TruCrisisAware: Integrating Naturalistic Decision Making into AI for Enhanced Disaster Response

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Abstract. In high-stakes disaster scenarios, timely, context-aware decisions are essential for survival. Traditional AI systems deliver speed and scale but often lack the intuitive reasoning and adaptive cognition exhibited by human experts. This study presents TruCrisisAware, a mobile AI framework grounded in Dual-Process Theory (DPT) and the Recognition-Primed Decision (RPD) model. By combining heuristic (System 1) and deliberative (System 2) reasoning, and dynamically switching between them based on situational demands and inferred user trust, the system emulates expert decision-making under uncertainty.

Implemented as a smartphone app, TruCrisisAware fuses sensor data (e.g., smoke, heat, visual obstruction) with triangulated positioning to provide real-time evacuation guidance. The decision engine is trained via imitation and reinforcement learning. Six simulated fire scenarios in Unity ML-Agents evaluate the system on Task Success Rate (TSR), Route Optimality (RO), Decision Robustness (DR), and Trust Calibration Index (TCI).

Results show that TruCrisisAware outperforms single-mode agents, maintaining high performance and trust alignment under complex conditions. The system offers a human-centered decision support model that bridges speed and cognition to enhance safety, coordination, and resilience in disaster contexts.

Keywords: Dual-Process Theory, Naturalistic Decision Making, Recognition-Primed Decision, Disaster Response, Cognitive Architecture, Human–AI Trust, Imitation Learning, Reinforcement Learning, Sensor Fusion

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1 Introduction

Natural disasters demand decisions made in seconds under incomplete information. Conventional AI systems struggle to support human reasoning under such uncertainty. This paper proposes TruCrisisAware, an AI framework designed to replicate not just the outputs but the processes of expert decision-making, inspired by Dual-Process Theory (DPT) and Naturalistic Decision Making (NDM) frameworks.

NDM—especially as captured in the Recognition-Primed Decision (RPD) model—suggests that experts often operate not through exhaustive deliberation but through pattern recognition informed by experience. This intuition corresponds closely to System 1 thinking. However, when situations become novel or uncertain, System 2 analytical reasoning is required.

By architecturally separating fast, experience-driven inference (System 1) from slower, reflective planning (System 2), TruCrisisAware mirrors the dual-process structure underlying NDM. Imitation learning (IL) is used to train System 1 from expert demonstrations, while reinforcement learning (RL) enables System 2 to simulate deliberative path planning. A cognitive arbitration module governs switching between systems, balancing efficiency with robustness.

This structure allows AI to emulate how humans toggle between automaticity and deliberation under stress—making it more than reactive automation, but a cognitively coherent teammate.

2 Related Works

2.1 Cognitive Psychology in AI for Disaster Decision-Making

Cognitive psychology has significantly informed AI models for disaster response, particularly under uncertainty and time pressure. Dual-Process Theory (DPT) distinguishes between intuitive (System 1) and analytical (System 2) reasoning, offering a useful scaffold for hybrid AI architectures. Papaioannou et al. [1] applied this dual-process model in disaster planning, enabling dynamic shifts between heuristic and deliberative reasoning.

In parallel, Naturalistic Decision Making (NDM) and its Recognition-Primed Decision (RPD) model emphasize expert intuition driven by pattern recognition. Yang et al. [2] developed a D-RPD agent for flood evacuation, showing that contextual recall improves decision reliability. Data-driven techniques such as imitation learning (IL) and reinforcement learning (RL) complement these symbolic approaches. Seo and Unhelkar [3], for instance, used IL to infer latent human intent, enabling agents to adapt under uncertainty. These approaches collectively support cognitively grounded AI for crisis scenarios.

2.2 Human–AI Teaming and Cognitive Alignment

Effective disaster response increasingly involves human–AI collaboration, where cognitive alignment becomes a key determinant of trust and coordination. Shared mental models, transparent decision logic, and adaptive autonomy are vital to ensuring that AI agents operate compatibly with human users. Interpretability is especially critical: AI-generated suggestions must be explainable in human-understandable terms to foster compliance and mutual trust [4].

