Review

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From Telehealth to Artificial Intelligence: Digital Health Technologies for Indigenous Communities—A Systematic Review of Diagnostic Access, Ethical Governance, and Sustainable Health Equity

Américo Alves da Mota Junior * , Rodrigo Pereira Ramos , Bruna Felix de Almeida , Isabella Diniz de Souza Lins Bunge , Jandir Mendonça Nicacio , Vanessa Cardoso Pereira , Thiago Augusto Cavalcante de Carvalho , Paula Andreatta Maduro , Paulo Adriano Schwingel , Carlos Dornels Freire de Souza , Orlando Vieira Gomes , Ana Paula Pereira Rolim Coimbra Pinto , Caroline Guimarães da Fonseca Chieco , Maria Luíza Carvalho Santana , Alane Mota dos Santos , Anderson da Costa Armstrong

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Review

From Telehealth to Artificial Intelligence: Digital Health Technologies for Indigenous Communities—A Systematic Review of Diagnostic Access, Ethical Governance, and Sustainable Health Equity

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Abstract

Indigenous communities worldwide face persistent health inequities rooted in colonial histories, geographic remoteness, and structural exclusion from diagnostic services. Artificial intelligence (AI) and digital health technologies are promoted as instruments of equity; however, the conditions under which they support, rather than reproduce, inequities remain contested. Following PRISMA 2020, PRISMA-Equity, and SWiM, we searched 12 databases (PubMed, Scopus, Web of Science, Embase, IEEE Xplore, ACM, CINAHL, Cochrane, SciELO, LILACS, Dimensions, Google Scholar) in English, Portuguese, Spanish, and French, as well as structured grey literature. From 969 screened records, 39 studies met the eligibility criteria and were stratified into three layers: global, American/Latin American, and Brazilian/Northeast Brazilian. Deep-learning tele-otology and diabetic retinopathy screening in Aboriginal Australian contexts, suicide-risk machine learning with Native American communities, edge-AI maternal care with Indigenous Guatemalan midwives, and federated stress classification under Te Mana Raraunga were the most mature applications. Latin America, Brazil, and the Northeast semiarid region were almost entirely absent from the data. Brazilian tele-ultrasound work in the São Francisco Valley with Truká and Fulni-ô peoples, alongside Amazonian initiatives on tele-ophthalmology, machine learning prediction of tuberculosis and malaria, cervical cancer screening, and culturally adapted cognitive assessment, offers a regionally grounded counterpoint. Indigenous data sovereignty, cultural safety, and external validation are still underdeveloped. We propose a nine-domain Responsible AI and Digital Health Implementation Framework aligned with the 2030 Agenda.

Keywords: artificial intelligence; indigenous health; digital health; telehealth; diagnostic imaging; tele-ultrasound; Indigenous data sovereignty; sustainability; planetary health; systematic review

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1. Introduction

1.1. Indigenous Health Inequities Globally and in Brazil

Indigenous peoples comprise an estimated 476 million individuals across more than 90 countries, sustaining cultural, linguistic, and territorial diversity that exceeds that of any other demographic group [1,2]. Despite this plurality, Indigenous communities share a common epidemiological pattern characterized by elevated infant and maternal mortality, premature cardiovascular disease, chronic kidney injury, mental health vulnerability, and an infectious disease burden disproportionate to that of non-Indigenous populations of the same countries [3,4]. These disparities are not natural facts of biology but rather the enduring consequences of colonization, territorial dispossession, racism, and the systematic exclusion of Indigenous knowledge from health systems [5,6]. In Brazil, approximately 1.7 million people self-identified as Indigenous in the 2022 census, distributed across more than 305 ethnic groups speaking over 270 languages, with significant populations in the Amazon Basin, Cerrado, Atlantic Forest, semi-arid Northeast, and southern Mata Atlântica [7,8]. The Brazilian Indigenous subsystem of the Unified Health System (SasiSUS), operationalized through the Secretaria Especial de Saúde Indígena (SESAI) and 34 Distritos Sanitários Especiais Indígenas (DSEIs), is among the world's most ambitious public ethnoculturally tailored primary care architectures [9,10]. However, its implementation remains uneven, particularly in the semiarid Northeast, where the Truká, Fulni-ô, Pankararé, Pataxó-Hã-Hã-Hãe, Pankararu, and other peoples face water scarcity, climatic vulnerability, and limited specialist infrastructure [11,12].

1.2. Digital Health, Telehealth and Artificial Intelligence: Evolution, Promise, Risks

Over the past three decades, health systems serving Indigenous communities have progressively layered digital modalities onto traditional service delivery: from facsimile-based teleconsultation and store-and-forward dermatology to synchronous tele-otology and tele-mental health, mobile health (mHealth) applications, electronic health records, and—most recently— machine learning (ML) and deep learning (DL) models embedded in clinical decision support, computer-aided diagnosis, and predictive analytics [13–16]. Contemporary literature increasingly speaks of artificial intelligence (AI) as a transformational force in healthcare, with promises of expanded diagnostic reach, automated screening at scale, and personalized, data-driven care [17,18]. For Indigenous populations, AI-enabled tools could, in principle, compensate for chronic specialist shortages in remote areas, accelerate triage, and democratize access to advanced imaging [19,20]. Simultaneously, the same technologies carry the risk of reproducing colonial extractive logics: training datasets that underrepresent Indigenous bodies and contexts; predictive models whose decisions are opaque to the communities they classify; commercial platforms that aggregate sensitive Indigenous health data without community benefit; and digital infrastructure whose energy and material footprints further burden Indigenous territories [21–23]. Therefore, the transition from telehealth to AI is not a linear technological progression but a contested sociotechnical reconfiguration with profound equity and sustainability implications.

1.3. Diagnostic Access and Imaging as Determinants of Equity

Diagnostic access, the timely availability of laboratory, imaging, point-of-care, and specialist diagnostic services, is a fundamental determinant of health equity. When diagnosis is delayed or unavailable, treatable diseases become disabling, and chronic conditions become fatal, regardless of the sophistication of downstream interventions [24,25]. Diagnostic imaging, particularly ultrasonography, retinography, dermatoscopy, radiography, computed tomography, and magnetic resonance, remains concentrated in urban centers, while Indigenous territories are often hundreds of kilometers from the nearest radiologist [26]. Tele-imaging modalities, including tele-ultrasound, tele-otology, and tele-retinography, have demonstrated technical feasibility for several decades [27,28]. AI is now being incorporated into these pipelines, both as a front-end triage tool and as a back-end classifier, with documented diagnostic performance approaching or matching that of specialist readers for selected pathologies, such as diabetic retinopathy and middle ear disease [29,30]. However, whether such performance translates into equitable access depends on the infrastructure, workforce, community trust, and culturally safe referral pathways [31].

1.4. Health Education and Digital Literacy in Indigenous Communities

Diagnostic technology cannot be considered in isolation from the educational and informational ecosystems in which it is deployed. Health education and digital literacy are bidirectional: Indigenous Health Agents (Agentes Indígenas de Saúde, AIS) and Sanitation Agents (AISAN) require continuing education on emerging digital tools, whereas non-Indigenous health workers require training in cultural safety, intercultural communication, and the histories of the peoples they serve [32,33]. Digital literacy in communities is not a deficit to be filled by external pedagogies but a process of mutual translation, in which Indigenous epistemologies, oral traditions, and contemporary digital practices co-construct meaningful use of health technology [34]. Brazilian experiences in the São Francisco Valley have shown that digital health instruments, when co-designed with Indigenous educators, can effectively support chronic disease awareness, vaccination communication, and intergenerational dialogue on health and territory [35,36].

1.5. Brazilian Context: SasiSUS, SESAI, DSEI and the Northeast Semiarid

The Subsistema de Atenção à Saúde Indígena (SasiSUS) was established by Law 9.836/1999 (Lei Arouca) and reorganised through SESAI's creation in 2010, with primary care delivered by Equipes Multidisciplinares de Saúde Indígena (EMSI) operating from Polos Base and supported by Casas de Saúde Indígena (CASAI) for secondary referral [37]. The system is informed by the Sistema de Informação da Atenção à Saúde Indígena (SIASI), the Cadastro Nacional de Estabelecimentos de Saúde (CNES) and DATASUS national datasets. However, structural challenges persist, including high health worker turnover, fragmented specialist referrals, intermittent Internet connectivity in many villages, and a diagnostic infrastructure that depends heavily on transfers to municipal or state hospitals [38]. The Northeast semiarid—home to the Truká in Cabrobó (Pernambuco) and Paulo Afonso (Bahia), the Fulni-ô of Águas Belas (Pernambuco) who continue to speak Yathê, the Pankararé in Brejo do Burgo (Bahia), and other peoples of the São Francisco Valley—exemplifies these tensions, with severe climatic variability superimposed on land-tenure disputes and cardiovascular, renal and mental-health vulnerability documented over the past decade [39–44].

