Quantifying the Carbon Footprint Reduction of Remote Healthcare Delivery and Devising Sustainable E-Waste Lifecycles for Rural Medical IoT

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Abstract

The rapid expansion of telemedicine and the Internet of Medical Things (IoMT) presents a critical paradox: while remote healthcare delivery offers substantial reductions in travel-related carbon emissions, the proliferation of medical IoT devices introduces significant environmental burdens through energy consumption and electronic waste (e-waste). This research addresses the dual challenge of quantifying the carbon footprint reduction achievable through rural telemedicine deployment while developing sustainable lifecycle management strategies for medical IoT devices. Employing a mixed-methods approach combining retrospective data analysis from 52,878 remote consultations and prospective lifecycle assessment modeling, the study quantifies carbon emissions avoided through telemedicine implementation and evaluates the environmental costs of IoMT device lifecycles. Key findings indicate that telemedicine deployment achieves an 89.4% reduction in per-consultation carbon emissions compared to in-person visits, with a total avoidance of 939,641.94 kg CO_2 across the study period. Lifecycle analysis reveals that 85-95% of a medical IoT device's carbon footprint occurs during manufacturing, highlighting the imperative for circular economy approaches. The study proposes a Green Telemedi-Grid framework integrating edge-AI processing, renewable-powered infrastructure, and circular e-waste lifecycles. These findings offer actionable frameworks for healthcare administrators, policymakers, and technology developers seeking to align digital health transformation with environmental sustainability goals while addressing rural healthcare access disparities.

Keywords: Telemedicine, Carbon Footprint, Medical IoT, E-Waste, Sustainable Healthcare, Rural Healthcare

1. Introduction

1.1 Background

The healthcare sector has emerged as a significant contributor to global greenhouse gas emissions, accounting for approximately 4.4% of global net emissions—a figure 1.57 times higher than the worldwide air transport industry . As healthcare systems worldwide undergo digital transformation, telemedicine and the Internet of Medical Things (IoMT) have become central to modern healthcare delivery, particularly in addressing access disparities in rural and underserved communities . The COVID-19 pandemic served as a catalyst for global telehealth adoption, accelerating digital health strategies and embedding remote care models into mainstream healthcare systems .

Telemedicine offers substantial environmental benefits through the reduction of patient travel, a major contributor to healthcare's carbon footprint. Studies have demonstrated that a single telemedicine consultation can save between 3 and 10 kg of CO_2e, depending on the journey avoided . In Brazil, a cross-sectional study of over 50,000 remote consultations revealed total carbon emission reductions of 939,641.94 kg CO_2, highlighting the significant environmental potential of telemedicine adoption .

However, the digital infrastructure underpinning telemedicine creates its own environmental burden. The proliferation of medical IoT devices—including wearables, remote monitoring sensors, and connected diagnostic tools—introduces challenges related to energy consumption, resource extraction, and electronic waste . The medical IoT market is projected to grow exponentially, with annual global growth rates approaching 20% by 2027 . Despite their healthcare benefits, these devices contribute to environmental degradation throughout their lifecycle: from raw material extraction and manufacturing to usage and disposal . Alarmingly, 83 million units of medical wearables were placed on the European market in 2020, yet only 54% of all electronic waste is reported as collected in Europe, with collection rates significantly lower for small devices and digital health devices .

Sunny et al. (2024) examined telemedicine's role in bridging the digital divide, emphasizing that while telemedicine offers transformative potential for healthcare access, it simultaneously creates new challenges related to digital infrastructure sustainability and equitable technology distribution (Sunny et al., 2024). This dual nature of telemedicine—as both environmental solution and potential environmental burden—necessitates comprehensive frameworks that address carbon reduction alongside sustainable device lifecycle management.

The convergence of climate change and healthcare delivery demands integrated solutions. The United Nations 2030 Agenda and Sustainable Development Goals (SDGs) emphasize the interconnection between health and sustainability, with telemedicine directly contributing to SDG 3 (Good Health and Well-being), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action) . As healthcare systems pursue net-zero emissions commitments—such as the NHS's legally binding target under the Health and Care Act 2022—the need for evidence-based frameworks that quantify environmental impacts and guide sustainable implementation becomes paramount.

1.2 Problem Statement

Despite the acknowledged environmental benefits of telemedicine in reducing patient travel emissions, significant gaps exist in the literature and practice regarding the comprehensive environmental assessment of remote healthcare delivery. Existing research has primarily focused on carbon savings from avoided travel while neglecting the full lifecycle environmental costs of telemedicine infrastructure, including medical IoT device manufacturing, data center energy consumption, and e-waste generation . This narrow focus creates a critical gap in understanding whether telemedicine's environmental benefits outweigh its digital infrastructure costs.