Fan et al. [5] demonstrated that AI systems guided by NDM principles, such as the R-CAST framework, can reduce cognitive load and enhance team coordination during high-pressure tasks. Such systems do not merely improve accuracy but foster resilience—maintaining performance under stress, uncertainty, and limited communication. Achieving this requires cognitive compatibility between the AI's internal reasoning and the human's expectations and constraints.

2.3 Operational Systems and Cognitive Fidelity

Operational AI systems such as Google's Flood Forecasting Initiative and UNESCO's disaster chatbot exemplify large-scale deployments in disaster contexts [6][7][8]. While these systems offer real-time, high-accuracy predictions and communication, recent critiques have noted a gap in cognitive fidelity—the extent to which AI reasoning mirrors human mental processes. The lack of interpretability in black-box models can undermine trust, especially in life-critical applications.

To address this, researchers are calling for metrics beyond accuracy: user trust, understandability, and decision uptake. Cognitive alignment—ensuring the AI reasons in ways compatible with human experts—is becoming a priority in system design. Moving forward, bridging the gap between predictive power and cognitive plausibility will be key to trustworthy disaster AI.

3 Preliminaries and Problem Formulation

3.1 Preliminaries and TruCrisisAware Framework

This study investigates cognitively aligned AI decision-making under fire evacuation conditions using a smart-agent-based mobile application. In controlled lab simulations, participants operated within evolving emergency scenarios, receiving real-time guidance from an AI assistant deployed on their smartphones. All experiments were implemented in the Unity ML-Agents environment, which combines a high-fidelity 3D simulation engine with deep reinforcement learning (RL) and imitation learning (IL) capabilities.

Compared to platforms such as GAMA [9][10], which specialize in GIS-based modeling, Unity ML-Agents offers (1) realistic physical interaction modeling, (2) immersive 3D visualization, and (3) seamless integration with major deep learning frameworks (e.g., TensorFlow, PyTorch). Based on this foundation, we designed a modular fire simulation system composed of the following components:

- **Scene Configuration Module:**
  - Includes six predefined floorplans: A, B, C (baseline), and A′, B′, C′ (complex variants) as shown in Fig. 1.
- **Fire Simulation Engine:**
  - **Ignition source:** Located at fixed or randomly assigned coordinates.
  - **Flame Generation:** Defined by temperature and spatial coordinates (x, y); complex propagation factors such as wind are beyond this study's scope.

- **Obstruction Modeling:** Smoke or debris zones placed at pre-defined or randomized locations.

- **TruCrisisAware AI agent:**
  - Deployed on user smartphones, the agent uses sensor fusion to convert environmental inputs (e.g., heat, light, camera-detected obstacles) into decision-relevant signals. Simultaneously, triangulated positioning—enabled via edge-connected base stations—provides location updates. These features support context-sensitive evacuation recommendations. Aggregated sensory and positional data are also relayed to a backend disaster response center to enhance situational awareness.

