

# Artificial intelligence supporting human decision-making in technological crises

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**Abstract:** *Technological crises refer to critical events—system failures and collapses, cybersecurity and data breaches, software meltdowns, critical infrastructure disruptions, etc.—in which the failure, malfunction, or disruption of technological systems creates significant risk to safety, operations, or the environment. These crises typically arise unexpectedly and require rapid, well-informed decision-making under conditions of uncertainty, time pressure, and missing or incomplete information, to prevent escalation. Artificial intelligence (AI) systems have emerged as powerful tools capable of augmenting human judgment in these contexts. This article examines the role of AI in supporting human decision-making during technological crises, analyzing its capabilities, limitations, and implications for organizational resilience. It emphasized that AI is most effective when used as a collaborative partner rather than a replacement for human expertise, and it outlines design principles for trustworthy, human-centered AI systems.*

**Keywords:** ARTIFICIAL INTELLIGENCE, DECISION-MAKING, TECHNOLOGICAL CRISES, CRISIS MANAGEMENT, HUMAN-AI COLLABORATION, SITUATIONAL AWARENESS

## 1. Introduction

Modern societies depend on complex technical systems—energy grids, transportation networks, industrial plants, and digital infrastructures—that are vulnerable to unexpected failures. When crises occur, decision makers must interpret rapidly evolving data, coordinate responses, and mitigate cascading consequences. Yet traditional decision support tools often struggle to keep pace with the scale and speed of contemporary challenges. In this context, artificial intelligence (AI) has become a foundational component of modern decision making, enabling organizations to extract meaningful insights from high-dimensional datasets.

The rapid expansion of data in contemporary organizational environments has transformed the nature of decision-making, requiring advanced analytical tools capable of identifying trends, patterns, and actionable insights. Artificial intelligence has emerged as a critical enabler of data-driven decision processes, offering capabilities that surpass traditional analytical methods in scale, speed, and complexity.

This article examines the role of AI tools—including machine learning, natural language processing, deep learning, and business intelligence systems—in enhancing organizational decision-making. Particular emphasis is placed on the application of AI in technical crisis situations, where human decision-makers face extreme time pressure, uncertainty, and information overload. In such contexts, AI supports human cognition by improving situational awareness, detecting early warning signals, accelerating root-cause analysis, and recommending evidence-based response actions. AI systems also reduce cognitive load by filtering noise, prioritizing alerts, and automating routine tasks, thereby minimizing the risk of human error. Furthermore, AI-driven communication tools enhance coordination across teams, while post-crisis analytical capabilities contribute to organizational learning and resilience. Despite these advantages, the article highlights the importance of maintaining a balanced human-AI partnership, as human judgment remains essential for ethical reasoning, contextual interpretation, and final decision authority. In doing so, the article underscores that sustainable performance emerges not from replacing humans, but from integrating AI in ways that elevate human insight. Overall, the integration of AI into decision-making processes—especially during technical crises—strengthens organizational responsiveness, accuracy, and strategic foresight, positioning AI as a foundational component of modern decision support systems.

## 2. AI in High-Pressure Decision Environment

The integration of artificial intelligence into organizational decision processes has been widely examined across domains such as emergency management, cybersecurity, industrial operations, and critical infrastructure protection. Existing research highlights that

AI excels in environments characterized by high data volume, rapid change, and the need for predictive insight—conditions that closely mirror technological crisis scenarios. In such contexts, decision makers must process heterogeneous information streams, ranging from sensor data and system logs to human reports and external intelligence. Traditional analytical approaches often fail to synthesize these inputs quickly enough to support timely intervention.

AI systems, particularly those based on machine learning and deep learning, offer capabilities that enhance human cognition by identifying latent patterns, forecasting system behaviour, and detecting anomalies that may precede failure. Natural language processing (NLP) tools further expand these capabilities by extracting meaning from unstructured text sources such as incident reports, operator notes, and real-time communications. Together, these technologies form the backbone of modern decision support systems designed for crisis environments.