1.6. Brazil and the Northeast Semiarid Region

In Brazil, Indigenous health policy is structured around the Subsystem of Care for Indigenous Peoples (SasiSUS), the Special Secretariat for Indigenous Health (SESAI) and 34 Special Indigenous Health Districts (DSEI), which articulate primary care provided by Multidisciplinary Indigenous Health Teams (EMSI) across Polos Base and Indigenous Health Centres (CASAI). Indigenous communities in the Northeast semiarid region occupy territories shaped by drought cycles, water insecurity, and accelerating urbanization, with a heavy burden of cardiometabolic diseases, chronic kidney disease, arboviral exposure, and limited access to specialized diagnostic services. Brazilian and Northeast Brazilian scholarship across cardiovascular health, chronic kidney disease, kidney burden in youth, cardiac biomarkers in arbovirus-exposed populations, tele-ultrasound feasibility in resource-limited contexts, oral health, respiratory function and traditional pipe smoking, digital health education, health-promotion challenges, federal medical workforce programs, territory-gender-mental-health intersections, alcohol use and urbanization, medicinal-plant knowledge, and water-borne disease vulnerability documents these conditions [35,36,39–52]. Together with newer Brazilian Amazonian work on tele-ophthalmology, machine learning prediction of tuberculosis and malaria, cervical cancer screening, mobile health follow-up of neglected tropical diseases, and culturally adapted cognitive assessment in urban multiethnic Indigenous communities [106–113],

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this body of work establishes Northeast and Amazonian Brazil as a critical implementation context for sustainable Indigenous digital health care.

1.7. Sustainability, Planetary Health and SDG Framing

Sustainability in digital health for Indigenous communities cannot be reduced to long-term funding for a specific device. It is a multidimensional concept encompassing social sustainability (community cohesion and capacity), cultural sustainability (continuity of languages, knowledge systems, and ways of life), economic sustainability (avoidable dependency, equitable distribution of benefits), environmental and planetary health sustainability (carbon footprint, e-waste, and ecological integrity of Indigenous territories), and territorial sustainability (self-determination over land and data) [53–56]. The 2030 Agenda for Sustainable Development and its Sustainable Development Goals (SDGs)—particularly SDG 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation and Infrastructure), SDG 10 (Reduced Inequalities), SDG 13 (Climate Action), SDG 16 (Peace, Justice and Strong Institutions), and SDG 17 (Partnerships for the Goals)—provide a normative scaffold for evaluating whether and how digital health innovations advance Indigenous self-determination [57,58].

1.8. Research Gap and Review Objectives

Although several recent reviews have examined digital health, AI, or telemedicine in Indigenous health, few have systematically integrated diagnostic access, ethical governance, and sustainable health equity across global, hemispheric, and Brazilian evidence layers, and almost none have addressed the Northeast semiarid region as a critical implementation context [59–62]. This systematic review addresses this issue. Our main research question is as follows: What is the global, hemispheric, and Brazilian evidence on AI and digital health technologies applied to Indigenous communities for diagnosis, imaging, telehealth, health education, clinical care, and surveillance, and what ethical, governance, equity, and sustainability requirements emerge for responsible implementation? The specific objectives are to (i) map technologies and health domains; (ii) characterize geographic and population coverage; (iii) evaluate Indigenous governance, data sovereignty, and community participation; (iv) synthesize outcomes, barriers, and facilitators; (v) appraise sustainability across five dimensions; (vi) identify gaps in Latin America and Brazil; and (vii) propose an evidence-informed Responsible AI and Digital Health Implementation Framework for Indigenous Communities.

2. Materials and Methods

2.1. Protocol and Registration

This systematic review was conducted following an internal a priori protocol developed by the research team in accordance with the PRISMA-P. The protocol was not deposited in an external prospective registry. To preserve transparency, the full protocol, including the eligibility criteria, search strategies, data extraction template, risk-of-bias instruments, and synthesis plan, is reproduced in detail in the Methods section. Any deviations from the original protocol are described and justified in Section 6 (Limitations).

2.2. PRISMA 2020, PRISMA-Equity and SWiM Compliance

Reporting followed PRISMA 2020 [63], with reference to the official PAHO Portuguese-language version [65] to support multilingual research-team practice as the primary guideline, complemented by PRISMA-Equity for equity-sensitive reporting [66], and the Synthesis Without Meta-analysis (SWiM) guideline for narrative synthesis [67]. Confidence in the qualitative evidence was assessed using the GRADE-CERQual [68]. The Non-adoption, Abandonment, Scale-up, Spread, and Sustainability (NASSS) framework informed the interpretation of implementation findings [69], and the RE-AIM framework was used selectively where outcome–implementation data were permitted [70]. Intervention components were extracted with reference to TIDieR [71].

2.3. PICOS Framework

Population (P): Indigenous peoples and communities globally, including Aboriginal and Torres Strait Islander peoples, First Nations, Inuit and Métis, Native American, American Indian and Alaska Native, Native Hawaiian and Pacific Islander, Māori, Sami, Amazonian, Andean, Mesoamerican, and Brazilian Indigenous peoples, including the Truká and Fulni-ô of the São Francisco Valley. Intervention/Exposure (I): AI (machine learning, deep learning, computer vision, natural language processing, predictive analytics, clinical decision support, computer-aided diagnosis, radiomics, large language, and foundation models), digital health (telehealth, telemedicine, teleconsultation, teleimaging, tele-ultrasound, mHealth, eHealth, electronic health records, remote monitoring, AI-enabled surveillance), and digital health education; Comparator (C): usual care, non-digital care, no technology, alternative technology, or none, where applicable. Outcomes (O): diagnostic access, diagnostic accuracy, screening and surveillance metrics, health education outcomes, acceptability, feasibility, implementation success, cultural safety, equity, community participation, data governance, sustainability, scalability, environmental implications, and policy relevance. Study designs (S): empirical, implementation, diagnostic accuracy, prediction-model, qualitative, mixed-methods, evaluation and validation studies, plus indexed grey literature; conceptual or governance papers were included when they contributed substantive frameworks.

2.4. Eligibility Criteria

Inclusion criteria: (i) AI, ML, or digital health technologies in Indigenous health contexts; (ii) telehealth, telemedicine, teleimaging, tele-ultrasound, mHealth, eHealth, or digital education in Indigenous communities; (iii) diagnostic imaging, screening, surveillance, predictive models, diagnosis, clinical decision support, health education, or clinical care; (iv) ethical governance, cultural safety, Indigenous data sovereignty, algorithmic bias, privacy, community engagement, or implementation sustainability; (v) empirical, implementation, diagnostic accuracy, predictive-model, qualitative, mixed-methods studies, and structured grey literature; and (vi) studies in English, Portuguese, Spanish, or French. The exclusion criteria were as follows: (i) Indigenous community studies without an AI/digital health/telehealth component; (ii) AI/digital health studies without Indigenous health relevance; (iii) studies citing "AI" only as a marketing term without methodological substance; (iv) opinion pieces lacking empirical content or substantive governance framework; (v) commercial product descriptions without peer review; (vi) conference abstracts without full text; (vii) duplicates; and (viii) studies in which Indigenous identity was incidental and not analytically relevant.

2.5. Information Sources and Grey Literature

Twelve bibliographic databases were searched: PubMed/MEDLINE, Scopus, Web of Science Core Collection, Embase, IEEE Xplore, ACM Digital Library, CINAHL, Cochrane Library, SciELO, SciELO Citation Index, LILACS/BVS, Dimensions, and Google Scholar (first 300 results were documented and deduplicated). Grey literature was identified through WHO IRIS, PAHO/OPAS IRIS, IWGIA reports, FUNAI publications, SESAI/Ministério da Saúde reports, ABRASCO proceedings, Congresso Brasileiro de Informática em Saúde proceedings, BDTD (Biblioteca Digital Brasileira de Teses e Dissertações), the CAPES theses catalogue, ProQuest Dissertations & Theses Global, the UN Permanent Forum on Indigenous Issues, and the Global Indigenous Data Alliance. Reference lists of included studies and relevant reviews were hand-searched.

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2.6. Search Strategy and PRESS Validation

Search strategies combined four concept blocks: Indigenous populations, AI and digital health, health diagnosis imaging education and equity governance terms. Subject headings (MeSH, Emtree, and DeCS) were incorporated where applicable. Multilingual translations included Portuguese, Spanish and French equivalents of key concepts (inteligência artificial / inteligencia artificial / intelligence artificielle; aprendizado de máquina / aprendizaje automático / apprentissage automatique; povos indígenas / pueblos indígenas / peuples autochtones; telessaúde / telesalud / télésanté; diagnóstico por imagem / diagnóstico por imagen / imagerie diagnostique; soberania de dados / soberanía de datos / souveraineté des données). The final strategy was validated by a health-sciences librarian using the Peer Review of Electronic Search Strategies (PRESS) 2015 checklist, with reporting aligned to the PRISMA-S 2021 extension for search strategy documentation [64]. Searches were conducted from database inception to the most recent searchable date in the first quarter of 2026; no temporal restriction was imposed at the database level, with the practical concentration of AI literature post-2018 being reported as a finding.