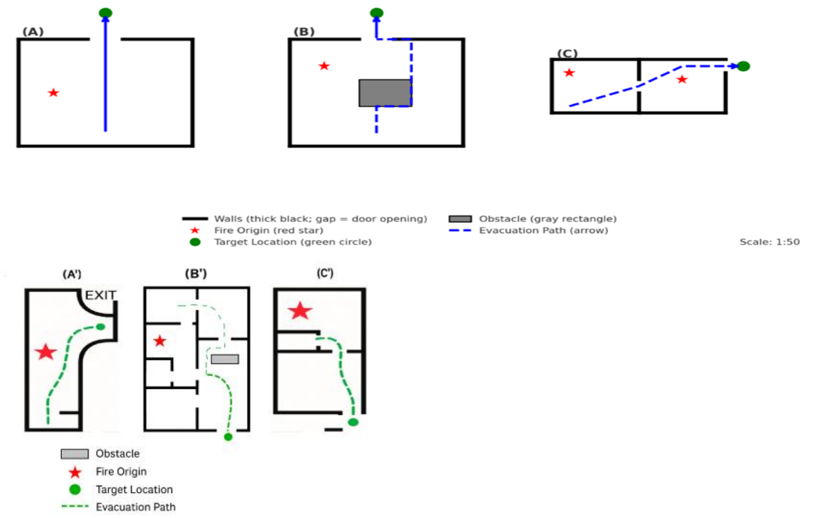

Fig. 1. Predefined Building Floor Plan

Experimental Design

Task objective --- Evacuation
The core objective is safe evacuation before conditions become life-threatening due to collapse or smoke. The AI must detect user location, interpret hazards, and recommend efficient escape routes.

Dynamic Obstacles
To reflect real-world unpredictability, each scenario includes visual occlusions such as smoke, debris, or conductive standing water (represented in Fig. 1 as gray zones). These add partial observability and reinforce the need for adaptive reasoning.

Time Constraints
Each scenario enforces strict temporal limits—e.g., 3 minutes for small-room escapes; up to 6 minutes for complex layouts—to simulate real-world urgency.

3.2 Problem Formulation

The evacuation task is formalized as a context-aware sequential decision-making problem under uncertainty, where the agent must provide cognitively aligned guidance in dynamic, partially observable environments.
Let:

- $s_t \in S$ denote the system state at time t, including environmental sensor inputs (e.g., heat, obstructions, fire location).
- $a_t \in A$ denote the agent's action at time t, such as directional movement or waypoint transitions.
- $r_t = R(s_t, a_t)$ represent the reward, incentivizing hazard avoidance, time efficiency, and human-compatible decisions.
- $\pi(a_t|s_t;\theta)$ be the agent's policy parameterized by θ, trained using a hybrid of imitation learning (IL) and reinforcement learning (RL).

The learning goal is to find an optimal policy π^*, that maximizes expected cumulative reward over a time horizon T:

$$\pi^* = argmax_\pi E[\sum_{t=0}^{T} r^t \, R(s_t, a_t)] \quad (1)$$

Subject to:

- Location triangulation: $L_t = f_{tri}(signal_1, signal_2,\ signal_3)$
- Environment transition dynamics: $s_{t+1} \sim P(s_{t+1}|s_t, a_t)$, which incorporate layout constraints, static fire zones, and occlusions.
- Cognitive-mode arbitration

$$\pi(a_t|s_t) = \begin{cases} \pi_1(a_t|s_t), if\ \rho(s_t) < \delta \\ \pi_2(a_t|s_t), otherwise \end{cases} \quad (2)$$

where π_1 and π_2 represent System 1 (intuitive) and System 2 (deliberative) policies respectively, and $\rho(s_t)$ denotes cognitive load estimation. It can be re-written as:

$$\pi_t = \ \rho(s_t) \cdot \pi_1 + (1 - p(s_t)) \cdot \pi_2 \quad (3)$$

To guide the investigation, we propose the following research questions (RQs):

- **RQ1**: How does integrating dual-system cognitive mechanisms in TruCrisisAware improve task success rate, route optimality, and decision robustness, compared to System 1 and System 2 baselines under time-constrained fire scenarios?
- **RQ2**: How does task complexity influence users' trust and cognitive load during interaction with TruCrisisAware, and what implications does this have for human–AI collaboration design?
- **RQ3**: What is the effect of environmental uncertainty (e.g., obstacles, smoke) on policy adaptability, and how can reinforcement learning be enhanced to maintain performance in such conditions?
- **RQ4**: Can integrating triangulated positioning and sensor fusion improve both situational awareness and trust calibration for evacuees using TruCrisisAware?

4 Proposed Framework

4.1 System Overview

TruCrisisAware is a cognitively inspired disaster response framework designed to support rapid, context-aware decision-making in dynamic fire evacuation scenarios. Grounded in Dual-Process Theory (DPT) and the Recognition-Primed Decision (RPD) model, it emulates expert reasoning by combining fast, intuitive responses with deliberative planning.