However, the literature also emphasizes that AI's effectiveness depends on its alignment with human cognitive processes [11], [15], [22]. Research in human-machine teaming suggests that AI should not replace human judgment but rather complement it by providing clarity, reducing uncertainty, and enabling faster comprehension of complex situations. This perspective underscores the need for human-centered AI design principles that prioritize transparency, interpretability, and trust. Scholars further argue that when AI systems are designed with an awareness of human cognitive limits—such as attention constraints and bias tendencies—they become far more reliable partners in high-pressure environments. As a result, effective integration requires not only technical sophistication but also a deep understanding of how humans perceive, reason, and make decisions under stress.

### 2.1. AI Capabilities Relevant to Technological Crisis Management

Technological crises are characterized by complexity, uncertainty, and rapid escalation, often involving tightly coupled systems where failures propagate unpredictably [18]. Human decision makers in such environments face cognitive overload, time pressure, and incomplete information, which can impair judgment and increase the likelihood of error [10], [11].

AI systems have emerged as critical tools for augmenting human cognition in these contexts. Machine learning, natural language processing, and predictive analytics enable organizations to process large volumes of heterogeneous data and detect patterns that would be difficult for humans to identify unaided [9]. From a socio-technical perspective, AI functions as a cognitive extension of human operators, supporting perception, comprehension, and projection—the three pillars of situational awareness [7], [8].

**Human decision making under stress and uncertainty:** In crisis conditions, human cognition is constrained by stress, fatigue, and information overload. Heuristics and intuitive judgments, while sometimes adaptive, can lead to systematic errors such as confirmation bias, tunnel vision, or overconfidence. Traditional decision support tools, which rely on static rules or manual data analysis, are often too slow or rigid to accommodate rapidly evolving situations. This creates a gap between the demands of the environment and the capabilities of human decision makers.

**Early Detection and Anomaly Identification:** AI-driven monitoring systems can detect deviations from normal operational patterns long before they escalate into full-scale crises. Machine learning models trained on historical system behaviour can identify subtle anomalies—such as irregular network traffic, abnormal sensor readings, or unusual equipment vibrations—that may indicate emerging threats. [4]. These early warning signals allow organizations to intervene proactively, reducing the likelihood of catastrophic failure.

**Enhancing Situational Awareness:** During crises, situational awareness deteriorates rapidly as information becomes fragmented and overwhelming. AI systems help reconstruct a coherent operational picture by aggregating data from multiple sources, filtering irrelevant information, and highlighting critical developments. Visualization tools powered by AI can dynamically map system interdependencies, enabling decision makers to understand cascading effects and prioritize response actions. AI-powered visualization systems assist crisis leaders by revealing interdependencies, vulnerabilities, and potential cascading failures across complex infrastructures. [6], [7], [14], [22].

**Accelerating Root Cause Analysis:** Identifying the underlying cause of a technological failure is often time-consuming, especially when multiple subsystems interact in complex ways. AI accelerates this process by analyzing logs, correlating events, and generating hypotheses about potential failure points. In cybersecurity incidents, for example, AI can trace intrusion paths, identify compromised assets, and recommend containment strategies [20].

**Reducing Cognitive Load:** Crisis environments impose significant cognitive strain on human operators. AI mitigates this burden by automating routine tasks, prioritizing alerts, and suppressing false positives. By reducing noise and focusing attention on the most critical issues, AI minimizes the risk of human error and supports more deliberate, informed decision-making. AI reduces cognitive load by filtering noise, clustering alerts, and automating routine tasks—critical in environments where information overload is common [5], [17].

**Decision Recommendation and Scenario Simulation:** Advanced AI models support decision makers by simulating potential response strategies and forecasting their outcomes. These tools evaluate trade-offs, estimate risks, and propose optimal courses of action based on available data. While humans retain final decision authority, AI-generated scenarios help reduce uncertainty and improve the quality of strategic choices. Simulation models and optimization algorithms help evaluate alternative response strategies and forecast outcomes under uncertainty [2], [13].

**Data Integration and Real-Time Monitoring:** AI-enabled monitoring systems can fuse sensor data, logs, and external intelligence into a unified operational picture, improving situational awareness and enabling early detection of anomalies [3], [22].

