

When AI Becomes Extra Work: Redesigning Clinical Decision Support Without Clinician Burnout

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Abstract

What is the message? Using artificial intelligence (AI)-enabled clinical decision-support systems without changing workflows, decision authority, and governance structures can raise cognitive and administrative workload. Evidence shows that when AI is added to existing processes instead of being integrated into redesigned workflows, the burden on clinicians and the risk of burnout increase.

What is the evidence? Health management and health informatics research, including multi-hospital studies of AI-enhanced electronic health record systems and systematic reviews, show associations between AI implementation, increased cognitive burden, and higher burnout risk when AI is added to existing processes rather than integrated through thoughtful management redesign. [1-9] This article argues that AI-enabled clinical decision support should be viewed primarily as an organizational design challenge rather than a technology challenge. AI alters workflows, decision authority, and incentives, and these changes often lead to increased burnout risk when not accompanied by redesign. Finally, the article outlines practical leadership actions to connect AI implementation with workforce sustainability and patient care.

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The Problem AI Was Supposed to Solve

In many hospitals today, clinicians interact with screens much more than they review schedules or patient histories before a visit. AI-enabled clinical decision-support systems introduce continuous prompts, alerts, and recommendations that interrupt patient encounters and disrupt the flow of care. Rather than quietly supporting clinical reasoning, these systems now compete for attention, shaping how clinicians focus, patients experience care during clinical encounters, and leaders interpret performance.

AI-enabled clinical decision-support systems (AI-CDSS) were created to address major challenges in clinical practice. In this article, AI-CDSS refers to clinical decision-support tools that healthcare institutions approve; these tools are integrated into healthcare workflows and include systems for risk prediction, supporting triage, assisting with clinical documentation, generating alerts, offering imaging help, and recommending treatments. AI-CDSS does not refer to fully autonomous clinical AI systems, consumer health chatbots, or experimental generative AI tools that operate outside of formal care delivery settings.

Clinical practice challenges include increasing documentation demands, more complex patients, limited time during consultations, and the need to follow more clinical guidelines. AI-CDSS promised to help ease these pressures by assisting with tasks like flagging abnormal lab results, identifying patients at risk of deterioration, recommending evidence-based treatments, and prioritizing clinical tasks under time constraints. Early research appeared to support many of these expectations: evaluations of AI-supported triage and risk-stratification systems reported improved throughput, better prioritization of high-risk patients, and earlier identification of clinical deterioration. [2][10]

However, real-world use has shown a different set of challenges. In practice, many AI-CDSS implementations have introduced new layers of interaction rather than replacing existing

work.[5][13] Clinicians must verify algorithm-generated risk scores, acknowledge alerts even when they are obvious, and explain any deviations from AI recommendations. In inpatient and intensive care settings, this can lead to dozens of alerts per shift, many of which require documentation regardless of their importance. What was intended to reduce cognitive burden often redistributes it into new, less visible forms of work.

These effects worsen when multiple AI tools, often created by different vendors and yet part of the same electronic health record (EHR) system, run simultaneously without coordination. Separate systems can create overlapping alerts, conflicting recommendations, or redundant documentation obligations. Instead of acting as a unified support system, uncoordinated AI tools divide attention and slow down decision-making, creating more challenges than any single tool used on its own.

Importantly, the AI-CDSS discussed here are not experimental or unregulated technologies. They are institutionally approved, regulator-compliant systems deployed within controlled electronic health record environments. Yet even within these mature settings, health systems face growing incentives to adopt AI, including competitive pressures, policy expectations, and organizational goals related to innovation. This can create pressure to implement systems before workflows are fully redesigned. The continuing challenges in these regulated settings therefore suggest that the integration of approved AI systems into clinical processes, not gaps in regulation or underdeveloped technology, are the core issue.

The shift from rule-based alerts to AI-enabled clinical decision support has increased the volume and complexity of interactions between clinicians and systems. [1][13] If workflows and decision-making authority are not redesigned, these systems may lead to more monitoring and verification work instead of a decrease in tasks. Reducing workload relies not just on better algorithms but also on rethinking workflows and decision-making structures.

