Big Data en salud: evidencia literaria para extraer principios de diseño que orienten la Trasformación de la atención, usando el enfoque CIMO

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RESUMEN

La transformación digital del sector salud ha generado una producción masiva de datos clínicos, administrativos y poblacionales, impulsada por la expansión de historias clínicas electrónicas, sistemas interoperables y herramientas de analítica avanzada. Sin embargo, pese al crecimiento sostenido del mercado de análisis de datos en salud y al aumento exponencial de información disponible, persiste una brecha significativa entre el potencial del Big Data y su aplicación efectiva en el rediseño de modelos de atención que generen valor clínico y operativo medible. Esta brecha constituye el problema central de la investigación: la limitada conversión de evidencia dispersa en reglas prácticas transferibles para la transformación sostenible de la atención en salud.

El objetivo general del estudio fue analizar la evidencia literaria sobre Big Data aplicada a modelos de atención en salud, con el fin de extraer principios de diseño verificables que orienten procesos de transformación organizacional. Para ello, se formularon preguntas orientadas a identificar qué intervenciones han sido implementadas, en qué contextos organizacionales, mediante qué mecanismos y con qué resultados, bajo una lógica explicativa que permitiera trascender la descripción de casos aislados.

El marco teórico integra cuatro perspectivas complementarias: (1) la noción de sistema de salud que aprende, que concibe los datos como insumo para mejora continua; (2) la teoría sociotécnica en tecnologías de información en salud, que enfatiza la interacción entre tecnología, personas y procesos; (3) la interoperabilidad y la historia clínica electrónica como infraestructura habilitadora; y (4) la ciencia de la implementación, que explica los determinantes de adopción, sostenibilidad y escalamiento de intervenciones digitales. Como marco de síntesis se empleó el enfoque CIMO (Contexto–Intervención–Mecanismo–Resultado), utilizado para estructurar configuraciones causales y derivar principios aplicables.

Metodológicamente, se desarrolló una investigación cualitativa de estado del arte con alcance exploratorio-descriptivo en su fase inicial y explicativo en su fase central. El diseño fue transversal, delimitado al periodo 2018–2025. Se realizó una búsqueda sistemática de literatura científica y técnica, identificando 1.256 registros iniciales. Tras aplicar criterios de inclusión y exclusión —priorizando estudios con aplicación asistencial directa y resultados medibles— se seleccionaron 98 estudios para análisis final. La información fue sistematizada mediante una matriz estructurada en Excel, que permitió extraer variables contextuales, características de intervención, mecanismos de cambio y resultados reportados. Posteriormente, se construyeron configuraciones CIMO y se analizaron patrones de éxito y fracaso.

Los resultados muestran que el impacto del Big Data en la transformación de modelos de atención depende menos de la sofisticación algorítmica y más de condiciones organizacionales específicas. Se identificaron cuatro condiciones críticas recurrentes: interoperabilidad estructural entre sistemas, calidad y

estandarización del dato, integración de las herramientas analíticas al flujo clínico y existencia de gobernanza organizacional clara. Cuando estas condiciones se cumplen, las intervenciones evidencian mejoras en seguridad del paciente, reducción de eventos adversos, optimización de reingresos hospitalarios, gestión poblacional del riesgo y eficiencia operativa. En contraste, cuando la tecnología se implementa de manera aislada o sin alineación cultural y estratégica, los resultados son limitados o no sostenibles.

Como principal aporte, el estudio traduce las configuraciones identificadas en un conjunto de principios de diseño verificables acompañados de criterios operativos que pueden orientar decisiones gerenciales. Estos principios buscan reducir la incertidumbre estratégica y facilitar procesos de escalamiento desde pilotos tecnológicos hacia transformaciones estructurales del modelo de atención.

Se concluye que la evidencia disponible sí permite derivar reglas prácticas transferibles, aunque su efectividad depende del nivel de madurez digital institucional, el contexto regulatorio y la capacidad de gestión del cambio. El trabajo aporta un marco integrador que articula evidencia internacional bajo lógica explicativa, contribuyendo tanto al debate académico como a la toma de decisiones en organizaciones de salud que buscan una transformación sostenible basada en datos.

Palabras clave: *Big Data, Transformación Sanitaria, Interoperabilidad, CIMO*

ABSTRACT

The digital transformation of the healthcare sector has led to a massive production of clinical, administrative, and population-level data, driven by the widespread adoption of electronic health records, interoperable systems, and advanced analytics tools. Despite sustained market growth in health data analytics and the exponential increase in available information, a significant gap persists between the strategic potential of Big Data and its effective application in redesigning care delivery models capable of generating measurable clinical and operational value. This gap constitutes the central problem of this research: the limited translation of dispersed evidence into transferable and practical design principles that support sustainable healthcare transformation.

The general objective of the study was to analyze the scientific literature on Big Data applied to healthcare delivery models in order to extract verifiable design principles that can guide organizational transformation processes. To achieve this, research questions were formulated to identify which interventions have been implemented, under what organizational contexts, through which mechanisms, and with what reported outcomes. The study adopts an explanatory logic that goes beyond descriptive case reporting and seeks to understand causal configurations that enable or constrain value generation.

The theoretical framework integrates four complementary perspectives: (1) the Learning Health System approach, which conceives data as a driver of continuous improvement; (2) sociotechnical theory in health information technologies, emphasizing the interaction between technology, people, and organizational processes; (3) interoperability and electronic health records as enabling infrastructure; and (4) implementation science, which explains determinants of adoption, sustainability, and scalability of digital interventions. As a synthesis framework, the CIMO approach (Context–Intervention–Mechanism–Outcome) was employed to structure causal configurations and derive actionable design principles.

Methodologically, the study is a qualitative state-of-the-art review with an exploratory-descriptive phase followed by an explanatory phase. The design is cross-sectional, covering the period 2018–2025. A systematic literature search identified 1,256 initial records. After applying inclusion and exclusion criteria—prioritizing studies with direct healthcare application and measurable outcomes—98 studies were selected for final analysis. Data were systematized through a structured extraction matrix, enabling the identification of contextual variables, intervention characteristics, mechanisms of change, and reported results. Subsequently, CIMO configurations were constructed and patterns of success and failure were analyzed.

Findings indicate that the impact of Big Data on care model transformation depends less on algorithmic sophistication and more on specific organizational conditions. Four recurrent critical conditions were identified: structural interoperability between systems, data quality and standardization, integration of analytics into clinical workflow, and clear organizational governance. When these conditions are met,

interventions demonstrate improvements in patient safety, reduction of adverse events, optimization of hospital readmissions, population risk management, and operational efficiency. Conversely, isolated technological implementations without cultural and strategic alignment tend to yield limited or unsustainable results.
As its primary contribution, the study translates the identified configurations into a set of verifiable design principles supported by operational criteria to guide managerial decision-making. These principles aim to reduce strategic uncertainty and facilitate the transition from technological pilots to scalable structural transformation. The research concludes that existing evidence allows for the derivation of transferable practical rules, although their effectiveness depends on institutional digital maturity, regulatory context, and change management capacity. Overall, the study provides an integrative and explanatory framework to support data-driven, sustainable healthcare transformation.

KeyWords: *Big Data, Healthcare Transformation, Interoperability, CIMO*

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