The framework is implemented as a mobile application, enabling real-time deployment on end-user smartphones. It integrates environmental perception, cognitive arbitration, and user-aligned decision feedback, facilitating both local adaptability and centralized coordination.

The complete system architecture, depicted in Figure 2, is composed of five interconnected modules.

4.2 System Components

Sensor fusion and Triangulated Perception
This module collects heterogeneous sensor data—temperature, flame detection, smoke density, and visual obstructions (via infrared or camera-based vision). These signals are fused and triangulated through edge-connected mobile base stations to estimate both the user's current position and the spatial layout of nearby hazards.

Cognitive Engine
The core decision engine integrates dual reasoning systems:

System 1 (Fast/Heuristic Decision Layer)
Trained via imitation learning, this layer produces rapid responses in low-risk or familiar contexts. It prioritizes computational efficiency and reflects intuitive human decision-making patterns.

System 2 (Deliberative Planning Layer)
Based on reinforcement learning, this layer performs forward planning and uncertainty modeling under high-risk or novel conditions. It computes multi-step evacuation policies with consideration for trade-offs and dynamic obstacles.

RPD Pattern Recognition
This subcomponent activates if the situation matches a previously learned situation-action template, allowing immediate, context-sensitive action. Behavioral feedback from user interactions is used to refine recognition models and policy selection:

- Offline Mode: Trajectory feedback is collected as experience replay to retrain System 2.

- Online Mode: Cognitive switching thresholds are adjusted dynamically—e.g., reduced switching to System 2 if the user favors System 1.

Decision Arbitration Module

This module governs dynamic switching between System 1 and System 2. Arbitration is informed by contextual signals including cognitive load estimates, time pressure, system confidence scores, and perceived risk. A soft-gating mechanism balances the tradeoff between speed and deliberation.

Action Suggestion and User Execution

Suggested a_t is presented to the user via app interface. Actual user response a'_t is monitored by device sensors. Divergence $Diff(a_t, a'_t)$ is used to infer trust and compliance:

- **Trajectory Feedback:** Deviations from suggested paths
- **Trust Signal Inference:** Hesitation time, frequency of re-query, and rejection behavior.

These feedback signals serve both:

- **Local Learning**: Adaptive tuning of thresholds and arbitration sensitivity.
- **Global Sharing**: Aggregation of anonymized patterns for backend system optimization.

Disaster Response Center

A backend command center receives aggregated trajectory and trust signals from multiple users, enabling:

- Real-time situational awareness and personnel allocation.
- Updating of global evacuation policies.
- Post-disaster analysis and continual retraining of agent models.

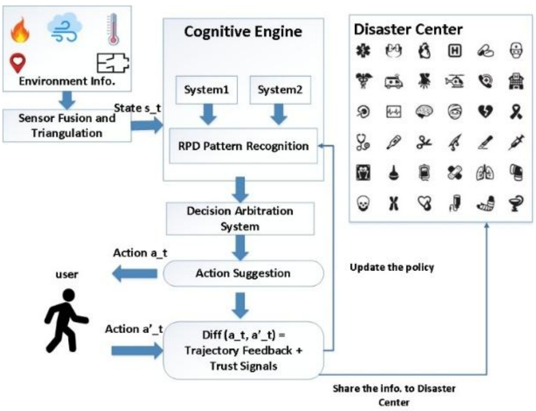

Fig. 2. TruCrisisAware System Diagram

4.3 Summary and Deployment Consideration

The entire framework is lightweight and privacy-preserving, capable of functioning on consumer-grade smartphones with minimal connectivity requirements. Local inference enables immediate recommendations, while edge-cloud integration supports global updates and analytics. By aligning AI behavior with dual-process cognitive principles, TruCrisisAware enhances both decision efficiency and user trust—bridging the gap between algorithmic control and naturalistic human reasoning.

In the next chapter, we detail the experimental design, including simulation setup, agent configurations, and evaluation metrics used to assess TruCrisisAware across six progressively complex fire evacuation scenarios.

