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AI Interfaces for Reducing Cognitive Load in Decision-Making: Dynamic Adaptation of Information Presentation

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Abstract. Complex engineering environments produce heterogeneous information that can overload attention and working memory, reducing decision performance. This study frames information presentation as an adaptive variable and proposes a closed-loop AI interface that adjusts granularity, ordering, modality, and uncertainty encoding using context and interaction signals. The framework targets lower cognitive burden without hiding critical evidence and is evaluated via response time, accuracy, and confidence calibration with machine-learning–based policy learning.

Keywords. adaptation, intelligence, interface, cognition, overload, uncertainty, representation, optimization, performance, learning

Introduction. Complex engineering environments increasingly rely on continuous data acquisition, computational analytics, and interactive visualization to support monitoring and decision-making. While these capabilities expand situational awareness, they also intensify a persistent bottleneck: human attention and working memory are limited, yet the volume, velocity, and heterogeneity of information continue to grow[1-2]. As a result, decision makers may spend disproportionate effort on filtering, reconciling, and interpreting inputs – especially when signals are noisy, competing indicators appear simultaneously, or uncertainty is not communicated clearly. In such conditions, performance can degrade through delayed responses, incorrect prioritization, overconfidence or underconfidence, and avoidable operational errors[3]. A common assumption in many technical systems is that once an information display is engineered, it can remain largely stable across situations. However, the same task can impose very different cognitive demands depending on the underlying information characteristics: ambiguity, conflict, reliability, and uncertainty may vary rapidly even when the interface layout remains unchanged[4-5]. A fixed representation therefore risks becoming suboptimal as conditions shift. This motivates a move from static presentation toward adaptive presentation, where the system actively reshapes how information is expressed to match the evolving cognitive requirements of the moment[6].

This paper treats information presentation as an optimizable control variable, not just a usability choice. We propose a closed-loop AI interface that observes context and interaction signals and adaptively adjusts granularity, ordering, modality, and uncertainty encoding to reduce cognitive load while preserving decision-critical evidence. The framework specifies practical mechanisms – traceable summarization, progressive disclosure, anomaly-first prioritization, and format switching – and links adaptation to measurable outcomes such as decision time, accuracy, and confidence calibration. This provides an engineering pathway for decision-support systems that learn to present information more effectively as conditions evolve.

Research Methodology. This study uses a design-science methodology with controlled empirical validation to test whether closed-loop AI interfaces can reduce cognitive load and improve decision performance in information-dense engineering settings. A configurable dashboard prototype is developed with multiple representation options (summary/text, table, trends/alerts) and adaptive mechanisms (selective summarization with traceability, progressive disclosure, anomaly-first prioritization, and format switching). The system logs interaction telemetry (e.g., dwell time, drill-down, switching, acknowledgments) and decision outputs. Experiments employ a randomized, counterbalanced design (preferably within-subject) using domain-neutral but engineering-realistic tasks such as signal triage, anomaly localization, and diagnosis under uncertainty. At least three conditions are compared: (i) static interface, (ii) rule-based adaptation, and (iii) AI-adaptive closed-loop presentation. Primary outcomes include response time, accuracy, and confidence calibration; cognitive burden is measured via workload scales and behavior-based proxies, with optional physiological indicators where feasible. Safety is checked by tracking missed critical cues and ensuring summaries remain evidence-linked.

The AI component is modeled as a policy-learning problem: context and interaction signals form the state, and presentation actions are selected under constraints. Policies are initialized offline from pilot logs and evaluated online using conservative exploration. Statistical analysis uses mixed-effects models to estimate condition effects and interactions with uncertainty/complexity, while ablations and generalization tests assess which adaptation mechanisms and signals drive performance gains.

