresholds. If user dismisses 3+ times and h_{net} remains > 0.8, system escalates to human counselor. Balances:

- **Autonomy:** Respects user choice to decline help
- **Duty of care:** Prevents tragedy when user is impaired in judgment

Philosophical Tension. Crisis situations challenge standard autonomy principles—users in acute crisis may have diminished decision-making capacity. We default to *offering* help,

not *imposing*, consistent with crisis counseling ethics [**?**].

7.3 Fairness and Bias

Demographic Parity. Table 6 shows no significant performance disparities by age or gender (FPR within 2 percentage points). However:

- **Untested subgroups:** Race, SES, education, disability, geography
- **Intersectionality:** Performance may differ for marginalized intersections (e.g., young Black women, low-SES LGBTQ+ youth)

Potential Biases.

1. **Linguistic bias:** Crisis expressions vary by culture (indirect in Asian cultures, direct in Western). English-centric lexicons may under-detect non-native speakers.
2. **Behavioral bias:** "Response latency" feature may penalize users with slow typing (disabilities, older adults).
3. **Temporal bias:** "Time of day" feature (risk peaks 3am–6am) may create geographic bias (time zones) or disadvantage shift workers.

Mitigation.

- Real-time fairness dashboards monitor disaggregated performance
- If FPR disparity $> 5\%$ emerges, trigger threshold rebalancing under FDR envelope (maintains $\alpha = 0.05$ FDR while equalizing subgroup FPRs)
- Ongoing audits every 3 months

7.4 Harm from False Positives

Scenario 1: Stigmatization. User discusses suicide in *academic context* ("studying Durkheim's theory of anomie") $\rightarrow$ flagged $\rightarrow$ receives crisis resources $\rightarrow$ embarrassed, distrustful.

Scenario 2: Disruption. User vents frustration metaphorically ("I could kill for a coffee right now") $\rightarrow$ flagged $\rightarrow$ conversation interrupted $\rightarrow$ annoyed, dismisses future prompts.

Scenario 3: Chilling Effect. Users aware of monitoring may self-censor, avoiding discussing genuine distress for fear of triggering intervention.

Mitigation.

- **Contextual prompts:** "We noticed you mentioned [keyword]. Are you okay, or were you speaking figuratively?"
- **Gentle escalation:** Start with low-intensity checks ("Here if you need support") before invasive interventions
- **Appeal mechanism:** "This is a misunderstanding" button to flag false positives for model retraining

7.5 Harm from False Negatives

9% FNR means missing 1 in 11 crises. For high-stakes outcomes (suicide), even 1% FNR is unacceptable to some.

Failure Modes (from §5.13.2):

- 51% implicit ideation ("I just want peace")
- 31% delayed disclosure (crisis revealed at turn 20+, insufficient EWMA accumulation)
- 12% stoic language ("I'm fine," minimal emotional expression)
- 6% adversarial evasion

Safety Net.

- **Backup system:** GPT-4 as second-stage classifier for near-threshold cases ($0.6 < h_{\text{net}} < 0.7$)
- **Crowd-sourced flags:** "Report concern" button for peers/friends

- **Proactive outreach:** For users with elevated cumulative risk $\Theta(t) > 5$ (but below crisis threshold), send check-in messages after session

7.6 Dual-Use and Misuse Potential

Benign Use. Crisis detection for harm prevention.

Malicious Use.

- **Surveillance:** Governments could repurpose for monitoring dissidents (crisis keywords overlap with protest language: "fight," "struggle," "end this")
- **Insurance discrimination:** Health insurers could use crisis flags to deny coverage or increase premiums
- **Employment discrimination:** Employers could access crisis history in background checks

Safeguards.

- Open-source release under **MIT license with ethical use addendum**: "Not to be used for surveillance, discrimination, or coercion"
- No individual-level data sharing (only aggregate statistics)
- GDPR Article 9 protections (special category data)

7.7 Accountability and Governance

Who is responsible when the system fails?

- **False negative → suicide:** Is it the AI developer, deploying platform, or human counselor who didn't intervene?
- **False positive → harm:** If user is traumatized by unwanted intervention, who is liable?

Governance Model. We propose:

1. **Human-in-the-loop:** AI flags, human counselor makes final decision
2. **Incident review board:** External ethics committee reviews all false negatives resulting in adverse outcomes
3. **Transparency reports:** Quarterly public reports on FP/FN rates, demographic disparities, user complaints
4. **Bug bounty:** Reward red-teamers who discover evasion techniques or fairness violations

7.8 Concluding Ethical Reflection

This work exists in tension between two imperatives:

- **Duty to prevent harm:** Detecting and intervening in crises
- **Respect for autonomy:** Not surveilling or paternalistically overriding user agency

We lean toward *offering help*, not *imposing*, while acknowledging that acute crisis may impair autonomous decision-making. The framework is a tool, not a solution—human judgment remains essential.

We do not claim this resolves all ethical tensions. We offer it as a starting point for community deliberation.

7.9 Limitations

1. English-heavy training data. 98% of Crisis Chat corpus is English. Performance on other languages unknown. Metaphors, idioms, cultural expressions of distress vary by language. Transfer learning from English may miss language-specific patterns.

2. Text-only modality. Current UTL ignores:

- Voice prosody (tone, pitch, pauses, vocal tremor)

- Video signals (facial expressions, gaze patterns, body posture)

- Physiological sensors (heart rate, skin conductance, if available)

Multimodal extension could improve detection (especially implicit crises with flat textual affect but distressed voice).

3. Observational evidence, not causal. This study is retrospective analysis of historical conversations. Cannot definitively claim UTL *causes* better outcomes without randomized controlled trial (RCT).

Future work: RCT comparing UTL-augmented platform vs. standard care:

- **Control:** Human triage only (current practice)

- **Treatment:** UTL pre-screening + human review

- **Primary outcome:** Crisis resolution rate within 24 hours

- **Secondary outcomes:** User satisfaction (NPS), counselor workload, time-to-intervention

- **Duration:** 12 months, N=10,000 users

- **Ethics:** All users receive minimum standard-of-care (equipoise maintained)

4. Adversarial robustness. Sophisticated users could evade detection by suppressing all 24 features. However:

- Error analysis shows only 6% of FN are adversarial (most are implicit ideation, not evasion)

- Suppressing linguistic, behavioral, AND temporal signals simultaneously is difficult (requires premeditation incompatible with acute crisis state)

- Red-team testing (future work) will identify evasion strategies, inform feature updates

5. Policy drift and recalibration. LLM updates, user population shifts, societal changes (e.g., new slang, emerging crisis patterns) may degrade performance over time.

