Arab Journal of Administrative Sciences

2026, Online First

Doi: 10.34120/ajas.2025.1507

Majdi A. Quttainah
Kuwait University
Kuwait

Strategic Governance Tools for AI in Digital Health: A Scoping Review Across the Innovation Lifecycle and ESG Dimensions

Abstract

Purpose: As artificial intelligence (AI) systems become integral to healthcare value chains, business and policy leaders face pressure to implement governance mechanisms that ensure technical robustness, ethical accountability, and environmental sustainability. This study aims to map and evaluate existing tools, frameworks, and guidelines for responsible AI governance in digital health.

Study design/methodology/approach: A scoping review was conducted following the PRISMA-ScR framework, covering literature published between 2015 and 2025 across academic and grey sources.

Sample and data: From 105 records screened, 46 documents met inclusion criteria. These tools were assessed across the AI innovation lifecycle (design, development, deployment, governance, and assessment), their intended stakeholder groups (e.g., developers, policymakers, end users), and their alignment with ESG principles such as transparency, accountability, sustainability, and inclusivity.

Results: Most frameworks originated in Europe and North America and concentrated on early-stage processes, particularly design (59%) and governance (72%). Developers and policymakers were the primary audiences. Transparency (76%) and accountability (70%) were emphasized, while environmental sustainability (17%) and user-centered inclusivity received limited attention.

Originality/value: This review provides the first systematic synthesis of AI governance tools in healthcare, explicitly through an ESG lens, highlighting both strengths and blind spots in current practices.

Research limitations/implications: While the study captures global literature, the dominance of Western sources may limit the representativeness of findings. Findings underscore the need for scalable, lifecycle-spanning, and context-sensitive governance mechanisms that support sustainable and equitable adoption of AI in health systems.

Keywords: Artificial Intelligence, Responsible Innovation, Digital Health, Sustainability, Governance Tools, ESG, Scoping Review.

JEL classification: G34, G38, G31, G30

Submitted: 10/6/2025, revised:13/8/2025, accepted: 20/8/2025.

To cite: Quttainah, M. A. (2026). Strategic governance tools for AI in digital health: A scoping review across the innovation lifecycle and ESG dimensions. *Arab Journal of Administrative Sciences*. Online first. https://doi.org/10.34120/ajas.2025.1507

الملخص

أدوات الحوكمة الاستراتيجية للذكاء الاصطناعي في الصحة الرقمية: مراجعة نطاقية عبر دورة حياة الابتكار وأبعاد الحوكمة البيئية والاجتماعية والمؤسسية

مجدي أنور قطينة
جامعة الكويت
الكويت

هدف الدراسة: مع تزايد أهمية أنظمة الذكاء الاصطناعي في سلاسل قيمة الرعاية الصحية، يواجه قادة الأعمال والسياسات ضغوطاً لتطبيق آليات حوكمة تضمن المتانة التقنية والمساءلة الأخلاقية والاستدامة البيئية. تهدف هذه الدراسة إلى تحديد الأدوات والأطر والمبادئ التوجيهية الحالية وتقييمها؛ لحوكمة الذكاء الاصطناعي المسؤولة في مجال الصحة الرقمية.

تصميم/ منهجية/ طريقة الدراسة: أُجريت مراجعة نطاقية وفقاً لإطار PRISMA-ScR، التي تغطي الأدبيات المنشورة بين عامَي 2015 و2025 عبر المصادر الأكاديمية والرمادية.

عينة الدراسة وبياناتها: فُحصت 105 سجلات، واستُوفي منها 46 وثيقة لمعايير الإدراج، وخضعت هذه الأدوات للتقييم على مدار دورة حياة ابتكار الذكاء الاصطناعي (التصميم والتطوير والنشر والحوكمة والتقييم)، وفئات أصحاب المصلحة المستهدفين مثل: (المطورين وصانعي السياسات والمستخدمين النهائيين)، ومدى توافقها مع مبادئ الحوكمة البيئية والاجتماعية والمؤسسية (ESG) مثل الشفافية والمساءلة والاستدامة والشمولية.

نتائج الدراسة: نشأت معظم أطر العمل في أوروبا وأمريكا الشمالية، وركزت على العمليات في مراحلها المبكرة، وخاصةً التصميم (59%) والحوكمة (72%). وكان المطورون وصانعو السياسات هم الجمهور الرئيسي. ورُكّز على الشفافية (76%) والمساءلة (70%)، بينما حظيت الاستدامة البيئية والشمولية التي تركز على المستخدم باهتمام محدود (17%).

أصالة الدراسة: توفر هذه المراجعة أول توليفة منهجية لأدوات حوكمة الذكاء الاصطناعي في الرعاية الصحية بوضوح من خلال عدسة (ESG)، مع تسليط الضوء على نقاط القوة والنقاط العمياء في الممارسات الحالية.

حدود الدراسة وتطبيقاتها: رغم أن الدراسة تعتمد على الأدبيات العالمية، إلا أن هيمنة المصادر الغربية قد تحد من تمثيلها، وتؤكد النتائج على الحاجة إلى آليات حوكمة قابلة للتطوير، وتغطي دورة حياة المنتج، وتراعي السياق، وتدعم تبني الذكاء الاصطناعي باستدامة وعدل في الأنظمة الصحية.

الكلمات المفتاحية: الذكاء الاصطناعي، الابتكار المسؤول، الصحة الرقمية، الاستدامة، أدوات الحوكمة، الحوكمة البيئية والاجتماعية والمؤسسية، مراجعة نطاق التطبيق.

الإشارة المرجعية: قطينة، مجدي أنور. (2026). أدوات الحوكمة الاستراتيجية للذكاء الاصطناعي في الصحة الرقمية: مراجعة نطاقية عبر دورة حياة الابتكار وأبعاد الحوكمة البيئية والاجتماعية والمؤسسية. *المجلة العربية للعلوم الإدارية*. النشر المبكر. https://doi.org/10.34120/ajas.2025.1507

Introduction

Artificial intelligence (AI) is reshaping the global healthcare landscape, enabling advances in clinical diagnostics, precision medicine, patient engagement, and administrative efficiency (Alowais et al., 2023; Bajwa et al., 2021; Maleki Varnosfaderani & Forouzanfar, 2024). As digital health technologies increasingly rely on AI-enabled tools, the associated governance, ethical, and sustainability concerns have become critical areas of interest for researchers, managers, and policymakers alike (Cheong, 2024; Radanliev, 2025). While AI offers opportunities to optimize service delivery and expand healthcare access, its implementation raises fundamental questions about accountability, equity, resource efficiency, and lifecycle oversight (Vandemeulebroucke, 2025).

Environmental, Social, and Governance (ESG) frameworks refer to sets of criteria used to evaluate the ethical and sustainable performance of organizations as well as technologies. In the context of AI in healthcare, ESG dimensions address environmental impacts such as energy efficiency and carbon footprint, social considerations including equity, accessibility, and inclusiveness, and governance aspects such as transparency, accountability, and compliance with ethical standards (Grunhut et al., 2022). Integrating ESG into AI governance ensures that innovation meets not only technical and clinical objectives but also aligns with broader societal and planetary health priorities.

Numerous frameworks have emerged to articulate principles of responsible AI,often centered on transparency, fairness, and privacy; yet few provide concrete guidance on operationalizing these principles across the innovation lifecycle, particularly in healthcare contexts (Fjeld et al., 2020; Morley et al., 2020). The translation of abstract ethics to practical tools has proven difficult in settings where innovation evoloves faster than regulation. Moreover, most existing efforts have disproportionately emphasized algorithmic fairness at the design stage, while giving limited attention to post-deployment monitoring, organizational accountability, and environmental sustainability (Chang & Ke, 2024; Ozkan, 2024).

From a managerial and governance perspective, this gap reflects broader tensions in digital innovation: the push for scalability and efficiency often conflicts with calls for ethical deliberation, inclusive stakeholder engagement, and alignment with ESG (Environmental, Social, and Governance) principles (Papagiannidis et al., 2025; Stahl et al., 2022). The health sector, in particular, faces a paradox, as it benefits immensely from AI while remaining ethically bound to uphold patient trust, equity, and sustainability. Despite this, few AI governance tools currently integrate frugal design principles or offer strategies for mitigating carbon footprints, even as awareness of AI's environmental toll (Strubell et al., 2020; Vinuesa et al., 2020).

This review maps existing tools governing AI in digital health, analyzing lifecycle coverage, stakeholder inclusiveness, and ESG integration. In doing so, it poses four critical questions: (1) What tools and frameworks currently support sustainable and accountable AI governance in digital health? (2) How do these tools address different phases of the AI lifecycle, from design to deployment and post-implementation oversight? (3) To what extent do they incorporate ESG-aligned and responsible innovation practices principles? and (4) Who are the intended users of these tools, and how inclusive are they in practice?