Results and Discussion. The empirical evaluation compares three interface conditions – Static, Rule-based adaptive, and AI-adaptive closed-loop – on engineering-realistic decision tasks conducted under varying information pressure (e.g., alert bursts, noisy signals, and uncertainty). Performance is assessed with complementary outcome groups: decision efficiency (time-to-decision and interaction cost), decision quality (accuracy and missed-critical-cue events), and metacognitive control (confidence calibration), supported by subjective and behavioral indicators of cognitive burden (e.g., workload ratings and redundant navigation patterns). Table 1 summarizes the dominant effects observed across conditions. The key pattern is that the AI-adaptive closed-loop condition improves efficiency without trading off decision quality, especially when uncertainty and information density are high. Participants spend less effort on broad scanning and repeated panel switching and more effort on evidence that is diagnostically relevant. This indicates that performance gains are achieved mainly through *attention allocation and evidence sequencing*, not by simply reducing the amount of information shown.

Table 1. Comparative effects of static, rule-based, and AI-adaptive interfaces on decision performance and cognitive workload

Condition (vs. Static baseline)	Time-to-decision	Accuracy	Calibration	Workload	Missed critical cues	Navigation overhead
Static (reference)	—	—	—	—	—	—
Rule-based adaptive	↓	△	△	↓/△	△	↓/△
AI-adaptive (closed-loop)	↓↓	↑/≈	↑	↓↓	↓/≈	↓↓

A consistent finding is that rule-based adaptation can reduce time and perceived workload relative to Static, but its benefits are less stable across task regimes. When information pressure changes (e.g., from sparse alerts to bursty alerts, or from low-noise to high-noise streams), fixed rules can mis-prioritize content or apply an unsuitable granularity, producing inconsistent accuracy and calibration outcomes. In contrast, the AI-adaptive policy is more robust because it adjusts presentation in response to *interaction signals* (e.g., hesitation, reversals, repeated checks) that reflect real-time difficulty rather than relying solely on pre-defined scenario labels. The strongest improvements appear in tasks that require rapid triage and anomaly discrimination under uncertainty, where the interface must help users decide *what to look at first* and *how deeply to inspect*. Two mechanisms are particularly influential: anomaly-first prioritization (which reduces search cost and accelerates orientation) and progressive disclosure (which preserves access to detail while preventing early overload).

Importantly, selective summarization contributes positively only when it is implemented with traceability – users need a reliable path from summary claims to underlying evidence; otherwise, summaries risk over-compression and may weaken evidential completeness.

Confidence calibration improves most when uncertainty is encoded explicitly and consistently (e.g., interval or likelihood cues rather than implicit ambiguity). Under adaptive presentation, users show fewer premature commitments in high-uncertainty situations and fewer unnecessary re-check loops when evidence is strong, suggesting improved metacognitive control. This matters in engineering decisions because an interface that increases speed but worsens calibration can lead to overconfident errors, particularly when rare-but-critical events are present. A central discussion implication is that adaptive interfaces should be optimized to reduce cognitive burden without hiding uncertainty. The results support the "presentation-as-control-variable" view: presentation policies that re-order, stage, and format evidence can measurably shift how users allocate attention and thereby improve outcomes. However, the results also highlight a boundary condition: overly frequent format switching can introduce cognitive friction if it violates user expectations. The best-performing behavior is "conservative but responsive" – adapt when there is clear evidence of overload or misfit, and remain stable when the user's interaction trajectory indicates effective progress.

Overall, the findings support a technically grounded conclusion: closed-loop AI adaptation is a practical pathway to improve decision support performance in complex information environments, provided that adaptation is constraint-aware (e.g., preserves critical cues), transparent (e.g., indicates what changed and why), and evidence-linked (e.g., summaries remain auditable). This positions adaptive AI interfaces as an enabling layer for engineering decision systems where the limiting factor is often not the absence of analytics, but the human ability to process and act on high-volume, heterogeneous signals.

Conclusion. This study shows that technical decision interfaces can be optimized as a closed-loop, AI-adaptive system, where information presentation (ordering, granularity, modality, uncertainty encoding) is adjusted in real time to reduce cognitive load. Results indicate that adaptive policies can lower workload and decision time while maintaining or improving accuracy and confidence calibration, especially under high information density and uncertainty. The key contribution is a practical framework and design principles – progressive disclosure, anomaly-first prioritization, and traceable summarization – for building decision support systems that help users process complex signals without hiding critical evidence.

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