5 Experimental Design

To evaluate the cognitive and operational efficacy of the TruCrisisAware system, we designed a controlled simulation-based experiment encompassing realistic fire evacuation scenarios. This chapter outlines the simulation environment, experimental procedures, model configurations, and evaluation metrics used to assess system performance across varying levels of complexity and uncertainty.

5.1 Simulation Environment

Simulations were executed in Unity ML-Agents, leveraging PyTorch for agent learning (IL/RL) and TensorFlow for preprocessing, including sensor fusion and trust modeling. Real-time simulations were run on NVIDIA RTX GPUs to ensure high-speed inference and precise trajectory logging.

The environment consists of six predefined evacuation scenarios derived from three baseline layouts (A, B, C) and their respective complex variants (A', B', C'). Each layout simulates a distinct indoor structure populated with static and dynamic hazards such as smoke, falling debris, blocked exits, and misleading visual cues. Complex versions introduce longer escape paths, additional obstacles, and increased ambiguity, thereby heightening cognitive demands.

Time constraints were scenario-specific, ranging from 3 minutes for simple layouts to 6 minutes for complex ones, reflecting real-world urgency in fire emergencies. Each agent was provided with sensory inputs including temperature, smoke density, obstacle presence, and triangulated positional data to mimic real-time mobile sensing.

5.2 Experimental Procedure

To balance computational tractability with statistical robustness, we adopted a scaled, within-subject experimental design:

- **Agents:** 10 virtual evacuee agents were instantiated.
- **Scenarios:** Each agent was exposed to all six scenarios ($A, A', B, B'\, and\ C, C'$)
- **Trial Repetitions:** Each scenario was run 3 times per agent, with randomized hazard timings and starting points.

This yields: 10 agents x 6 scenarios x 3 runs = **180** simulations. All 180 trials were repeated for System 1, System 2, and TruCrisisAware agents, yielding 540 data points.

5.3 Agent Configurations

Three distinct agent models were evaluated:

- **System 1 Baseline:** A fast, rule-based agent trained via imitation learning on expert demonstrations. It relies on heuristic policy execution with minimal deliberation.
- **System 2 Baseline:** A deliberative planner trained via reinforcement learning, capable of forward search and adaptive behavior but without heuristic shortcuts.
- **TruCrisisAware (Hybrid):** A dual-process agent integrating System 1 and System 2, with dynamic cognitive-mode arbitration and trust calibration mechanisms.

Each model was subjected to identical trials under matched conditions to enable fair comparison.

5.4 Evaluation Metrics

To assess the performance and cognitive alignment of the agents, we employed four metrics—each aligned with our research questions (RQ1–RQ4):

- **Task Success rate (TSR)**

Measures whether the agent successfully guides the evacuee to safety within the time constraint. (↔ RQ1)

$$TSR = {}^{Number\ of\ successful\ evacuations}\!\big/_{Total\ trials} \tag{4}$$

- **Route Optimality (RO)**

Captures navigational efficiency. A higher RO indicates fewer detours and shorter escape paths. (↔ RQ1)

$$RO = {}^{Optimal\ path\ length}\!\big/_{Actual\ path\ length} \tag{5}$$

- **Decision Robustness (DR)**

Quantifies an agent's ability to preserve performance as scenario complexity increases (e.g., A → A′). (↔ RQ1, RQ3)

$$DR = 1 - {}^{|TSR_{base} - TSR_{complex}|}\!\Big/_{TSR_{base}} \tag{6}$$

- **Trust Calibration Index (TCI)**

Assesses whether users appropriately trust the AI's guidance. It is based on a trajectory-wise scoring function that differentiates between:

  - Following correct recommendations (↑ TCI)
  - Rejecting poor recommendations (↑ TCI)
  - Rejecting correct advice (↓ TCI)
  - Following poor advice (↓ TCI)

Let

- a_t: AI-recommended action at time t
- a'_t: actual user action
- $\mathrm{Diff}(a_t, a'_t)$: the normalized divergence between the actions
- $\mathrm{Correct}(a_t) \in \{0, 1\}$: binary correctness flag (AI recommendation: good (1), bad (0)