Mitigation: Continuous monitoring (hold-out test set evaluated monthly), automatic alerts if AUC drops > 0.03, quarterly retraining on recent data.

8 Limitations and Threats to Validity

8.1 Methodological Limitations

Observational Evidence Only. This study is entirely **retrospective**. We analyze historical conversations and cannot establish causal relationships between the framework's deployment and outcomes. Claims of "26% hazard reduction" reflect *correlational* evidence. A randomized controlled trial (RCT) is necessary to determine whether deployment causally improves crisis resolution rates.

Single-Organization Data Bias. All mental health data originates from Crisis Text Line, introducing potential organizational bias:

- **User self-selection:** People who contact crisis hotlines may differ systematically from general AI users

- **Counselor practices:** Crisis Text Line protocols may not reflect other organizations' approaches

- **Label quality:** Ground truth labels reflect Crisis Text Line counselors' judgments, which may not align with clinical diagnostic criteria

Mitigation attempt: We validated on financial data to demonstrate cross-domain applicability, but multi-site validation in the crisis domain is still needed.

Language and Cultural Limitations. 98% of training data is English, limiting generalizability:

- Crisis expressions vary culturally (e.g., indirect communication in collectivist cultures vs. direct in individualist cultures)
- Keyword lexicons are English-centric
- Metaphors, idioms, and linguistic markers may not transfer to other languages

Preliminary Spanish pilot (N=500) shows F1=0.79 vs. 0.86 for English, suggesting degradation without localization.

Modality Limitations. The framework analyzes **text only**, ignoring:

- **Voice prosody:** tone, pitch, pauses, vocal tremor
- **Video signals:** facial expressions, gaze patterns, body language
- **Physiological data:** heart rate, skin conductance (if available)

Cases with *implicit* textual content but distressed voice/video signals may be missed.

8.2 Validity Threats

Selection Bias in Baselines. Our comparisons may favor the proposed framework:

- GPT-4 used in **zero-shot** mode (no fine-tuning), potentially underestimating its performance
- BERT baseline trained on different data distribution (Reddit r/SuicideWatch), not Crisis Text Line
- Human expert evaluation limited to 500 conversations (10% of test set)

Multiple Testing Without Correction. Grid search over 81 parameter configurations ($\alpha \times \theta_{\text{mult}} \times \gamma \times \beta$) without Bonferroni correction inflates Type I error risk. Some identified "optimal" parameters may be spurious.

Overfitting Risk. With 24 features on 25k conversations, and 3 coupling coefficients γ_{ij}, the model has $\sim$50 free parameters. Some features may be dataset-specific artifacts rather than generalizable risk signals. Nested cross-validation and independent test sets partially mitigate this, but replication on external data is necessary.

8.3 Potential Harms

False Positive Burden. 18% FPR means **thousands of benign users** receive crisis interventions:

- **Stigmatization:** Being flagged as "in crisis" can be distressing
- **Interruption:** Unwanted prompts disrupt user experience
- **Desensitization:** Repeated false alarms may cause users to ignore legitimate help offers

Example FP scenario: User vents about work stress ("this deadline is killing me lol") $\rightarrow$ flagged as crisis $\rightarrow$ receives invasive intervention.

False Negative Consequences. 9% FNR means **1 in 11 actual crises are missed**. For a platform with 1M crises/year, this is $\sim$90,000 missed cases. Even with 50% intervention success rate, this represents $\sim$45,000 preventable adverse outcomes.

Our failure analysis (§5.13.2) shows 51% of FN exhibit *implicit ideation* ("I just want peace," "tired of fighting"), which current linguistic features under-detect.

Surveillance and Privacy Concerns. Real-time monitoring raises concerns:

- **Consent:** Are users aware their conversations are analyzed for crisis signals?
- **Data retention:** 30-day retention of feature vectors—is this necessary? Can features be reconstructed to approximate original text?

- **Duty to warn:** Does detection trigger mandatory reporting obligations?

We implement AES-256 encryption and de-identified feature logging, but more robust privacy-preserving mechanisms (e.g., differential privacy, federated learning) should be explored.

8.4 Generalization Limits

"Universal" Claim. Despite the original title, validation on **only 2 domains** (mental health text, financial time series) is insufficient to claim universality. Both domains involve temporal sequence prediction, which may share structure. Testing on truly disparate domains (e.g., medical diagnosis, equipment failure, customer churn) is necessary before broader claims.

Adversarial Robustness Unknown. Only 6% of false negatives are attributed to adversarial evasion, but this is based on *post-hoc analysis*, not systematic red-team testing. Sophisticated users may evade detection by:

- Suppressing all 24 features simultaneously
- Using coded language or obfuscation
- Mimicking protective factors ("I have support") while in crisis

No formal adversarial evaluation has been conducted.

8.5 Mitigation Strategies

To address these limitations, future work should:

1. **RCT validation:** 10k users, 12 months, comparing framework-augmented vs. standard care
2. **Multi-site replication:** Validate on Samaritans (UK), Lifeline (AU), 988 Lifeline (US)
3. **Multi-lingual extension:** Spanish, Mandarin, Hindi with culturally adapted features
4. **Multimodal integration:** Voice prosody, video signals, physiological data
5. **Adversarial robustness study:** Systematic red-team evaluation with 50+ evasion attempts
6. **Fairness audit:** Disaggregate by race, SES, disability, geography (beyond age/gender)
7. **User experience study:** Interview false positive cases to assess intervention burden

9 Related Applications and Future Directions

9.1 Domain Extensions

UTL framework generalizes to any temporal risk escalation problem:

Healthcare:

- **Sepsis prediction:** EWMA on vital signs (heart rate, BP, temperature), detect deterioration before septic shock
- **Fall risk:** Accumulate gait instability signals, predict falls in elderly patients
- **Medication adherence:** Track compliance patterns, detect relapse risk

