

## A Blueprint for Partnership between AI and MD

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### Abstract

Healthcare delivery is experiencing a digital inflection point. Despite widespread adoption of electronic health records (EHRs) and expanding diagnostic technologies, clinicians increasingly report administrative overload, fragmented information systems, and reduced time for direct patient care. Data volume has increased, but clarity has not. This commentary proposes a four-pillar framework for transforming healthcare data from a source of cognitive burden into a driver of clinical, operational, and financial value. The framework includes: (1) early detection of clinical deterioration through AI-enabled analytics; (2) proactive operational adjustments using predictive capacity modeling; (3) population-level predictive capability to prevent avoidable hospitalizations; and (4) operational efficiency through automation of documentation and coding workflows. Rather than replacing physicians, artificial intelligence systems should function as intelligent assistants that synthesize data, reduce clerical burden, and support clinical judgment. We also discuss how integration of multi-omics data may further enhance early detection and personalized care. Moving from data fragmentation to actionable insight is not solely a technology challenge. It is a workforce sustainability issue and a public health priority.

### Introduction

Healthcare is at a turning point. Over the last two decades, the industry has undergone a significant digital shift, with the near-universal adoption of Electronic Health Records (EHRs) and the spread of new diagnostic technologies. Yet for clinicians at the bedside and administrators in the C-suite, this technological "progress" often feels like a step backward in usability and clarity. More data has not meant better data, and the result is a different kind of chaos.

Caregivers, whose job is patient care, now spend much of their time functioning as data entry clerks, overwhelmed by fragmented records, inconsistent documentation, and a flood of low-value alerts. This is more than an inconvenience. It is a driver of the "burnout crisis" facing medicine. Recent studies indicate that for every hour physicians provide direct clinical face time to patients, nearly two additional hours are spent on EHR and desk work.<sup>1</sup> This imbalance drains professional energy, impacts patient outcomes, and undermines the financial stability of health systems.

To move forward, healthcare organizations must fundamentally rethink their relationship with data. The goal is no longer simply to *capture* information but to *liberate* it. The aim is to transform data overload into actionable value. This commentary outlines a blueprint for that transformation, moving from a reactive posture to one of predictive, proactive, and precise care delivery.

## The Cost of Poor Data Quality

Quality data is not a luxury; it is the foundation of patient safety and operational excellence. In the current landscape, clinical information is often siloed in proprietary formats across EHRs, laboratory information systems, imaging archives, and even paper files. This fragmentation creates what you might call "operational friction," slowing down decision-making and introducing error.

The consequences of this friction are measurable. Inaccurate or delayed information can lead to medication errors, missed diagnoses, and redundant testing. Financially, poor data quality complicates quality reporting and reimbursement, leading to revenue leakage and increased administrative costs. Research linking clerical burden and EHR design characteristics to physician burnout demonstrates a direct association between digital workload and professional distress.<sup>2</sup> When the tools meant to help clinicians become a source of exhaustion, something has gone wrong.

## The Strategic Imperative: A Four-Pillar Framework

To resolve this chaos, health systems must adopt a "Data-Driven Transformation" strategy. This approach does not advocate for more technology for technology's sake, but for the deployment of intelligent layers that synthesize (or normalize) data into insight. This transformation rests on four pillars (Figure 1).