### 3. Human–AI Collaboration Models in Crisis Management

Effective crisis management requires a clear understanding of how responsibility, autonomy, and oversight are distributed between human decision makers and AI systems. The literature identifies three foundational models—Human-In-the-Loop (HITL), Human-On-the-Loop (HOTL), and Human-Out-of-the-Loop (HOOTL)—which describe different configurations of human–AI interaction (see Fig.1) [5], [21]. These models are particularly relevant in technological crises, where the balance between speed, accuracy, and accountability is critical. Selecting the appropriate model is not merely a technical choice but a strategic one, shaped by the nature of the crisis, the reliability of available data, and the ethical implications of delegating authority to automated systems. Understanding these models helps organizations calibrate AI autonomy in ways that enhance performance without compromising safety or human oversight.

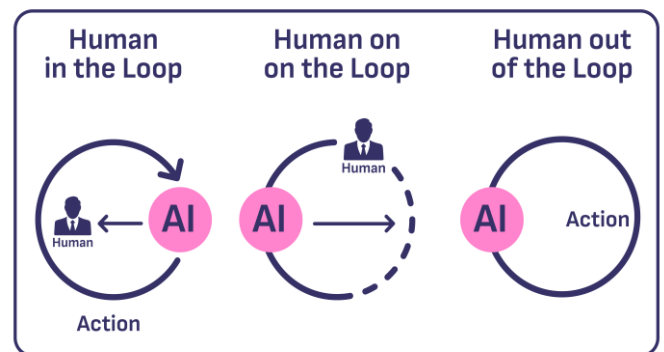


Fig. 1 Three roles of humans in AI systems

#### 3.1 Human-In-the-Loop (HITL): Human as Primary Decision Authority

In the HITL model, humans remain central to all critical decisions. AI systems provide analytical support—such as anomaly detection, risk assessment, or scenario generation—but no action is executed without explicit human approval. This model aligns with research showing that human judgment is essential for contextual interpretation, ethical reasoning, and handling uncertainty [12], [16]. HITL is particularly valuable in ambiguous or ethically sensitive situations where human intuition, moral reasoning, and situational awareness cannot be fully replicated by algorithms. However, this model can introduce delays in fast-moving crises, making it most suitable for environments where accuracy and accountability outweigh the need for immediate action.

#### 3.2 Human-On-the-Loop (HOTL): Human as Supervisor and Intervener

The HOTL model grants AI systems a degree of autonomy to act within predefined boundaries, while humans maintain supervisory control and can intervene when necessary. This model is widely used in high-reliability domains such as aviation, cybersecurity, and industrial automation [5], [7]. HOTL is particularly effective when the speed or volume of data exceeds human cognitive capacity, but oversight remains essential to prevent automation surprises. By allowing AI to manage routine or time-critical tasks, HOTL reduces cognitive load and frees human operators to focus on strategic decision making. Yet, this model also requires robust interface design and clear alerting mechanisms to ensure that humans can re-enter the decision loop quickly and effectively when anomalies occur.

### 3.3 Human-Out-of-the-Loop (HOOTL): AI as Autonomous Decision Maker

In the HOOTL model, AI systems operate independently without real-time human involvement. This model is used in environments requiring millisecond-level responses, such as autonomous shutdown systems, intrusion prevention systems, or industrial safety controls [1]. However, HOOTL raises concerns about accountability, transparency, and the potential for cascading failures if the AI misinterprets a situation [19]. While full autonomy can dramatically increase operational speed and reduce human error in highly structured environments, it also concentrates decision authority in systems that may lack contextual understanding or the ability to adapt to novel conditions. Consequently, HOOTL is most appropriate only when system behaviour is well-defined, risks are tightly controlled, and fail-safe mechanisms are rigorously tested.