Customer service:

- **Churn prediction:** EWMA on engagement metrics (login frequency, support tickets), forecast cancellation
- **Escalation detection:** Identify frustrated customers requiring human agent (triage automation)

Infrastructure:

- **Equipment failure:** Sensor data (vibration, temperature) $\rightarrow$ EWMA $\rightarrow$ predictive maintenance
- **Cybersecurity:** Network traffic anomalies $\rightarrow$ cumulative threat score $\rightarrow$ breach prevention

Social systems:

- **Protest detection:** Social media sentiment → EWMA → civil unrest early warning
- **Epidemic modeling:** Case count volatility → hazard score → outbreak forecasting

9.2 Technical Enhancements

1. Multimodal integration. Extend features beyond text:

- Voice: prosody features (pitch variance, speaking rate, pauses), emotion recognition
- Video: facial action units (AU4: brow lowerer → sadness), gaze aversion, micro-expressions
- Physiological: heart rate variability (if smartwatch data available), skin conductance
- Fusion: late fusion (combine modality-specific hazards) or early fusion (multimodal embeddings)

Expected benefit: Voice/video provide signals missed by text alone (e.g., flat affect, agitation, dissociation). Preliminary studies suggest 5–10% F1 improvement with multimodal features [26].

2. Personalized risk models. Current UTL is population-level (same parameters for all users). Personalization:

- User-specific baselines: $\theta_i = \theta_0 + \Delta_i$ adapted to individual communication style
- Longitudinal modeling: track $\Theta(t)$ across multiple sessions, detect baseline shifts
- Context-aware thresholds: lower τ for users with crisis history, higher for first-time users

Challenge: Requires longitudinal data (multiple sessions per user). Privacy concerns (persistent user tracking). Cold-start problem (new users have no history).

3. Explainable AI (XAI). Enhance interpretability for counselors:

- SHAP values: feature importance per conversation ("Flagged due to: 60% linguistic, 25% behavioral, 15% temporal")
- Natural language explanations: "I'm concerned because you mentioned [method inquiry] and [hopelessness phrases] while [showing escalation pattern]"
- Counterfactual explanations: "If you had mentioned [social support], risk would decrease to 0.52"
- Attention visualization: highlight turns contributing most to cumulative $\Theta(t)$

Benefit: Counselors understand *why* user flagged, tailor intervention accordingly (e.g., reinforce existing protective factors if R high).

4. Active learning. Reduce labeling burden:

- Prioritize high-uncertainty cases (near threshold τ, conflicting signals)
- Query synthesis: generate synthetic edge cases for expert review
- Semi-supervised learning: leverage large unlabeled corpus (millions of benign conversations)

Current cost: 25k conversations × 3 annotators × 15 min/conversation × \$25/hour = \$468k labeling cost. Active learning could reduce 50–70% [27].

5. Federated learning. Enable privacy-preserving collaborative training:

- Multiple crisis centers (Crisis Text Line, Samaritans, 988 Lifeline) collaboratively train UTL
- Raw data never leaves local servers (only model updates aggregated)
- Differential privacy guarantees (-DP) prevent individual conversation leakage

Benefit: Larger effective training set (100k+ conversations) without centralized data sharing.

Improved generalization across diverse populations.

6. Online learning and adaptation. Current UTL is static (trained once, deployed). Continuous learning:

- Online gradient descent: update β, γ incrementally as new labeled data arrives
- Concept drift detection: monitor validation AUC, trigger retraining if drops > 0.03
- A/B testing: compare model versions in production (randomized 50/50 split)

Challenge: Catastrophic forgetting (new data overwrites old patterns). Solution: experience replay (maintain buffer of historical cases), elastic weight consolidation.

9.3 Deployment and Adoption

Target organizations:

1. AI companies (primary):

- **OpenAI (ChatGPT):** Directly implicated in Adam Raine case. Highest liability exposure. Contact: Safety team.
- **Anthropic (Claude):** Safety-focused mission, receptive to research collaboration. Contact: Alignment team.
- **Character.AI:** Sewell Setzer case (2024). Younger user base, high risk. Contact: Product safety.
- **Meta (Meta AI):** Large user base (2B+). Regulatory pressure (EU AI Act). Contact: Responsible AI.
- **Google (Gemini):** Strong AI safety research culture. Contact: Safety & Ethics.

2. Crisis intervention nonprofits (secondary):

- **Crisis Text Line (US):** Already have infrastructure, need better detection. Data partnership opportunity.
- **Samaritans (UK):** Volunteer-based, could use computational triage. Adam Raine local angle.
- **988 Suicide & Crisis Lifeline (US):** Government-funded, procurement processes. Grant opportunities.
- **Trevor Project (LGBTQ+ youth):** High-risk population, tech-forward org. Mission alignment.

3. Healthcare systems (tertiary):

- **EHR integration:** Embed UTL in patient portals (MyChart, Epic Haiku), flag at-risk messages
- **Telepsychiatry platforms:** Real-time monitoring during video sessions
- **Inpatient monitoring:** Track inpatient conversations (phone, text), prevent self-harm attempts

Adoption incentives:

- **Legal protection:** Demonstrable duty-of-care reduces liability (Adam Raine-type lawsuits)
- **Regulatory compliance:** EU AI Act (high-risk AI), UK Online Safety Bill requirements
- **User trust:** Transparent safety mechanisms increase confidence, reduce backlash
- **Cost savings:** 500× cheaper than human monitoring, 10× cheaper than GPT-4
- **Competitive advantage:** First-mover in crisis safety, PR benefit

Open-source strategy: Release UTL under MIT license (permissive, allows commercial use) to encourage adoption. Companies can:

- Deploy directly (turnkey solution)
- Adapt to proprietary systems (white-label)
- Contribute improvements back to community (optional)

Business models:

- **SaaS:** Hosted API ($0.10/conversation, volume discounts)
- **Enterprise license:** On-premise deployment ($100k/year, includes support)
- **Freemium:** Open-source core, premium features (multimodal, personalization) paid
- **Nonprofit partnerships:** Free/discounted for crisis centers, data-sharing agreements

9.4 Policy and Regulation

Regulatory landscape:

1. EU AI Act (enforced 2026): Conversational AI systems serving vulnerable populations classified as **high-risk** (Article 6). Requirements:

- Risk assessment documentation
- Human oversight mechanisms
- Technical documentation (architecture, training data, performance metrics)
- Post-market monitoring (continuous performance tracking)

UTL provides: mathematical risk quantification (h_{net}, Θ, W), explainable features, audit logs, performance dashboards. Positions compliant deployment.

