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CENTRO DE INTELIGENCIA ARTIFICIAL Y SALUD PARA AMÉRICA LATINA Y EL CARIBE

# WHAT INDICATORS OF ARTIFICIAL INTELLIGENCE IMPLEMENTATION IN HEALTH EXIST?

## TECHNICAL DOCUMENT 11

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# Content

# Executive Summary

This review systematically documents the **lack of published composite indices for assessing the implementation of artificial intelligence (AI) in healthcare services, organizations, and systems** . Despite the rapid adoption of AI in healthcare and the proliferation of composite indices in other fields, no instrument was identified that met the established methodological criteria.

The review was conducted following the JBI methodology and the PRISMA-ScR guidelines, with searches in PubMed, Scopus, Web of Science, IEEE, and a wide range of grey literature from international organizations (WHO, UNESCO, ECLAC, OECD), global consulting firms, and think tanks, complemented by searches assisted by generative artificial intelligence. 597 academic articles and 3138 institutional documents were retrieved, but all were excluded because they did not constitute composite indexes with a transparent methodology specifically adapted to AI in health.

The absence of such instruments reflects deeply rooted epistemological, methodological, and cultural barriers in the healthcare sector: heterogeneity of units of analysis, fragmented and non-interoperable data, ethical and regulatory restrictions, lack of consensus on what constitutes "AI implementation," and a disciplinary culture that has historically prioritized technical development over measuring implementation.

This finding represents a critical gap that requires urgent attention. **Without standardized instruments to measure the readiness, maturity, adoption, governance, and sustainability of AI in real-world healthcare settings, the field is proceeding blindly** . The review concludes with a conceptual proposal for the development of future indices that incorporates eight technical and organizational dimensions, a cross-cutting pillar of epistemic inclusion, and three levels of analysis (micro, meso, and macro). It calls for the collective development of measurement tools that enable the responsible, equitable, and sustainable implementation of AI in health systems, particularly in Latin America and the Caribbean.

# 1. Introduction

The integration of artificial intelligence into healthcare systems has accelerated significantly over the past decade, driven by three converging factors: advances in machine learning algorithms, the increasing availability of large volumes of clinical and administrative data, and the progressive digitization of healthcare services. This set of technological innovations offers substantial opportunities to improve operational efficiency, quality of care, and the timeliness of interventions in areas such as clinical diagnosis, population risk stratification, healthcare resource management, and evidence-based policymaking. However, the rapid deployment of these solutions has raised critical questions regarding their responsible implementation and the need to ensure their alignment with the strategic objectives of healthcare services, organizations, and systems as a whole.

In this context, various international organizations, academic institutions, and consulting firms have developed indices and assessment tools to quantify the level of AI readiness, adoption, and diffusion in different areas. **A composite index is defined as a quantitative measure that integrates multiple dimensions of a complex phenomenon through a set of indicators selected based on an explicit conceptual framework** . Constructing a composite index involves defining this conceptual framework, selecting and preparing relevant variables, managing missing data, applying multivariate analysis, normalizing and weighting variables, adding components, and evaluating the robustness and validity of the index, in order to subsequently interpret and communicate its results. The best examples are the Human Development Index, the Global Innovation Index, and the Consumer Price Index. These instruments transform complex data into practical tools that facilitate strategic decision-making, policy formulation, benchmarking between units, ranking entities, and monitoring progress toward defined goals. In this way, **the indices provide leaders and management teams with an objective empirical basis to guide their decisions on the implementation of AI.**

**Despite the proliferation of these indices in the broader field of AI, the available evidence specifically for the healthcare sector remains fragmented and limited** . There is a need to rigorously map and systematize the set of instruments that assess AI implementation in healthcare services, organizations, and systems. Furthermore, significant knowledge gaps persist regarding the dimensions evaluated, the predominant methodological approaches, the geographical contexts covered, and, especially, the extent to which these instruments incorporate critical principles such as patient safety, equity of access, sustainability of interventions, and the protection of fundamental rights.

# 2. Aim

The objective of this document is **to identify and characterize the main indices, describe their purposes and methodologies, and highlight gaps and opportunities for the future development of more comprehensive and contextualized assessment tools** . This synthesis seeks to provide useful evidence for researchers, managers, and health policymakers interested in strengthening the governance and responsible implementation of AI in health services, organizations, and systems.

# 3. Methodology

A scope review was conducted, considering the most appropriate design given the emerging, heterogeneous and conceptually diverse nature of the evaluation indices of the implementation of artificial intelligence (AI) in health, as well as the absence of standardized definitions and consensus frameworks specifically oriented to the health sector.