In addressing these questions, the review contributes to academic and practitioner debates by highlighting strategic gaps in current governance models, offering insight into how sustainability and responsibility are operationalized, and providing a foundation for future work that bridges ethics, management, and innovation within AI-driven healthcare systems.

This review builds on the foundational methodologies of Arksey and O'Malley (2005), and refines them using the PRISMA-ScR guidelines (Tricco et al., 2018). It contributes a managerial and policy-relevant synthesis of tools for responsible AI governance in healthcare. It also extends recent work by scholars who have called for deeper integration of sustainability and business ethics into AI frameworks (Dwivedi et al., 2021; Stahl et al., 2022). By providing an organized inventory of such tools and frameworks, this review aims to support health system leaders, developers, and policymakers in designing AI interventions that are not only innovative but also ethical, sustainable, and socially equitable. While ethical principles such as transparency and accountability are widely discussed, few frameworks explicitly integrate environmental, social, and governance (ESG) considerations, despite their relevance for AI systems that affect human well-being, operate in high-impact environments, and increasingly consume substantial computational resources.

Methodology

Review Design

This study employed a scoping review methodology based on the framework developed by Arksey and O'Malley (2005), enhanced by recommendations from Levac et al. (2010), and reported following the PRISMA Extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2018). Given the emerging nature of responsible AI in healthcare, an area that intersects ethics, governance, sustainability, and digital innovation, a scoping review is appropriate to systematically explore and map the breadth of literature across academic and grey sources. Consistent with scoping review methodology, no formal quality appraisal of included tools was conducted. The goal was to map the breadth and characteristics of available governance instruments, rather than evaluate their effectiveness or methodological rigor.

Objectives and Research Questions

The primary objective of this review was to identify, categorize, and assess frameworks, tools, and guidelines that support the sustainable and accountable AI implementation in digital health. Specifically, the review addressed four research questions:

i. What tools, frameworks, and guidelines exist to support sustainable and accountable AI governance within digital health?

ii. How do these tools operationalize responsibility principles across different phases of the AI innovation lifecycle (e.g., design, development, governance, assessment, and use)?

iii. To what extent do these tools incorporate environmental sustainability and ESG-aligned principles?

iv. Who are the intended users of these tools, and at what lifecycle stages are they most applicable?

Eligibility Criteria

Explicit inclusion and exclusion criteria were developed and rigorously applied throughout the screening process to ensure that only data meeting the relevance, consistency, and quality standards were included in this scoping review.

Inclusion Criteria

Documents were considered eligible for inclusion if they met the following criteria. First, a 10-year window (2015–2025) was chosen to capture tools developed after the emergence of ethical AI as a global policy issue. Second, documents needed to be published in English, as this is the primary language accessible to the research team. Third, each document had to describe a concrete tool, framework, checklist, guideline, or assessment method explicitly related to the implementation ofresponsible artificial intelligence in digital health settings.

Furthermore, eligible documents were required to offer sufficient detail regarding the implementation, structure, or application of the tool in question, so that it could be evaluated in terms of purpose, scope, and relevance. Lastly, to ensure credibility, all sources had to be developed or endorsed by recognized entities, including academic institutions, government agencies, non-governmental organizations (NGOs), or private-sector consultants with demonstrated involvement in health innovation or technology governance. Only tools that were publicly available or described in sufficient detail to permit analysis were included.

Exclusion Criteria

Documents were excluded from the review if they did not meet the above requirements. Specifically, publications released before 2015 were excluded to maintain the review’s focus on tools aligned with current AI governance landscape. Similarly, documents published in languages other than English were excluded due to the reviewers' language limitations.

Regarding content, sources were excluded if they presented general or conceptual discussions of AI ethics without providing a concrete, operationalizable tool. Additionally, documents consisting solely of software code or repositories (e.g., GitHub pages) without explanatory content or usage guidance were excluded. Items were also removed if they lacked specific relevance to the healthcare or digital health context, even if they addressed AI governance in a broader sense. Finally, non-scholarly or incomplete materials, such as patents, full academic theses, promotional brochures, inaccessible gray literature, or broken hyperlinks, were excluded to maintain the methodological integrity of the review.

The exclusion of non-English documents was due to the limited translation capacity within the research team and the need to ensure methodological consistency. While this limitation may affect global coverage, the decision reflects a pragmatic balance between scope and feasibility.

Information Sources and Search Strategy

Searches were conducted across multiple academic and gray literature sources from January 15 to May 3, 2025, to ensure a comprehensive and systematic identification of relevant literature. The academic search strategy targeted well-established databases known for their interdisciplinary coverage and relevance to healthcare, technology, and policy research. These included PubMed, incorporating Medical Subject Headings (MeSH) for enhanced precision, Web of Science, IEEE Xplore, Scopus; arXiv, particularly for preprints in computer science and engineering; IBSS ProQuest for social science literature; and Sociological Abstracts, which offered valuable insights into ethical and governance issues within the digital health landscape.

In parallel, gray literature searches were conducted to capture non-peer-reviewed but policy-relevant sources that often contain practical frameworks and emerging tools not published in academic journals. These searches included systematic queries on Google Advanced Search and DuckDuckGo, along with targeted exploration of websites from globally recognized institutions. These included the World Health Organization (WHO), OECD.AI, the World Economic Forum, the U.S. FDA's Digital Health Center of Excellence, and the Brookings Institution. Gray literature documents were evaluated for relevance based on credibility (institutional source), accessibility (public availability), and the presence of tool-level detail. Only records with actionable frameworks or structured guidance were retained. Priority was given to institutional reports, guidelines, and position papers isuued by recognized bodies such as WHO, OECD.AI, and Brookings. Each website was explored using on-site search bars and, where necessary, through external advanced search functions using domain-specific filters and file-type restrictions.

To guide the identification of relevant materials, Boolean search strings were constructed using a combination of terms capturing key themes in artificial intelligence technologies, digital health domains, governance tools, and responsible innovation. Representative search queries included combinations such as: ("Artificial Intelligence" OR "Machine Learning" OR "AI") AND ("Digital Health" OR "E-Health" OR "M-Health") AND ("Framework" OR "Tool" OR "Checklist") AND ("Ethics" OR "Responsibility" OR "Sustainability" OR "Frugality" OR "ESG").

All retrieved search results were imported into the EndNote reference management software for organization and deduplication. The curated set was then exported to Covidence, a platform designed to streamline systematic reviews, where the screening and selection processes were subsequently conducted. This dual-system approach ensured technical robustness and traceability throughout the review process.

Screening and Selection Process

The screening and selection of documents followed a systematic, multi-phase process intended to ensure transparency, consistency, and methodological rigor. The process was facilitated using EndNote for reference management and Covidence for streamline screening, collaboration, and documentation of inclusion decisions. For transparency and reproducibility, all included tools are listed in Appendix A, which providesdetails on the tool name, year, developer, type, lifecycle stage, and source type.

Initial Screening: Title and Abstract Review

All records retrieved from the database and gray literature searches were imported into EndNote for deduplication during the first stage. Following this, the remaining unique records were uploaded to Covidence for screening. Two reviewers independently evaluated each document against the eligibility criteria outlined above during the title and abstract screening phase to determine its preliminary relevance. Items that did not meet inclusion requirements were excluded at this stage, while those that were ambiguous or appeared potentially relevant were retained for full-text assessment. Reviewer disagreements were resolved through discussion and, where necessary, arbitration by a third team member.

Full-text Review and Final Inclusion

Documents that passed the initial screening proceeded to full-text review. In this phase, the same reviewers independently assessed each full document for inclusion, using a standardized decision form aligned with the inclusion and exclusion criteria. Each document was evaluated on multiple dimensions, including the presence of a practical or operational tool, its connection to digital health and responsible AI, and the credibility of its source. Where inclusion decisions remained uncertain, reviewers convened to discuss the case and achieve consensus. Of the 105 records screened through this two-stage process, 46 documents met all eligibility criteria and were included in the final dataset for data extraction and analysis.

Documentation and Reproducibility

Throughout the screening process, reasons for exclusion during the full-text stage were systematically documented within Covidence, ensuring both reproducibility and auditability. A PRISMA-ScR flow diagram was developed to illustrate the screening stages, including the number of records identified and screened to those ultimately included in the review, as shown in Figure 1. This documentation enhances transparency and traceability, reinforcing the methodological robustness of the review process.