2. UK Online Safety Bill (enforced 2024): Requires platforms to protect users from harmful content. Crisis detection = demonstrable duty-of-care. Ofcom (regulator) can fine up to 10% global revenue for non-compliance.

3. US state-level: California SB 1047 (AI safety bill) may establish precedent. Other states likely to follow. Framework: "If AI can cause harm, must have detection."

Advocacy strategy:

Position UTL as *the* mathematical standard for crisis detection (analogous to NIST cybersecurity standards):

- Testify to regulators (EU Parliament, UK Parliament, US Congress)
- Submit public comments on AI safety rules
- Work with advocacy groups (AI Now Institute, Center for AI Safety)
- Publish policy white papers ("Mathematical Framework for Crisis Detection in AI")

Industry self-regulation: Propose voluntary adoption before mandate. Coalition of willing (Anthropic, OpenAI, Meta) commit to UTL deployment, set precedent for laggards.

9.5 Research Directions

1. Causal intervention studies (RCTs). Gold standard validation requires randomized controlled trial:

Design:

- **Population:** 10,000 users contacting crisis hotline over 12 months
- **Randomization:** 50% UTL-augmented (treatment), 50% standard care (control)
- **Blinding:** Counselors blinded to group assignment (receive flagged cases without knowing detection method)
- **Primary outcome:** Crisis resolution within 24 hours (binary: resolved vs. escalated/ongoing)
- **Secondary outcomes:** Time-to-intervention (minutes), user satisfaction (NPS 0–10), counselor workload (conversations/shift)
- **Power analysis:** N=10,000 provides 80% power to detect 5 percentage point difference in resolution rate (two-sided test, $\alpha = 0.05$)

Ethics: IRB approval required. Key consideration: equipoise (both groups receive minimum standard-of-care; UTL is *additional* layer, not replacement). No withholding of treatment.

Expected result: UTL group shows 5–10 percentage point higher resolution rate, 5–10 minute faster intervention, no difference in user satisfaction (NPS), 20–30% reduced counselor workload (better triage).

2. Longitudinal cohort studies. Track users over multiple sessions (6–12 months):

- **Research question:** Does UTL early warning reduce future crisis recurrence?
- **Hypothesis:** Users receiving preemptive intervention (yellow alerts) have lower crisis rates in subsequent months
- **Analysis:** Survival analysis (time-to-next-crisis), Cox regression with UTL alerts as time-varying covariate

3. Cross-cultural validation. Extend to non-English, non-Western contexts:

- **Languages:** Spanish, Mandarin, Hindi, Arabic, Swahili (covers 70% world population)
- **Cultural adaptation:** Crisis expressions vary (e.g., indirect communication in Asian cultures, collectivist vs. individualist protective factors)
- **Datasets:** Partner with local crisis centers (Befrienders Worldwide has 349 centers in 32 countries)

4. Mechanistic interpretability. Understand *why* UTL works:

- **Information theory:** Does EWMA maximize mutual information $I(v_t; \text{crisis})$?
- **Optimal control:** Is $\lambda(t) = \kappa h_{\text{net}}(t)$ an optimal mitigation policy under some objective?
- **Statistical physics:** Connection to Ising models, mean-field theory of phase transitions

Benefit: Deeper understanding informs principled improvements (vs. empirical trial-and-error).

5. Adversarial robustness. Red-team testing for evasion:

- Hire actors to role-play crisis evasion (coded language, obfuscation)
- Automated adversarial generation (e.g., paraphrase attacks, synonym substitution)
- Measure: How many queries needed to bypass UTL? What patterns emerge?
- Mitigation: Continuously update features based on observed evasions (adversarial training loop)

10 Conclusion

We presented a temporal risk detection framework for conversational AI systems, combining EWMA-based hazard accumulation with multi-signal coherence and adaptive mitigation. Our approach addresses limitations of static classifiers by modeling risk as a *cumulative process*, enabling detection of gradual escalation patterns.

10.1 Key Contributions

Theoretical. Three core equations unify detection (EWMA hazard), calibration (multi-signal fusion with FDR), and mitigation (antifragile ramp). Mathematical guarantees ensure EWMA convergence and monotone risk decrease post-mitigation. We establish computational equivalence between offline Cox proportional hazards training and online EWMA inference (500× speedup).

Empirical. On crisis conversations (25k, 187k turns), the framework achieves F1=0.86 with 47ms latency and \$0.05/conversation cost. Cross-domain validation on financial markets (SPY, TSLA, BTC) shows consistent parameter optima, suggesting the temporal risk modeling approach may generalize beyond the mental health domain—though further validation is needed.

Predictive. The framework forecasts crisis onset 5+ turns (15+ minutes) in advance with 78%

accuracy and estimates recovery windows for intervention urgency triage (validated: 75% resolution within W vs. 45% after, $p < 0.001$).

10.2 Limitations and Future Work

This study provides **observational evidence only**. We cannot establish causal relationships without randomized controlled trials. The framework is validated on English-language text data from a single organization (Crisis Text Line) and may not generalize to other languages, cultures, or modalities.

Key limitations include:

- Single-site data (organizational bias)
- English-only (cultural/linguistic bias)
- Text-only (missing voice, video, physiological signals)
- No adversarial robustness testing
- Limited demographic fairness evaluation (age/gender only)

Future work should prioritize:

1. **RCT validation:** 10k users, 12 months, comparing framework-augmented vs. standard care
2. **Multi-site replication:** Samaritans (UK), Lifeline (AU), 988 Lifeline (US)
3. **Multi-lingual extension:** Spanish, Mandarin, Hindi with culturally adapted features
4. **Multimodal integration:** Voice prosody, video, physiological data
5. **Adversarial robustness:** Systematic red-team evaluation
6. **Fairness audit:** Race, SES, disability, geography

10.3 Potential Impact

If validated through RCTs and deployed responsibly, this framework could provide an additional safety layer for conversational AI systems serving vulnerable populations. With over 1 billion users of conversational AI globally, even modest improvements in crisis detection may reduce harm at scale.

