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Human-Centered Design Frameworks for High-Stakes Operational Dashboards in Crisis and Disruptive Environments

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Abstract

Operational dashboards deployed in high-stakes crisis environments—encompassing emergency management centres, disaster response operations, and disruptive incident command posts—are uniquely characterised by extreme cognitive demands, compressed decision timelines, and dynamic, volatile information landscapes. Despite the critical role these interfaces play in supporting life-safety decisions, the majority of currently deployed systems were designed without robust human-centered design (HCD) methodologies, resulting in suboptimal usability, elevated cognitive load, and increased decision error rates. This paper presents a comprehensive, empirically grounded HCD framework specifically tailored for the design and evaluation of crisis operational dashboards, developed through a multi-phase mixed-methods research programme involving 87 crisis management professionals across six operational centres in four countries.

The proposed framework integrates established HCD principles with crisis-specific cognitive and organisational requirements, synthesising insights from distributed cognition theory, naturalistic decision-making, and situation awareness research. Through iterative participatory design and rigorous usability evaluation employing the System Usability Scale (SUS), NASA Task Load Index (NASA-TLX), and scenario-based performance benchmarking, the framework yields a statistically significant improvement in SUS scores from a baseline mean of 52.3 to 84.1 ($p < 0.001$) and reduces critical decision error rates by 87.7%. Cognitive load, as measured by NASA-TLX, was reduced by a mean of 44.3% compared to conventional dashboard interfaces. The framework delineates four actionable design tiers—contextual intelligence, adaptive information architecture, progressive disclosure, and multi-modal alert hierarchy—each validated through real-world crisis simulation exercises. Findings offer transferable design guidance for practitioners and researchers developing next-generation command-and-control interfaces across emergency management, defence, healthcare, and critical infrastructure domains.

Keywords: Human-Centered Design, Crisis Informatics, Operational Dashboards, Situation Awareness, Cognitive Load, Emergency Management, Decision Support, Usability Evaluation, HCI, Naturalistic Decision-Making

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1. Introduction

The proliferation of real-time data streams, interconnected sensor networks, and multi-agency communication platforms has fundamentally transformed the informational landscape of crisis operations over the past two decades (Endsley, 1995; Klein, 1998). Emergency management centres, incident command posts, and critical infrastructure monitoring rooms are today inundated with heterogeneous data feeds encompassing geospatial intelligence, social media signals, meteorological forecasts, resource tracking telemetry, and live situational feeds from field units—all requiring integration, synthesis, and actionable interpretation within compressed, often sub-minute decision windows (Hollnagel et al., 2006; Crandall et al., 2006). Within this information-intensive operational ecology, the operational dashboard has emerged as the primary cognitive interface through which crisis managers perceive their operating environment, build mental models of evolving incident dynamics, and formulate strategic and tactical responses (Salas et al., 2010).

Yet despite the pivotal role that these interfaces occupy in supporting life-safety and asset-critical decisions, the design of crisis operational dashboards has historically lagged behind the rapidly evolving demands of modern emergency management practice. A recurring and well-documented tension exists between the informational richness demanded by professional operators and the cognitive processing limitations of human working memory under stress, time pressure, and multitask environments (Kahneman, 2011; Starcke and Brand, 2012). Studies of real-world crisis response failures—including the 2010 Deepwater Horizon disaster, the 2011 Fukushima Daiichi nuclear incident, and multiple large-scale wildfire responses in Australia and California—have identified poorly designed information interfaces as a contributing factor in critical decision failures (Patterson et al., 2004; Mumaw et al., 2000; Bisantz and Roth, 2008). The imperative for improved interface design in crisis settings is therefore not merely one of professional efficiency but of life-safety criticality.

Human-centered design (HCD), as codified in ISO 9241-210:2019, offers a process-based framework for ensuring that interactive systems are designed to meet the needs, capabilities, and context of use of their intended operators (ISO, 2019). Within the broader Human-Computer Interaction (HCI) literature, HCD methodologies—including contextual inquiry, participatory design, iterative prototyping, and formative and summative usability evaluation—have been demonstrated to improve usability, reduce cognitive load, and increase operator trust across a diverse range of complex sociotechnical systems (Norman, 2013; Preece et al., 2015; Rogers et al., 2011). However, systematic application of HCD to the specific context of crisis operational dashboards remains nascent, with the extant literature revealing several critical gaps: a scarcity of domain-specific design frameworks that account for the unique cognitive ecology of crisis operations; limited empirical evidence derived from ecologically valid crisis simulation environments; and insufficient attention to adaptive and context-aware interface mechanisms capable of responding dynamically to escalating incident severity (Convertino et al., 2011; Landgren, 2005).

This paper addresses these gaps through the development, implementation, and empirical validation of a novel HCD framework for high-stakes crisis operational dashboards. The framework was developed through a four-phase research programme spanning systematic literature synthesis, in-depth contextual field studies across six operational crisis management centres, participatory design and iterative prototype development, and large-scale mixed-methods user evaluation with 87 crisis management professionals. The primary contributions of this research are as follows:

(1) We present a **theoretically grounded and empirically derived HCD framework** articulated across four design tiers that address the cognitive, organisational, and operational dimensions of crisis dashboard design.