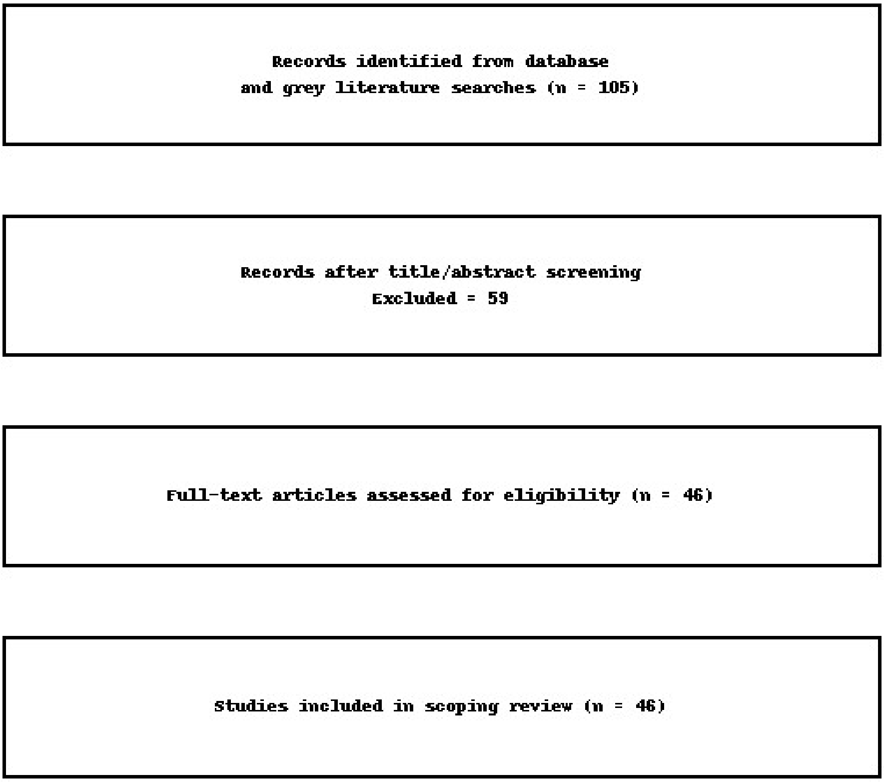

Figure 1: PRISMA-ScR Flow Diagram for Study Selection

Data Extraction and Coding

A structured codebook guided data extraction, aligning tools with predefined dimensions of responsible innovation, such as transparency, fairness, frugality, environmental sustainability, and data governance. This approach ensured consistent and comprehensive coding throughout the documents, as shown in Table 1.

Table 1
Key Variables for Data Extraction and Coding

Variable Category	Description
Publication characteristics, e.g., the WHO Digital Health Guidelines (2022)	Year of publication, authorship, and source type (academic or gray literature)
Field of application	Area of application: AI, AI in health, digital health, or general digital technologies
Type of organization	Origin of the tool: academic, government, NGO, private sector, or multisectoral
Methodological rigor	Whether a formal development process was reported (Yes / No / Not mentioned)
Tool type, e.g., Ethical AI Checklist (normative), Model Cards (operational)	Reflective (thinking), Normative (guidelines), Operational (actionable), or Mixed
Application phase	Stage of the AI lifecycle that the tool addresses: design, development, governance, assessment, deployment, or multiple
Intended users	Primary audience: developers, managers, endusers, regulators, researchers, or multiple stakeholders
Responsible innovation dimensions, e.g., environmental sustainability (energy impact calculator), transparency (model facts label)	Ethical and sustainability-related features: environmental sustainability, fairness, transparency, data governance, human-centric design, etc.

Note: Tools were assessed based on their ability to translate high-level responsibility principles, such as transparency, equity, frugality, or eco-responsibility, into operational components across the AI lifecycle.

Synthesis and Analysis

Following data extraction, a structured approach to data synthesis and analysis was employed to identify key patterns, thematic clusters, and gaps within the body of literature. The goal of this stage was to interpret and categorize the diverse set of governance tools and frameworks by categorizing them according to their functional attributes, lifecycle focus, and alignment with responsible innovation principles—particularly sustainability and accountability.

Descriptive Mapping of Tool Characteristics

Initially, a descriptive mapping was conducted to summarize the general characteristics of the included documents. This involved organizing tools by publication year, type of source (academic or gray literature), geographic or institutional origin and the organizational sector responsible for development (e.g., academic, governmental, private, NGO, or multisectoral).

Each tool was then classified according to its type, whether it was reflective (promoting ethical awareness or deliberation), normative (providing ethical guidelines or principles), operational (offering actionable procedures or assessment methods), or hybrid (combining two or more functions). Tools were also mapped to the AI lifecycle they addressed, including design, development, governance, deployment, and evaluation. This classification enabled the identification of areas with the dense tool clustering (e.g., governance or development) and areas with notable gaps (e.g., deployment or post-market audit).

Thematic Analysis of Responsible Innovation Dimensions

A thematic analysis was conducted to assess how tools Incorporatedprinciples of responsible innovation. Coding categories covered environmental sustainability, data governance, transparency, fairness, accountability, human-centric design, and equity. The presence or absence of each of these dimensions was systematically recorded and quantified across the included tools.

This step focused on identifying tools that incorporate Environmental, Social, and Governance (ESG) considerations and their explicit alignment withResponsible Research and Innovation (RRI) principles. For example, tools were examined for features that addressed energy efficiency, environmental impact assessments, lifecycle emissions, and frugality in resource use-core components of sustainable AI. Similarly, the analysis examinedwhether tools provided mechanisms for risk mitigation, bias audits, user inclusion, and institutional transparency.

Stakeholder and User Mapping

Tools were further analyzed according to their intended users, including developers, managers, policymakers, regulators, researchers, and multi-stakeholder groups. This helped determine whether governance resources were designed for use within technical teams, policy contexts, or operational healthcare environments. The degree to which the tools were actionable and context-specific was also recorded, highlighting those most likely to be practical in real-world healthcare contexts.

Results

Following a structured screening of 105 records, a total of 46 documents were included in this scoping review. These comprised both academic publications and gray literature published between 2015 and 2025, originating from various global regions and institutional types. The reviewed tools varied in scope, design, and practical application, yet most aimed to Integrateethical and responsible AI practices into digital health systems. A complete list of all 46 tools and frameworks included in this review, along with their source, type, and lifecycle stage, is provided in Appendix A.

Overview of Included Tools and Frameworks

The included tools were analyzed based on general characteristics such as source type, geographic origin, and the type of developing organization. As shown in Table 2, a slight majority (54.4%) of the tools came from gray literature, reflecting the growing role of policy institutions, NGOs, and regulatory bodies in shaping practical frameworks for AI governance. Academic sources accounted for 45.6% of the dataset. Geographically, tools were concentrated in Europe (41.3%) and North America (28.3%), while only a small number originated in Africa, Asia, and Latin America (10.8%), indicating significant regional disparities in governance tool development. Most tools were produced by academic institutions (37%), followed by governmental bodies (21.7%) and NGOs (15.2%).

Table 2
Summary of Responsible AI Tools Included in Digital Health (n = 46)

Characteristic	Category	Frequency (n)	% of Total
Source Type	Academic Literature	21	45.6%
	Gray literature	25	54.4%
Geographic Origin	Europe	19	41.3%
	North America	13	28.3%
	Global/Multiregional	9	19.6%

Cont. Table 2
Summary of Responsible AI Tools Included in Digital Health (n = 46)

Characteristic	Category	Frequency (n)	% of Total
Type of Organization	Africa, Asia, Latin America	5	10.8%
	Academic	17	37.0%
	Governmental or Regulatory	10	21.7%
	NGO / Non-profit	7	15.2%
	Private Sector	6	13.0%
	Multisectoral Collaboration	6	13.0%

Tool Classification by Function and Lifecycle Phase

Tools were categorized by their functional type and their AI lifecycle stage focus. As illustrated in Table 3, the majority were normative tools (41.3%), offering general guidelines or ethical principles. Operational tools (26.1%) provided concrete actions or assessment checklists, while reflective tools (17.4%) focused on promoting ethical reflectionduring the design phase. A smaller share (15.2%) was mixed, combining multiple functions.

Table 3
Tool Type and Lifecycle Phase Application

Tool Type	Count (n)	%	Common Lifecycle Phases Addressed
Reflective	8	17.4%	Design, early development
Normative	19	41.3%	Governance, Policy Guidance
Operational	12	26.1%	Assessment, Audit, Deployment
Mixed/Hybrid	7	15.2%	Design to Deployment

Lifecycle mapping revealed that most tools focused on governance (72%) and design (59%), with fewer addressing post-deployment or assessment stages. This distribution is shown in Figure 2.