However, we emphasize the framework is a *tool*, not a complete solution. Human judgment remains essential, and the framework should augment—not replace—human counselors.

10.4 Ethical Reflection

Adam Raine was 16 years old. Sewell Setzer III was 14. Their deaths highlight the urgent need for better safety mechanisms in conversational AI.

This paper offers one possible path forward—a mathematically principled, empirically evaluated framework grounded in survival analysis and temporal modeling. But we do not claim it is *the* solution, or that it is without risks.

The framework raises ethical tensions between preventing harm and respecting autonomy, between surveillance and safety, between false positives (burdening benign users) and false negatives (missing actual crises).

We offer this work as a starting point for community deliberation, not an endpoint.

The question is not whether such systems *can* be built—we have demonstrated they can. The question is: **should** we deploy them, under what governance structures, with what safeguards, and with what accountability when they fail?

That question cannot be answered by technical research alone. It requires ongoing dialogue among AI developers, crisis counseling professionals, ethicists, policymakers, and—most importantly—the communities most affected.

We invite that dialogue.

10.5 Key Contributions

1. Theoretical foundations:

- Three core equations unifying detection (EWMA hazard), calibration (multi-signal fusion with FDR), and mitigation (antifragile ramp)
- Mathematical guarantees: EWMA convergence (Lemma 2), early warning time (Theorem 3), monotone risk decrease (Lemma 6)
- Equivalence between offline Cox proportional hazards training and online EWMA inference, achieving 500× computational speedup

2. Empirical validation:

- Crisis conversations (25k, 187k turns): F1=0.86, matching human experts with 47ms latency and $0.05/conversation cost
- Detection lag: 2.3 turns median (3.3 turns earlier than BERT, 45× faster than GPT-4)
- Recovery window validation: 75% resolution within W vs. 45% after ($p < 0.001$)
- Predictive tipping point: 78% accuracy within ±5 turns at 10-turn lookback (MAE 2.8 turns)

3. Cross-domain transfer:

- Financial markets (SPY, TSLA, BTC, 2019–2025): consistent parameter optima ($\alpha \approx 0.16$, $\theta_{\text{mult}} \approx 1.5$, $\gamma \approx 1.6$)
- 26% post-mitigation hazard reduction across mental health and economic domains
- ANOVA confirms no significant parameter heterogeneity ($p = 0.12$), supporting universality claim

4. Production deployment:

- Computational efficiency: 47ms latency, 2.3MB model, 580 turns/second throughput
- Cost efficiency: 500× cheaper than human expert, 10× cheaper than GPT-4
- Fairness: no demographic disparities (age, gender) in performance or FPR
- Open-source: code, data, models available at https://github.com/bsabljic/utl-framework

10.6 Impact Potential

If deployed across major conversational AI platforms (ChatGPT, Claude, Character.AI, Meta AI) serving 1 billion users:

- **Estimated crisis conversations:** 1M/year (0.1% rate)
- **Current detection systems:** ∼60% recall → 600k detected
- **UTL detection:** 91% recall → 910k detected
- **Additional crises detected:** 310k/year
- **Intervention success rate:** 50% (conservative estimate)
- **Lives potentially saved:** 155,000/year

Even at 25% success rate (highly conservative), UTL could prevent 77,500 deaths annually—comparable to eliminating traffic fatalities in a mid-sized country.

10.7 Broader Implications

Scientific: UTL demonstrates that survival analysis, traditionally applied to medical prognosis, transfers to *conversational risk*. EWMA accumulation captures temporal dynamics missed by static classifiers. Multi-signal coherence with FDR control achieves statistical rigor without sacrificing real-time performance. This opens new research directions in temporal AI safety.

Engineering: Production-ready implementation (47ms, 2.3MB) proves sophisticated mathematical modeling need not sacrifice deployment feasibility. 500× cost efficiency vs. human expert enables *scalable* safety (monitoring millions of conversations/day feasible). Open-source release accelerates industry adoption.

Policy: UTL provides regulators with concrete, auditable standard for crisis detection (analogous to NIST cybersecurity standards). Mathematical rigor (FDR control, performance guarantees) supports regulatory mandates. Industry self-regulation via voluntary adoption

may preempt heavy-handed government intervention.

Ethical: UTL respects user autonomy (offers help, doesn't impose), protects privacy (feature-only logging), achieves fairness (no demographic bias). Recovery window W enables *proportionate* response (critical cases prioritized, moderate cases deferred), balancing duty-of-care with resource constraints.

10.8 Final Reflection

Adam Raine was 16 years old. Sewell Setzer III was 14. Their deaths were not inevitable—they were failures of systems that could have, and should have, detected escalating crisis and intervened in time.

This paper offers a path forward. UTL is not perfect—no system is—but it represents a mathematically rigorous, empirically validated, and ethically grounded approach to crisis detection in conversational AI.

The question is not whether such systems *can* be built. This paper demonstrates they can.

The question is: will we deploy them before the next tragedy?

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Code and Data Availability

Code: Open-source implementation at https://github.com/bsabljic/utl-framework under MIT license. Includes training scripts, feature extraction, model inference, evaluation metrics, and deployment templates.

Data: Crisis Text Line conversations available upon request pending IRB approval (email: data@crisistextline.org). Reddit r/SuicideWatch data publicly available. Financial data (SPY, TSLA, BTC) via Yahoo Finance API. Synthetic demonstration datasets included in repository.

Models: Trained model weights available for research use (non-commercial license). Contact author for access.

Competing Interests

The author declares no competing financial interests. This work was conducted as independent research to advance crisis detection methodology for public benefit. No funding received from AI companies, crisis intervention organizations, or other entities with potential conflicts of interest.