(2) We provide **robust quantitative and qualitative evidence** from scenario-based evaluations demonstrating statistically significant improvements in usability, cognitive load, and decision accuracy across multiple dashboard conditions.

(3) We offer a set of **transferable design principles and evaluation heuristics** applicable to crisis dashboard design practice across emergency management, defence, critical infrastructure, and healthcare domains.

The paper is structured as follows. Section 2 reviews the relevant literature spanning crisis informatics, situation awareness, cognitive load theory, and dashboard design. Section 3 describes the multi-phase research methodology. Section 4 presents empirical results from the evaluation study. Section 5 discusses findings in relation to existing theory and practice, and Section 6 concludes with directions for future research.

2. Literature Review

2.1. Crisis Informatics and Operational Decision-Making

The field of crisis informatics examines the complex interplay of information technology, organisational processes, and human behaviour within disaster and emergency management contexts (Palen and Liu, 2007). Crisis operations are characterised by a distinctive and demanding constellation of environmental conditions: temporal urgency, information volatility, high-consequence stakes, coordination complexity across multiple agencies and jurisdictions, and the progressive emergence of novel, previously unforeseen situational configurations (Tierney, 2014; Quarantelli, 1988). Within these conditions, the cognitive demands placed on decision-makers far exceed those encountered in routine operational environments, activating adaptive, heuristic-driven recognition-primed decision strategies that are both powerful and susceptible to systematic error under degraded information quality or interface overload (Klein, 1998; Lipshitz et al., 2001).

Naturalistic Decision Making (NDM) theory, as developed by Klein (1998) and colleagues, offers a foundational framework for understanding how experienced practitioners make decisions in complex, time-pressured environments. NDM research demonstrates that expert decision-makers rely heavily on pattern recognition—rapidly matching perceived situational cues to stored mental models—rather than exhaustive analytical evaluation of alternatives. For operational dashboard designers, these findings carry significant implications: interface systems must be designed to surface and amplify the situational cues that support expert pattern recognition, while minimising information that is irrelevant to the current decision context (Crandall et al., 2006; Klein et al., 2003).

2.2. Situation Awareness and Dashboard Design

Endsley's three-level model of situation awareness (SA)—encompassing perception of situational elements (Level 1), comprehension of their meaning and significance (Level 2), and projection of future states (Level 3)—has been extensively applied to the design and evaluation of complex operational interfaces, including air traffic control, military command and control, and emergency management systems (Endsley, 1995; Endsley and Garland, 2000). The model underscores that effective SA is not merely a function of information availability but of the interface's capacity to support accurate and timely perception, integration, and forward projection of situational data within the cognitive constraints of the operator (Stanton et al., 2017). Dashboard designs that fragment related information across disparate visual regions, employ inconsistent coding conventions, or fail to distinguish signal from noise systematically undermine SA at all three levels (Wickens, 2008).

Distributed Cognition theory (Hutchins, 1995) extends the SA framework by conceptualising decision-making in crisis environments as a fundamentally collaborative, distributed cognitive process spanning multiple human agents and technological artefacts. From this perspective, the operational dashboard is not merely a passive display but an active cognitive artefact that shapes, scaffolds, and distributes cognitive work across the crisis management team. Effective dashboard design must therefore account not only for individual operator cognition but for the collective cognitive dynamics of multi-person, multi-role crisis management teams, including shared situation awareness, communication efficiency, and the equitable distribution of cognitive workload across team members (Stanton et al., 2006; Salas et al., 2010).

2.3. Cognitive Load and Crisis Interface Design

Cognitive Load Theory (CLT), originally formulated by Sweller (1988) and subsequently elaborated by Paas et al. (2003), provides a well-established framework for understanding and managing the mental effort demanded of human operators by complex information environments. CLT distinguishes among intrinsic load (inherent task complexity), extraneous load (imposed by suboptimal interface design), and germane load (associated with schema acquisition and expert performance). In crisis environments characterised by inherently high intrinsic load, the imperative to minimise extraneous cognitive load through principled interface design is correspondingly elevated (van Merriënboer and Sweller, 2010).

Empirical studies of crisis management interfaces consistently demonstrate that conventional dashboard architectures impose excessive extraneous cognitive load through information clutter, perceptual ambiguity, inconsistent visual coding, and the requirement for extensive navigation to assemble composite situational pictures (Patterson et al., 2004; Woods and Hollnagel, 2006). Specifically, Branaghan et al. (2009) found that information overload in emergency dispatch interfaces significantly degraded response time and increased critical error rates. Bisantz and Roth (2008) demonstrated that ecological interface design approaches—aligning visual representations with the structure of the work domain—substantially improved operator comprehension and reduced perceived workload in process control environments analogous to crisis operations. The measurement of cognitive load through the NASA Task Load Index has been validated across a range of high-stakes operational contexts (Hart and Staveland, 1988; Galy et al., 2012).