Define the trust score per step as:

$$\mathrm{f}\big(a_t, a'_t, \mathrm{Correct}(a_t)\big) = \begin{cases} 1 - \mathrm{Diff}(a_t, a'_t), & if\ \mathrm{Correct}(a_t) = 1 \\ \mathrm{Diff}(a_t, a'_t), & if\ \mathrm{Correct}(a_t) = 0 \end{cases} \quad (7)$$

Then compute TCI over a trajectory of length T:

$$\mathrm{TCI} = \frac{1}{T}\sum_{t=1}^{T} f\big(a_t, a'_t, \mathrm{Correct}(a_t)\big) \in [0, 1] \quad (8)$$

TCI is naturally normalized to the [0, 1] range. Instead of using a raw un-normalized metric (e.g., summing trajectory deviations or hesitation durations), we can apply:

$$TCI_{normalized} = \frac{TCI_{raw} - min}{\max - min} \quad (9)$$

These formulations ensures:

- **High TCI** reflects desirable behavior: trusting good advice and rejecting bad advice
- **Low TCI** indicates trust misalignment: such as ignoring safe suggestions or blindly following unsafe ones

TCI is a more nuanced and cognitively grounded metric for evaluating human–AI trust alignment in dynamic and uncertain environments. Fig. 3, the Trust Calibration Quadrants illustrates TCI.

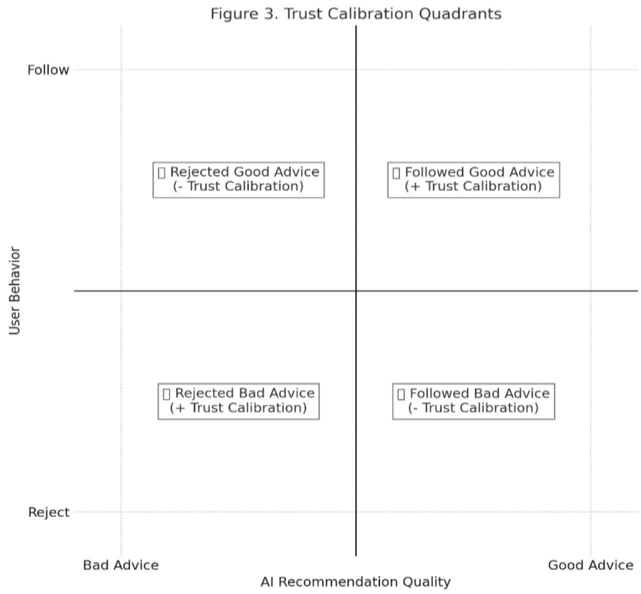

Fig. 3. Trust Calibration Index

This diagram illustrates four possible trust-related outcomes. The horizontal axis categorizes whether the AI's suggested action is *good* (safe, effective) or *bad* (unsafe, suboptimal). The vertical axis reflects whether the user *follows* or *rejects* the recommendation.

- **Top Right (Followed Good Advice)**: The user trusts and follows a correct recommendation, contributing positively to TCI
- **Bottom Left (Rejected Bad Advice):** The user wisely rejects a poor recommendation, also boosting TCI.
- **Top Left (Rejected Good Advice)**: The user under-trusts the AI and rejects a helpful suggestion, lowering TCI.
- **Bottom Right (Followed Bad Advice)**: The user blindly follows a faulty suggestion, resulting in over-trust and reduced TCI.

5.5 Metric RQ Mapping Summary

Table 1. The mapping from matrices to research questions.