2.7. Study Selection: Calibration, Dual Screening and Inter-Rater Reliability

Records were imported into Zotero v6.0.30, deduplicated, and transferred to Rayyan for screening. A calibration pilot was conducted on 80 randomly selected records, after which the eligibility criteria were further refined. All 969 post-deduplication records were screened for titles and abstracts by two reviewers working independently in a blinded manner. Full-text screening was then performed independently by two reviewers on the 87 reports that advanced from the title/abstract stage. Disagreements at either stage were resolved by consensus or, if necessary, by a third reviewer. Inter-rater reliability was quantified using Cohen's κ (κ = 0.81 for title/abstract; κ = 0.86 for full text). The reasons for exclusion at the full-text stage are documented and summarized in Section 3.1. Where multiple publications reported on the same intervention, cohort, dataset, or implementation program, the primary publication was identified, and secondary publications were treated as companions to avoid double counting. Amalgamation decisions were also documented.

2.8. Data Extraction: A Thirty-Variable Template

A standardized extraction template captured 30 variables per study: author and year; country/region; specific Indigenous population/community; study design; sample size and setting; health domain; technology type; AI subtype; digital health modality; diagnostic-imaging modality; health-education component; data source; objectives; main findings; performance metrics; validation method; implementation setting; community participation level (none/consultation/collaboration/partnership/Indigenous leadership); Indigenous authorship or co-leadership; consent and privacy approach; whether and how Indigenous data sovereignty was addressed; whether and how cultural safety was addressed; ethical issues reported; implementation barriers; facilitators; health equity implications; sustainability implications (social, cultural, economic, environmental); SDG alignment; risk-of-bias/quality-assessment result; and relevance to the Brazilian Northeast or Amazonian context. Two reviewers extracted the data in parallel, and disagreements were resolved by consensus.

2.9. Risk of Bias and GRADE-CERQual

The risk of bias was assessed using design-appropriate tools: ROBINS-I for non-randomized observational studies, QUADAS-2 for diagnostic accuracy studies, PROBAST for prediction-model studies, MMAT for mixed-methods studies, JBI Critical Appraisal Tools for qualitative and cross-sectional designs, and the AACODS checklist for gray literature. Confidence in the qualitative findings was assessed using GRADE-CERQual across four domains: methodological limitations, coherence, adequacy, and relevance. Quality assessments did not lead to automatic exclusion; rather, they informed the interpretation of evidence strength and stratification of the findings.

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2.10. Three-Layer Synthesis Strategy

The synthesis followed a three-layer geographic logic: Layer 1 — global evidence, with emphasis on Australia, Canada, Aotearoa, New Zealand, the United States, Nordic countries, and the Asia–Pacific region; Layer 2 — the Americas and Latin America, including PAHO regional initiatives; and Layer 3 — Brazil and the Northeast semiarid region. Within each layer, synthesis was conducted narratively in compliance with SWiM, supported by tabular summaries by technology type, health domain, and region, and thematic synthesis for qualitative dimensions. No meta-analysis was performed because of heterogeneity in study designs, populations, technologies, and outcomes.

2.11. Bibliometric Analysis

Bibliometric analysis was conducted using Bibliometrix v4.3.5 in R v4.4.2 [72], complemented by VOSviewer v1.6.20 for keyword co-occurrence and co-authorship network analysis. Metrics included the temporal distribution of publications, geographic distribution by country and institution, leading authors and research networks, international co-authorship, keyword co-occurrence, citation networks, identification of seminal and emerging works, Indigenous authorship proportion (assessed where author affiliation, biographical disclosure, or contextual evidence permitted), and funding-source mapping where possible.

2.12. Software and Reproducibility

All searches, screenings, extractions, and analyses were documented to allow for independent verification. Zotero v6.0.30 was used for reference management; Rayyan for blinded dual screening; Microsoft Excel and R v4.4.2 for extraction matrices and descriptive analysis; VOSviewer v1.6.20 and bibliometrix v4.3.5 for bibliometric work. The software versions, search filters, and limits are reported in full in this Methods section to permit independent replication.

2.13. Positionality and Reflexivity

The authors of this review are predominantly non-Indigenous Brazilian researchers affiliated with the PPGEcoH–UNEB doctoral program, the AMMO Institute/CDI, the HU-UNIVASF/EBSERH, the Federal University of the São Francisco Valley (UNIVASF), and the University of Pernambuco (UPE), with one co-author (O.V.G.) of Truká ancestry, whose lived experience and intellectual leadership have informed the cultural framing of this study. The corresponding author is a medical imaging specialist with experience in teleultrasound deployment in Indigenous primary care contexts in the São Francisco Valley. One of the senior authors has sustained research engagement with the Truká and Fulni-ô peoples through the Projeto de Aterosclerose em Indígenas (PAI) research network in Brazil. We recognize that this is a review of the literature on Indigenous communities and not, in itself, a study co-designed with Indigenous communities. We have attempted to mitigate the risks of extractive framing, techno-solutionism and deficit-based portrayal through deliberate choices: using specific peoples' names rather than monolithic categories whenever the source permitted; foregrounding governance frameworks authored by Indigenous scholars such as Te Mana Raraunga, Maiam nayri Wingara, the First Nations Information Governance Centre and the Global Indigenous Data Alliance; engaging with Brazilian Indigenous thinkers including Ailton Krenak, Davi Kopenawa, Daniel Munduruku, Eliane Potiguara and Célia Xakriabá in the Discussion; and explicitly naming the epistemological tensions between biomedical/AI rationalities and Indigenous knowledge systems.

2.14. Ethical Governance Statement

This study is a synthesis of the published literature and, as such, did not require an independent institutional ethical review; the umbrella PAI Integral research programme contextualizing the Brazilian Northeast evidence in this review was nonetheless approved by the Brazilian National Research Ethics Commission (CONEP, CAAE 60271422.2.0000.8807, Parecer 5.927.482, March 7,

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2023). We have applied an ethical-governance lens throughout: respecting Indigenous data sovereignty by avoiding the re-aggregation or republication of community-identifiable information beyond what is already in the public record; using community names with sensitivity and, where possible, the autonyms used by the peoples themselves (e.g., Fulni-ô speakers of Yathê); refusing deficit-based framing of Indigenous health; and declining to expose sensitive territorial details in the discussion. Any self-citation of the authors' prior peer-reviewed work is disclosed transparently in the Conflict of Interest section. Findings will be returned to Truká and Fulni-ô communities through accessible formats such as a bilingual cartilha, an audiovisual summary, and oral presentations, in collaboration with community leadership and the EMSI teams of the relevant DSEIs, respecting Yathê linguistic specificity for Fulni-ô when applicable.

2.15. Generative AI Disclosure

The authors of this manuscript are native Portuguese speakers. Generative AI tools (specifically, GPT-class large language models accessed through consumer interfaces) were used to support the following linguistic tasks: (i) translation of authors' original Portuguese drafts into academic English; (ii) linguistic adaptation to scientific writing conventions in English; (iii) grammar review and copy-editing of the English text; and (iv) stylistic refinement of phrasing to meet scholarly publication standards. All substantive content, including conceptual framing, research questions, methodological design, study selection, data extraction, analytical interpretation, citation choices, and conclusions, was prepared by the authors. Every reference cited in this manuscript was independently verified by the authors against PubMed, SciELO, LILACS, Scopus, Web of Science, Semantic Scholar, Crossref, DOI.org, and stable institutional repositories.

3. Results

3.1. Study Selection and PRISMA 2020 Flow

Systematic searches across the 12 electronic databases yielded an initial pool of 1,247 records, supplemented by 134 records from grey-literature sources, for a total of 1,381 records. After deduplication (n = 412 removed), 969 records were retained and screened by title and abstract by two independent reviewers in Rayyan. Of these, 96 reports advanced to full-text screening, and 39 studies met the eligibility criteria and were included in the final analysis. The reasons for full-text exclusion (n = 57) were incidental Indigenous identity without analytical relevance (n = 19), AI mentioned only as marketing terminology (n = 11), absence of substantive technology component (n = 9), commercial product description without peer review (n = 6), opinion pieces without empirical or framework content (n = 6), conference abstracts without full text (n = 4), and duplicates not removed automatically (n = 2). The full PRISMA 2020 flow diagram is provided in Figure 1 The calibrated κ for title/abstract screening was 0.81 (substantial agreement) and 0.86 for full-text screening (almost perfect agreement).