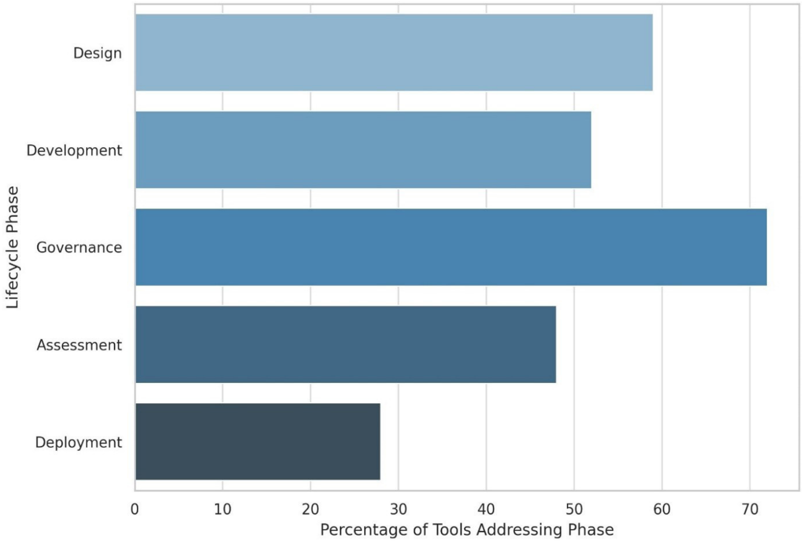

Figure 2: Frequency of Tool Application Across AI Lifecycle Phases

Stakeholder Targeting and Intended Users

The tools were also categorized by their intended users, as summarized in Table 4. Most were designed for developers (54.3%) and policymakers or regulators (47.8%). Fewer tools targeted managers (28.3%) and researchers (21.7%), with only 8.7% being designed with end users, such as patients or clinicians, in mind. This underscores a significant gap in user-centered design and governance within the current tool ecosystem.

Table 4
Intended Users of Responsible AI Tools

Intended User Group	Number of Tools (*n*)	% of Total
Developers	25	54.3%
Policymakers/Regulators	22	47.8%
Managers/Executives	13	28.3%
Researchers	10	21.7%
End Users	4	8.7%
Multiple/Generic	14	30.4%

This distribution is visualized in Figure 3, highlighting the dominance of technical and regulatory user orientations over broader stakeholder inclusion.

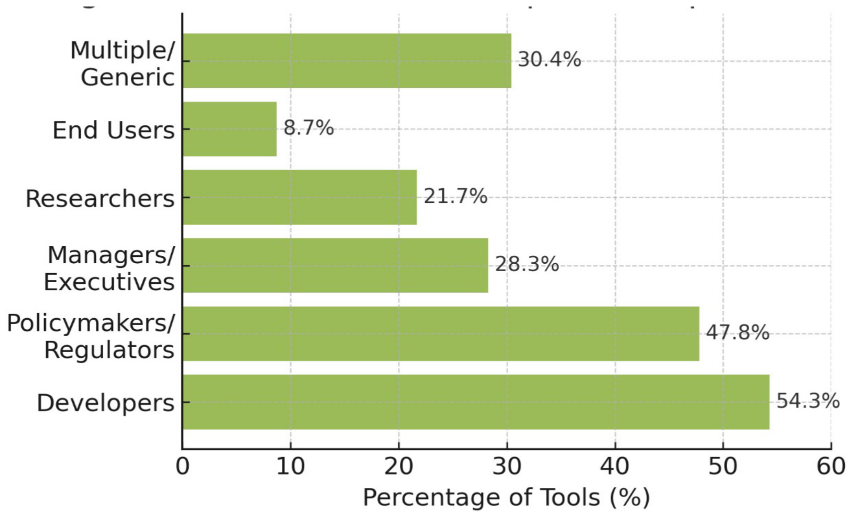

Figure 3: Intended Users of Responsible AI Tools

Integration of Responsible Innovation and ESG Principles

A key focus of the review was assessing how the tools integrated principles aligned with Responsible Innovation and ESG (Environmental, Social, and Governance) frameworks. As displayed in Table 5, the most frequently embedded values were transparency (76.1%), accountability (69.6%), and data governance (60.9%). In contrast, environmental sustainability (17.4%) and frugality (10.9%) were mentioned far less often.

Transparency: clarity in AI decision-making processes; Accountability, assignment of responsibility for AI outcomes; Data governance, policies for secure, ethical, and lawful data handling; Fairness/Equity, prevention of bias and promotion of equal benefit; Human-centered design, inclusion of user needs in system design; Environmental sustainability, minimization of environmental footprint; Frugality, designing AI solutions to operate effectively in low-resource settings.

Table 5
Responsible Innovation Dimensions Coded Across Included Tools

Dimension	Number of Tools (*n*)	% of Total
Transparency	35	76.1%
Accountability	32	69.6%
Data Governance	28	60.9%
Fairness/Equity	24	52.2%
Human-Centered Design	19	41.3%
Environmental Sustainability	8	17.4%
Frugality/Low-Resource Use	5	10.9%

This breakdown is also visualized in Figure 4, emphasizing the need to better integratesustainability and low-resource considerations in future AI governance tools for healthcare.

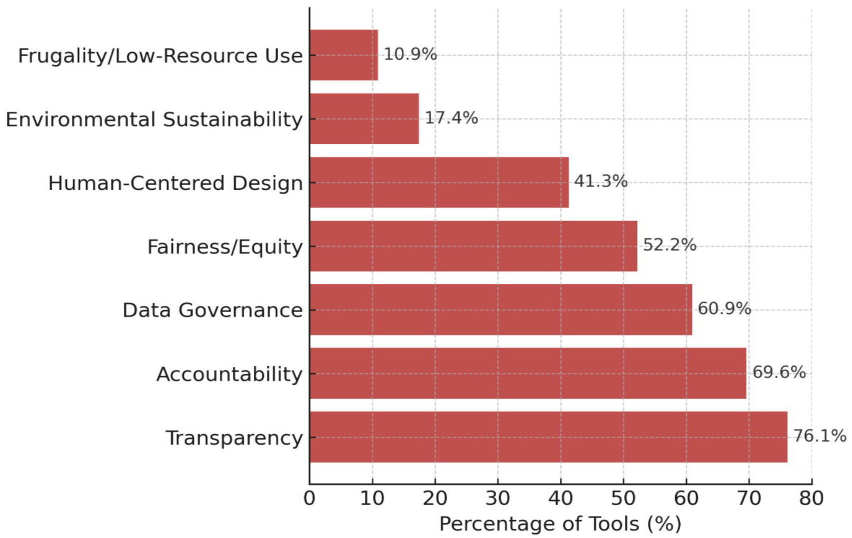

Figure 4: Integration of Responsible Innovation Dimensions across Tools

Summary of Findings

This scoping review reveals a diverse landscape of governance tools and frameworks that promote responsible and ethical AI in digital health. The analysis of 46 included documents provided a comprehensive view of how accountability, sustainability, and operational ethics are integrated into AI systems across different stages of the innovation lifecycle.

First, to address the research question of what tools and frameworks exist, the review identified a broad mix of instruments ranging from high-level ethical principles to detailed implementation checklists and auditing mechanisms. These resources were almost evenly distributed between peer-reviewed academic publications and gray literature sources developed by governments, NGOs, international organizations, and private sector consortia. Most of the tools originated from Europe and North America, reflecting regions with more mature regulatory ecosystems and sustained investment in AI ethics and digital health governance.

Second, the review found that while many tools offer valuable guidance on ethical principles, their operational focus varies considerably across the AI lifecycle. Most tools addressed early lifecycle stages, particularly the design, development, and governance phases. Far fewer provided structured guidance for deployment and post-deployment assessment, highlighting a notable gap in tools that support long-term oversight and impact monitoring of AI systems in real-world healthcare settings. This lifecycle imbalance suggests that current governance mechanisms may not fully account for the dynamic risks and contextual variations that emerge after AI tools are deployed.

Third, regarding responsible innovation dimensions, most tools emphasized familiar themes such as transparency, accountability, fairness, and data governance. These findings align with existing literature on AI ethics but also underscore a significant shortfall in environmental sustainability integration. Only a small subset of tools, less than one-fifth, explicitly referenced environmental concerns, energy use, or frugal innovation principles. Even fewer provided concrete strategies to assess or mitigate the ecological impact of AI deployment in healthcare, revealing a persistent disconnect between AI ethics and the broader sustainability agenda. This gap is particularly particularly relevant as healthcare organizations face increasing pressure to align digital innovation with environmental, social, and governance (ESG) priorities.

Finally, concerning the intended users of these tools, the review strongly emphasized developers, policymakers, and regulatory actors. While some tools targeted healthcare managers or multidisciplinary teams, only a few were designed for end users, such as patients, clinicians, or community health workers. This imbalance underscores the need more inclusive, human-centered tools that empower non-technical stakeholders to understand, evaluate, and effectively engagewith AI systems in healthcare settings.

These findings highlight both the promising developments and the persistent gaps withinthe landscape of responsible AI governance in healthcare. In particular, the field would benefit from greater attention to tools that (a) support later-stage deployment and long-term monitoring, (b) embed sustainability and ESG considerations, and (c) are usable by diverse, non-technical stakeholders. Addressing these gaps could substantially strengthen health systems' capacity to implement AI in ways that are not only effective and ethical but also sustainable and socially equitable.