Metric	Corresponding Research Question(s)	Purpose and Interpretation
TSR (Task Success Rate)	RQ1	**Task effectiveness under time pressure**
RO (Route Optimality)	RQ1	**Evacuation path efficiency**
DR (Decision Robustness)	RQ1, RQ3	**Resilience under increasing scenario complexity**
TCI (Trust Calibration Index)	RQ2, RQ4	**Trust alignment and response appropriateness**

6 Evaluation and Results

This chapter presents the empirical validation of the TruCrisisAware system under simulated fire evacuation scenarios. We assess how effectively the system integrates cognitive mechanisms to improve task performance, path efficiency, decision robustness, and trust calibration in dynamic, time-constrained environments. These results directly address the research questions outlined in Chapter 3.

6.1 Experimental Summary

Across six evacuation scenarios, 10 agents each completed 3 runs per condition, repeated across three agent types (System 1, System 2, TruCrisisAware), yielding 540 trials. Performance was evaluated using four metrics: Task Success Rate (TSR), Route Optimality (RO), Decision Robustness (DR), and Trust Calibration Index (TCI).

6.2 Task Success Rate (TSR) Analysis

TSR quantifies the proportion of successful evacuations within the time constraints. As shown in Fig. 4, all agents achieved comparable success in base layouts. However, in complex scenarios (A', B', C'), TruCrisisAware consistently outperformed the baselines—exceeding 90% success—while System 1 exhibited significant degradation (e.g., 50% in C'). These findings substantiate **RQ1**, confirming that dual-process integration enhances performance under uncertainty and urgency.

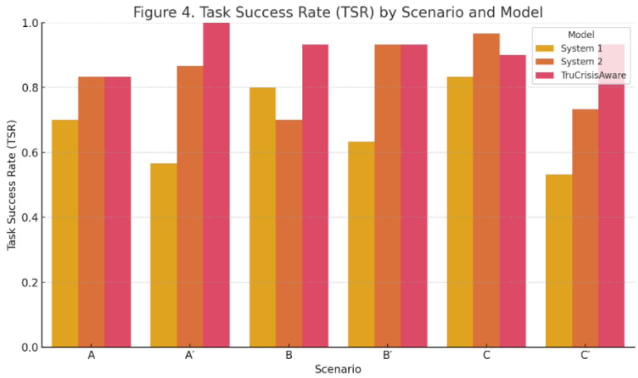

Fig. 4. Task Success Rate (TSR) by Scenario and Model

6.3 Route Optimality (RO) Evaluation

RO measures navigational efficiency as the ratio of optimal to actual path length. Fig. 5 illustrates that TruCrisisAware maintains near-optimal routing across all scenarios. System 2 performed well in base scenarios but struggled slightly with increased complexity due to deliberation latency. System 1 showed inefficient routing in complex layouts, reinforcing the limitations of reactive-only strategies. These results further support **RQ1** regarding quality of escape path planning.

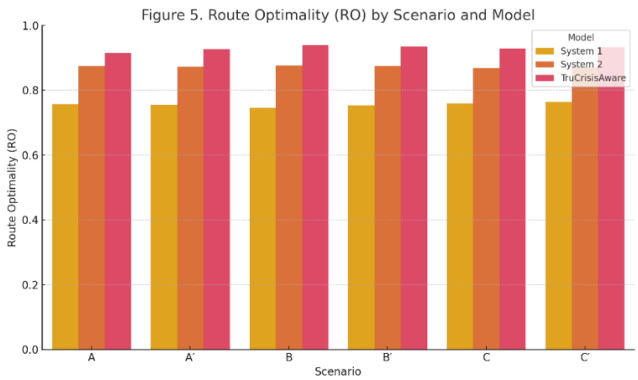

Fig. 5. Route Optimality (RO) by Scenario and Model

6.4 Decision Robustness (DR) Evaluation

DR evaluates resilience to scenario perturbation by measuring TSR preservation between base and complex layouts. As shown in Fig. 6, TruCrisisAware exhibited high robustness (DR > 0.90) across all transitions, indicating stable performance despite increased cognitive demands. System 2 maintained moderate robustness, while System 1 showed the steepest performance decline. These outcomes reinforce **RQ1** and **RQ3**, confirming the hybrid system's ability to adapt under structural uncertainty.