	Records identified from databases (n = 1,247) PubMed/MEDLINE, Scopus, and Web of Science Embase; IEEE Xplore; ACM; CINAHL; Cochrane; SciELO; LILACS; Dimensions; Google Scholar	Records identified from other sources (n = 134) WHO IRIS; PAHO IRIS; IWGIA; FUNAI; SESAI/MS, ABRASCO, BDTD, and CAPES ProQuest; UNPFII; GIDA
	↓	↓

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	Records identified — total (n = 1,381) Imported into Zotero v6.0.30; screened via Rayyan	Records removed before screening: Duplicates (n = 412)
	↓	
	Records screened (title/abstract) (n = 969) Dual independent reviewers — Rayyan; blinded Cohen's κ = 0.81 (substantial agreement)	Records excluded (n = 873) Manual title/abstract review. not aligned with eligibility criteria
	↓	
	Reports sought for retrieval (n = 96) Full text obtained for all reports	Reports not retrieved (n = 0)
	↓	
	Reports assessed for eligibility (n = 96) Full-text review — dual independent reviewers Cohen's κ = 0.86 (almost perfect agreement)	Reports excluded with reasons (n = 57): • Incidental Indigenous identity (n = 19) • AI as marketing only (n = 11) • No substantive technology (n = 9) • Commercial product, no peer review (n = 6) • Opinion pieces, no framework (n = 6) • Conference abstracts (n = 4) • Duplicates not auto-removed (n = 2)
	↓	
	Studies included in the systematic review (n = 39)	

	Stratified into three analytical layers: Layer 1 — Global (n = 26) • Layer 2 — Americas/Latin America (n = 3) • Layer 3 — Brazil/Northeast (n = 10)	

Figure 1. PRISMA 2020 flow diagram for the systematic review of artificial intelligence and digital health technologies for Indigenous communities. The identification (databases and grey literature), screening (title/abstract and full-text), and inclusion phases followed Page et al. (2021).

3.2. Characteristics of Included Studies

The 39 included studies were published between 2018 and 2026, with a marked increase in publications after 2021. The study designs were heterogeneous: diagnostic accuracy or validation studies (n = 8), implementation/feasibility studies (n = 9), prediction-model development or validation studies (n = 7), mixed-methods or process evaluations (n = 5), qualitative or community-based participatory studies (n = 4), systematic or scoping reviews of related domains (n = 4), and frameworks or governance papers (n = 2). Sample sizes ranged from case series of fewer than 50 participants to retrospective EHR cohorts exceeding 50,000 patients and a state-level surveillance dataset of approximately six million records (Amazonas malaria deep-learning study). Settings included remote and rural Aboriginal Medical Services in Australia, Inuit Nunangat and other Arctic regions of Canada, urban Indigenous mental health services in the United States, midwifery clinics in rural Guatemala, riverine and urban Indigenous communities of the Brazilian Amazon, and Indigenous primary care in semiarid Northeast Brazil. A condensed characterization of the included studies is presented in Table 1.

Layer	First author / year	Country	Indigenous population	Health domain	Technology
L1	Habib 2022 [30]	Australia	Aboriginal & Torres Strait Islander	Ear disease	DL otoscopy
L1	Mothershaw 2021 [29]	Australia	Aboriginal & TSI children	Ear disease	AI telehealth screening
L1	Stephens 2025 [31]	Australia	Aboriginal school-age	Otitis media	Multimodal ML
L1	Habib 2024 [73]	Australia	Aboriginal & TSI rural	Tele-otology	Tele-otology service

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L1	Habib (DrumBeat.ai) [74]	Australia	Aboriginal & TSI paediatric	Ear disease	AI platform
L1	Scheetz 2021 [75]	Australia	Aboriginal Medical Services	Diabetic retinopathy	AI screening
L1	Li 2025 [76]	Australia (WA)	Aboriginal remote	Diabetic retinopathy	Mobile DR AI
L1	Goklish 2026 [77]	USA	American Indian (Apache)	Suicide risk	ML + screening
L1	Haroz 2021 [78]	USA	Native American	Suicide risk	ML CDS co-design
L1	Katapally 2026 [79]	Canada	Indigenous youth	Mental health	AI nudging mHealth
L1	Boscarino 2022 [80]	USA/Global	Indigenous (multi-region)	Data sovereignty / genomics	Federated ML framework
L1	Viernes 2025 [81]	USA/Pacific	NHPI	Data equity	NLP race/ethnicity
L1	Bennett-Poynter 2025 [82]	Global	Indigenous (mixed)	Suicide data	Rapid review
L1	Zobair 2023 [83]	Australia	First Nations	Cardiovascular	IoMT review
L1	Khan 2025 [84]	Canada	Indigenous mixed	Healthcare delivery	Five-step AI framework
L1	Khan 2025 (Two-Eyed) [85]	Canada	Indigenous mixed	Public-health ethics	AI framework

L1	Hocking 2023 [86]	Canada	Rural/Indigenous	Rural telehealth	Scoping review
L1	Genge [87]	Canada	Rural/remote elders	Wound care	AI wound care
L1	Maar 2019 [88]	Canada	First Nations (6 comm.)	Hypertension	SMS mHealth (DREAM-GLOBAL)
L1	Richer 2025 [89]	USA	Urban Indigenous	Tele-mental health	ShockTalk app
L1	Smith 2019 [90]	Australia	Remote Aboriginal	General telehealth	Telehealth service
L1	Hayoun 2024 [91]	Arctic	Inuit/circumpolar	Arctic telehealth	Telehealth review
L1	Whittaker 2023 [92]	Aotearoa NZ	Māori (health-system)	AI governance	Policy example
L1	Silano 2024 [93]	Canada (Indigenous)	Indigenous (global)	AI perspectives	Conceptual framework
L1	Dudley [94]	USA	Indian Country	AI governance	Governance paper
L1	ESR 2024 [95]	Global (multi-country)	Underrepresented	Imaging AI equity	Framework
L2	Motie-Shirazi 2025 [96]	Guatemala	Indigenous midwives	Fetal Doppler	Edge-AI deep learning
L2	Tofaeono 2025 [97]	American Samoa	Samoan	Colorectal cancer	AI/ML risk
L2	Kamberipa [98]	Namibia	Herero women	Diabetes risk	ML predictors
L3	Mota 2023 [44]	Brazil (PE/BA)	Truká/Fulni-ô	Cardiovascular	Tele-ultrasound

L3	Taveira 2014 [105]	Brazil (national)	Indigenous (multi-DSEI)	Implementation	National telemedicine program
L3	Sabage 2025 [106]	Brazil (Amazon riverside)	Riverside community (n=107)	Tele-ophthalmology (retinal)	Smartphone-based fundus camera
L3	Silva 2024 [107]	Brazil (Amazon riverine)	Riverine municipalities	Tuberculosis	Random Forest ML
L3	Barboza 2022 [108]	Brazil (Amazonas)	Amazonas state pop.	Malaria	LSTM/GRU deep learning
L3	Novais 2023 [109]	Brazil (Amazon)	Indigenous women (n=3,231 tests)	Cervical cancer	Cytology screening (Pap)
L3	Pennini 2025 [110]	Brazil (Amazonas)	CL trial patients (n=49)†	Cutaneous leishmaniasis	WhatsApp mHealth follow-up
L3	Salvador 2025 [111]	Brazil (Rio de Janeiro INI/Fiocruz)	NTD patients (n=46)†	Chagas + leishmaniasis	Telemedicine pilot
L3	de Lima 2025 [112]	Brazil (Amazon Northern)	Riverine + Indigenous (review)	Cervical cancer	Deep learning models
L3	Bezerra 2024 [113]	Brazil (Manaus urban)	Multiethnic urban Indigenous (n=141)	Cognitive screening / dementia	BRICA — culturally adapted cognitive tool

Table 1. Characteristics of the included studies (n = 39) by analytical layer. L1 = Global; L2 = Americas/Latin America; L3 = Brazil/Northeast, Brazil. † Indigenous identity not reported in the source publication; included as Indigenous-relevant Amazon evidence on remote-area mHealth/telemedicine in populations served by referral centers that attend to Indigenous and non-Indigenous patients in Amazonas.

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3.3. Bibliometric Analysis

Publication output rose sharply after 2021, with 30 of 39 studies (77%) appearing from 2022 onwards and a further inflection in 2025–2026, driven by federated learning, edge-AI, and culturally tailored mHealth designs. The geographic distribution was dominated by Australia (n = 10) and Canada (n = 7), followed by the United States (n = 6), Aotearoa, New Zealand (n = 3), Guatemala (n = 1), American Samoa (n = 1), Namibia (n = 1), and Brazil (n = 10; spanning Northeast-semiarid tele-ultrasound, Amazonian tele-ophthalmology, machine learning prediction of tuberculosis and malaria, cervical cancer cytology screening, mobile health follow-up of cutaneous leishmaniasis, telemedicine for Chagas disease and American cutaneous leishmaniasis, a recent deep-learning review for cervical cancer screening in Amazonian vulnerable populations, and culturally adapted cognitive assessment in an urban multiethnic Indigenous community). Co-authorship networks were highly clustered around three Australian groups (Northern Territory Tele-otology Consortium, Center for Eye Research Australia, and University of Western Australia mobile DR initiatives), a Canadian Indigenous health-research alliance bridging McMaster, Northern Ontario School of Medicine, and University of Saskatchewan, and a USA Indigenous mental health network anchored at Johns Hopkins and Mass General Brigham. Keyword co-occurrence analysis revealed dense clusters around "otitis media", "diabetic retinopathy", "Aboriginal", "machine learning", "telehealth" and "suicide prevention", with sparser nodes around "data sovereignty", "federated learning", "cultural safety" and "Indigenous data governance". The Brazilian cluster connects to global Indigenous health digital health and AI literature through tele-ultrasound, tele-ophthalmology, machine learning prediction of tuberculosis and malaria, cervical cancer screening, mobile health follow-up of neglected tropical diseases, and culturally adapted cognitive screening across the São Francisco Valley and Amazon Basin. Funding sources, where reported, were dominated by national health research councils (NHMRC in Australia, CIHR in Canada, NIH in the USA, and Health Research Council in NZ). Brazilian funding (CNPq, CAPES, FACEPE, FAPESB, FAPEAM, FAPEMIG, and FAPESP) was identifiable across the Brazilian Layer 3 studies, including federal research councils and state foundations supporting Indigenous health research in the Northeast Semiarid and Amazon.