**Table 1: AI–Human Collaboration in High-Pressure Decision Environments**

Dimension	Human Strengths	AI Strengths	Collaborative Advantage
Information Processing	Interprets ambiguity; applies contextual judgement	Processes large, heterogeneous data streams rapidly	Improved situational awareness under time pressure
Pattern Recognition	Experience-based intuition	Detects latent patterns, anomalies, correlations	Earlier detection of failures or emerging threats
Decision Speed & Accuracy	Ethical reasoning; ensures accountability	Provides rapid computation, forecasting, and scenario evaluations	Timely, well-informed decisions in crisis conditions
Adaptability	Creative problem-solving; improvisation	Consistent monitoring; scalable analysis	Resilient response among dynamic and evolving crises
Communication & Interpretation	Negotiations; stakeholder coordination	NLP-based extraction from unstructured reports and logs	Reduced cognitive load; clearer information flow
Autonomy Models (HITL/HOTL/HOOTL)	Oversight; value-based judgment	Automation of routine or time-critical tasks	Balanced autonomy, safety, and accountability

Table 1 outlines the complementary roles of humans and artificial intelligence in high-pressure decision environments, emphasizing how their distinct strengths can be integrated to enhance overall performance. Humans contribute contextual judgment, ethical reasoning, improvisation, and interpersonal communication—capabilities that remain essential when dealing with ambiguity, value-laden choices, and complex stakeholder dynamics. In contrast, AI systems excel at rapid data processing, large-scale pattern detection, continuous monitoring, and automated execution of routine or time-critical tasks.

When combined, these strengths create a collaborative advantage across several dimensions. Joint information processing improves situational awareness by merging human contextual insight with AI's ability to analyze heterogeneous data streams. Pattern recognition benefits from both human intuition and AI's capacity to detect latent anomalies, enabling earlier identification of emerging

risks. Decision-making becomes faster and more accurate when human accountability and ethical oversight are paired with AI-driven forecasting and scenario evaluation. Collaboration also enhances adaptability: human creativity complements AI's consistent, scalable analysis to support resilient responses in dynamic crises.

Finally, communication and autonomy models benefit from this partnership. Human negotiation and coordination skills are reinforced by AI's natural-language processing capabilities, reducing cognitive load and improving information flow. Across different configurations—human-in-the-loop, human-on-the-loop, and human-out-of-the-loop—balanced integration ensures safety, accountability, and effective task allocation. Overall, the table highlights that optimal performance in high-pressure environments emerges not from replacing human decision-makers, but from designing systems that strategically combine human judgment with AI's computational strengths.

## 4. Conclusion

Technological crises expose the limits of human cognition and traditional decision support tools, demanding rapid, informed action under uncertainty and time pressure. Artificial intelligence offers a powerful set of capabilities that can substantially enhance crisis management: augmenting situational awareness, identifying weak signals and emergent anomalies, accelerating diagnostic processes, and structuring high-dimensional decision spaces in ways that exceed unaided human capacity. Yet its greatest value emerges not when it replaces human judgment, but when it functions as a collaborative partner embedded within socio-technical systems.

Realizing this potential requires organizations to confront the limitations and risks inherent in AI systems. Issues such as data bias, model opacity, overreliance on automated outputs, and susceptibility to adversarial manipulation can undermine trust and compromise crisis response. Addressing these vulnerabilities demands sustained investment in human-centered design, transparent model development, rigorous validation, and governance structures that promote calibrated trust rather than blind dependence. Equally important is cultivating a workforce capable of understanding AI's strengths and constraints, ensuring that human operators remain empowered to question, interpret, and override automated recommendations when necessary.

Future research should advance theoretical and empirical understanding of adaptive human–AI collaboration models capable of evolving dynamically as crises unfold. Promising directions include the development of AI systems that support cross-domain transfer of crisis knowledge, the integration of AI with emerging infrastructures such as digital twins, distributed sensing networks, and edge computing architectures, and the exploration of hybrid intelligence frameworks that combine machine learning with human expertise, institutional memory, and contextual reasoning. Such efforts must be accompanied by interdisciplinary inquiry into the organizational, legal, and ethical implications of AI-mediated crisis response.

By aligning AI capabilities with human expertise, institutional processes, and robust governance mechanisms, organizations can enhance systemic resilience, mitigate the impacts of technological disruptions, and navigate an increasingly complex risk landscape with greater foresight, adaptability, and confidence. Ultimately, the future of crisis management will depend not on the ascendancy of autonomous systems, but on the deliberate design of socio-technical ecosystems in which humans and AI function as mutually reinforcing partners.

## 5. Literature

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