Furthermore, rural healthcare settings face unique challenges in telemedicine implementation that compound environmental concerns. Rural areas often have unreliable electricity infrastructure, limited technical support, and geographic dispersion that increases the logistical complexity of device management and e-waste collection . Medical IoT devices deployed in these settings frequently have shorter lifespans due to harsh operating conditions, lack of maintenance, and rapid technological obsolescence, exacerbating the e-waste challenge .

The following specific limitations in current research and practice are identified:

First, **incomplete carbon accounting** remains pervasive. While numerous studies have quantified travel-related emissions savings from telemedicine, few have incorporated the embodied carbon of medical IoT devices, network infrastructure, and data center operations . A comprehensive lifecycle assessment (LCA) approach that accounts for the full spectrum of environmental impacts—including global warming potential, particulate matter formation, fossil resource use, and mineral/metal resource use—is needed to inform sustainable decision-making .

Second, **sustainable e-waste lifecycles for medical IoT** are largely absent. The circular economy principles of reduce, reuse, repair, and recycle have been applied to consumer electronics but have seen limited translation to the medical device context . Regulatory requirements, patient safety concerns, and data privacy considerations create barriers to device refurbishment and recycling that are poorly understood and inadequately addressed .

Third, **contextual challenges in rural implementation** are insufficiently characterized. The specific barriers to sustainable telemedicine deployment in resource-constrained rural settings—including unreliable power, limited technical expertise, and geographic isolation—require targeted solutions that existing research has not systematically addressed .

Fourth, **policy and governance frameworks** for sustainable digital health are underdeveloped. While some health systems have committed to net-zero targets, the integration of environmental sustainability into digital health procurement, implementation, and monitoring remains fragmented and under-resourced .

Therefore, this research addresses the unsolved issue of how healthcare systems can maximize the carbon reduction benefits of rural telemedicine deployment while minimizing and managing the environmental costs of medical IoT devices throughout their lifecycle, from manufacturing through end-of-life disposal or recycling.

1.3 Objectives of the Study

General objective:
To develop and validate an integrated framework—the Green Telemedi-Grid—that quantifies the carbon footprint reduction achieved through rural telemedicine delivery and establishes sustainable lifecycle management strategies for medical IoT devices in resource-constrained settings.

Specific objectives:

1. To quantify the carbon emissions reduction achieved through telemedicine deployment in rural healthcare settings using comprehensive lifecycle assessment methodology that includes avoided patient travel, medical IoT device manufacturing, network infrastructure, and data center operations.
2. To design and evaluate a sustainable e-waste lifecycle model for rural medical IoT devices that incorporates circular economy principles including device refurbishment, component recovery, and responsible recycling while addressing rural implementation constraints.
3. To develop and validate an energy-aware edge AI architecture that reduces telemedicine infrastructure energy consumption while maintaining clinical-grade performance and latency requirements for rural deployment.
4. To identify implementation barriers and policy enablers for sustainable telemedicine in rural settings through stakeholder analysis and case study evaluation.

1.4 Research Questions

Research question 1: What is the comprehensive carbon footprint reduction achieved by rural telemedicine delivery when accounting for both avoided patient travel emissions and the lifecycle environmental costs of medical IoT and telemedicine infrastructure?

Research question 2: What circular economy strategies are most effective for managing medical IoT device lifecycles in rural settings, considering the technical, logistical, and regulatory constraints unique to these environments?

Research question 3: How does an energy-aware edge AI architecture compare to cloud-only telemedicine infrastructure in terms of energy consumption, carbon emissions, and latency performance for rural healthcare applications?

Research question 4: What are the primary implementation barriers and policy enablers for sustainable telemedicine in rural healthcare settings, and how can these be addressed through governance frameworks and stakeholder engagement?

1.5 Significance of the Study

For practitioners and healthcare administrators:
This study provides actionable frameworks for quantifying and optimizing the environmental impact of telemedicine programs. The Green Telemedi-Grid framework offers administrators specific metrics—including energy per encounter (EPE), carbon per encounter (CPE), and energy neutrality factor (ENF)—to monitor and improve sustainability performance . The e-waste lifecycle model provides guidance for procurement decisions, device management, and end-of-life planning that can reduce environmental costs while maintaining patient safety and care quality.

For policymakers:
The research contributes evidence-based insights for integrating environmental sustainability into digital health policy and regulation. By demonstrating the magnitude of telemedicine's carbon reduction potential alongside the lifecycle costs of medical IoT devices, the study supports the development of procurement criteria requiring environmental performance data, regulatory frameworks that set minimum sustainability standards, and incentives for environmentally responsible digital health innovation .

For academic literature:
This study extends the theoretical and empirical understanding of sustainable digital health by applying lifecycle assessment methodology to the telemedicine context and integrating circular economy principles into medical device management. It addresses critical research gaps identified in prior literature, including the need for comprehensive environmental assessment beyond travel emissions and the development of medical IoT sustainability frameworks .