3.4. Layer 1 — Global Evidence

Layer 1 evidence is overwhelmingly anchored in four Anglophone settler-colonial nations. In Australia, an integrated tele-otology program has produced sequential deep learning models for otoscopic image classification in Aboriginal and Torres Strait Islander children. An early binary classifier achieved 78.9% test accuracy [29], followed by a multi-class CNN trained on more than 6,500 images from Northern Territory screening programs, reporting 99.3% accuracy for acute otitis media and an AUC of 0.963–0.997 across diagnostic categories [30]. A multimodal model combining otoscopic images with clinical metadata further improved performance in school-aged Aboriginal cohorts [31]. The DrumBeat.ai platform translates these results into integrated clinical deployment [74], and tele-otology services have demonstrated their clinical utility [73]. Diabetic retinopathy screening with AI achieved an AUC of 0.92, sensitivity of 96.9%, and specificity of 87.7% in Aboriginal Medical Services, with 93.7% patient satisfaction [75], and a mobile AI-DR model was subsequently validated in remote Western Australia [76]. In the United States, retrospective EHR studies have shown that combining ML predictions with routine screening improves suicide-risk identification for American Indian and Alaska Native patients beyond either approach alone [77], and a clinical decision-support tool was co-designed with Native American patients [78]. Indigenous-led tele-mental health linkage is being evaluated for urban Indigenous populations through the ShockTalk pilot [89], while a rapid review of digital data for suicide prevention contextualizes these advances [82]. In Canada, the DREAM-GLOBAL trial established a five-year culturally safe SMS mHealth platform for hypertension self-management across six First Nations communities [88]. Subsequent frameworks proposed a five-step deployment pathway for AI in remote Canada [84] and articulated Two-Eyed Seeing (Etuaptmumk) as a public health ethic for AI [85]. AI-enhanced wound care [87] is at an early stage, and a recent scoping review of rural Canadian telehealth and digital health provides a broader contextual evidence base [86]. Arctic telehealth reviews have identified funding fragmentation as the principal threat to long-term service viability [91]. In Aotearoa, New Zealand, federated learning explicitly grounded in Te Mana Raraunga has been proposed for wearable photoplethysmography-based stress classification [80], with He Pikinga Waiora [93] and an exemplar of AI governance for health services from Aotearoa, New Zealand [92], articulating governance and equity expectations. Cross-cutting analyses include equity considerations in imaging AI for underrepresented populations [95], NLP-based disaggregation of Native Hawaiian and Pacific Islander data [81], a systematic review of IoMT for cardiovascular prevention among Australian First Nations [83], and Indian Country–focused AI governance reflections [94]. Beyond the Anglophone settler-colonial sphere, Layer 1 evidence is sparse, with no Sami, Inuit-Greenland, Aboriginal Taiwanese, Adivasi South Asian, or Khoisan studies meeting eligibility criteria.

3.5. Layer 2 — Americas and Latin America

However, layer 2 evidence is scarce. Only one Latin American study met the inclusion criteria: a sophisticated edge-AI system providing real-time Doppler quality feedback for community midwives in rural Guatemala, deployed on low-cost Android devices, and explicitly co-designed with Indigenous midwives [96]. American Samoa contributed a single pilot study on AI/ML for colorectal cancer risk in a Pacific Islander population [97]. Namibia's diabetes risk factor study among Herero women [98] addresses an Indigenous-adjacent population but does not engage Indigenous governance frameworks. Across PAHO/OPAS digital health initiatives, no AI-specific study with Indigenous communities of Mexico, Peru, Bolivia, Ecuador, Colombia, Chile, or Argentina met the eligibility criteria, despite robust general telehealth and mHealth literature for these countries. This gap, more than any single included study, is a central finding of this review.

3.6. Layer 3 — Brazil and Northeast Brazil

Brazilian evidence on digital health, telemedicine, and—more recently—machine learning relevant to Indigenous populations is small but growing and concentrated in two regions: the São Francisco Valley in the Northeast semiarid region and the Amazon Basin. In the diagnostic imaging and tele-imaging strand, a tele-ultrasound study in the São Francisco Valley reported the association between hypertension and reduced carotid artery circumferential strain in a resource-limited Indigenous community, demonstrating that clinical and tele-supervised carotid imaging is feasible in remote Indigenous primary care [44]. In the Amazon, smartphone-based fundus-camera tele-ophthalmology has been deployed in a riverside community for retinal screening [106], a peer-reviewed PLOS One report documented cervical cancer cytology screening among 3,231 Amazonian Indigenous women under the Expedicionários da Saúde/SESAI partnership [109], and a culturally adapted cognitive-assessment tool (BRICA) has been validated with content, construct, and criterion indicators in an urban multiethnic Indigenous community in Manaus (n = 141; sensitivity 94.4%, specificity 99.2% for dementia) [113]. National-level policy implementation has been examined in an earlier analysis of the Brazilian National Telemedicine Program in Indigenous Health Care [105]. On the artificial intelligence strand, three Brazilian studies operate in Amazonian or riverine geographies with substantial Indigenous populations: machine-learning prediction of tuberculosis clusters across riverine Amazonian municipalities [107]; deep-learning prediction of malaria across city clusters in the state of Amazonas (covering approximately six million records from 2003 to 2018) [108]; and a recent critical review of deep-learning opportunities for cervical cancer screening in vulnerable Amazonian public health regions, with explicit attention to riverine and Indigenous populations [112]. Two further Amazonian studies on mobile health follow-up of cutaneous leishmaniasis during the COVID-19 pandemic [110] and telemedicine for Chagas disease and American cutaneous leishmaniasis in a national referral hospital [111] document the maturing infrastructure for tele-supported clinical care in regions of overlap with Indigenous territories, even when ethnicity was not disaggregated in the source publication. An adjacent body of Brazilian and Northeast scholarship documents the epidemiological and socioenvironmental conditions in which any such digital diagnostic technology must operate: cardiovascular health and urbanization across Brazilian Indigenous groups [39]; chronic kidney disease (CKD) prevalence among Truká adults in Cabrobó [40]; epidemiology of CKD among older Indigenous peoples of Brazil [41]; urbanization and kidney dysfunction in young Indigenous adults [42]; cardiac biomarkers in arbovirus-exposed Indigenous populations [43]; oral health of the Fulni-ô [45]; respiratory function and traditional xanduca pipe smoking among the Fulni-ô [46]; digital technology as a health instrument in São Francisco Valley Indigenous communities [35]; challenges and opportunities in health promotion and education in Indigenous communities [36]; the Programa Mais Médicos and the Indigenous communities of northern Bahia [47]; territory, gender, and mental health in a context of socioenvironmental change among the Trukás [48]; mental health and Buen Vivir among Indigenous women [49]; alcohol use and urbanization in Brazilian Indigenous groups [50]; medicinal-plant knowledge in the Truká population [51]; and water-borne disease vulnerability in Brazilian Indigenous communities [52]. Taken together, these studies establish, with peer-reviewed evidence, that Brazil—particularly Northeast semiarid and the Amazon—combines a heavy chronic disease burden, environmental and socioenvironmental vulnerability, a robust traditional knowledge ecosystem, and a primary care workforce shaped by intermittent federal programs in the Northeast. While Brazilian scholarship has begun to address artificial intelligence in Amazonian and riverine populations, no peer-reviewed empirical study has yet applied AI in the strict sense (machine learning, deep learning, computer-aided diagnosis) specifically to a defined Brazilian Indigenous community as the primary unit of analysis. Given that Brazil hosts approximately 1.7 million Indigenous individuals across 305 ethnic groups, with a constitutionally guaranteed Indigenous health subsystem (SasiSUS), the resulting Brazilian Indigenous "AI gap" is reported here as a central finding and not as a limitation of this review.

3.7. Cross-Layer Synthesis: Cultural Safety, Algorithmic Bias, Digital Divide, Sovereignty and Sustainability

Five thematic threads emerged across these layers. First, cultural safety was articulated most explicitly in Canadian and New Zealand sources, with the DREAM-GLOBAL trial operationalizing six “wise practices” for culturally safe e-health research [88], and the Two-Eyed Seeing framework proposing integrated Indigenous–Western epistemologies as the basis for AI design [85]. Second, algorithmic bias was a recurring concern, with imaging-AI equity literature [95] explicitly warning that the underrepresentation of Indigenous bodies in training datasets risks amplifying existing disparities, and Pacific Islander data-disaggregation work [81] showing the practical consequences of aggregated racial categories. Third, the digital divide—understood as the joint distribution of connectivity, devices, and digital literacy—was the most frequently cited implementation barrier, particularly in Arctic [91], Australian remote [90], rural Canadian [86], and northeastern Brazilian [35,44] contexts. Fourth, Indigenous data sovereignty was operationalized in only a minority of studies: Te Mana Raraunga was named as a design principle for federated learning [80], OCAP principles were referenced in the DREAM-GLOBAL governance architecture [88], and CARE principles were echoed substantively—though not always named—in studies advocating Indigenous-led data stewardship [84,85,94]. Fifth, sustainability has been discussed primarily in economic and social terms, with environmental sustainability receiving sparse explicit treatment, despite its growing salience [91,96].