This review used exclusively publicly available secondary sources of information. Therefore, it did not require approval from a research ethics committee. The results will be reported in full, without manipulation of the findings and with proper attribution of sources.

**Data collection:**

A systematic search was conducted in bibliographic databases ( PubMed, Scopus, Web of Science, IEEE ) and in grey literature, including international organizations, consultancies, think tanks, Google and generative AI tools (Gemini, ChatGPT, Claude, DeepSeek, Qwen).

Generative AI was used to complement the search and identify potential indexes not indexed in traditional databases or accessible through Google. The prompt used was: *"Act as a documentation and archiving assistant. Your only task is to identify and locate documents (reports, publications, articles, technical documents, or working papers) that present, propose, or use composite indexes or composite indicators, global scores, maturity models, or readiness assessment tools specifically applied to the implementation of artificial intelligence in the healthcare sector. Key restriction: Do not generate new indexes, make implementation recommendations, or perform extensive analysis. Simply list existing documents in your knowledge base. If you are unsure about a document, indicate this with '[Source not confirmed]' instead of fabricating it ."* A person then verified the links to confirm the existence of the documents.

The records were selected by two independent reviewers and information was extracted on the characteristics, methodology and validation of the indices.

**Eligibility criteria:**

*Inclusion criteria:*
- Studies, technical reports or institutional documents that describe indices, rankings, scorecards or composite instruments (defined as quantitative measures that synthesize multiple dimensions from a set of selected indicators) used to evaluate the implementation of artificial intelligence.
- Explicit application to the health sector, with a focus on health services, organizations or systems.

- The index should aim to evaluate one or more of the following implementation constructs: readiness, maturity, adoption, acceptability, feasibility, capacity, governance, integration,

sustainability, scalability, or other constructs related to the AI implementation process.
- Languages: English, Spanish, Portuguese, French.
- Published between 2010 and April 2026.

*Exclusion criteria:*
- Studies or reports focused exclusively on the technical performance of the algorithms (e.g., accuracy metrics or clinical validation of models).
- Studies that present an index without a sufficient methodological description to identify its dimensions, indicators, or form of aggregation.
- Editorials, letters to the editor, opinions or conference summaries without a complete methodological development.

**Synthesis:**

A specific form was designed to extract, from each included document, standardized information on identification (name, institution, year and frequency of update), geographical scope and level of care, main construct evaluated, methodology (conceptual framework, indicators, standardization techniques, weighting and aggregation), and validation (content and construct validity, reliability, sensitivity analysis and consultation with interest groups); all this information was carried out in a summary table and synthesized through descriptive and narrative analysis, complemented with comparative tables to highlight convergences and divergences.

# 4. Context

The landscape of AI assessment in healthcare reveals a paradoxical situation. On the one hand, there is a growing recognition of the need to measure and monitor the implementation of AI in healthcare systems . International organizations, governments, and academic institutions have called for frameworks to assess the readiness, maturity , and impact of AI in healthcare settings. On the other hand, the tools available to conduct such assessments remain largely underdeveloped.

**Composite indices have become standard tools in fields such as economics, education, and social policy, where they support benchmarking, resource allocation, and policy evaluation.** The Human Development Index , the Global Innovation Index , and the Consumer Price Index are mature, standardized instruments that have been widely used for decades. In these fields, indices serve as heuristics that synthesize complex realities into quantifiable metrics, enabling comparisons across time and space.

In the healthcare sector, however, the development of analogous tools for AI implementation has lagged considerably. This gap reflects structural differences between these fields and the health domain. Healthcare systems exhibit high heterogeneity in their units of analysis, ranging from clinical services to complex hospital networks and national systems . <sup>5</sup> Data availability remains a persistent challenge, with fragmented information systems, a lack of interoperability,<sup> 6</sup> and significant limitations in data standardization .<sup> 7</sup> Furthermore, health data are subject to strict ethical and regulatory protections which, while necessary, complicate the development of standardized metrics.<sup>8,9</sup>

The very concept of "AI implementation" remains poorly defined. It is an emerging and multidimensional construct, operationalized through various concepts such as readiness, maturity, adoption, and sustainability. This conceptual ambiguity complicates efforts to develop consensus-based measurement frameworks.