Discussion

This scoping review contributes to the emerging literature on responsible and sustainable artificial intelligence (AI) governance in digital health by systematically identifying and analyzing 46 tools, frameworks, and guidelines. The findings reveal a promising but uneven landscape where significant progress coexists with critical gaps, particularly in operationalization, post-deployment oversight, and environmental sustainability.

Governance-Implementation Gap

For example, the "Model Facts" label developed by Duke Health offers a practical approach to bridging the gap between principle and practice by translating complex model behavior into clinician-friendly summaries. Consistent with prior studies, this review highlights a persistent disconnect between high-level ethical principles and their application in practice, a "principle-operational gap" (Fjeld et al., 2020; Mittelstadt, 2019). Although (72%) of the tools reviewed addressed governance and (59%) addressed design, only (28%) engaged with deployment and post-deployment oversight. This lifecycle imbalance mirrors findings from Jobin et al. (2019), who noted that fewer than (15%) of over 80 global AI ethics guidelines provided concrete implementation strategies. The underrepresentation of tools that support longitudinal monitoring raises questions about how effectively AI systems can be managed after deployment in complex clinical environments (Sendak et al., 2020).

Stakeholder Representation and Inclusivity

Strategies to improve inclusivity could include participatory co-design workshops with patients, simulation testing with frontline clinicians, and the adaptation of tools into multiple languages and literacy levels. The tools mainly reviewed target developers (54.3%) and regulators (47.8%), echoing concerns from Edwards and Veale (2018) and Sigfrids et al. (2023) that end-users such as clinicians, patients, and frontline health workers are often marginalized in AI governance. Only (8.7%) of the tools addressed this group explicitly, indicatinga missed opportunity to embed human-centered design and participatory approaches that align AI tools with contextual realities and user needs (Friedrich et al., 2024; van Leersum & Maathuis, 2025). Prior studies affirm that inclusive design methods are essential for ensuring usability, trust, and effectiveness in diverse healthcare settings (Topol, 2019).

Environmental Sustainability and ESG Integration

Standards from other sectors, such as the Global Reporting Initiative (GRI) in sustainability reporting or ISO 14064 for greenhouse gas accounting, could be adapted to evaluate AI systems in healthcare. One of the most striking gaps is the limited attention to environmental sustainability. Despite increasing awareness of AI's energy demands and carbon footprint (Ding et al., 2025; Strubell et al., 2020), only (17%) of the tools in this review incorporated environmental sustainability, and an even smaller number offered actionable metrics. This finding aligns with broader critiques suggesting thatsustainability is often an afterthought in AI ethics (Stahl et al., 2022; Vinuesa et al., 2020). Unlike sectors such as finance that have begun integrating ESG metrics into algorithmic design (Ozkan, 2024) Healthcare AI governance continues to lag behindbehind in embedding climate-conscious principles.

Comparison to Prior Reviews

Compared to prior reviews (Fjeld et al., 2020; Jobin et al., 2019) This study, which focused on global AI ethics principles, offers a more granular view of health-specific tools and maps them systematically across the AI lifecycle. The review also expands existing research by quantifying the integration of responsible innovation dimensions, particularly transparency, fairness, and data governance, while documenting the notable shortfall in operational depth and sustainability integration. As Chassang et al. (2025) noted, ethical AI in healthcare must be operationalized within real-world constraints and institutional capacities, something most existing tools fail to achieve.

Call for Integrated, Contextualized Tools

There is an urgent need for tools that align with ESG standards and are also usable by non-technical actors in low-resource settings. Frameworks such as model cards (Mitchell et al., 2019) and datasheets for datasets (Gebru et al., 2021) are rarely adapted for healthcare contexts despite their potential to enhance transparency and contextual awareness. Additionally, regulatory bodies should adopt lifecycle-based auditing and sustainability disclosure requirements to foster greater accountability.

Policy Implications

The WHO could integrate ESG-aligned AI governance tools into its Digital Health Strategy, ISO could establish sector-specific sustainability metrics for AI in healthcare, and OECD.AI could facilitate cross-country benchmarking of ESG integration in health AI. The results of this scoping review point to clear and actionable priorities for policymakers, institutional leaders, and international bodies overseeing AI adoption in healthcare.

First, there is a pressing need to move beyond principle-based ethics frameworks toward operational governance models that span the full AI innovation lifecycle. Policymakers and regulatory bodies should develop or endorse tools that support ethical AI design, deployment, performance monitoring, and post-implementation accountability. Standards bodies such as the WHO, ISO, and OECD.AI could play a central role in harmonizing expectations and enabling cross-border trust.

Second, the integration environmental sustainability and frugal innovation into AI governance remains largely absent. Policy frameworks must now incorporate climate-conscious AI metrics and carbon accountability into digital health evaluations. For example, procurement policies and innovation funding should favor tools that demonstrate lifecycle efficiency and sustainable computing practices.

Third, contextual equity and inclusiveness must be built into digital health strategies. Most governance tools identified in this review are developed in the Global North, often with limited adaptability to low-resource settings. International agencies and funders should prioritize the development of culturally sensitive, locally co-designed tools accessible to health systems in the Global South.

Finally, effective governance requires interdisciplinary and cross-sector collaboration. Ministries of health, AI developers, sustainability experts, and patient representatives should work jointly to co-create governance frameworks that are ethically sound, technically feasible, and practically implementable. Embedding ESG-aligned tools within institutional governance structures can strengthen accountability, build public trust, and ensure that AI delivers equitable and sustainable value for health systems.

Implications for Practice

The findings of this review offer several practical takeaways for those involved in designing, deploying, and managing AI systems in healthcare.

Operational Tools Must be Prioritized over Aspirational Principles

AI implementers in hospitals, ministries, or digital health startups need practical, context-sensitive tools that help translate ethical values into design choices, performance benchmarks, and user protocols. Frameworks should be clear about responsibilities, adaptable across settings, and integrated into existing quality improvement and audit systems.

Lifecycle Thinking Should Guide AI Integration

Healthcare organizations often deploy AI solutions without long-term governance structures. These findings underscore the need for a lifecycle-aligned governance strategy for AI systems in healthcare. This ensures ongoing oversight and responsiveness to evolving risks and needs.

Stakeholder Inclusion Should Shape Implementation

Most existing tools target developers and policymakers but overlook clinicians, patients, and frontline staff. Inclusive co-design practices and human-centered toolkits can ensure that AI solutions are aligned with end-user needs, culturally sensitive, and likely to be adopted sustainably.

Sustainability and Frugality Must be Integrated into Procurement and Planning

As healthcare systems seek to modernize, they must evaluate the environmental footprint and resource intensity of AI systems. Decision-makers should favor tools and frameworks that support low-resource deployment, energy efficiency, and carbon-conscious infrastructure design.

Limitations and Directions for Future Research

Future studies could apply implementation science frameworks such as CFIR (Consolidated Framework for Implementation Research) to assess real-world uptake of governance tools. For climate accountability, life cycle assessment (LCA) methodologies should be adapted to evaluate AI systems in healthcare settings. This review highlights several critical areas for further research at the intersection of AI governance, digital health, and ESG-aligned innovation.

Evaluation of Governance Tool Effectiveness

Few of the frameworks identified in this review have been empirically evaluated in real-world health systems. Future research should assess how governance tools influence AI adoption, performance, trust, and long-term sustainability outcomes. Comparative studies across regions and institutional types can also identify contextual factors that shape tool effectiveness.

Longitudinal and Post-Deployment Monitoring Studies

There is a significant gap in understanding how AI systems evolve after deployment. Future studies should explore how governance tools can enable adaptive oversight, continuous learning, and effective error correction in dynamic healthcare environments—particularly in LMICs where infrastructure constraints may affect oversight capacity.

ESG and Climate Accountability in AI

The environmental impact of AI systems remains an under-researched area. Research is needed to develop metrics, auditing tools, and procurement guidelines that support climate-aligned digital transformation in healthcare. This includes life cycle assessments (LCA) of AI models, data centers, and hybrid care pathways.

Tool Co-Development and Usability Studies

Co-designing governance frameworks with frontline health workers, patients, and local policymakers, particularly in underrepresented regions, can ensure that tools are practical, culturally relevant, and inclusive. Human-centered design and usability testing should become standard components of responsible AI development.

Cross-Sectoral Learning and Standardization

Healthcare can draw on insightsfrom finance, education, and smart city infrastructure, where AI accountability tools are often more mature. Future work should explore how standards, governance models, and ESG reporting practices can be adapted across sectors.