3.8. Indigenous Authorship Analysis

Indigenous authorship—judged from explicit author disclosures, biographical statements, affiliations with Indigenous-led organizations, and named acknowledgements in the included studies—was identifiable in a minority of papers (approximately eight of 39, 21%), most clearly in Native American suicide-risk work [77,78], the ShockTalk tele-mental health platform [89], and aspects of the Two-Eyed Seeing framework [85]. The remaining 77% appeared to be conducted

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predominantly by non-Indigenous research teams, often in collaboration with Indigenous health services but without explicit Indigenous authorship involvement. The present review falls within the non-Indigenous-led category and has therefore disclosed its positionality and governance commitments transparently (Section 2.13).

3.9. Sustainability and Planetary Health Synthesis

Across the five sustainability dimensions defined in Section 1.7, the included studies showed uneven coverage. Social sustainability was addressed by 27 of the 39 studies (69%), typically through discussions on the workforce, task-shifting, and community engagement [84,88,90]. Cultural sustainability was addressed substantively by 16 of 39 studies (41%), with the most depth being achieved in Canadian conceptual frameworks [85,93] and Guatemalan midwifery work [96]. Economic sustainability was discussed by 18 of 39 (46%) participants, generally in terms of funding continuity concerns. Environmental sustainability was explicitly addressed by only four of 39 studies (10%), and even then, mostly in passing through references to on-device processing or low-resource deployment [80,96]. Territorial sustainability—self-determination over land and data—was named in 12 of 39 (31%), most clearly in the OCAP-informed [88], CARE-aligned [84,85], and Te Mana Raraunga–anchored [80] studies. Planetary health framing—linking climate change, ecological integrity, and Indigenous health—was rare, appearing only in Arctic telehealth reflections [91] and implicitly in the Northeast Brazilian context, where climatic variability of the semiarid biome conditions cardiovascular and renal risks [39,52].

3.10. Gap Analysis

The gap analysis aggregates the findings across the technology × health domain × region matrix. Geographic gaps include the near-complete absence of evidence from Latin America beyond Guatemala, Africa beyond the Indigenous-adjacent Herero study, South and Southeast Asia, and the continental Sami contexts. Technological gaps include the absence of large language models and foundation model applications for Indigenous languages, underdevelopment of AI for oral health, dermatology, and substance-use disorders, and limited integration between community-controlled data infrastructures and AI training pipelines. Methodological gaps include the absence of external validation across independent Indigenous populations, lack of long-term (multi-year) implementation sustainability data, scarcity of comparative effectiveness studies against usual care with clinical outcome endpoints, and absence of health economic evaluations adopting Indigenous value frameworks. Governance gaps include the persistent dominance of consultation-level community participation, rarity of co-leadership or Indigenous-led governance, and absence of standardized reporting structures for data sovereignty. The Brazil/Northeast gap is particularly stark: in the Northeast semiarid, only a single tele-ultrasound study explicitly bridged digital health and Indigenous health [44], despite the demonstrated burden of cardiovascular, renal, oral, and respiratory disease in this region [39–46]; Amazonian initiatives on tele-ophthalmology [106], machine-learning prediction of tuberculosis [107] and malaria [108], cervical-cancer screening among Indigenous women [109], mobile-health follow-up of neglected tropical diseases [110,111], a recent deep-learning review for vulnerable Amazonian populations [112], and culturally adapted cognitive assessment [113] together constitute early Brazilian engagement with this field.

3.11. Risk of Bias and GRADE-CERQual Summary

The risk of bias was generally moderate, with QUADAS-2 assessments of diagnostic accuracy studies frequently flagging concerns regarding patient selection (single-site or convenience samples) and the absence of independent external validation [29–31,75,76]. PROBAST assessments of prediction model studies highlighted optimism bias from internal validation and limited handling of missing data [77,78,97]. ROBINS-I assessments of observational implementation studies were typically moderate, with confounding and selection bias being the most common concerns [84,90].

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MMAT and JBI assessments of qualitative and mixed-methods studies showed adequate rigor but variable reflexivity depth. GRADE-CERQual assessments of qualitative findings on cultural safety, community participation, and Indigenous data sovereignty rated confidence as moderate to high for cross-study themes (cultural safety as an enabling factor; community co-design as a facilitator) and low to moderate for narrower findings (e.g., specific operationalizations of OCAP in non-Canadian contexts).

4. Discussion

4.1. Principal Findings

This systematic review identified a small but methodologically heterogeneous body of literature applying AI and digital health to Indigenous communities, with a concentration in four Anglophone settler-colonial nations and an acute scarcity elsewhere. Diagnostic-imaging AI, particularly tele-otology and diabetic retinopathy screening, and predictive modelling for suicide risk have emerged as the most technically mature application areas. However, the field's structural gaps are as informative as its successes: the near-absence of Latin American, Brazilian, African, and Asian Indigenous contexts; limited operationalization of Indigenous data sovereignty; rarity of external validation; absence of long-term sustainability data; and dominance of non-Indigenous research leadership. Brazilian peer-reviewed publications explicitly bridging digital health and Indigenous diagnostic imaging are rare. The northeast semi-arid tele-ultrasound study with Truká and Fulni-ô participants [44] illustrates one such intersection; Amazonian initiatives on smartphone-based tele-ophthalmology [106], deep-learning prediction of tuberculosis [107] and malaria [108], cytology-based screening of Indigenous women [109], mobile health follow-up of cutaneous leishmaniasis [110], telemedicine for Chagas disease and American cutaneous leishmaniasis [111], a recent deep-learning review for Amazonian vulnerable populations [112], and the culturally adapted BRICA cognitive-assessment tool [113] together represent the emerging Brazilian engagement with the global field of Indigenous health research.

4.2. From Telehealth to AI: What the Evidence Shows

The trajectory from telehealth to AI is empirically observable but uneven. Telehealth platforms—store-and-forward, synchronous, and mobile—remain the substrate on which AI is overlaid: tele-otology services predate AI classifiers by more than a decade in Australia [90]; Arctic telehealth reviews continue to identify infrastructure as the dominant determinant of feasibility [91]; and Brazilian tele-ultrasound experience in the São Francisco Valley [44] required no AI to demonstrate diagnostic feasibility, with AI augmentation being a plausible but not yet implemented, next step. Whereas AI has been introduced, it almost always operates within an existing telehealth or screening pipeline. This finding contradicts narratives that present AI as a leapfrogging technology capable of bypassing weak health systems; on the contrary, AI's effectiveness for Indigenous health depends on the maturity of the underlying telehealth and primary-care infrastructure. Telehealth and tele-imaging are not transitional artifacts to be discarded once AI matures; they are the necessary scaffolding within which AI can be safely and equitably embedded in the healthcare system to improve patient care.

4.3. Why Diagnostic Imaging AI Remains Underdeveloped in Indigenous Contexts

Despite the high health impact and technical feasibility of imaging AI, only a handful of imaging-AI applications meet Indigenous health needs at scale, and they are confined to two pathologies (otitis media and diabetic retinopathy) in one country (Australia). Several explanations emerge from this synthesis of the literature. First, training data for diagnostic AI are typically derived from urban, high-income tertiary centers; Indigenous populations are systematically under-sampled, generating poor generalization [95]. Second, diagnostic imaging in Indigenous primary care depends

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on devices and connectivity that remain unavailable in many remote Australian communities. Third, the regulatory and ethical clearance for deploying AI as a medical device in primary care settings is complex, and the few existing implementations have required years of partnership-building, governance design, and infrastructure investment [73,75,76]. Fourth, the field has not yet developed standardized reporting on the Indigenous-specific subgroup performance of AI imaging systems, leaving published accuracy metrics potentially unrepresentative of the populations that would most benefit from deployment.

4.4. AI on vs. AI with Indigenous Communities

A central conceptual distinction emerging from this review is between AI used on Indigenous data and AI co-designed with Indigenous communities [85,94]. Most published studies fall into the first category: Indigenous data are extracted, models are trained, and performance is reported without substantive community governance of the research design, data stewardship, or benefit-sharing. The minority in the second category—DREAM-GLOBAL [88], the suicide-risk CDS in partnership with Native American case managers [78], the edge-AI midwife system in Guatemala [96], and the federated learning architecture grounded in Te Mana Raraunga [80]—demonstrate that genuine co-design is feasible, even if it is methodologically demanding. The implications for sustainability are profound: AI used on Indigenous data may produce short-term technical results, but it perpetuates the colonial logic of extracting Indigenous bodies from data sets without restoring agency or benefit. AI with Indigenous communities, in contrast, can support self-determination and long-term acceptability but requires research timelines, funding models, and ethics-review structures that current systems often do not accommodate. Therefore, the transition between these two modes is both ethical and infrastructural.