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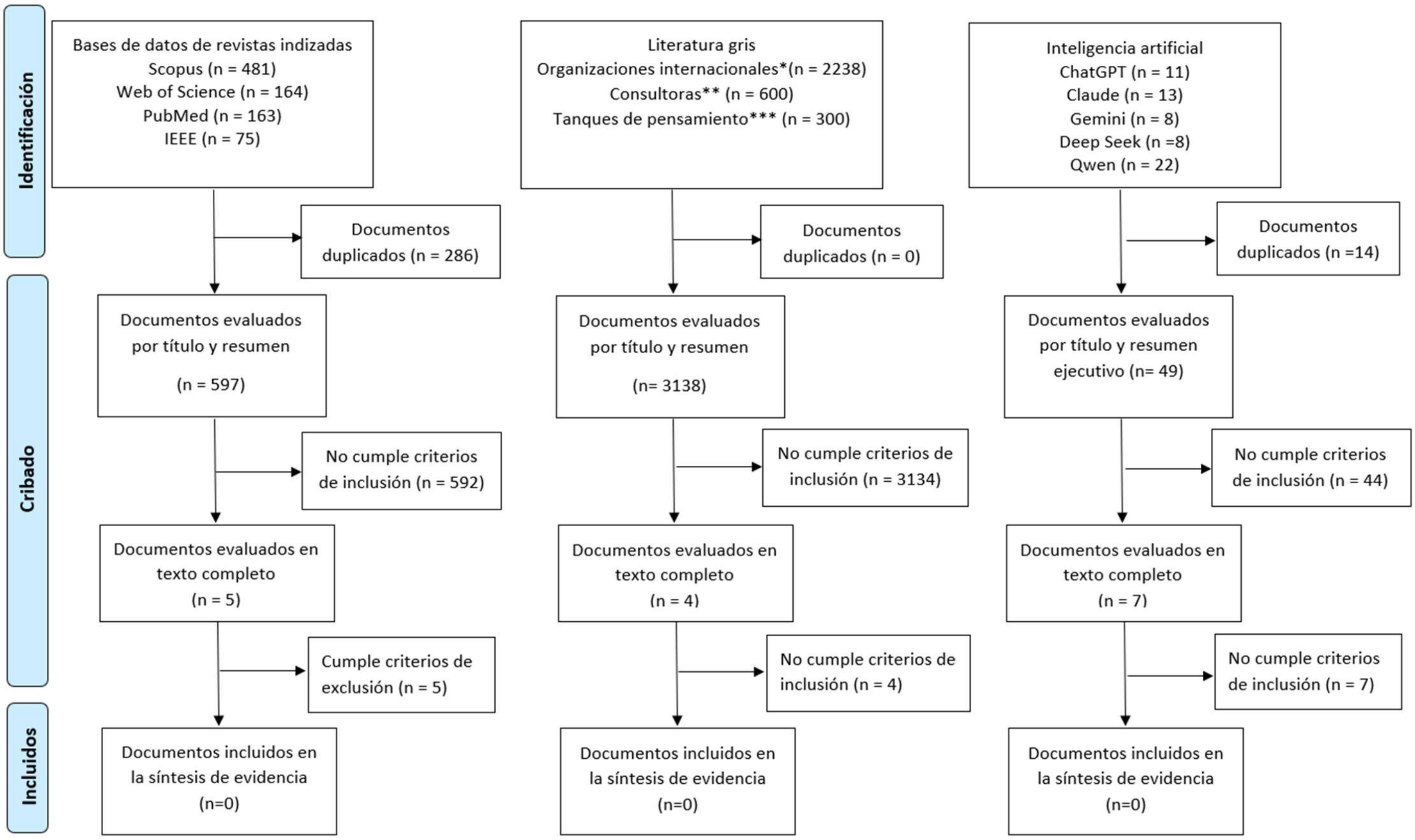
[1] Andersen ES, et al. Monitoring performance of clinical artificial intelligence in health care: a scoping review. JBI Evid Synth. 2024;22(12):2423-2446. doi: 10.11124/JBIES-24-00042.
[2] United Nations Development Program. Human Development Index (HDI) [Internet]. New York: UNDP; [cited 2026 Jun 10]. Available from: https://hdr.undp.org/data-center/human-development-index#/indicies/HDI
[3] World Intellectual Property Organization. Global Innovation Index [Internet]. Geneva: WIPO; [cited 2026 Jun 10]. Available from: https://www.wipo.int/en/web/global-innovation-index
[4] Federal Reserve Bank of Minneapolis. Consumer Price Index, 1913– [Internet]. Minneapolis (MN): Federal Reserve Bank of Minneapolis; [cited 2026 Jun 10]. Available from: https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913-
[5] Bosco LJ, et al. Heterogeneity and Interoperability in Local Public Health Information Systems. J Public Health Manag Pract. 2021;27(5):529-533. doi: 10.1097/PHH.0000000000001404.
[6] Tsafnat G, et al. Converge or Collide? Making Sense of a Plethora of Open Data Standards in Health Care. J Med Internet Res. 2024;26:e55779. doi:10.2196/55779.
[7] Tuly SR, et al. From Silos to Synthesis: A comprehensive review of domain adaptation strategies for multi-source data integration in healthcare. Comput Biol Med. 2025;191:110108. doi: 10.1016/j.compbiomed.2025.110108.
[8] Bosco LJ, et al. Heterogeneity and Interoperability in Local Public Health Information Systems. J Public Health Manag Pract. 2021;27(5):529-533. doi: 10.1097/PHH.0000000000001404.
[9] Ahmed MM, et al, Lucero-Prisno Iii DE. The ethics of data mining in healthcare: challenges, frameworks, and future directions. BioData Min 2025;18(1):47. doi:10.1186/s13040-025-00461-w.