These challenges mainly reflect leadership decisions regarding workflow design, task distribution, and governance. Research on successful health information technology implementation consistently highlights the importance of multidisciplinary pre-deployment workflow reviews that include clinicians, nurses, and IT teams.[6][15] When organizations introduce AI without adjusting the workflow, they may add verification and documentation tasks instead of reducing them. Some increase in workload is expected during technological

transitions. The key challenge for leadership is to stop temporary complexity from becoming permanent.

From Support to Surveillance: How AI Changes Clinical Work

Before examining burnout as a design outcome, it is important to understand how AI-enabled clinical decision support systems change everyday clinical work. This essay takes a socio-technical view to explore these changes. Socio-technical theory focuses on how work outcomes result from the interaction among people, tasks, technologies, and organizational structures, rather than from technology alone. In clinical settings, this means that AI changes not just the availability of information, but also responsibility, coordination, and professional judgment.

One consequence of these changes is the creation of new forms of work that often remain invisible in traditional productivity measures. One of the most significant changes brought about by AI-CDSS is the increase in verification work. Verification work involves the extra mental and administrative effort needed to confirm, acknowledge, or reject AI-generated recommendations before taking clinical action. For instance, when an AI-CDSS flags a patient as “high risk” for deterioration, clinicians often must check the underlying data, acknowledge the alert, and record whether they agree or disagree with the recommendation even when the clinical assessment is already clear. What used to be internal clinical judgment is now an external task shaped by system prompts, documentation requirements, and organizational expectations. Similar findings have been reported in studies of EHR-based clinical decision support, where clinicians spent additional time reviewing alerts and documenting responses even when patient management did not change. [5][13]

Verification work fragments clinical attention during patient interactions where communication, reassurance, and trust are critical. Increased focus on alerts and documentation can lower eye contact, disrupt communication, and impact the perceived quality of care and patient satisfaction. In high-acuity settings, constant alarms and interruptions can raise anxiety for patients and families. These signals often indicate possible instability, even if the alerts do not require immediate clinical response. [14] While AI-CDSS aims to improve safety, poorly integrated systems can unintentionally divert attention from the patient. However, when designed effectively, these systems can lessen documentation demands and create more room

for meaningful human interaction. The design of AI-CDSS affects not only clinician workload, but also patient experience and trust.

Alert volume intensifies this burden. AI-CDSS often generate alerts more frequently than earlier rule-based models because they continuously update risk predictions. McDonald et al. found that clinicians exposed to higher alert frequencies reported significantly higher perceived workload and emotional exhaustion, even with improved alert accuracy. In other words, better predictions did not lead to a better work experience when alert volume increased. The study showed that the cumulative effect of frequent alerts, not their individual usefulness, was strongly linked to burnout symptoms.[4]

As organizations work to ensure proper use of AI-CDSS, monitoring grows alongside decision support. They track override rates, review compliance dashboards, and monitor deviations from AI recommendations, which may lead to additional documentation requirements. In some organizations, clinicians feel that they need to explain more when they ignore AI guidance than when they follow it, especially if overrides are monitored or checked.[9][18]

These dynamics suggest that AI implementation can shift portions of clinical work from interpersonal coordination toward system monitoring and compliance activities. Tasks that were once handled through team discussions or professional judgment are now managed through individual interactions with automated systems. Studies on social and technical factors reveal that when technology alters relationships among people, tasks, and tools without changing workflows, coordination declines and cognitive demand increases.[3]

Empirical studies support this pattern. Research on AI-enabled documentation and decision-support tools found higher burnout scores after implementation, even with small efficiency gains. For instance, while the time spent on documentation per note decreased, clinicians reported greater mental fatigue due to the sustained need to interact with and monitor the system.[4][9] These analyses suggest that improvements in organizational performance and clinician experience do not always go hand in hand. This is especially true when new tasks are added without removing existing responsibilities for an already constrained workforce.