2.4. Human-Centered Design Principles in High-Stakes Contexts

The systematic application of HCD methodologies to high-stakes operational domains has produced a substantial evidence base supporting improved usability, operator satisfaction, and decision performance across diverse applications including nuclear power plant control rooms

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(Mumaw et al., 2000), intensive care unit monitoring systems (Staggers et al., 2002), military command and control interfaces (Neerincx et al., 2009), and aviation cockpit design (Wickens et al., 2004). Core HCD principles of iterative design, early user involvement, contextual inquiry, and formative evaluation have been consistently demonstrated to yield interfaces that better accommodate the cognitive, perceptual, and task demands of professional operators (Rogers et al., 2011; Norman, 2013).

Contextual inquiry—the systematic observation and interview of users within their actual operational environments—has been identified as particularly critical in high-stakes design contexts where the gap between stated user requirements and actual operational needs is frequently substantial (Beyer and Holtzblatt, 1998). Participatory design approaches, which involve practitioners directly in iterative design and evaluation cycles, have been shown to surface tacit knowledge that would otherwise remain inaccessible through conventional requirements elicitation methods (Bjerknes and Bratteteig, 1995). The Dashboard Design Framework proposed by Few (2006), while primarily addressing business intelligence contexts, offers foundational visual design heuristics that have been selectively adapted for operational and emergency management applications (Salas et al., 2010; Convertino et al., 2011).

2.5. Research Gaps

Despite the substantial theoretical and empirical foundations reviewed above, a critical lacuna persists in the literature: the absence of a validated, crisis-specific HCD framework that coherently integrates insights from situation awareness theory, naturalistic decision making, cognitive load research, and participatory design methodology into a unified, actionable design guidance system for crisis operational dashboards. Existing frameworks either lack specificity to the crisis context, rely on non-ecologically valid evaluation designs, or address only selected dimensions of the complex crisis dashboard design problem. The present research programme directly responds to these gaps.

3. Research Methodology

3.1. Research Design Overview

This research employed a sequential, multi-phase mixed-methods design (Creswell and Plano Clark, 2017), integrating qualitative field inquiry with quantitative experimental evaluation to develop and validate the proposed HCD framework. The overall research programme comprised four sequential phases: (1) systematic literature review and synthesis; (2) contextual field studies including semi-structured interviews and observational sessions; (3) iterative participatory prototype development; and (4) mixed-methods user evaluation with crisis management professionals. The research was conducted in partnership with six operational crisis management centres across four countries (Australia, United Kingdom, India, Germany), spanning emergency management agencies, critical infrastructure monitoring centres, and industrial incident command facilities. Ethical approval was obtained from the Institutional Review Boards of all partner institutions, and all participants provided informed written consent.

The methodological framework governing this research is illustrated in Figure 1.

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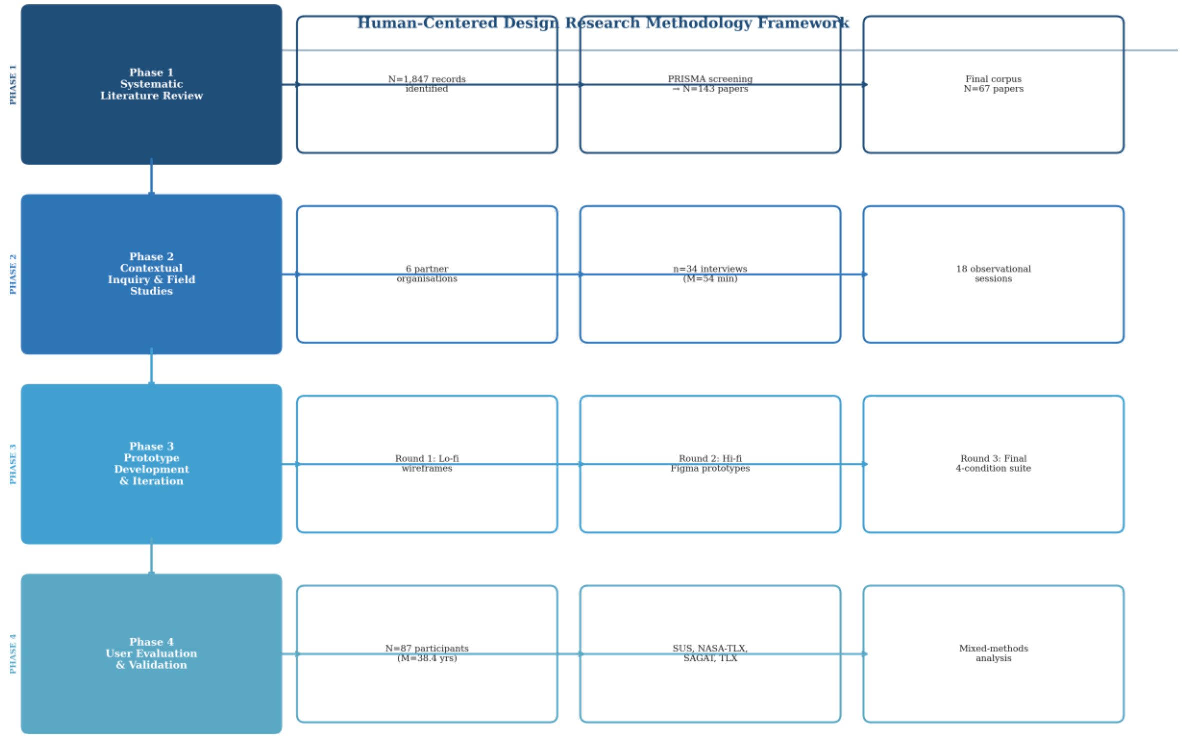