# 5. Results and discussion

## 5.1. A void that is hard to ignore

Despite an exhaustive search of academic databases, institutional grey literature, publications from global consulting firms, and searches assisted by generative artificial intelligence, no document met all the established inclusion criteria (see Figure 1). **This scoping review did not identify any index or composite instrument for evaluating the implementation of artificial intelligence in health services, organizations, or systems** . This finding highlights a significant methodological gap and underscores the need to develop conceptual frameworks and instruments to assess and guide AI implementation, particularly in low- and middle-income countries.

**Figure 1.** PRISMA flow for information search and review.




** The documents came from the WHO (n = 1,068), ECLAC (n = 400), UNESCO (n = 280), OECD (n = 235), PATH (n = 93), World Bank (n = 55), International Telecommunication Union (n = 49), Broadband Commission (n = 40) and Inter-American Development Bank (n = 18).*
*** The documents came from Ernst & Young (EY) (n = 100), McKinsey (n = 100), Deloitte (n = 100), PwC (n = 100), KPMG (n = 100) and Bain & Company (n = 100).*
**** Papers came from Research ANd Development Corporation (n = 100), Center for Security and Emerging Technology (n = 100), and Stanford Institute for Human-Centered AI (n = 100).*
***Note:** The search for documents from consulting firms and think tanks was carried out with the support of Google and the official website of each of the institutions; the first 100 results were reviewed.*

The lack of composite indices for evaluating the implementation of artificial intelligence in healthcare can be attributed to the epistemological, methodological, and organizational characteristics of the healthcare sector. Unlike fields such as economics, where these instruments are widely established, the healthcare sector faces challenges stemming from the heterogeneity of its units of analysis, limitations in data availability, quality, and interoperability, and the ethical and regulatory restrictions associated with its use. Furthermore, the absence of a consensus-based conceptual framework for AI implementation, the multidimensional nature of this construct, and the predominance of research focused on technological development and algorithm performance, rather than on its implementation in real-world settings, have limited the development of metrics and composite indices for evaluating its adoption in healthcare systems.

Nor were any indices identified in the grey literature of international consulting firms, probably because these organizations offer customized and commercial evaluations rather than standardized, public and methodologically transparent instruments.

## 5.2. Emerging approaches

During the search, partial approaches were identified that did not reach the methodological threshold to be considered as composite indices. Several documents and initiatives related to AI in the health field were identified ,[6-11] some even using the term "index," which presented some elements conceptually close to the objective of this review, but were excluded for not fully meeting the eligibility criteria. Table 2 presents the list of documents.

**Table 2.** Documents identified during the review that assess the readiness, maturity or adoption of AI in health, but are not composite indices.