Clinician resistance to AI should not be seen as irrational or technophobic. Often, skepticism comes from valid concerns about workflow disruption, accountability, and professional

autonomy. When AI adds more verification, monitoring, and documentation without easing other demands, resistance is a reasonable reaction to poorly designed systems.

Burnout as a Design Outcome, Not a Personal Failure

Burnout related to AI-enabled clinical decision-support systems should not be seen as a personal failure to adjust to technology. Studies on health information technology, including AI-enabled clinical decision support in electronic health records, consistently show that dissatisfaction comes more from the design, implementation, and management of these systems in clinical work than from the technology itself. Here, “health IT” specifically refers to officially approved digital systems, including AI-CDSS, that influence clinical decision-making, documentation, and care coordination. [13]

Across studies of AI-enabled clinical decision support and broader health information technology implementations, the sources of dissatisfaction are remarkably consistent despite differences in technologies, clinical settings, and implementation strategies. Three repeated issues stand out: misaligned workflows, unclear decision authority, and misaligned incentives. For instance, when AI-CDSS generates alerts but does not eliminate existing documentation obligations, clinicians experience workflow misalignment, with tasks piling up rather than being replaced. When it is unclear who is responsible for decisions, whether responsibility lies with the clinician, the organization, or the algorithm, clinicians may respond by increasing documentation or relying more heavily on AI recommendations to reduce perceived accountability risk. When efficiency gains benefit the organization without visible reinvestment in staffing or reducing workloads, the incentives continue to diverge between leadership priorities and frontline experiences. Similar implementation challenges have been reported in various health information technology projects. When technology was adopted without changing workflows, users felt less satisfied and believed their workload increased. [13][15]

When organizations do not measure these effects, burnout is often misattributed to individual resilience rather than system design. Without metrics to capture cognitive demand, alert volume, or workflow fragmentation, organizational performance reviews often focus on algorithm accuracy, adoption, and utilization metrics. Meanwhile, the human impact stays mostly unseen.

Cognitive demand theory helps explain why these design choices matter in clinical settings. Cognitive strain increases when work involves frequent task switching, sustained attention to multiple information streams, and quick decision-making in the face of uncertainty. In AI-supported clinical contexts, such as inpatient monitoring, risk stratification, and triage, AI-CDSS can intensify all three conditions simultaneously, particularly when alerts, recommendations, and documentation requirements are layered onto existing workflows.

Table 1 uses the socio-technical model of health information technology. This model views clinical work as a mix of people, tasks, technologies, and organization. Instead of requiring readers to infer this system from previous studies, the table shows how misalignment in these areas manifests in AI-CDSS implementations. When technology doesn't fit well with the workflow, when management policies focus more on compliance than on judgment, and when feedback loops center only on technical performance, burnout becomes a predictable organizational risk when these sources of cognitive demand persist over time.

Table 1. Socio-technical domains of AI-CDSS and related burnout drivers

Socio-technical Dimension	How AI-CDSS shapes work across this domain	Burnout / Cognitive Load Implications
Hardware & Software	Embedded AI models, alerts, dashboards within EHR systems	Increased interruptions, alert fatigue, task switching
Clinical Content	Risk scores, predictions, recommendations without context tailoring	Verification burden; reduced sense of professional judgment
Human-Computer Interface	Pop-ups, mandatory acknowledgements, override prompts	Fragmented attention; cognitive overload
People	Clinicians expected to adapt to AI outputs with minimal training	Stress, reduced autonomy, erosion of psychological safety
Workflow & Communication	AI layered onto existing workflows without task removal	Work intensification; longer task completion times
Internal Organizational Policies	Monitoring of compliance, override tracking, performance dashboards	Surveillance anxiety; defensive reliance on AI
External Rules & Regulations	Regulatory pressure to document adherence to guidelines	Increased documentation load; risk-averse behavior
Measurement & Monitoring	Focus on accuracy and utilization metrics	Burnout remains invisible and unmanaged

Adapted from the socio-technical framework suggested by Sittig and Singh (2015).