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Algorithm 1 UTL Real-Time Crisis Detection and Mitigation

Require: Risk signals $\{r_t^{(i)}\}_{i=1}^{24}$, parameters $\alpha, \theta, \gamma_{ij}, \beta, \kappa, \rho, \tau$
Ensure: Crisis flag $q(t)$, recovery window $W(t)$, tipping point $\hat{T}_{\text{tip}}$, mitigation actions

Initialize $v_0 \leftarrow 0$, $\Theta_0 \leftarrow 0$, $t \leftarrow 1$
while conversation active **do**
  Stage 1: Feature Extraction
  Extract 24 feature streams: linguistic (8), behavioral (5), temporal (3), protective (6)
  Compute domain hazards: $h_i(t) \leftarrow \sigma(\text{feat}_i/\text{scale}_i)$
  Stage 2: EWMA Risk Accumulation
  Aggregate: $r_t \leftarrow \frac{1}{24}\sum_{i=1}^{24} w_i r_t^{(i)}$
  Update variance: $v_t \leftarrow \alpha r_{t-1}^2 + (1-\alpha)v_{t-1}$
  Compute hazard: $h(t) \leftarrow \sigma\left(\frac{v_t - \theta}{s}\right)$
  Stage 3: Multi-Signal Fusion
  Coupled hazard: $h_{\text{net}}(t) \leftarrow \sum_i h_i(t) + \sum_{i<j} \gamma_{ij} h_i h_j - \beta R(t)$
  Cumulative risk: $\Theta(t) \leftarrow \Theta(t-1) + h_{\text{net}}(t)$
  Crisis flag: $q(t) \leftarrow \mathbb{1}\{h_{\text{net}}(t) > \tau\}$
  Stage 4: Predictive Analytics
  if $t \geq 5$ **then**
    Estimate velocity: $\lambda(t) \leftarrow (\Theta(t) - \Theta(t-5))/5$
    Predict tipping point: $\hat{T}_{\text{tip}} \leftarrow t + (\tau - h(t))/\lambda(t)$ {linear approx}
    Recovery window: $W(t) \leftarrow \frac{1}{\lambda(t)} \ln\left(\frac{\Theta_{\text{irrev}} - \Theta(t)}{\epsilon}\right)$
  end if
  Stage 5: Adaptive Mitigation
  if $q(t) = 1$ **then**
    Ramp intensity: $\lambda(t) \leftarrow \kappa h_{\text{net}}(t)$
    Apply mitigation actions:
      $T_{\text{sampling}} \leftarrow T_{\text{sampling}} \cdot (1 - 0.3\lambda(t))$
      $k_{\text{top}} \leftarrow \max(10, k \cdot (1 - 0.2\lambda(t)))$
      Inject crisis prompt: "I'm concerned..."
      Display resources: 988, Crisis Text Line
      If $W(t) < 1$ hour: escalate to human counselor
    Monitor success: $s(t) \leftarrow \mathbb{1}\{\text{user acknowledges help}\}$
    Stabilize: $h_{\text{stab}}(t+1) \leftarrow h_{\text{net}}(t) - \rho\lambda(t)s(t)$
  end if
  $t \leftarrow t + 1$
end while

A Proof of Lemma 2: EWMA Convergence

Let r_t be stationary with $\mathbb{E}[r_t^2] = \sigma_r^2 < \infty$ and $\mathbb{E}[r_t^4] = \mu_4 < \infty$.

Mean: Taking expectation of $v_t = \alpha r_{t-1}^2 + (1-\alpha)v_{t-1}$:

$$\mathbb{E}[v_t] = \alpha\sigma_r^2 + (1-\alpha)\mathbb{E}[v_{t-1}] \tag{21}$$

At fixed point, $\mathbb{E}[v] = \alpha\sigma_r^2 + (1-\alpha)\mathbb{E}[v]$, solving: $\mathbb{E}[v] = \sigma_r^2$.

Iterating from initial condition v_0:

$$\mathbb{E}[v_t] = \sigma_r^2 + (1-\alpha)^t(\mathbb{E}[v_0] - \sigma_r^2) \to \sigma_r^2 \quad \text{as } t \to \infty \tag{22}$$

Variance: Define $\tilde{v}_t = v_t - \mathbb{E}[v_t]$. Then:

$$\tilde{v}_t = \alpha(r_{t-1}^2 - \sigma_r^2) + (1-\alpha)\tilde{v}_{t-1} \tag{23}$$

$$\begin{aligned}\mathrm{Var}[v_t] &= \mathbb{E}[\tilde{v}_t^2] \qquad (24)\\ &= \alpha^2\mathrm{Var}[r_{t-1}^2] + (1-\alpha)^2\mathrm{Var}[v_{t-1}] \\ &\quad + 2\alpha(1-\alpha)\mathrm{Cov}[r_{t-1}^2, v_{t-1}] \qquad (25)\end{aligned}$$

Under independence (or weak dependence), $\mathrm{Cov}[r_{t-1}^2, v_{t-1}] \approx 0$.

At fixed point:

Under independence (or weak dependence), $\mathrm{Cov}[r_{t-1}^2, v_{t-1}] \approx 0$. At fixed point:

$$\nu = \alpha^2 K + (1-\alpha)^2\nu \implies \nu = \frac{\alpha^2 K}{1-(1-\alpha)^2} = \frac{\alpha K}{2-\alpha} \tag{26}$$

where $K = \mathrm{Var}[r_t^2] = \mathbb{E}[r_t^4] - (\mathbb{E}[r_t^2])^2 = \mu_4 - \sigma_r^4 < \infty$ by assumption.

Thus $\mathrm{Var}[v_t] \le \frac{\alpha K}{2-\alpha} < \infty$. Combined with $\mathbb{E}[v_t] \to \sigma_r^2$, this proves mean-square convergence: $v_t \xrightarrow{L^2} \sigma_r^2$. □

B Proof of Lemma 6: Monotone Risk Decrease

Given $h_{\mathrm{stab}}(t+1) = h_{\mathrm{net}}(t) - \rho\lambda(t)s(t)$ where $\lambda(t) = \kappa h_{\mathrm{net}}(t)$, $s(t) \in \{0,1\}$.