| Name (year of publication) | Responsible institution | Geographic scope | Methodology | Dimensions, indicators or metrics | Multivariate structure analysis technique, standardization, aggregation, and weighting |
|---|---|---|---|---|---|
| **Advancing artificial intelligence in health maturity (2022)** [10] | The Novartis Foundation and PATH | Argentina, Brazil, Chile, Uruguay, the Philippines, and Vietnam | It uses the conceptual framework of "Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity" from the Broadband Commission's Working Group on Digital Health and AI. A digital self-assessment tool based on six pillars or dimensions was applied. It assigns maturity levels (Explorer, Emerging, or Leader) using quantitative scores (on a scale of 0 to 10) and generates comparative charts by actor category and by pillar. There is no single standardized global quantitative "index." | Pillars or dimensions: - People, - data, - governance, - design, - partnerships, - business models | None. It is not a composite quantitative measure that synthesizes multiple dimensions (it is not an index per se). |
| **Artificial Intelligence in Public Health:** | World Health Organization (Regional Office for the | WHO Region of the Americas | It does not use a conceptual framework for implementation. It relies on an iterative approach based on expert consensus, review of | Dimensions: - governance, - infrastructure, - workforce, - data | None. It is not a composite quantitative measure that |

| | | | | | |
|---|---|---|---|---|---|
| **Readiness Assessment Toolkit (2024)** [11] | Americas), Pan American Health Organization, Inter-American Development Bank. | | scientific evidence, and support from generative AI tools to develop, refine, and validate the document's content. It is an assessment tool, but not a standardized, quantitative, global "index." | management, - financing, - public participation, - implementation, - evaluation | synthesizes multiple dimensions (it is not an index per se). |
| **Health AI Readiness Assessment (2025)** [12] | Digital Medicine Society (DiMe) | USA with global reach | It uses the "Health AI Maturity Model" framework, which is part of "The Playbook of Implementing AI in Healthcare," developed by members of the Digital Medicine Society. The methodology used is not mentioned. There is no single, standardized, global quantitative "index." | Dimensions: Leadership, governance and compliance; Data infrastructure and analytics; Technology, infrastructure and integration; Staff development and change management; Clinical integration and implementation; Financial sustainability and return on investment; Stakeholder and community engagement | None. It is not a composite quantitative measure that synthesizes multiple dimensions (it is not an index per se). |
| **Healthcare AI Adoption Index 2025/ AI Dx Index (2025)** [13] | Bain & Company, Bessemer Venture Partners, and Amazon Web Services (AWS) | USA with global reach | It does not use a conceptual framework for implementation. It was developed using buyer surveys, market analysis, and operational metrics (adoption, opportunities, development). There is no single, standardized, global quantitative "index." | Absolute and relative frequency<br>- Adoption by segment (provider, payer, pharmacist), - Opportunity score, - Adoption score, - Areas of greatest investment. | None. It is not a composite quantitative measure that synthesizes multiple dimensions (it is not an index per se). |
| **Artificial intelligence is reshaping health systems: state of readiness across the WHO European Region (2025)** [14] | World Health Organization (Regional Office for Europe) | 50 countries in the WHO European Region | It does not use a conceptual framework for implementation. It is based on a 2024–2025 survey sent to Member States (94% response rate: 50 out of 53) on AI in health; it collects national data through designated coordinators, with input from national experts in AI and health; and it is supplemented by country profiles. There is no single standardized, quantitative global "index." | Thematic areas:<br>- Strategic-operational context, - governance and legal/ethical regulation, - health data governance, - workforce capacity and stakeholder participation ,<br>- use of AI applications in health, - AI opportunities in health, - barriers to AI adoption. | None. It is not a composite quantitative measure that synthesizes multiple dimensions (it is not an index per se). |

| | | | | | |
|---|---|---|---|---|---|
| **AI Index Report 2026 (Medicine section) (2026)** [15] | Stanford Human-Centered AI (HAI) and Responsible AI for Scale and Equitable Health (RAISE Health) | USA with a global reach (thematic sections) | It does not use a conceptual framework for implementation. It collects and analyzes multiple open sources (publications, patents, datasets, investment, industrial activity) in a descriptive manner, without a clear methodology. There is no single standardized global quantitative "index". | Absolute and relative frequency - Publications on AI in medicine (PubMed), - growth of biological models, - reported clinical applications, - FDA-approved medical devices, - publications on ethical aspects, - investment in health-AI, - clinical trials. | None. It is not a composite quantitative measure that synthesizes multiple dimensions (it is not an index per se). |

These approaches confirm the interest in these tools and suggest the existence of an unmet demand for standardized measurement mechanisms, but they also highlight the challenge and lack of methodological rigor in producing a composite index capable of representing the implementation phenomenon.