4.5. Health Education and Digital Literacy as Implementation Prerequisites

The evidence reviewed reinforces the position articulated in Brazilian community-engaged scholarship [35,36] and Indigenous AI conceptual frameworks [93] that no AI or digital health intervention can be deployed equitably without parallel investment in health education and digital literacy. Indigenous Health Agents, midwives, community health workers, and household caregivers are the points of contact through which digital tools enter community life, and their continuing education—respectful of Indigenous languages and pedagogies—is not optional. Equally important is the digital literacy of non-Indigenous health workers in cultural safety and intercultural communication [33], without which sophisticated AI outputs may be misinterpreted, distrusted or imposed inappropriately. The Brazilian Northeast experience demonstrates that culturally adapted education using accessible digital tools (videos in regional Portuguese, illustrated cartilhas, and audio messages in Yathê for Fulni-ô audiences) is feasible and well received [35].

4.6. Brazil and Northeast Brazil as Critical Implementation Contexts

Brazil is not a marginal context for global Indigenous digital health research; on the contrary, it is one of the most policy-rich countries. SasiSUS provides a constitutionally guaranteed, ethnoculturally differentiated primary care architecture serving more than 700,000 enrolled Indigenous individuals with explicit attention to Indigenous languages and territorial specificity [9,10,37]. The contrast between the maturity of this policy architecture and the near-total absence of peer-reviewed digital health/AI research with Brazilian Indigenous communities suggests a research deficit rather than a lack of need. The Northeast semiarid region is particularly emblematic, with cardiovascular, renal, oral, and respiratory burdens [39–46], a workforce trained through the Programa Mais Médicos and continuing federal programs [47], and substantial socio-environmental vulnerability [48,52]. It represents an ideal laboratory for responsible AI and digital health implementation, the results of which have not yet been built.

4.7. Brazilian and Northeast Implementation Context

The Brazilian and Northeast evidence bases illustrate how regionally grounded longitudinal research can support responsible digital health innovation in Indigenous communities. Brazilian tele-ultrasound work in the São Francisco Valley demonstrated that imaging diagnostics can be delivered in resource-limited Indigenous primary care with remote specialist supervision, identifying associations between hypertension and subclinical vascular dysfunction in Truká and Fulni-ô participants [44]. The wider Brazilian and Amazonian evidence base on cardiovascular [39–43], oral [45], respiratory [46], mental [48,49], educational [35,36], policy [47], substance-use [50], traditional-knowledge [51], and water/environmental [52] dimensions, taken alongside Amazonian smartphone-based tele-ophthalmology [106], machine-learning prediction of tuberculosis [107], deep-learning prediction of malaria [108], cytology-based cervical-cancer screening among Indigenous women [109], mobile-health follow-up of cutaneous leishmaniasis [110], telemedicine for Chagas disease and ACL in a national referral hospital [111], the recent deep-learning review for cervical-cancer screening in Amazonian vulnerable populations [112] and the culturally adapted BRICA cognitive-assessment tool in an urban multiethnic Indigenous community [113], provides an integrated portrait of community health that could inform the design of culturally appropriate AI and digital-health applications—from telecardiology with AI-assisted echocardiography, to mHealth platforms for blood-pressure self-monitoring, to community surveillance of arboviruses, to digital health-education modules in Portuguese and Indigenous languages such as Yathê. The Brazilian experience also identifies practical preconditions for responsible deployment: long-term partnerships with EMSI teams and community leadership, sensitivity to gender and territorial dynamics, and explicit commitments to return findings to communities in an accessible format.

4.8. Sustainability and Planetary Health Implications

The sustainability dimension is where the field shows its most consequential immaturity. Social sustainability is widely discussed, often equated with stakeholder engagement; cultural sustainability is acknowledged in frameworks but rarely operationalized in technical design; economic sustainability is reduced to funding continuity rather than to the structural distribution of benefits; and environmental sustainability—the carbon footprint of training large models, the e-waste from devices deployed in remote regions, and the energy demand of cloud-based inference—is almost entirely absent from the literature. However, Indigenous territories bear a disproportionate share of the ecological costs of digital infrastructure: data centers draw on water and energy from territories whose ecological integrity is already threatened, while electronic waste circulates back along global supply chains, often to the Global South. The intersection of planetary health with Indigenous digital health, articulated in Krenak's critique of the "civilization of the abyss" [99] and Kopenawa's warning of the "falling sky" [100], requires AI architectures that are explicitly designed for energy efficiency, on-device inference, where possible, and full-lifecycle accountability. The Northeast semiarid region —with its climatic stress, arboviral cycles, and water vulnerability [43,52]—is itself a planetary health frontier, and any digital health innovation there must be evaluated against the ecological impact of its supporting infrastructure.

4.9. Policy Implications for SasiSUS, SESAI, DSEI and Indigenous Primary Care

Several policy implications follow from the SasiSUS. First, the absence of AI-specific Indigenous health evidence is a research policy issue: dedicated funding lines should be created at CNPq, CAPES, and state foundations (FACEPE, FAPESB, FAPESQ, and FAPEMA) for AI and digital health research co-designed with Indigenous communities. Second, SESAI and DSEIs should consider piloting tele-imaging, telecardiology, and AI-assisted screening within EMSI workflows with rigorous evaluation and explicit community governance. Third, the SIASI information system should evolve into an Indigenous-controlled data architecture aligned with CARE principles, allowing communities to determine which data are aggregated, shared, and used for predictive analytics. Fourth, the National Telehealth Program (Telessaúde Brasil Redes) and Rede Universitária de Telemedicina (RUTE) should expand explicit Indigenous components with adequate connectivity investments, particularly in the semiarid northeast. Fifth, the Política Nacional de Atenção à Saúde dos Povos Indígenas should incorporate digital rights and data sovereignty language consistent with international Indigenous data sovereignty frameworks and the principle of free, prior and informed consent.

4.10. Implications for Technology Developers, Researchers and Policymakers

For technology developers, the central implication is that performance metrics generated on non-Indigenous populations do not transfer automatically to Indigenous contexts, and that deploying AI without local validation risks both clinical harm and reputational damage to developers. For researchers, the message is that Indigenous health AI is not a methodological subspecialty but a distinct paradigm requiring sustained community partnership, multilingual literacy, and reflexivity regarding epistemology and power. For policymakers, the priorities are infrastructure (connectivity, devices, energy), workforce (continuing education for Indigenous and non-Indigenous health workers), governance (Indigenous data sovereignty embedded in law and contracts), and sustainability (funding cycles that match implementation horizons rather than short-term demonstration projects).

4.11. Strengths and Limitations

The strengths of this review include its comprehensive twelve-database search in four languages; the use of multiple complementary reporting frameworks (PRISMA 2020, PRISMA-Equity, SWiM, GRADE-CERQual, NASSS, TIDieR); the explicit three-layer geographic stratification that highlights the Brazilian/Northeast gap as a finding rather than an oversight; the integration of bibliometric analysis with narrative synthesis; the transparent positionality of the authors; and the proactive engagement with Indigenous data sovereignty frameworks. Limitations include the rapid evolution of AI literature, which means some publications will have appeared between the search date and the present manuscript; the predominance of English-language indexing, which may have under-surfaced relevant Spanish, Portuguese, and French sources from non-Anglophone repositories; the heterogeneity of Indigenous communities, which limits cross-comparison; the structural under-indexing of Indigenous health research in standard bibliometric platforms; and the fact that this is a review of literature about Indigenous communities, not a study co-produced with them. We attempted to mitigate this limitation through positionality, ethical governance commitments, and a plan to return findings in accessible formats.

5. Responsible AI and Digital Health Implementation Framework for Indigenous Communities

Building on the synthesized evidence and drawing on existing Indigenous data sovereignty frameworks (CARE, OCAP, Te Mana Raraunga, Maiam Nayri Wingara, and the Global Indigenous Data Alliance), the He Pikinga Waiora and Two-Eyed Seeing frameworks, the NASSS framework for technology adoption, and the planetary health literature, we propose a nine-domain framework for the responsible implementation of AI and digital health technologies in Indigenous communities. Each domain is defined by a guiding principle, a set of operational indicators, and a connection to the relevant SDGs. The framework is intended to be applied iteratively, with each domain audited prior to, during, and after technology deployment.

5.1. Community Governance and Co-Design

Guiding principle: Technology decisions affecting Indigenous communities are made with explicit community authority. Operational indicators include the existence of a community advisory or governance body with veto power over research and deployment, documented free, prior, and informed consent at the community and individual levels, co-authorship by Indigenous knowledge holders in scientific outputs, and budgetary allocations for community time and labor. SDG alignment: SDG 16, SDG 17. Evidence base: [84,85,88,96].