Figure 1. Four-Pillar Framework for AI-Enabled Clinical Support

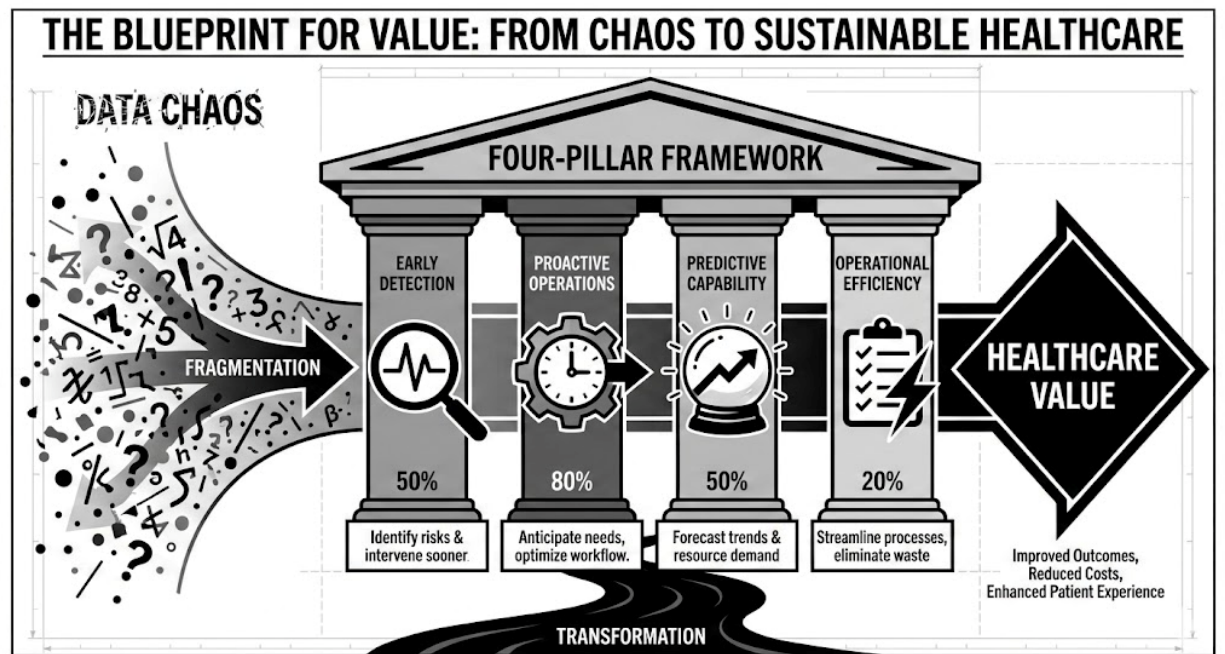


Figure 1 was generated using an AI-assisted image generation tool (Google Nano Banana) and modified by the authors for illustrative purposes.

## 1. Early Detection

The first pillar is the ability to identify clinical deterioration before it becomes catastrophic. Traditional clinical deterioration often relies on manual vital sign checks and the intuition of overburdened staff. By integrating real-time analytics and AI-driven tools into the clinical workflow, providers can surface subtle physiological changes that might otherwise go unnoticed.

Consider sepsis. It remains a leading cause of hospital mortality, yet its early signs are often non-specific. Machine learning models can now predict sepsis onset hours before clinical consensus, allowing for rapid antibiotic administration and fluid resuscitation.<sup>3,4</sup> Similar approaches are being applied to acute kidney injury, where early detection of subtle changes in renal biomarkers can prompt timely intervention and prevent progression to organ failure. The result is that care teams can intervene earlier, improving survival rates.

## 2. Proactive Operational Adjustments

Healthcare operations have historically been reactive: managing a bed crunch only after the Emergency Department is overcrowded, or calling in extra staff only after the shift has become unmanageable. The second pillar involves using data to anticipate these bottlenecks.

Predictive bed management tools can now forecast ICU occupancy and patient surges with high accuracy. By analyzing historical admission patterns, local epidemiological data, and real-time patient flow, leaders can allocate resources *before* a crisis emerges. This includes anticipating staffing needs, forecasting nursing and physician coverage requirements so that scheduling reflects expected demand rather than scrambling in response to it. This proactive stance reduces the "crisis management" mode that contributes to leadership fatigue and ensures that patients receive timely care in the appropriate setting.

## 3. Predictive Capability

While "Early Detection" focuses on the acute inpatient setting, "Predictive Capability" extends the horizon to the population level. Predictive analytics harness historical claims data, social determinants of health (SDOH), and clinical records to forecast adverse events such as heart failure exacerbations or diabetic ketoacidosis.

This capability is essential for value-based care models. By identifying patients at the highest risk of readmission or high-cost utilization, health systems can deploy targeted outreach and interventions, including proactive patient engagement, home health visits, and medication reconciliation, to prevent the event entirely.<sup>5</sup> This shifts care from the hospital to the home, aligning financial incentives with patient well-being.