Limitations

Given the rapid pace of AI research and development, the results presented here reflect the current state of governance tools. However, they may require updating within two to three years to remain relevant. This review has several limitations. First, although the search strategy was comprehensive and included both academic and gray literature, it is possible that some relevant tools were missed, particularly those not explicitly labeled under "responsible AI" or "governance" terminology. Second, the review did not include a formal quality appraisal of the tools or frameworks included, which was in line with the scoping review methodology. As a result, the tools' depth, rigor, and real-world applicability could not be systematically assessed. Third, the review focused on publicly available documents in English or French, potentially overlooking valuable frameworks published in other languages or internal organizational repositories. Fourth, while the study captured global representation, most included tools originated from Europe and North America, reflecting a geographical bias in tool development and dissemination. Lastly, this review concentrated on documented frameworks rather than their practical implementation or effectiveness. Future studies could extend this work by evaluating how these tools perform in live healthcare settings, particularly in low- and middle-income countries (LMICs) where contextual adaptation is critical.

Conclusion

This scoping review identified and analyzed 46 tools and frameworks designed to support responsible and sustainable AI governance in digital health. The findings reveal significantefforts to embed principles such as transparency and accountability into digital innovation, but also expose critical gaps, particularly in post-deployment oversight, stakeholder inclusivity, and environmental sustainability. Most tools concentrate on early lifecycle phases and primarily target developers and policymakers, offering limited applicability for end-users or health systems in low-resource settings. Additionally, ESG dimensions, especially environmental sustainability and frugality, remain underrepresented in current governance frameworks. To ensure AI in healthcare is ethical but also practical and sustainable, future governance models must be inclusive, lifecycle-spanning, and responsive to social and environmental risks. This review provides a foundation for developing such models and highlights urgent opportunities for action by researchers, practitioners, funders, and policy leaders. Urgent action is required from funders, policymakers, and international agencies to develop, standardize, and scale ESG-aligned governance tools that ensure AI in healthcare is ethical, inclusive, and environmentally responsible.

References

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Aldairem, A., Alrashed, M., Bin Saleh, K., Badreldin, H. A., Al Yami, M. S., Al Harbi, S., & Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education, 23*, 689. https://doi.org/10.1186/s12909-023-04698-z

Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology, 8*(1), 19–32. https://doi.org/10.1080/1364557032000119616

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: Transforming the practice of medicine. *Future Healthcare Journal, 8*(2), e188–e194. https://doi.org/10.7861/fhj.2021-0095

Chang, Y.-L., & Ke, J. (2024). Socially responsible artificial intelligence empowered people analytics: A novel framework towards sustainability. *Human Resource Development Review, 23*(1), 88–120. https://doi.org/10.1177/15344843231200930

Chassang, G., Béranger, J., & Rial-Sebbag, E. (2025). The emergence of AI in public health is calling for operational ethics to foster responsible uses. *International Journal of Environmental Research and Public Health, 22*(4), 568.

Cheong, B. C. (2024). Transparency and accountability in AI systems: Safeguarding wellbeing in the age of algorithmic decision-making. *Frontiers in Human Dynamics, 6*. https://doi.org/10.3389/fhumd.2024.1421273

Ding, Z., Wang, J., Song, Y., Zheng, X., He, G., Chen, X., Zhang, T., Lee, W.-J., & Song, J. (2025). Tracking the carbon footprint of global generative artificial intelligence. *The Innovation, 6*(5), 100866. https://doi.org/10.1016/j.xinn.2025.100866

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B.,Medaglia, R., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edwards, L., & Veale, M. (2018). Enslaving the algorithm: From a "right to an explanation" to a "right to better decisions"? *IEEE Security and Privacy, 16*(3), 46–54. https://doi.org/10.1109/MSP.2018.2701152

Fjeld, J., Achten, N., Hilligoss, H., Nagy, A., & Srikumar, M. (2020). *Principled artificial intelligence: Mapping consensus in ethical and rights-based approaches to principles for AI*. SSRN. https://doi.org/10.2139/ssrn.3518482

Friedrich, J., Brückner, A., Mayan, J., Schumann, S., Kirschenbaum, A., & Zinke-Wehlmann, C. (2024). Human-centered AI development in practice—Insights from a multidisciplinary approach. *Zeitschrift Für Arbeitswissenschaft, 78*(3), 359–376. https://doi.org/10.1007/s41449-024-00434-5

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., Daumé Iii, H., & Crawford, K. (2021). Datasheets for datasets. *Communications of the ACM, 64*(12), 86–92. https://doi.org/10.1145/3458723

Grunhut, J., Marques, O., & Wyatt, A. T. M. (2022). Needs, challenges, and applications of artificial intelligence in medical education curriculum. *JMIR Medical Education, 8*(2), e35587. https://doi.org/10.2196/35587

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*, 389–399. https://doi.org/10.1038/s42256-019-0088-2

Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: Advancing the methodology. *Implementation Science, 5*, 69. https://doi.org/10.1186/1748-5908-5-69

Maleki Varnosfaderani, S., & Forouzanfar, M. (2024). The role of AI in hospitals and clinics: Transforming healthcare in the 21st century. *Bioengineering, 11*(4), 337. https://doi.org/10.3390/bioengineering11040337

Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., & Gebru, T. (2019). Model cards for model reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency (FAT* '19) (pp. 220–229). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287596

Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence, 1*, 501–507. https://doi.org/10.1038/s42256-019-0114-4

Morley, J., Machado, C. C. V., Burr, C., Cowls, J., Joshi, I., Taddeo, M., & Floridi, L. (2020). The ethics of AI in health care: A mapping review. *Social Science & Medicine, 260*, 113172. https://doi.org/10.1016/j.socscimed.2020.113172

Ozkan, B. (2024). The transformative impact of AI on CSR, ESG, and sustainability: Critical review and case studies. In J. Jay Choi, & Jimi Kim (Eds.), *Responsible firms: CSR, ESG, and global sustainability* (*International Finance Review* (Vol. 23)). Emerald Publishing Limited. https://doi.org/10.1108/S1569-376720240000023012

Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The Journal of Strategic Information Systems, 34*(2), 101885. https://doi.org/10.1016/j.jsis.2024.101885

Radanliev, P. (2025). AI ethics: Integrating transparency, fairness, and privacy in AI development. *Applied Artificial Intelligence, 39*(1), 2463722. https://doi.org/10.1080/08839514.2025.2463722

Sendak, M. P., Gao, M., Brajer, N., & Balu, S. (2020). Presenting machine learning model information to clinical end users with model facts labels. *Npj Digital Medicine, 3*, 41. https://doi.org/10.1038/s41746-020-0253-3

Sigfrids, A., Leikas, J., Salo-Pöntinen, H., & Koskimies, E. (2023). Human-centricity in AI governance: A systemic approach. *Frontiers in Artificial Intelligence, 6*. https://doi.org/10.3389/frai.2023.976887

Stahl, B. C., Antoniou, J., Ryan, M., Macnish, K., & Jiya, T. (2022). Organisational responses to the ethical issues of artificial intelligence. *AI & SOCIETY, 37*, 23–37. https://doi.org/10.1007/s00146-021-01148-6

Strubell, E., Ganesh, A., & McCallum, A. (2020). Energy and policy considerations for modern deep learning research. *Proceedings of the AAAI Conference on Artificial Intelligence, 34*(9), 13693–13696. https://doi.org/10.1609/aaai.v34i09.7123

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*, 44–56. https://doi.org/10.1038/s41591-018-0300-7

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., Lewin, S., Godfrey, C. M., Macdonald, M. T., , Langlois, E. V., Soares-Weiser, K.., Moriarty, J., Clifford, T., Tunçalp, O., & Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine, 169*(7), 467–473. https://doi.org/10.7326/M18-0850

Vandemeulebroucke, T. (2025). The ethics of artificial intelligence systems in healthcare and medicine: From a local to a global perspective, and back. *Pflügers Archiv - European Journal of Physiology, 477*, 591–601. https://doi.org/10.1007/s00424-024-02984-3

van Leersum, C. M., & Maathuis, C. (2025). Human centred explainable AI decision-making in healthcare. *Journal of Responsible Technology, 21*, 100108. https://doi.org/10.1016/j.jrt.2025.100108

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the sustainable development goals. *Nature Communications, 11*(1), 233. https://doi.org/10.1038/s41467-019-14108-y