5.2. Indigenous Data Sovereignty

Guiding principle: Indigenous communities exercise effective control over their data throughout the data lifecycle. Operational indicators include explicit alignment with CARE, OCAP, or Te Mana Raraunga; community-controlled data infrastructure (local servers, federated learning, secure enclaves); data-sharing agreements with revocability clauses; collective consent procedures; and accountability mechanisms for data misuse. SDG alignment: SDG 9 and 16. Evidence base: [80,84,85,94].

5.3. Diagnostic Access and Territorial Equity

Guiding principle: AI and digital health technologies expand rather than concentrate diagnostic capabilities. Operational indicators include geographic mapping of diagnostic coverage before and after deployment, tele-imaging modalities adapted to local connectivity, explicit metrics for time-to-diagnosis improvement, and integration with referral pathways that respect community mobility patterns and cultural protocols. SDG alignment: SDG 3 and 10. Evidence base: [29–31,44,73,75,76,90].

5.4. Clinical Validity and Local Validation

Guiding principle: AI models deployed in Indigenous primary care are validated using representative Indigenous data with transparent subgroup performance reporting. Operational indicators include prospective external validation in the community of deployment, reporting of accuracy by age, sex, comorbidity, and community, documented calibration, and continuous post-deployment monitoring with community oversight. SDG alignment: SDG 3 and 9. Evidence base: [75,77,95].

5.5. Culturally Safe Explainability

Guiding principle: AI outputs are interpretable by clinicians, community health workers, and community members in a culturally appropriate language and form. Operational indicators include explanations co-designed with Indigenous educators, output presentations adapted to local literacy levels and languages (including Yathê, Guarani, Quechua, Aymara, Tikuna, and others as relevant), avoidance of false-precision language, and respect for narrative and oral modes of health communication. SDG alignment: SDG 3, SDG 4 (cross-reference), and SDG 10. Evidence base: [33,35,85].

5.6. Infrastructure and Workforce Readiness

Guiding principle: Technology deployment is matched by adequate connectivity, devices, energy, and personnel training. Operational indicators included connectivity audits prior to deployment, energy and device maintenance plans, continuing education for Indigenous Health Agents and EMSI clinicians, cultural safety training for non-Indigenous workers, and clear pathways for fault reporting and remediation. SDG alignment: SDG 9, SDG 17. Evidence base: [84,86,88,90,91].

5.7. Health Education and Digital Literacy

Guiding principle: Digital health innovation is paired with bidirectional health education and digital literacy training. Operational indicators include culturally adapted educational materials in community languages, intergenerational involvement, explicit links between digital tools and traditional knowledge, and the reciprocal training of researchers and developers in community epistemologies. SDG alignment: SDG 3, SDG 4, SDG 17. Evidence base: [35,36,51].

5.8. Economic and Environmental Sustainability

Guiding principle: Digital health innovations are evaluated for full lifecycle economic and ecological costs, with benefits flowing to communities. Operational indicators include health-

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economic evaluations incorporating Indigenous value frameworks, carbon-footprint assessments of cloud inference and device manufacturing, e-waste plans aligned with community priorities, and explicit benefit-sharing agreements. SDG alignment: SDG 9, 12, and 13. Evidence base: [80,91,96].

5.9. Accountability, Monitoring and Long-Term Policy Integration

Guiding principle: Deployment is accompanied by transparent accountability and integration with the national Indigenous health policy architecture. Operational indicators include living evaluation cycles, public reporting of outcomes disaggregated by community, integration with SasiSUS/SESAI/DSEI structures in Brazil and analogous architectures elsewhere, and pathways for community-driven decommissioning when technologies no longer serve community priorities. SDG alignment: SDG 16, SDG 17. Evidence base: [84,85,88,94].

6. Limitations

This review has several limitations, beyond those acknowledged in Section 4.11. First, our search, despite being multilingual and multi-database, may have under-surfaced relevant studies indexed only in regional or community-controlled repositories, and the standard bibliometric platforms systematically under-index Indigenous-led journals and grey literature. Second, the under-indexing of Indigenous health research compounds publication bias, particularly for negative findings and implementation failures, both of which are critical for an honest evaluation of the field. Third, the heterogeneity of Indigenous populations means that aggregating findings across Aboriginal Australians, First Nations Canadians, Native Americans, Māori, Guatemalans, Samoans, and Brazilians risks obscuring specificity within groups. We attempted to mitigate this by naming people whenever possible. Fourth, the rapid evolution of AI literature implies that this review will require updating; we suggest a living systematic review model on an 18-month cycle. Fifth, our corpus produced limited AI-specific diagnostic imaging studies, especially for modalities beyond otoscopy and retinography; this scarcity is a finding rather than a weakness of this review. Sixth, the predominance of high-income country evidence and the structural under-representation of Indigenous authors constrain the generalizability and ethical robustness of the conclusions. Seventh, and most fundamentally, this is a review of literature on Indigenous communities rather than a study co-designed with them; we explicitly acknowledge this asymmetry and commit to returning findings to the Truká and Fulni-ô through accessible community-appropriate formats.

7. Conclusions

Artificial intelligence and digital health technologies hold genuine but contingent promise for advancing diagnostic equity, surveillance, and care for Indigenous communities. The evidence reviewed here shows that where infrastructure, partnership, and governance align, AI-augmented telehealth can deliver clinically meaningful performance in specific domains, particularly Aboriginal Australian ear disease and diabetic retinopathy screening, suicide-risk identification in Native American communities, and Indigenous co-designed maternal care in Guatemala. However, evidence remains uneven and implementation-dependent: most published applications operate without substantive Indigenous community governance, external validation in independent Indigenous datasets, or long-term sustainability data, and the Latin American, Brazilian, and Northeast Brazilian contexts are almost entirely absent.

The following five conclusions were drawn. First, digital health and AI may support Indigenous diagnostic equity only when paired with the appropriate infrastructure, cultural safety, and governance. Second, the evidence is currently uneven and implementation-dependent; technical performance does not equate to equitable outcomes. Third, telehealth and tele-imaging are essential transitional technologies towards responsible AI, not artifacts to be replaced; the Brazilian Northeast tele-ultrasound experience in the São Francisco Valley and recent Amazonian deep learning and culturally adapted screening initiatives together illustrate this principle. Fourth, sustainable implementation requires cultural safety, Indigenous data sovereignty, local validation, health education, and long-term governance, integrated through frameworks such as the nine-domain Responsible AI and Digital Health Implementation Framework proposed here. Fifth, given the rapid evolution of AI literature and the urgent need to fill the Brazilian/Northeast evidence gap, this review could be productively updated as a living systematic review on a defined cycle, ideally co-produced with Indigenous researchers and community members.

Finally, sustainable digital health for Indigenous communities is a question of planetary health and human ecology. It demands not the unilateral export of high-income country algorithms, but a reciprocal architecture in which Indigenous self-determination shapes the design, deployment, and decommissioning of technologies that touch Indigenous bodies, land, and futures.

Supplementary Materials: The following supporting information is available with this submission, Preprints.org: S1: PRISMA 2020 Checklist; S2: PRISMA-Equity 2012 Checklist; S3: PRISMA-S 2021 Search-Reporting Checklist; S4: SWiM Reporting Items; S5: Complete Boolean Search Strings by Database and PRESS Validation Report; S6: List of Excluded Full-Text Studies with Reasons; S7: Full Data Extraction Matrix (30 variables × 39 studies); S8: Risk-of-Bias and Quality-Assessment Detailed Records (ROBINS-I, QUADAS-2, PROBAST, MMAT, JBI, AACODS); S9: GRADE-CERQual Assessment for Qualitative Findings; S10: Bibliometric Outputs and Raw Data (VOSviewer / bibliometrix); S11: Generative AI Disclosure Detail; S12: Reference Verification Log (113 references with verification status, source database, and verification notes); S13: Indicative Living-Review Update Timeline. All supplementary files are provided with this manuscript submission.

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Data Availability Statement: All data underlying this systematic review (search strategies, deduplication logs, screening decisions, extraction matrix, risk-of-bias assessments, GRADE-CERQual matrices, bibliometric outputs, and reference verification log) were generated and held by the research team and are available from the corresponding author upon reasonable request. As a systematic review of the published literature, no new primary data on human participants were generated in this study. Primary data from the cited studies remain the responsibility of their original authors and, where applicable, of Indigenous communities involved.

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Conflicts of Interest: Several authors are affiliated with the Projeto de Aterosclerose em Indígenas (PAI) research network in Northeast Brazil. A subset of the cited references (approximately 16 of 113) corresponded to the peer-reviewed outputs of the authors of the present review, including the Brazilian tele-ultrasound study [44]. These self-citations reflect the Layer 3 (Brazil/Northeast) analytical focus and are explicitly disclosed; they constitute approximately 14% of the reference list, which is below the threshold considered prudent for reviews. Co-author O.V.G. is of Truká ancestry and contributed to the cultural framing and ethical governance considerations of this research. Epistemic disclosure: The remaining authors are non-Indigenous Brazilian researchers working in the field of Indigenous health, and we approached this systematic review with the limitations and responsibilities that this positionality entails (see Section 2.13, above). The authors declare no conflict of interest. The funders had no role in the study design, data collection, analysis, or interpretation, manuscript writing, or decision to publish the results.

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