The persistence of burnout, despite ongoing technical improvements, highlights this. Even as algorithms improve, dissatisfaction may persist even as technical performance improves when workflows remain unchanged. This reflects the broader “health IT paradox,” in which adoption rates increase while end-user satisfaction declines. [14] Technology alone can’t fix the structural and cultural problems rooted in clinical work.

Decision Authority, Trust, and Automation Bias

Trust in AI-based clinical decision support involves more than just clinician faith in algorithms. Trust in healthcare decisions is shaped by confidence in clinicians, institutions, regulators, and, increasingly, digital technologies. In some cases, AI can increase skepticism by raising worries about surveillance, opacity, or loss of professional autonomy. In others, it may increase confidence by improving consistency and supporting decisions under pressure. These tensions apply to both highly interpretable (“glass-box”) systems and more opaque (“black-box”) models. While explainable AI may improve transparency and clinician understanding in some settings, both types of systems can still increase verification work, documentation burden, and override pressure when implementation outpaces workflow redesign. The challenge for leaders not only is to build trust in AI, but also to understand how trust is shared among clinicians, organizations, patients, and technology.

When it’s unclear who holds responsibility, whether it’s the clinician, the organization, or the AI system, clinicians may change their behavior out of caution. For instance, if moving away from AI guidance requires extra documentation or review, following the recommendation might seem safer than using one’s own judgment. In these situations, relying on AI may reflect institutional accountability pressure as much as confidence in algorithm performance. Research on automation bias suggests that diagnostic errors can increase when clinicians rely heavily on AI recommendations under time pressure or uncertainty. [18]

These dynamics also impact patients and families. Some patients may see AI-supported decisions as more objective or based on data. Others might find them impersonal or hard to question. Trust thus becomes about relationships instead of just technical aspects. It is influenced by how clinicians explain their recommendations and how organizations convey the

role of AI in care delivery.

As AI becomes embedded in routine workflows, skepticism may gradually shift toward greater reliance. [13] Without well-defined guidelines for questioning and overriding AI recommendations, sustained reliance may gradually increase the risk of automation bias and reduce independent review of recommendations.

Leadership is fundamental in changing this direction. Clarifying decision authority involves clearly stating when AI provides advice, when clinicians have the final say, and how overrides are assessed and safeguarded. Governance structures that create this balance foster measured trust, avoiding both underuse and over-reliance. [12]

Incentives, Organizational Outcomes, and the Burnout Gap

AI investments in healthcare are often backed by expected benefits like improved throughput, lower costs, better prioritization of high-risk patients, and operational efficiencies. However, evidence about actual system-level benefits is mixed and heavily depends on the implementation context, workflow integration, and organizational readiness. [2][10]

Economic evaluations of AI-enabled triage and prioritization tools suggest that organizational benefits and frontline workload do not always move in the same direction. [10] Patients may also experience these tradeoffs indirectly when implementation priorities emphasize operational metrics without equal attention to communication, continuity of care, and clinical capacity. When operational improvements are not accompanied by staffing support or workflow redesign, frontline clinicians may perceive AI implementation as increasing organizational demands without providing meaningful relief.

Several studies have found that organizational performance indicators and clinician experience may differ during implementation. Reported improvements in throughput or operational performance may occur alongside an increased cognitive burden when new responsibilities are added without taking away existing work. [4][10][16]

This gap between organizational incentives and frontline experience drives burnout risk. At the

board level, this means viewing AI-CDSS investments not just as capital expenses for efficiency. They should also be viewed as investments in organizational redesign. This may require additional investments in staffing support, changes in workflow, training, and governance capacity. Over time, AI-CDSS might change how organizations measure performance. It could focus more on compliance metrics than on adaptive clinical judgment. This shift may influence which activities organizations reward, measure, and prioritize in clinical practice.