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[10] The Novartis Foundation, PATH. Advancing artificial intelligence in health maturity [Internet]. Geneva: The Novartis Foundation; 2022. Available at: https://www.novartisfoundation.org/news-and-resources/media-library/advancing-artificial-intelligence-health-maturity

[11] Pan American Health Organization, World Health Organization Regional Office for the Americas, Inter-American Development Bank. Artificial Intelligence in Public Health: Readiness Assessment Toolkit [Internet]. Washington (DC): PAHO; 2024. Available at: https://www.paho.org/en/documents/artificial-intelligence-public-health-readiness-assessment-toolkit

[12] Digital Medicine Society (DiMe). Health AI Readiness Assessment [Internet]. Boston (MA): Digital Medicine Society; 2025. Available at: https://dimesociety.org/ai-implementation-in-healthcare-playbook/ai-evaluation-readiness/health-ai-readiness-assessment/

[13] Bain & Company, Bessemer Venture Partners, Amazon Web Services. Healthcare AI Adoption Index 2025 (AI Dx Index) [Internet]. Boston (MA): Bain & Company; 2025. Available at: https://www.bain.com/insights/the-healthcare-ai-adoption-index/

[14] World Health Organization Regional Office for Europe. Artificial intelligence is reshaping health systems: state of readiness across the WHO European Region [Internet]. Copenhagen: WHO Regional Office for Europe; 2025. Available at: https://www.who.int/europe/publications/i/item/WHO-EURO-2025-12707-52481-81028

[15] Stanford Institute for Human-Centered Artificial Intelligence, Responsible AI for Scale and Equitable Health. AI Index Report 2026 [Internet]. Stanford (CA): Stanford University; 2026. Available at: https://hai.stanford.edu/ai-index/2026-ai-index-report

## 5.3. Towards an AI index in health that transcends the technical

This lack of clarity underscores the need to develop and implement composite indices for AI adoption in healthcare. While composite indices are artificial constructs that can mask value judgments if they are not transparent, updatable, and methodologically robust, they possess significant heuristic value by facilitating the synthesis of complex phenomena, fostering dialogue among diverse stakeholders, and supporting the systematic monitoring of trends and gaps. Such instruments would allow for the comparison of healthcare services, organizations, and systems, guide resource allocation, monitor progress over time, and identify priority areas for strengthening. The development of future indices should consider the following recommendations.

## Recommendations

**1. Develop a consensus conceptual framework for the implementation of AI in healthcare:** It is a priority to build an international theoretical framework that defines in a consensual way what constitutes the implementation of AI in health.

Debates about the implementation of AI in healthcare mainly revolve around three conceptual tensions: 1) the lack of consensus on what "implementation" means—whether it is a one-off event or a continuous process that includes monitoring and sustainability, and whether terms like adoption, deployment, and implementation are synonymous or distinct processes; 2) whether classical implementation science frameworks are suitable for AI or whether, due to its dynamic and changing nature, it requires its own frameworks, since it may differ from the implementation of evidence-based practices in terms of which determinants, strategies, and outcomes are relevant; and 3) the tension between a purely technical approach (focused on algorithm performance) and a sociotechnical one (which incorporates clinical flow, trust, and governance), compounded by the doubt as to whether these frameworks—designed mostly in high-income countries—are applicable to public health systems in middle- and low-income countries.

This process should be carried out using consensus methodologies, such as the Delphi method, and involve medical informatics specialists, implementation science specialists, healthcare managers, regulators, physicians, patients, and representatives from diverse regions, cultures, and languages, ensuring representation that transcends high-income countries.

**2. Design composite indices with methodological rigor and transparency:** Future indices should be developed following international standards for constructing composite indicators, such as those proposed by the OECD, and incorporate an explicit conceptual framework, indicator selection and validation, standardization, weighting, sensitivity analysis, and external validation. It is also recommended that the indices, their methodology, and validation data be published in open access to facilitate their evaluation, reproducibility, and adoption.

**3. Incorporate key dimensions of AI implementation:** The indices should comprehensively assess the technical and organizational capabilities needed to implement AI in health, including governance, leadership, technological infrastructure, data management, staff capacity development, financing, clinical integration, stakeholder engagement, evidence generation, and innovation.

**4. Integrate epistemic inclusion as a cross-cutting theme:** In addition to technical capabilities, the indices should incorporate epistemic inclusion criteria that assess linguistic and cultural diversity, the effective participation of patients and communities, transparency and the ability to challenge automated decisions, data sovereignty, and the building of informed trust. This will help ensure that AI implementation promotes equity and avoids perpetuating inequalities or structural biases.