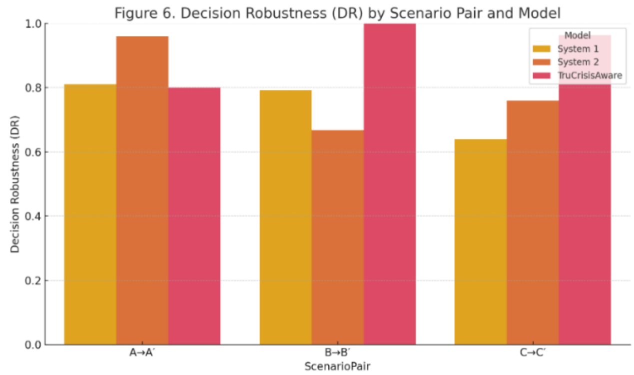

Fig. 6. Decision Robustness (DR) by Scenario and Model

6.5 Trust Calibration Index (TCI) Evaluation

TCI captures the alignment between AI recommendations and user actions, reflecting trust appropriateness. Fig. 7 shows that TruCrisisAware achieved consistently higher TCI, particularly in B′ and C′, where dynamic hazards tested user confidence. System 2 achieved moderate alignment, whereas System 1 produced low TCI due to either over-trust in flawed suggestions or under-trust in valid ones. These results substantiate:

- **RQ2**: Trust is better preserved in cognitively aligned agents as scenario complexity increases.
- **RQ4**: Sensor fusion and triangulated perception enhance situational awareness and recommendation clarity, improving trust calibration.

TCI thus is human-centered metric, validating system's ability to foster reliance in uncertain, high-stakes environments.

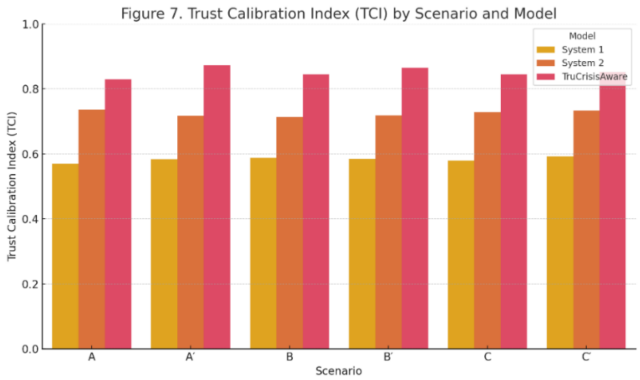

Fig. 7. Trust Calibration Index (TCI) by Scenario and Model

7 Conclusion, Limitations and Future Work

This study introduced TruCrisisAware, a cognitively inspired AI system designed for high-risk evacuation scenarios. Grounded in Dual-Process Theory and the Recognition-Primed Decision model, the system integrates intuitive and deliberative reasoning modes, regulated through a dynamic arbitration mechanism responsive to environmental and behavioral cues.

Empirical evaluation across 540 trials confirmed that TruCrisisAware outperforms single-process agents on four dimensions: task success, route efficiency, decision robustness, and trust calibration. The hybrid model demonstrates that aligning AI reasoning with human cognitive patterns fosters adaptability and maintains user trust under increasing complexity and uncertainty.

Nonetheless, several limitations merit consideration. First, the simulation environment, while realistic, cannot fully emulate real-world variability in human behavior, infrastructure, or sensory noise. Second, the learning models were trained offline, assuming consistent user compliance and optimal feedback, which may not generalize to live deployments.

Future research will extend this work through:

- **Increased realism**, incorporating multi-floor buildings, evolving hazard conditions, and multi-agent coordination.
- **Human-in-the-loop validation**, using mixed-reality trials to evaluate cognitive load and real-time trust.
- **Online learning and adaptation**, enabling dynamic policy updates based on live trajectory and trust feedback.
- **Stress testing cognitive fidelity**, through intentionally ambiguous or deceptive environments to assess system resilience.

By anchoring AI in cognitively valid frameworks, TruCrisisAware moves toward AI systems that are not only technically capable but also psychologically aligned with human users in crisis contexts.

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