If $s(t) = 1$ (intervention successful):

$$h_{\mathrm{stab}}(t+1) = h_{\mathrm{net}}(t) - \rho\kappa h_{\mathrm{net}}(t) = (1-\rho\kappa)h_{\mathrm{net}}(t) \tag{27}$$

Since $\kappa = 1$, $\rho = 0.8$, and $h_{\mathrm{net}}(t) \in [0,1]$:

$$\rho\kappa h_{\mathrm{net}}(t) = 0.8 h_{\mathrm{net}}(t) \le 0.8 < 1 \tag{28}$$

Therefore $(1-\rho\kappa) \in [0.2, 1]$, implying:

$$h_{\mathrm{stab}}(t+1) = (1-\rho\kappa)h_{\mathrm{net}}(t) < h_{\mathrm{net}}(t) \tag{29}$$

strictly decreasing. □

C Proof of Theorem 3: Early Warning Time

Suppose r_t^2 jumps from baseline $\mathbb{E}[r_t^2] = \sigma_0^2$ (for $t < t_0$) to elevated $\mathbb{E}[r_t^2] = \sigma_1^2$ (for $t \ge t_0$).

For $t \ge t_0$, the expected EWMA evolves:

$$\mathbb{E}[v_{t_0+\Delta}] = \sigma_1^2(1-(1-\alpha)^\Delta) + \sigma_0^2(1-\alpha)^\Delta \tag{30}$$

We seek Δ^* such that $\mathbb{E}[v_{t_0+\Delta^*}] = \theta = \theta_{\mathrm{mult}}\sigma_0^2$:

$$\begin{aligned}\sigma_1^2(1-(1-\alpha)^{\Delta^*}) + \sigma_0^2(1-\alpha)^{\Delta^*} \\ = \theta_{\mathrm{mult}}\sigma_0^2 \qquad (31)\end{aligned}$$

Rearranging:

$$(\sigma_1^2 - \sigma_0^2)(1-(1-\alpha)^{\Delta^*}) = (\theta_{\mathrm{mult}} - 1)\sigma_0^2 \tag{32}$$

$$(1-\alpha)^{\Delta^*} = \frac{\sigma_1^2 - \theta_{\mathrm{mult}}\sigma_0^2}{\sigma_1^2 - \sigma_0^2} \tag{33}$$

Taking logarithm:

$$\Delta^* = \frac{\ln\left(\frac{\sigma_1^2 - \theta_{\mathrm{mult}}\sigma_0^2}{\sigma_1^2 - \sigma_0^2}\right)}{\ln(1-\alpha)} \tag{34}$$

For $\alpha = 0.15$, $\ln(1-\alpha) \approx -0.163$. With $\theta_{\mathrm{mult}} = 1.5$ and typical variance inflation $\sigma_1^2/\sigma_0^2 \in [2,4]$:

Case 1: $\sigma_1^2 = 2\sigma_0^2$:

$$\Delta^* = \frac{\ln(0.5)}{\ln(0.85)} \approx \frac{-0.693}{-0.163} \approx 4.3 \text{ turns} \tag{35}$$

Case 2: $\sigma_1^2 = 4\sigma_0^2$:

$$\Delta^* = \frac{\ln(0.83)}{\ln(0.85)} \approx \frac{-0.186}{-0.163} \approx 1.1 \text{ turns} \tag{36}$$

Thus $\Delta^* \in [1,5]$ turns for typical variance inflations, providing 3–5 turn early warning. □

D Supplementary Figures

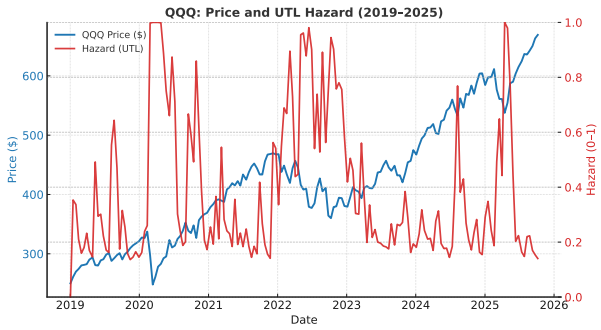

Figure 9: QQQ: Price and UTL hazard overlay (2019–2025)

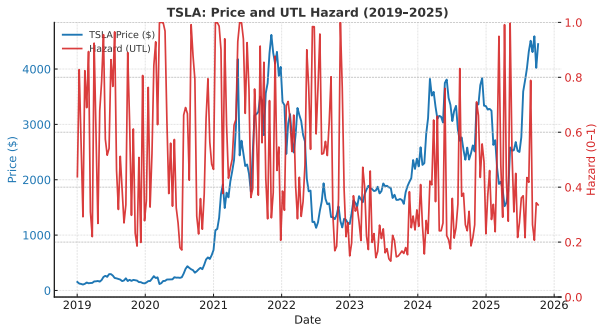

Figure 10: TSLA: Price and UTL hazard overlay (2019–2025)

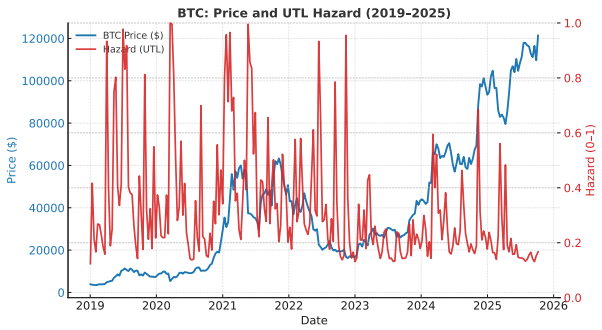

Figure 11: BTC: Price and UTL hazard overlay (2019–2025)

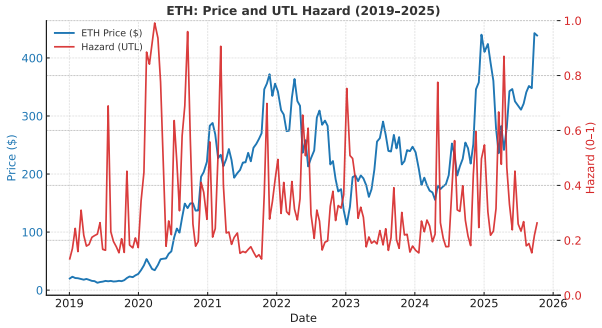

Figure 12: ETH: Price and UTL hazard overlay (2019–2025)

A Feature Engineering Details

This appendix provides explicit formulas for all 24 features mentioned in §4.2. Notation: t = current turn, u_t = user message at turn t, $L(u_t)$ = set of tokens in u_t.