**5. Develop indices adapted to the different levels and contexts of the health system:** It is recommended to design specific instruments for the micro (services), meso (organizations) and macro (health systems) levels, adaptable to different care contexts, including primary care, hospitals of different levels of complexity, rural areas and various health system models, which favors their applicability and comparability.

In this regard, based on the conceptual frameworks described in the "Emerging Approaches" section, a framework integrating eight technical and organizational dimensions was synthesized. However, these dimensions alone only reflect the material and institutional capacities of health systems, without considering who benefits from AI implementation, who participates in its design, or what the implications are for excluded groups.<sup> [16,17] </sup> Consequently, it is proposed to incorporate a cross-cutting pillar of epistemic inclusion that guides the consensus toward a comprehensive framework for AI implementation in health services and systems and that, in turn, facilitates the future development of composite AI implementation indices (Figure 2). These indices should be developed for the different levels of the health system—micro (services), meso (organizations), and macro (health systems)—and adapted to a wide variety of contexts. Consequently, these principles should be applicable not only to highly complex hospitals, but also to smaller hospitals, primary care facilities, rural settings, and different healthcare system models. This framework constitutes a theoretical starting point that will need to be discussed, refined, and empirically validated in future research to determine its operability and relevance in diverse healthcare contexts.

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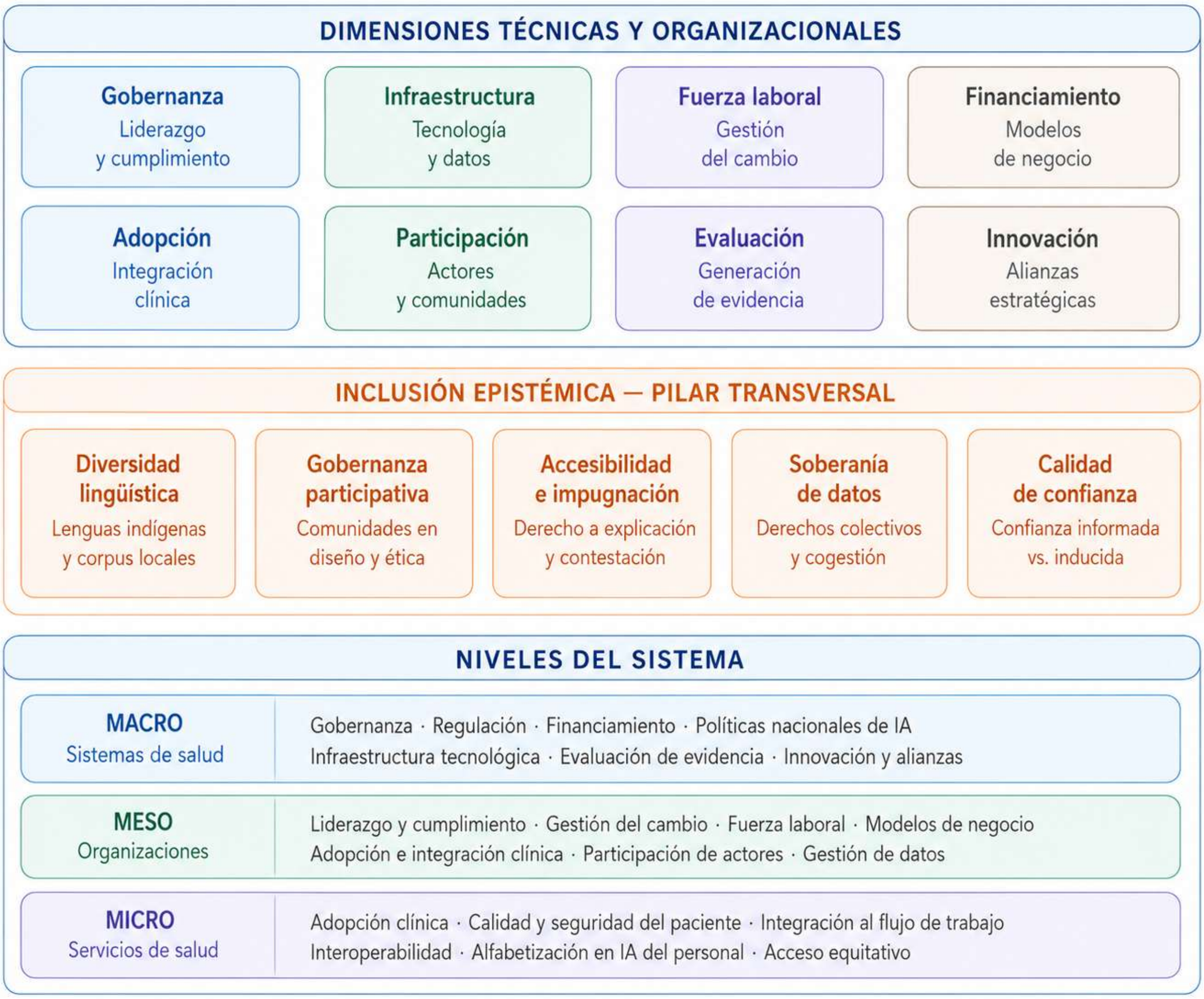
[16] Cachipuendo-Contero IJ. The epistemic readiness gap: rethinking AI readiness indices through ILIA 2025. AI Soc. 2026;1-14.
[17] Mariniello M. Colonialism 4.0 and Coloniality 4.0.AI Soc. 2026;41(4):3621-35.