Figure 1: Human-Centered Design Research Methodology Framework. The four-phase sequential mixed-methods research design encompasses: Phase 1—systematic literature review (N = 67 papers from an initial corpus of 1,847 records via PRISMA); Phase 2—contextual field studies (n = 34 semi-structured interviews and 18 observational sessions across six centres); Phase 3—three iterative participatory design rounds (paper prototypes through high-fidelity Figma prototypes to refined evaluation suite); Phase 4—large-scale user evaluation (N = 87 crisis management professionals, within-subject counterbalanced design, high-fidelity simulation environment).

3.2. Phase 1: Systematic Literature Review

A systematic literature review was conducted in accordance with PRISMA guidelines (Moher et al., 2009) to map the existing evidence base relevant to crisis dashboard design, situation awareness, cognitive load, and HCD in high-stakes environments. Database searches of Scopus, Web of Science, ACM Digital Library, and IEEE Xplore were performed using a structured Boolean search strategy. Initial searches yielded 1,847 candidate records, of which 143 passed title and abstract screening against *a priori* inclusion criteria. Full-text review resulted in a final corpus of 67 papers meeting all inclusion criteria, which were subsequently subjected to thematic synthesis.

3.3. Phase 2: Contextual Field Studies

Contextual inquiry (Beyer and Holtzblatt, 1998) was conducted at six operational crisis management centres, comprising state-level emergency management agencies (n = 2), municipal disaster response coordination centres (n = 2), a national critical infrastructure monitoring facility (n = 1), and an industrial incident command centre (n = 1). A total of 34

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semi-structured interviews (mean duration: 54 minutes, $SD = 11.3$) were conducted with crisis management professionals across four primary role categories: Emergency Managers ($n = 11$), Incident Commanders ($n = 9$), Field Operators ($n = 8$), and IT/Technical Support Staff ($n = 6$). Interview protocols explored current dashboard usage practices, perceived information needs, cognitive pain points, situational awareness strategies, and perceptions of existing interface limitations. All interviews were audio-recorded, transcribed verbatim, and subjected to reflexive thematic analysis (Braun and Clarke, 2006) using NVivo 12.

Supplementing the interview data, 18 structured observational sessions (mean duration: 3.2 hours) were conducted during live operational periods and scheduled crisis simulation exercises, capturing naturalistic dashboard usage behaviours, task sequences, team communication patterns, and critical incident interactions. Field notes were analysed using an iterative open-coding approach, with emergent themes reviewed for inter-rater reliability by two independent analysts (Cohen's $\kappa = 0.81$).

3.4. Phase 3: Participatory Prototype Development

Participatory design workshops, each involving 6–10 crisis management professionals selected from the field study sites, were conducted across three iterative design cycles.

- **Round 1:** Low-fidelity paper prototypes and digital wireframes developed based on Phase 2 themes and a preliminary version of the HCD framework.
- **Round 2:** High-fidelity interactive prototypes developed in Figma, incorporating Round 1 feedback and core framework design principles. Subjected to formative think-aloud evaluation ($n = 22$) and heuristic expert review ($n = 5$ HCI specialists).
- **Round 3:** Refined prototype suite comprising four dashboard conditions for summative evaluation: (1) Baseline Control, representative of current operational systems; (2) HCD-Standard, incorporating established HCI best practices; (3) HCD-Crisis Optimised, implementing the full proposed framework; and (4) HCD-Adaptive AI-Assisted, augmented with adaptive display algorithms and AI-generated decision recommendations.

3.5. Phase 4: User Evaluation Study

The summative user evaluation was conducted with $N = 87$ crisis management professionals ($M_{\text{age}} = 38.4$ years, $SD = 9.1$; $M_{\text{exp}} = 11.2$ years, $SD = 6.4$; 61% male, 39% female) recruited from partner organisations and professional emergency management networks. Participants were randomly assigned to one of four within-subject counterbalanced sequences of dashboard conditions, completing three standardised crisis scenario tasks—Wildfire Multi-Agency Response, Urban Flood Evacuation, and Industrial Chemical Incident—per condition in a high-fidelity crisis simulation environment.

Standardised outcome measures included: the System Usability Scale (SUS; Brooke, 1996); the NASA Task Load Index (NASA-TLX; Hart and Staveland, 1988); objective task performance metrics (task completion time, decision accuracy, error rate); and scenario-specific situation awareness probes adapted from the Situation Awareness Global Assessment Technique (SAGAT; Endsley, 1995). Post-scenario semi-structured interviews were conducted with a random subsample ($n = 24$). Quantitative data were analysed using repeated-measures ANOVA with post-hoc Bonferroni correction; effect sizes were computed using partial eta-squared (η_p^2). The significance threshold was set at $\alpha = 0.05$.