Appendix A. Tools and Frameworks Included in the Scoping Review

Ref No	Author/Title/Year	Source Type	Thematic Focus / Notes
1	Ahmad et al. (2019). LCA of hospital solid waste treatment alternatives.	Academic	LCA and sustainability in hospital waste management
2	Arandah et al. (2025). Optimizing energy and carbon emissions in Egyptian residential buildings using simulation-based EDGE standards.	Academic	Energy efficiency modeling in Egyptian residential buildings
3	Al-Rikaby et al. (2023). Telehealth for melanoma patients during COVID-19.	Academic	Telemedicine for cancer patient follow-up during COVID-19
4	Tsagkaris et al. (2021). Telemedicine for a lower carbon footprint.	Academic	Reducing healthcare emissions through telemedicine
5	Subrahmanya et al. (2022). Data science in healthcare.	Academic	Data science applications in healthcare
6	Vayena et al. (2018). Big data policy in health.	Academic	Policy implications of health big data
7	Birk and Samuel (2020). Digital phenotyping and mental health.	Academic	Digital tools for mental health diagnostics
8	Davies (2021). Personal health surveillance': The use of mhealth in healthcare responsibilisation.	Academic	Health tracking and monitoring tech
9	Sharpe et al. (2016). Social media for flu surveillance.	Academic	Surveillance using digital platforms
10	Insel (2017). Digital phenotyping for behavioral science.	Academic	Behavioral insights via mobile data
11	Reinsel et al. (2018). The digitisation of the world.	Grey	Global data growth and sustainability
12	Lannelongue et al. (2021). Green algorithms in computing.	Academic	Carbon footprint of computation
13	Koot and Wijnhoven (2021). Energy forecasting in data centers.	Academic	Data infrastructure sustainability
14	Grealey et al. Bioinformatics carbon footprint.	Academic	Emissions from biomedical computing

Cont. Appendix A. Tools and Frameworks Included in the Scoping Review

Ref No	Author/Title/Year	Source Type	Thematic Focus / Notes
15	Rautela et al. (2021). E-waste and environment.	Academic	Pollution from electronic waste
16	Forti et al. (2020). Global e-waste monitor 2020.	Grey	Global monitoring of e-waste
17	EEA. (2015). Safeguarding people from environmental risks.	Grey	Environmental health risks in Europe
18	Cowls et al. (2023). The AI gambit: leveraging artificial intelligence to combat climate change—opportunities, challenges, and recommendations.	Grey	Environmental concerns in AI systems
19	Samuel et al. (2022a). Sustainable biobanks.	Academic	Environmental governance in biobanks
20	WHO. (2024). Electronic waste (e-waste).	Grey	Health risks from e-waste
21	Thompson (2021). Impacts of digital health.	Academic	Environmental impact of digital health
22	Spyropoulos et al. (2017). Smart green hospitals.	Grey	Data-driven sustainable hospitals
23	Sodhro et al. (2019). Green medical IoT.	Academic	Green Internet of Medical Things
24	Godbole and Lamb (2018). Green IT in healthcare.	Grey	Cloud and green IT for health
25	Saiyeda (2020). Green computing in health.	Grey	Sustainable software/ hardware design
26	Woolen et al. (2023). Radiology imaging & sustainability.	Academic	Choosing low-impact imaging tools
27	Tongue (2019). Digital health sustainability.	Grey	Integrating sustainability in digital healthcare
28	Chevance et al. (2020). Digital health and the Anthropocene.	Academic	Health tech in a climate crisis era
29	Gala and Doss (2021). Green computing in COVID-19.	Grey	Pandemic response and digital sustainability
30	Ouhbi et al. (2015). Are mobile blood donation apps green?	Grey	Environmental assessment of health apps

Cont. Appendix A. Tools and Frameworks Included in the Scoping Review

Ref No	Author/Title/Year	Source Type	Thematic Focus / Notes
31	Secureprivacy. (2025). Sustainability-linked privacy practices: Integrating data protection with environmental and social governance.	Grey	Data Protection with Environmental and Social Governance
32	Godbole and Lamb (2015). IT energy efficiency in hospitals.	Grey	Measuring IT sustainability in health systems
33	Samuel et al. (2022b). Environmental sustainability and biobanking. *New Genetics and Society*.	Academic	Ethics and sustainability in bio-research
34	Lucivero et al. (2020). Data-driven sustainability.	Grey	Environmental data governance
35	Samuel and Lucassen (2022). Responsible innovation in green IT.	Grey	Ethical tech and sustainability
36	Völker et al. (2020). Indicator development as a site of collective imagination?	Grey	Circular economy policy and health
37	Data Age (2025). The digitization of the world from edge to core.	Grey	Critical view on digital solutionism
38	Cribb (2020). Ethical uncertainty in health tech.	Academic	Managing ethics in digital health
39	Mousume Roy (2023). Cloud technologies: A game changer for overcoming global challenges.	Grey	Cloud tech and global instability
40	Ruckenstein and Schüll (2017). Datafication of health.	Academic	Social impacts of health data
41	Forti et al. (2020). Global e-waste monitor 2020.	Grey	Global waste data
42	Datta Burton et al. (2022). Rethinking value in biomedicine.	Academic	Redefining value in health data research
43	Finlay (2016). Genomics and personalized medicine.	Grey	Personalized medicine and sustainability
44	Dheensa et al. (2017). Recontacting in clinical genomics.	Academic	Ethical implementation in genomic care
45	van Beers et al. (2019). Promoting the common good.	Grey	Health justice and research ethics
46	Shuja et al. (2017).Greening IT technologies.	Academic	Eco-friendly IT in healthcare systems

References

Ahmad, R., Liu, G., Santagata, R., Casazza, M., Xue, J., Khan, K., Nawab, J., Ulgiati, S., & Lega, M. (2019). *LCA of hospital solid waste treatment alternatives in a developing country: The case of District Swat, Pakistan*. *Sustainability, 11*(13), 3501. https://doi.org/10.3390/su11133501

AlRikaby, A., Sulaiman, A., Thompson, J. R., Saw, R. P. M., Boyle, F., Taylor, N., Carlino, M. S., Morton, R. L., Nieweg, O. E., Thompson, J. F., & Bartula, I. (2023). Telehealth followup consultations for melanoma patients during the COVID19 pandemic: Patient and clinician satisfaction. *Cancer Medicine, 12*(23), 21373–21388. https://doi.org/10.1002/cam4.6679

Arandah, W. M. M., Hassan, M. S., Saleh, N. M., & AbdelHamid, M. (2025). Optimizing energy and carbon emissions in Egyptian residential buildings using simulation-based EDGE standards. *HBRC Journal, 21*(1), 265–283. https://doi.org/10.1080/16874048.2025.2479990

Birk, R. H., & Samuel, G. (2020). Can digital data diagnose mental health problems? A sociological exploration of 'digital phenotyping.' *Sociology of Health & Illness, 42*(8), 1873–1887. https://doi.org/10.1111/1467-9566.13175

Chevance, G., Hekler, E. B., Efoui-Hess, M., Godino, J., Golaszewski, N., Gualtieri, L., Krause, A., Marrauld, L., Nebeker, C., Perski, O., Simons, D., Taylor, J. C., & Bernard, P. (2020). Digital health at the age of the Anthropocene. *The Lancet Digital Health, 2*(6), e290–e291. https://doi.org/10.1016/S2589-7500(20)30130-8

Cribb, A. (2020). Managing ethical uncertainty: Implicit normativity and the sociology of ethics. *Sociology of Health & Illness, 42*(S1), 21–34. https://doi.org/10.1111/1467-9566.13010

Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2023). The AI gambit: Leveraging artificial intelligence to combat climate change—Opportunities, challenges, and recommendations. *AI & Society, 38*(1), 283–307. https://doi.org/10.1007/s00146-021-01294-x

Data Age (2025). *The digitization of the world from edge to core.* https://www.platinasystems.com/report-the-digitization-of-the-world-from-edge-to-core

Datta Burton, S., Kieslich, K., Paul, K. T., Samuel, G., & Prainsack, B. (2022). Rethinking value construction in biomedicine and healthcare. *BioSocieties, 17*, 391–414. https://doi.org/10.1057/s41292-020-00220-6

Davies, B. (2021). Personal health surveillance: The use of mhealth in healthcare responsibilisation. *Public Health Ethics, 14*(3), 268–280. https://doi.org/10.1093/phe/phab013

Dheensa, S., Carrieri, D., Kelly, S., Clarke, A., Doheny, S., Turnpenny, P., & Lucassen, A. (2017). A "joint venture" model of recontacting in clinical genomics: Challenges for responsible implementation. *European Journal of Medical Genetics, 60*(7), 403–409. https://doi.org/10.1016/j.ejmg.2017.05.001

EEA. (2015). *Safeguarding people from environmental risks*. https://www.eea.europa.eu/soer/2015/synthesis/report/5-riskstohealth

Finlay, T. (2016). [Review of the book *Genomics and the reimagining of personalized medicine*, by R. G. Tutton]. *Sociology of Health & Illness, 38*(6), 1000–1001. https://doi.org/10.1111/1467-9566.12393

Forti, V., Baldé, C. P., Kuehr, R., Bel, G., Jinhui, L., Khetriwal, D. S., Linnell, J., Magalini, F., Nnorom, I. C., Onianwa, P., Ott, D., Ramola, A., Silva, U., Stillhart, R., Tillekeratne, D., Van Straalen, V., Wagner, M., & Yamamoto, K. (2020). *The global e-waste monitor 2020: Quantities, flows, and resources*. United Nations University (UNU), International Telecommunication Union (ITU) & International Solid Waste Association (ISWA).