**Figure 2.** Proposed conceptual framework for the development of an index for the implementation of artificial intelligence in health.



# 6. Limitations

This review has limitations that are important to point out. First, publication bias cannot be ruled out, as ministries of health or regulatory bodies may have developed internal monitoring indicators that are not found in academic or open-access grey literature. Furthermore, some instruments may be documented only in languages not included in this search, particularly Mandarin Chinese, given China's remarkable progress in artificial intelligence. Due to the dynamic nature of this field, some indices may be under editing or available as preprints at the time of this review. Finally, the strict application of the criteria established in the OECD Handbook may have excluded simpler tools, such as checklists or roadmaps, which, while not strictly composite indices, could be useful for evaluating implementation.

Despite these caveats, the review possesses methodological strengths that support the robustness of its conclusions. First, the research question was not posed in a narrow or restrictive manner, but rather adopted a broad and flexible notion of both "implementation" and "artificial intelligence." This deliberate openness maximized the sensitivity of the search and minimized the risk of inadvertently omitting relevant indices. The fact that, even with this broad strategy, no index meeting the inclusion criteria was found reinforces the strength of the result: the lack is not due to a narrow definition of the problem, but rather demonstrates a real and significant gap in the scientific literature. Second, the search was broad and multifaceted, encompassing four academic databases, numerous sources of institutional and consulting grey literature, as well as a complementary exploration using generative artificial intelligence tools, the results of which were subsequently compared with the primary sources. The eligibility criteria were explicitly defined and aligned with international standards, taking as a reference the OECD's Population, Concept, and Context framework and Handbook. The selection process was meticulous, involving two independent reviewers, resolving disagreements by consensus, and resorting to a third reviewer when necessary.

# 7. Final reflections

This review documents the absence of composite indices to assess the implementation of AI in health, reflecting the methodological particularities of the sector, characterized by the heterogeneity of its contexts, the limited interoperability of data, the lack of agreed conceptual frameworks and a historical approach focused on technological development rather than on the evaluation of implementation.

The rapid advancement of artificial intelligence in healthcare makes this gap unsustainable. Without instruments to measure the readiness, maturity, adoption, and sustainability of AI in real-world settings, the field is moving blindly. The lack of indices is not merely an academic curiosity; it is a practical problem. Healthcare systems making significant investments in AI lack the tools to monitor progress, identify gaps, and guide strategic decisions. Latin American and Caribbean countries, with their limited resources and pressing healthcare needs, are particularly disadvantaged by this gap.

This brief review is therefore a methodological wake-up call and an invitation to collectively build the tools the health sector needs for the effective, equitable, and sustainable implementation of artificial intelligence. The proposed conceptual framework—which integrates technical and organizational dimensions, epistemic inclusion, and multiple levels of analysis—offers a starting point. But frameworks alone are insufficient. A concerted effort involving researchers, healthcare managers, regulators, communities, and international organizations is required to develop, validate, and test indices adapted to diverse contexts.

The task ahead is substantial. It involves not only technical work but also political and ethical work. It requires confronting the colonial assumptions embedded in many measurement frameworks, ensuring that indices respond to the needs of diverse populations, and building mechanisms for genuine participation. It demands a shift in academic culture, from valuing technical novelty to valuing the science of implementation. It requires investment in data infrastructure, interoperability, and health information systems that support robust measurement.

This stark review is not a conclusion but a beginning. It marks the recognition that the healthcare sector cannot afford to implement AI without the tools to understand what is being implemented, for whom, and with what effects. The metrics we build—or fail to build—will shape the future of AI in healthcare for generations. The choice is ours.

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