## 4. Operational Efficiency

The final pillar addresses the administrative burden that weighs on clinical practice. Operational efficiency is achieved by automating the "low-value" tasks that consume provider time.

AI-driven documentation tools, for example, can now listen to patient-provider conversations and draft accurate clinical notes, reducing "pajama time," the hours physicians spend charting at night. Furthermore, AI-assisted coding tools can improve coding accuracy, reduce claim denials, and ensure appropriate reimbursement, while record review optimization can flag gaps in care and ensure revenue integrity, all without requiring manual chart audits. By removing these

clerical hurdles, we allow providers to focus on the human elements of care: empathy, judgment, and connection.

## **Practical Application: Provider Record Review Optimization**

A practical illustration of this framework is the optimization of provider record reviews. Traditionally, ensuring that a patient's chart accurately reflects their acuity and care needs required manual audits: a slow, error-prone, and expensive process.

AI-enabled solutions can now automatically scan clinical notes to identify inconsistencies, suggest appropriate diagnostic codes, and surface care gaps (e.g., a missing diabetic foot exam). This "intelligent assistant" does not replace the physician's judgment but augments it, ensuring that the medical record is a true reflection of the patient's complexity. The result is improved quality reporting, appropriate reimbursement, enhanced clinician satisfaction by relieving the burden of manual audits, and, most importantly, a more complete clinical picture for the next provider in the chain of care.

## **Impact Across the Health System**

Taken together, these four pillars generate value that extends beyond any single department. For patients, predictive models reduce preventable hospitalizations and improve the overall care experience. For health systems, real-time dashboards provide continuous visibility into quality, safety, and performance metrics, enabling leadership to make informed decisions with confidence rather than intuition. This alignment of clinical, operational, and financial outcomes is what separates organizations that use data well from those that simply collect it.

## **Future Directions: The Role of 'Omics'**

Looking to the horizon, the integration of "omics" data (genomics, proteomics, transcriptomics, and metabolomics) represents a significant next step in healthcare value. Currently, most clinical decisions are made based on population averages. The integration of omics data will allow for truly personalized medicine, where prevention and treatment are tailored to the unique molecular profile of the individual.<sup>6</sup>

For example, pharmacogenomics can predict how a specific patient will metabolize a drug, preventing adverse drug reactions that currently cost the healthcare system billions annually. While the full realization of this "multi-omics" future faces challenges in data storage and interpretation,<sup>7</sup> it aligns perfectly with the four pillars: enhancing early detection, refining predictive capability, and enabling precise operational adjustments.

## **Implementation Roadmap: A Stepwise Approach at the Helen F. Graham Cancer Center and Research Institute**

Translating this framework from aspiration to action requires a disciplined, phased approach. At the Helen F. Graham Cancer Center and Research Institute, we are committed to building a Center for AI Innovation through a stepwise implementation strategy designed to generate measurable value at each stage.

In the first six to twelve months, our efforts will concentrate on four priority areas within oncology: (1) leveraging AI to accelerate translational bench-to-bedside research currently

underway at our facility; (2) applying AI tools to reduce administrative burden and streamline daily workflows for oncology clinicians; (3) deploying predictive models to anticipate and manage patient responses to systemic cancer treatment, including prediction of adverse reactions, side effects, unplanned hospital admissions, and ultimately anticancer clinical response; and (4) utilizing population science data to predict cancer incidence, improve screening rates, and shift outcomes at a community health level.

In months twelve through twenty-four, we will expand the lessons learned from the oncology service line into adjacent areas, including heart and vascular medicine and neurology. This deliberate sequencing allows us to build institutional knowledge and governance structures in a high-stakes but well-defined domain before scaling across the enterprise.

## Conclusion

The journey from data chaos to healthcare value is not just a technology problem. It is a practical and ethical necessity. The current state of fragmented data and administrative overload is unsustainable for our caregivers and unsafe for our patients. By prioritizing data quality and embracing the pillars of early detection, proactive operations, predictive capability, and operational efficiency, we can improve outcomes, strengthen operations, enhance financial resilience, and stabilize the healthcare environment.

Technology should reduce the demands on our attention, not add to them. When data works for clinicians rather than against them, caregivers can get back to what they do best.

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