Gala, I., & Doss, S. (2021). Scrutinizing the level of awareness on green computing practices in combating Covid-19 at Institute of Health Science-Gaborone. In *Human Communication Technology* (pp. 371–400). Wiley. https://doi.org/10.1002/9781119752165.ch14

Godbole, N. S., & Lamb, J. (2015). Using data science & big data analytics to make healthcare green. In *2015 12th International Conference & Expo on Emerging Technologies for a Smarter World (CEWIT)* (pp. 1–6). IEEE. https://doi.org/10.1109/CEWIT.2015.7338161

Godbole, N. S., & Lamb, J. (2018). Research into making healthcare green with cloud, green IT, and data science to reduce healthcare costs and combat climate change. In *2018 9th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)* (pp. 189–195). IEEE. https://doi.org/10.1109/UEMCON.2018.8796529

Grealey, J., Lannelongue, L., Saw, W.-Y., Marten, J., Méric, G., Ruiz-Carmona, S., & Inouye, M. (2022). The carbon footprint of bioinformatics. *Molecular Biology and Evolution, 39*(3), msac034. https://doi.org/10.1093/molbev/msac034

Insel, T. R. (2017). Digital phenotyping: Technology for a new science of behavior. *JAMA, 318*(13), 1215–1216. https://doi.org/10.1001/jama.2017.11295

Koot, M., & Wijnhoven, F. (2021). Usage impact on data center electricity needs: A system dynamic forecasting model. *Applied Energy, 291*, 116798. https://doi.org/10.1016/j.apenergy.2021.116798

Lannelongue, L., Grealey, J., & Inouye, M. (2021). Green algorithms: Quantifying the carbon footprint of computation. *Advanced Science, 8*(12), 2100707. https://doi.org/10.1002/advs.202100707

Lucivero, F., Samuel, G., Blair, G., Darby, S. J., Fawcett, T., Hazas, M., Ten Holter, C., Jirotka, M., Parker, M., Webb, H., & Yuan, H. (2020). Data-driven unsustainability? An interdisciplinary perspective on governing the environmental impacts of a data-driven society. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3631331

Mousume Roy (2023). *Cloud technologies: A game changer for overcoming global challenges.* https://www.hcltech.com/trends-and-insights/cloud-technologies-game-changer-overcoming-global-challenges

Ouhbi, S., Fernández-Alemán, J. L., Toval, A., Idri, A., & Pozo, J. R. (2015). Free blood donation mobile applications. *Journal of Medical Systems, 39*(5), 52. https://doi.org/10.1007/s10916-015-0228-0

Rautela, R., Arya, S., Vishwakarma, S., Lee, J., Kim, K.-H., & Kumar, S. (2021). E-waste management and its effects on the environment and human health. *Science of The Total Environment, 773*, 145623. https://doi.org/10.1016/j.scitotenv.2021.145623

Reinsel, D., Gantz, J., & Rydning, J. (2018). *The digitization of the world—from edge to core*. IDC White Paper, Doc #US44413318. International Data Corporation. https://www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-dataage-whitepaper.pdf

Ruckenstein, M., & Schüll, N. D. (2017). The datafication of health. *Annual Review of Anthropology, 46*(1), 261–278. https://doi.org/10.1146/annurev-anthro-102116-041244

Saiyeda, A. (2020). Challenges and opportunities with green and sustainable computing in healthcare. In *Green automation for sustainable environment* (pp. 19–35). CRC Press. https://doi.org/10.1201/9781003000792-2

Samuel, G., Hardcastle, F., & Lucassen, A. M. (2022a). Environmental sustainability and biobanking: A pilot study of the field. *New Genetics and Society, 41*(2), 157–175. https://doi.org/10.1080/14636778.2022.2093707

Samuel, G., Lucivero, F., & Lucassen, A. M. (2022b). Sustainable biobanks: A case study for green global bioethics. *Global Bioethics, 33*(1), 50–64. https://doi.org/10.1080/11287462.2021.1997428

Samuel, G., & Lucassen, A. M. (2022). The environmental sustainability of data-driven health research: A scoping review. *Digital Health, 8*, 205520762211112. https://doi.org/10.1177/2055207622111129

Secureprivac. (2025). *Sustainability-linked privacy practices: Integrating data protection with environmental and social governance.* https://secureprivacy.ai/blog/sustainable-privacy-data-protection-environmental-social-governance

Sharpe, J. D., Hopkins, R. S., Cook, R. L., & Striley, C. W. (2016). Evaluating Google, Twitter, and Wikipedia as tools for influenza surveillance using Bayesian change point analysis: A comparative analysis. *JMIR Public Health and Surveillance, 2*(2), e161. https://doi.org/10.2196/publichealth.5901

Shuja, J., Ahmad, R. W., Gani, A., Abdalla Ahmed, A. I., Siddiqa, A., Nisar, K., Khan, S. U., & Zomaya, A. Y. (2017). Greening emerging IT technologies: Techniques and practices. *Journal of Internet Services and Applications, 8*(1), 9. https://doi.org/10.1186/s13174-017-0060-

Sodhro, A. H., Sangaiah, A. K., Pirphulal, S., Sekhari, A., & Ouzrout, Y. (2019). Green media-aware medical IoT system. *Multimedia Tools and Applications, 78*(3), 3045–3064. https://doi.org/10.1007/s11042-018-5634-0

Spyropoulos, B., Alexandropoulos, A., Boci, N., Chatziapostolou, E., Frappa, E., Georgiadou, E., Louts, I., Pantelakis, I., Poultsaki, M., & Xenaki, M. (2017). Toward the data-driven “smart” and “green” hospital-care. In *2017 ITU Kaleidoscope: Challenges for a data-driven society (ITU K)* (pp. 1–9). IEEE. https://doi.org/10.23919/ITU-WT.2017.8246993

Subrahmanya, S. V. G., Shetty, D. K., Patil, V., Hameed, B. M. Z., Paul, R., Smriti, K., Naik, N., & Somani, B. K. (2022). The role of data science in healthcare advancements: Applications, benefits, and future prospects. *Irish Journal of Medical Science (1971–)*, *191*(4), 1473–1483. https://doi.org/10.1007/s11845-021-02730-z

Thompson, M. (2021). The environmental impacts of digital health. *Digital Health, 7*, 20552076211033421.https://doi.org/10.1177/20552076211033421

Tongue, B. (2019). Designing sustainability into the digital healthcare revolution. *British Journal of Healthcare Management, 25*(4), 1–3. https://doi.org/10.12968/bjhc.2019.0038

Tsagkaris, C., Hoian, A. V., Ahmad, S., Essar, M. Y., Campbell, L. W., Grobusch, L., Angelopoulos, T., & Kalaitzidis, K. (2021). Using telemedicine for a lower carbon footprint in healthcare: A twofold tale of healing. *The Journal of Climate Change and Health, 1*, 100006. https://doi.org/10.1016/j.joclim.2021.100006

van Beers, B., Sterckx, S., & Dickenson, D. (Eds.). (2018). *Personalised medicine, individual choice and the common good*. Cambridge University Press. https://doi.org/10.1017/9781108590600

Vayena, E., Dzenowagis, J., Brownstein, J. S., & Sheikh, A. (2018). Policy implications of big data in the health sector. *Bulletin of the World Health Organization, 96*(1), 66–68. https://doi.org/10.2471/BLT.17.197426

Völker, T., Kovacic, Z., & Strand, R. (2020). Indicator development as a site of collective imagination? The case of European Commission policies on the circular economy. *Culture and Organization, 26*(2), 103–120. https://doi.org/10.1080/14759551.2019.1699092

WHO. (2024). *Electronic waste (e-waste)*. https://www.who.int/news-room/fact-sheets/detail/electronic-waste-(e-waste)

Woolen, S. A., Kim, C. J., Hernandez, A. M., Becker, A., Martin, A. J., Kuoy, E., Pevec, W. C., & Tutton, S. (2023). Radiology environmental impact: What is known and how can we improve? *Academic Radiology, 30*(4), 625–630. https://doi.org/10.1016/j.acra.2022.10.021

Majdi A. Quttainah is an Associate Professor at Kuwait University specializing in Corporate Governance, Entrepreneurship, and Organizational Development. He has earned multiple academic degrees and awards, including the Best Young Researcher (2016/2017) and multiple Best Paper Awards globally. He serves as Senior Editor of FIIB Business Review and actively contributes to research.
(majdi.quttainah@ku.edu.kw)