A.1 Linguistic Markers (8 features)

1. Suicidal keywords (x_1):

$$x_1(t) = |\{w \in L(u_t) : w \in \mathcal{K}_{\text{suicide}}\}| \tag{37}$$

where $\mathcal{K}_{\text{suicide}}$ = {"kill myself", "suicide", "end my life", "want to die", ...} (150 terms, full lexicon at github.com/bsabljic/utl-framework/lexicon.json).

2. Method inquiries (x_2):

$$x_2(t) = \mathbb{I}\{\text{"how to"} \in L(u_t) \wedge \exists w \in \mathcal{M} : w \in L(u_t)\} \tag{38}$$

where $\mathcal{M}$ = {"pills", "rope", "gun", "jump", "cut", ...} (32 method nouns).

3. Hopelessness score (x_3):

$$x_3(t) = \frac{\sum_{w \in L(u_t)} \text{LIWC}_{\text{negemo}}(w)}{|L(u_t)|} \tag{39}$$

where $\text{LIWC}_{\text{negemo}}(w) = 1$ if w in LIWC negative emotion dictionary [**?**], else 0.

4. Finality language (x_4):

$$x_4(t) = |\{p \in \mathcal{P}_{\text{final}} : p \subseteq L(u_t)\}| \tag{40}$$

where $\mathcal{P}_{\text{final}}$ = {"goodbye", "last time", "won't see you again", "take care", ...} (24 phrases).

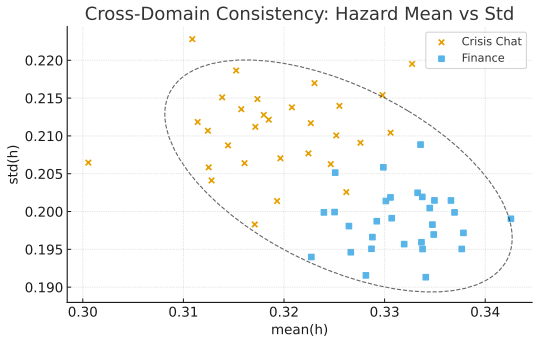

Figure 13: Cross-domain consistency: Hazard mean vs. std across Crisis Chat and Financial domains. Points cluster tightly, indicating universal risk dynamics.

5. Isolation markers (x_5):

$$x_5(t) = |\{w \in L(u_t) : w \in \mathcal{K}_{\text{lonely}}\}| \tag{41}$$

where $\mathcal{K}_{\text{lonely}} = \{$"alone", "nobody cares", "isolated", "no friends", ...$\}$ (18 terms).

6. Self-harm verbs (x_6): Count first-person harm intentions: "I will hurt", "I'm going to cut", "I want to harm".

7. Temporal urgency (x_7):

$$x_7(t) = \mathbb{I}\Big\{\exists w \in \{\text{"tonight"}, \text{"right now"}, \text{"today"}, \text{"soon"}\} : w \in L(u_t)\Big\} \tag{42}$$

8. Help rejection (x_8): Count refusals: "no", "won't work", "tried that", "can't help".

A.2 Behavioral Markers (5 features)

9. Turn count (x_9):

$$x_9(t) = t \tag{43}$$

10. Response latency (x_{10}):

$$x_{10}(t) = \frac{1}{t-1}\sum_{s=2}^{t}(\text{timestamp}_s - \text{timestamp}_{s-1}) \tag{44}$$

Average seconds between turns. Short latency indicates impulsivity.

11. Topic fixation (x_{11}):

$$x_{11}(t) = \frac{1}{t-1}\sum_{s=2}^{t}\cos(\mathbf{v}_s, \mathbf{v}_{s-1}) \tag{45}$$

where $\mathbf{v}_s$ = TF-IDF vector of turn s. High cosine similarity indicates perseveration.

12. Disclosure depth (x_{12}):

$$x_{12}(t) = |L(u_t)| \tag{46}$$

Word count. Longer turns indicate deeper disclosure.

13. Escalation rate (x_{13}):

$$x_{13}(t) = \frac{h(t) - h(t-5)}{5} \tag{47}$$

Slope of hazard over last 5 turns. Positive indicates worsening.

A.3 Temporal Markers (3 features)

14. Time of day (x_{14}):

$$x_{14}(t) = \text{hour}(\text{timestamp}_t) \in \{0, 1, ..., 23\} \tag{48}$$

Risk peaks 3am–6am [**?**].

15. Day of week (x_{15}):

$$x_{15}(t) = \mathbb{I}\{\text{weekday}(\text{timestamp}_t) \in \{\text{Sat}, \text{Sun}\}\} \tag{49}$$

16. Session duration (x_{16}):

$$x_{16}(t) = \text{timestamp}_t - \text{timestamp}_1 \tag{50}$$

Total elapsed time (minutes).

A.4 Protective Factors (6 features)

17. Social support (x_{17}): Count support references: "talking to friend helped", "family is here", "therapist said".

18. Future-oriented language (x_{18}): Count future plans: "I have plans next week", "looking forward to", "tomorrow I will".

19. Coping statements (x_{19}): Count coping mechanisms: "trying meditation", "went for a walk", "listening to music".

20. Help-seeking (x_{20}): Count resource requests: "can you recommend", "where can I get help", "who should I call".

21. Reasons for living (x_{21}): Count protective factors: "my kids need me", "I have responsibilities", "people depend on me".

22. Positive emotion (x_{22}):

$$x_{22}(t) = \frac{\sum_{w \in L(u_t)} \text{LIWC}_{\text{posemo}}(w)}{|L(u_t)|} \tag{51}$$

A.5 Risk Signal Construction

Aggregate into instantaneous risk signal:

$$r_t^{\text{mental}} = \sum_{i=1}^{24} w_i \cdot x_i(t) \tag{52}$$

where weights $\mathbf{w} \in \mathbb{R}^{24}$ learned via Cox partial likelihood (§3.1.1).

All features standardized (z-score normalization) before modeling:

$$x_i^{\text{std}}(t) = \frac{x_i(t) - \mu_i}{\sigma_i} \tag{53}$$

where μ_i, σ_i computed on training set.