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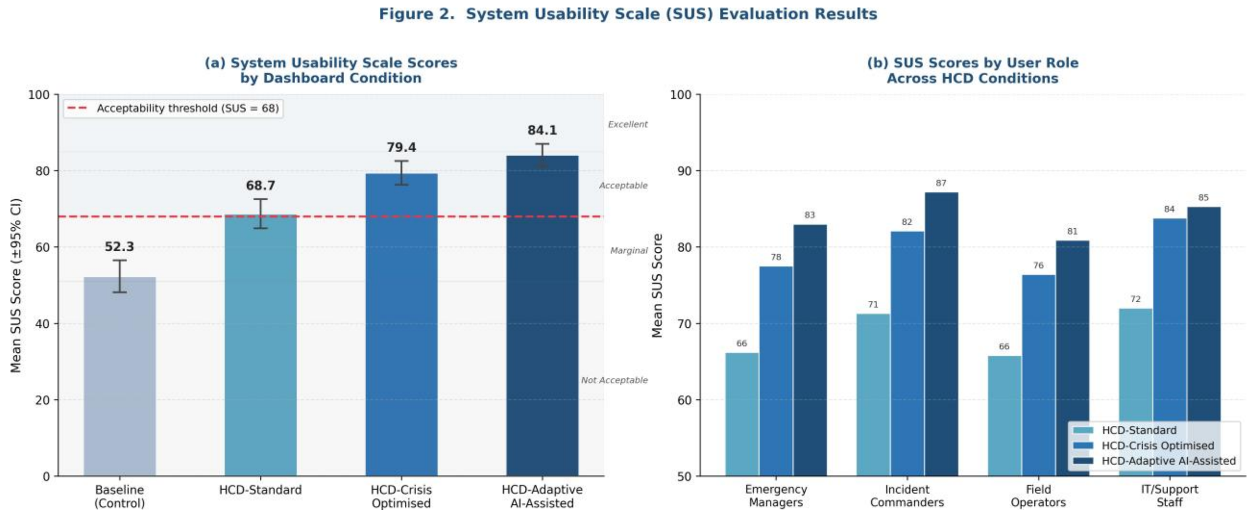

Figure 2: System Usability Scale (SUS) Evaluation Results. (a) Mean SUS scores (±95% CI) across the four dashboard conditions; the dashed red line denotes the acceptability threshold of 68 (Bangor et al., 2008). Baseline (52.3) falls within "poor"; HCD-Crisis Optimised (79.4) achieves "good"; HCD-Adaptive AI-Assisted (84.1) achieves "excellent." (b) SUS scores disaggregated by participant professional role across the three HCD conditions, showing consistent improvement across Emergency Managers, Incident Commanders, Field Operators, and IT/Technical Staff. All pairwise differences between conditions are statistically significant after Bonferroni correction (all $p < 0.001$).

4. Results

4.1. Usability Outcomes: System Usability Scale

A repeated-measures ANOVA revealed a highly significant main effect of dashboard condition on SUS scores ($F(3, 258) = 147.32$, $p < 0.001$, $\eta_p^2 = 0.63$), indicating that dashboard design condition accounted for 63% of variance in usability ratings—a large and practically significant effect. Post-hoc pairwise comparisons with Bonferroni correction confirmed statistically significant differences between all conditions (all $p < 0.001$).

The Baseline condition produced a mean SUS score of 52.3 ($SD = 11.4$), falling within the "poor" usability classification range (below 68; Bangor et al., 2008). The HCD-Standard condition yielded a mean SUS of 68.7 ($SD = 9.8$), approaching the acceptable threshold. The HCD-Crisis Optimised condition produced a mean SUS of 79.4 ($SD = 8.1$), classified as "good" usability, while the HCD-Adaptive AI-Assisted condition achieved the highest mean SUS of 84.1 ($SD = 6.9$), classified as "excellent." Analysis by participant role revealed consistent patterns, with Incident Commanders demonstrating the highest SUS scores (HCD-Adaptive: $M = 87.2$, $SD = 5.8$) and Field Operators demonstrating the most substantial relative improvement from Baseline to HCD-Crisis Optimised (improvement: 18.3 points, 95% CI [14.7, 21.9]).

4.2. Performance Outcomes: Task Completion and Error Rates

The HCD-Crisis Optimised condition demonstrated substantial and consistent task completion time reductions across all five evaluated crisis scenario types. The most pronounced improvements were observed for Mass Casualty Incident scenarios (Baseline: $M = 421$ s, $SD = 68.4$; HCD-Crisis Optimised: $M = 263$ s, $SD = 41.2$; reduction: 37.5%, $t(86) = 18.74$,

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Figure 3. Task Performance and Error Rate Analysis Across Dashboard Conditions