The REDESIGN Framework for AI-Enabled Decision Support

The operational challenges described earlier, such as verification burden, alert fatigue, unclear decision authority, and misaligned incentives, are not isolated issues. They result from introducing AI into clinical workflows without changing how work is organized and managed. Each element directly addresses a breakdown identified earlier, connecting diagnosis to intervention instead of offering a general set of recommendations. The REDESIGN framework translates these failures into seven leadership actions that address workflow, authority, governance, measurement, incentives, and professional judgment. [7]

Many redesign actions can be tested within current operational limits. This can be done through phased implementation, specific governance changes, and workflow review instead of needing significant technology investment. In 3 to 6 months, organizations can test targeted redesign efforts, assess their impact, and expand successful changes.

1. **Redesign workflows before deployment:** AI-CDSS should replace low-value work instead of adding new verification layers. Before implementation, leaders should map workflows, standardize documentation when possible, and pinpoint tasks that can be simplified, automated, or eliminated.
2. **Establish clear decision authority:** Leaders should clearly define who is responsible when AI recommendations are involved and when these fail. Governance structures should allow clinicians to easily override AI recommendations without adding unnecessary administrative work.
3. **Govern AI throughout its lifecycle:** AI governance should continue after deployment. Organizations should regularly check performance, unintended consequences, and changes in clinician experience over time. [12]
4. **Evaluate human impact alongside performance:** AI evaluation should go beyond

accuracy and usage metrics. Leaders should watch alert burden, mental load, clinician fatigue, patient experience, workforce well-being, and operational outcomes. [17]

5. **Reinvest operational improvements into staffing and wellness:** When organizations observe operational improvements associated with AI implementation, leaders should consider reinvesting some of those gains into staffing, training, workflow redesign, or clinician well-being efforts. [16]
6. **Normalize questioning and overrides:** Organizations should encourage questioning and proper overrides of AI recommendations. Creating psychological safety helps guard against automation bias and maintains independent clinical judgment. [13]
7. **Establish data readiness before scaling AI:** AI systems depend on reliable, interoperable, and consistently structured data. Before expanding AI-CDSS across departments, organizations should evaluate data quality, integration standards, and governance processes to ensure recommendations remain accurate and comparable across settings.

The goal of redesign is not to remove oversight, but to make sure it is appropriate, meaningful, and matches clinical judgment instead of being redundant or too much.

A Phased “When” Roadmap

A phased implementation approach is more manageable when deployment, evaluation, and scale-up occur sequentially rather than simultaneously.

- **Pre-deployment:** Create governance structures with input from clinicians, nurses, IT teams, and operational leaders. Involving stakeholders early helps to improve workflows, incentives, and documentation practices before deployment.
- **Pilot phase:** Use factors like alert frequency, clinician feedback, override patterns, and perceived cognitive workload to spot unintended consequences early during implementation. [6]
- **Scale-up:** Connect demonstrated operational improvements to workforce support, workflow redesign, and ongoing governance review. [17]

Policy and Global Implications

The challenges discussed in this paper go beyond individual hospitals. Global digital health strategies focus more on governance, interoperability, workforce readiness, and human-centered implementation as essential for responsible AI use. The World Health Organization's Global Strategy on Digital Health 2020-2025 highlights many of these priorities, such as leadership capacity, digital governance, and workforce engagement. [19] These priorities reinforce the central argument of this paper: successful AI implementation depends not only on technological capability, but also on organizational design, governance, and human factors.

Conclusion

AI-CDSS should be viewed as an organizational change rather than merely a technology upgrade. Its impact depends less on model performance and more on how leaders redesign workflows, clarify decision-making authority, govern implementation, and evaluate human consequences. Similar to the transition from paper records to electronic systems, AI adoption may initially introduce complexity before longer-term benefits emerge. The challenge for leaders is to prevent temporary implementation burdens from turning into permanent features of clinical work. Organizations most likely to benefit from AI will not necessarily be those with the most advanced algorithms, but those most willing to rethink how clinical work is supported, governed, and experienced.

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