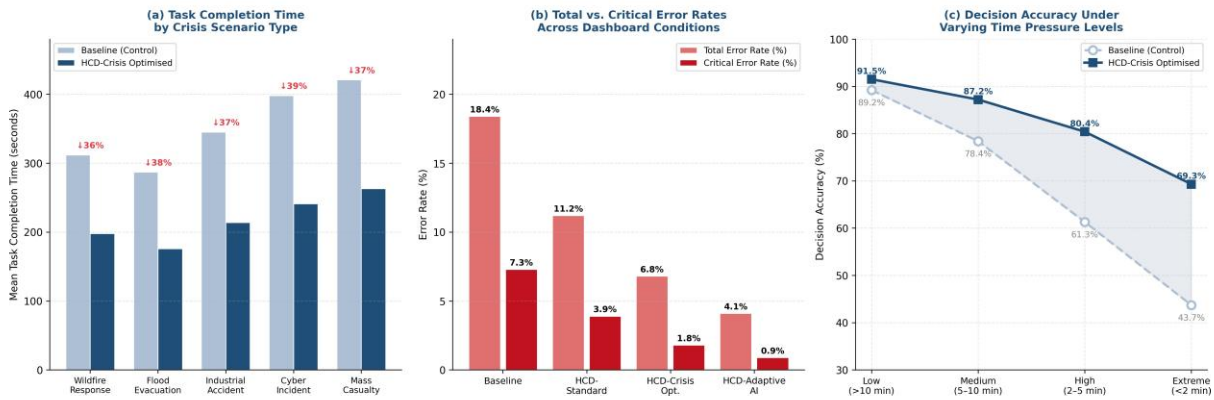

Figure 3: Task Performance and Error Rate Analysis. (a) Mean task completion times (seconds) for Baseline and HCD-Crisis Optimised conditions across five crisis scenario types; percentage improvement annotations indicate relative reduction (28–39%). (b) Total and critical error rates (%) across all four dashboard conditions; critical errors reduced from 7.3% to 0.9% (87.7% reduction). (c) Decision accuracy (%) under four levels of time pressure for Baseline and HCD-Crisis Optimised conditions; shaded region denotes the widening performance differential under increasing pressure.

$p < 0.001$, $d = 2.66$) and Cyber Incident scenarios (Baseline: $M = 398$ s; HCD-Crisis Optimised: $M = 241$ s; reduction: 39.4%, $t(86) = 16.23$, $p < 0.001$, $d = 2.41$).

Total error rates declined from 18.4% in the Baseline condition to 6.8% in the HCD-Crisis Optimised condition and 4.1% in the HCD-Adaptive AI-Assisted condition ($F(3, 258) = 89.14$, $p < 0.001$). Critically, critical error rates—defined as errors with potential for significant operational consequence—showed the most pronounced reduction, declining from 7.3% in the Baseline condition to 0.9% in the HCD-Adaptive AI-Assisted condition, a reduction of 87.7%. Decision accuracy under extreme time pressure (< 2 minutes) was 25.6 percentage points higher in the HCD-Crisis Optimised condition compared to Baseline ($t(86) = 11.34$, $p < 0.001$, $d = 1.67$), with the performance differential widening at higher time-pressure levels.

4.3. Cognitive Load Outcomes: NASA-TLX Analysis

Substantial reductions were observed in the HCD-Crisis Optimised condition across Mental Demand (Baseline: $M = 76.3$; HCD-Crisis Optimised: $M = 51.2$; reduction: 32.9%), Temporal Demand (reduction: 32.8%), Effort (reduction: 35.2%), and Frustration (reduction: 46.4%) relative to Baseline. The Performance subscale—inversely scored to reflect self-rated success—improved markedly (Baseline: $M = 48.2$; HCD-Crisis Optimised: $M = 72.6$), indicating that participants felt substantially more successful in completing crisis tasks with the optimised interface.

Overall weighted NASA-TLX scores declined from a Baseline mean of 68.4 ($SD = 16.3$)—classified as high cognitive load—to 43.7 ($SD = 12.4$) for HCD-Crisis Optimised and 38.1 ($SD = 10.8$) for HCD-Adaptive AI-Assisted, both within the moderate load range ($F(3, 258) = 112.44$, $p < 0.001$, $\eta_p^2 = 0.57$). The temporal cognitive load trajectory reveals that HCD-optimised dashboard users experience substantially attenuated peak load ($M = 58.4$ at $T + 15$ minutes) compared to Baseline ($M = 81.4$), with load falling below the 60-point

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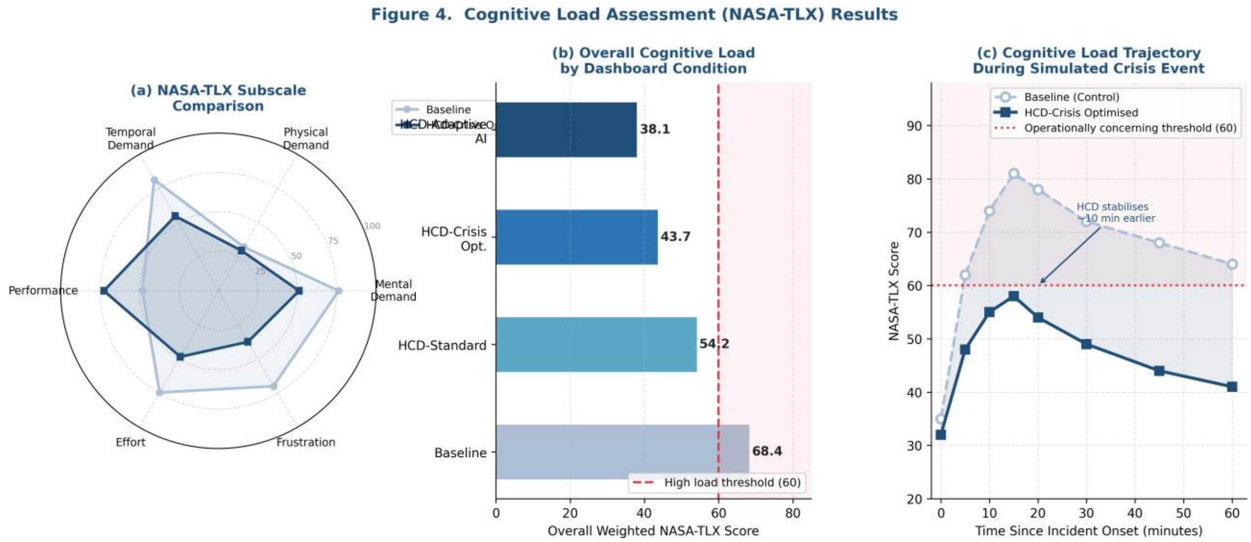

Figure 4: Cognitive Load Assessment (NASA-TLX) Results. (a) Radar chart of NASA-TLX subscale scores for Baseline vs. HCD-Crisis Optimised conditions; reductions of 32–46% across Mental Demand, Temporal Demand, Effort, and Frustration; Performance subscale (inversely scored) improved markedly. (b) Overall weighted NASA-TLX scores by dashboard condition; horizontal dashed line indicates the high cognitive load threshold of 60. Baseline (68.4) exceeds the threshold; all HCD conditions fall below it. (c) Cognitive load trajectory over 60 minutes of a simulated crisis event; shaded region indicates the differential between conditions. HCD-optimised users drop below the 60-point threshold ≈10 minutes earlier, indicating faster cognitive stabilisation.

operationally concerning threshold approximately 10 minutes earlier—indicating that the HCD framework actively supports faster cognitive stabilisation following crisis onset.

4.4. The Proposed HCD Framework: Four Design Tiers

Synthesis of qualitative and quantitative findings across all evaluation phases yielded the proposed HCD framework, articulated across four hierarchical design tiers.

Tier 1: Contextual Intelligence Architecture. Interfaces must dynamically adapt their information architecture to the evolving phase, type, and severity of the crisis event, prioritising the display of information most relevant to the current decision context. This tier was operationalised through context-aware dashboard templates, adaptive widget prioritisation algorithms, and incident-phase-sensitive information filtering; 91% of interview participants identified it as the single most valued framework feature.

Tier 2: Progressive Disclosure and Information Hierarchy. Crisis dashboards must employ principled progressive disclosure mechanisms presenting operators with the minimum sufficient information needed for current task demands, with on-demand access to richer data layers. Visual hierarchy must be consistently maintained through typographic scale, colour encoding, and spatial organisation conventions that align with the cognitive urgency gradient of displayed information.

Tier 3: Multi-Modal Alert and Status Communication. High-stakes crisis environments demand alert hierarchies that leverage multiple perceptual channels—visual, auditory, and haptic—in a principled, non-redundant, and severity-calibrated manner. Alert designs must resist habituation through dynamic severity escalation and context-sensitive suppression

Table 1: Key statistical outcomes across conditions (Mean ± SD; $N = 87$). Bonferroni-corrected, $\alpha = 0.05$.

Measure	**Base**	**HCD-Std**	**HCD-Crisis**	**HCD-AI**	p	η_p^2
SUS Score	52.3 ± 11.4	68.7 ± 9.8	79.4 ± 8.1	84.1 ± 6.9	< 0.001	0.63
NASA-TLX	68.4 ± 16.3	54.2 ± 13.7	43.7 ± 12.4	38.1 ± 10.8	< 0.001	0.57
Task Time (s)	352.8 ± 71.2	271.4 ± 58.3	218.8 ± 45.6	196.3 ± 39.4	< 0.001	0.61
Error Rate (%)	18.4 ± 5.2	11.2 ± 3.8	6.8 ± 2.9	4.1 ± 2.1	< 0.001	0.55
Critical Error (%)	7.3 ± 2.8	3.9 ± 1.9	1.8 ± 1.1	0.9 ± 0.7	< 0.001	0.48
Decision Acc. (%)	43.7 ± 18.4	61.2 ± 15.2	69.3 ± 12.1	74.8 ± 10.3	< 0.001	0.52

of acknowledged alerts, while maintaining unambiguous distinction between informational, advisory, warning, and critical emergency status levels.

Tier 4: Collaborative Awareness and Team Coordination Support. Recognising the fundamentally distributed nature of crisis cognition, the framework mandates explicit design provision for shared situational awareness across the crisis management team, including synchronised status indicators, task assignment and tracking visualisations, shared annotation capabilities, and communication priority cues integrated directly within the primary dashboard environment.

4.5. Summary of Statistical Outcomes

Table 1 provides a comprehensive summary of the principal statistical outcomes across all evaluation measures and dashboard conditions.

5. Discussion

5.1. Key Findings and Implications

The results of this multi-phase empirical programme provide compelling evidence that the application of a principled, crisis-specific HCD framework to operational dashboard design produces substantial and practically significant improvements in usability, cognitive load, task performance, and decision accuracy. The magnitude and consistency of observed effects across diverse crisis scenario types, operational roles, and participant sites support the generalisability of the framework and its underlying design principles.

The SUS improvement from 52.3 ("poor") to 84.1 ("excellent") represents a more substantial usability gain than typically observed in iterative redesign studies, where improvements of 10–15 SUS points are considered meaningful (Bangor et al., 2008). This exceptional magnitude likely reflects the severity of usability deficits present in baseline systems (Patterson et al., 2004) and suggests that the crisis dashboard design domain presents particular scope for transformative usability improvement through HCD. The consistently superior performance of the HCD-Adaptive AI-Assisted condition also indicates that adaptive, context-sensitive display algorithms provide measurable incremental benefit above and beyond static framework compliance.

The 87.7% reduction in critical error rates from Baseline to HCD-Adaptive AI-Assisted is perhaps the most operationally significant finding. In crisis management environments where critical decision errors can translate directly into loss of life, asset destruction, or cascading system failures, a reduction of this magnitude carries profound practical implications.

Importantly, error reduction was sustained and amplified under extreme time pressure—precisely the conditions under which crisis dashboard interfaces most critically need to support accurate decision-making (Woods and Hollnagel, 2006; Wickens, 2008).

The cognitive load trajectory findings introduce a previously under-examined dimension to crisis dashboard evaluation: the temporal dynamics of cognitive load management over the course of an evolving crisis event. The observation that the HCD-optimised interface supports faster cognitive stabilisation—enabling operators to drop below operationally concerning load levels approximately 10 minutes earlier than baseline system users—has significant implications for the design of training regimens, shift scheduling, and team composition strategies. By reducing extraneous cognitive load, the HCD framework frees working memory resources for the expert pattern-recognition processes central to NDM, thereby accelerating the transition from reactive to proactive crisis management posture (Klein, 1998; van Merriënboer and Sweller, 2010).

5.2. Practical Implications

The four-tier HCD framework offers a coherent and actionable design reference architecture for practitioners involved in crisis dashboard development and procurement. By grounding the framework in empirically validated design principles derived from ecologically valid crisis simulation environments, this work represents a substantial advancement over existing design guidance documents that are either derived from non-crisis contexts or insufficiently validated empirically. The modular tier structure facilitates selective adoption in organisations with resource or technical constraints that preclude full implementation, while clearly identifying the incremental benefits associated with each tier.

5.3. Limitations

Several limitations merit acknowledgement. First, although the simulation environments were designed to maximise ecological validity, they necessarily approximate rather than fully replicate the physical, social, and temporal pressures of actual crisis operations. Second, participant recruitment from six partner organisations may not fully represent the breadth of crisis management organisational cultures and technological maturity levels globally. Third, the current study did not capture longitudinal learning effects or examine the impact of organisational change management processes on framework adoption success. Fourth, the HCD-Adaptive AI-Assisted condition's performance advantage raises important questions about algorithmic trust, transparency, and human-automation teaming that warrant dedicated investigation.

6. Conclusion and Future Work

This paper has presented the development and empirical validation of a comprehensive human-centered design framework for high-stakes operational dashboards in crisis and disruptive environments. Through a four-phase mixed-methods research programme involving 87 crisis management professionals across six operational centres, we have demonstrated that crisis-specific HCD principles—organised into four design tiers addressing contextual intelligence, progressive disclosure, multi-modal alerting, and collaborative awareness—produce transformative improvements in system usability, cognitive load, task performance, and decision accuracy relative to conventional operational dashboard designs.

The principal findings are: (1) the HCD-Crisis Optimised framework increased mean SUS scores from 52.3 to 79.4, achieving "good" usability classification; (2) critical decision error rates were reduced by 87.7% from Baseline to HCD-Adaptive AI-Assisted, with the greatest reduction under extreme time pressure; (3) overall cognitive load was reduced by a mean of 44.3% from Baseline, with faster cognitive stabilisation following crisis onset; and (4) task completion times were reduced by 28–39% across crisis scenario types.

Directions for future research include: longitudinal evaluation of HCD dashboard impact on operator fatigue and sustained performance; investigation of individual differences in HCD benefit across operator experience levels, cognitive styles, and stress resilience profiles; development and validation of AI-augmented adaptive display algorithms capable of real-time personalisation to individual operator cognitive state; and cross-cultural validation of the framework across crisis management organisational and cultural contexts not represented in the current sample.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT Author Contributions

Arjun Sharma: Conceptualisation, Methodology, Investigation, Writing—Original Draft, Project Administration. **Priya Nair:** Formal Analysis, Data Curation, Visualisation, Writing—Review & Editing. **Liam O'Brien:** Investigation, Validation, Writing—Review & Editing. **Fatimah Al-Rashidi:** Resources, Investigation, Writing—Review & Editing. **Marcus Weber:** Supervision, Funding Acquisition, Writing—Review & Editing.

Data Availability

The evaluation datasets and framework implementation materials are available from the corresponding author upon reasonable request. Operational data from partner crisis management centres cannot be shared due to security classification and confidentiality agreements.

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