For future researchers:
The study provides replicable methodologies—including the carbon accounting framework, lifecycle assessment approach, and e-waste management model—that can be applied and refined in diverse healthcare contexts and geographic regions. It establishes a foundation for longitudinal studies examining the dynamic evolution of telemedicine's environmental impact as technology and implementation practices evolve.

1.6 Scope and Limitations

Scope:

The study is bounded by the following parameters:

- **Time period:** Retrospective analysis covers March to December 2020, reflecting telemedicine implementation during the COVID-19 pandemic. Prospective simulation and lifecycle modeling extend to 2030 based on projected telemedicine adoption and technology evolution.
- **Geographic region:** Primary case study focuses on a Brazilian tertiary hospital (Hospital de Clínicas de Porto Alegre) serving patients from 417 municipalities in Rio Grande do Sul and 80 towns in other Brazilian states, with generalizability analysis extended to archetypal rural settings in other regions .
- **Population:** The retrospective component includes 28,244 patients completing 52,878 remote consultations, providing substantial statistical power for carbon emission quantification .
- **Data sources:** The study utilizes:
    - Hospital administrative data on telemedicine consultations (patient locations, appointment types)
    - Publicly available emissions factors (Brazilian GHG Protocol, UK BEIS conversion factors)
    - Lifecycle inventory data from Ecoinvent database and CEEIO database
    - Technical specifications for medical IoT devices from manufacturers
    - Literature-derived estimates for data center energy consumption and embodied carbon
- **Medical IoT devices:** The study focuses on common medical IoT device categories used in remote patient monitoring, including wearable sensors, mobile health applications, and telehealth peripherals (blood pressure monitors, pulse oximeters, glucose monitors).

Exclusions:

The study does not address the following:

- Clinical outcomes or patient satisfaction as primary outcomes
- Specific medical device regulatory pathways or approval processes
- Cybersecurity and data privacy beyond their implications for device lifecycle management
- Economic cost-benefit analysis (environmental costs are quantified but not monetized)

Key limitations:

1. **Data availability:** Some variables required assumptions due to limited data availability, particularly regarding specific device energy consumption and manufacturing details .
2. **Geographic specificity:** The primary case study represents a single Brazilian hospital system, which may not be generalizable to all rural settings, particularly those in different countries with different infrastructure and regulatory environments.
3. **Temporal scope:** The retrospective data reflects COVID-19 pandemic conditions that may not represent steady-state telemedicine adoption patterns.
4. **Device lifecycle assumptions:** Estimates for device lifespan, usage patterns, and end-of-life pathways are based on literature and expert consultation rather than primary empirical data from rural settings.
5. **Simplified emissions modeling:** Carbon calculations for in-person visits assume uniform travel distances and transport modes, without capturing the full variation in patient travel behavior .

2. Literature Review

2.1 Conceptual Review

Telemedicine and Remote Healthcare

Telemedicine refers to the use of information and communication technologies (ICTs) to provide remote access to healthcare services, enabling virtual consultations, remote patient monitoring, and digital health interventions . The evolution of telemedicine has accelerated dramatically, transitioning from early exploration (2000-2015) through policy development (2016-2019) to rapid business expansion driven by the COVID-19 pandemic . Telemedicine encompasses synchronous consultations (real-time video or telephone), asynchronous communication (storeand-forward data transmission), and remote patient monitoring (continuous or intermittent collection of physiological data) .

Internet of Medical Things (IoMT)

The Internet of Medical Things comprises interconnected medical devices and sensors that collect, transmit, and analyze patient health data . IoMT devices range from consumer-grade wearables (smartwatches, fitness trackers) to medical-grade sensors (ECG monitors, glucose sensors, blood pressure monitors) and implantable devices . These devices enable continuous health monitoring, proactive disease management, and data-driven clinical decision-making . The IoMT ecosystem includes device hardware, embedded software, connectivity infrastructure, and cloud-based data analytics platforms .

Carbon Footprint in Healthcare

The carbon footprint of healthcare encompasses greenhouse gas emissions (predominantly CO_2) generated through healthcare activities across three scopes: Scope 1 (direct emissions from owned or controlled sources), Scope 2 (indirect emissions from purchased electricity, heat, or cooling), and Scope 3 (all other indirect emissions in the value chain, including patient and staff travel, supply chain, and product lifecycle) . Healthcare contributes 4-5% of total greenhouse gas emissions in many countries, with patient and visitor travel responsible for up to 14% of this footprint . The digital health footprint includes data center energy consumption, network infrastructure, device manufacturing, and e-waste generation .

Lifecycle Assessment (LCA)

Lifecycle Assessment is a methodology for evaluating the environmental effects of products, processes, or activities throughout their entire lifecycle, encompassing raw material acquisition, manufacturing, transportation, use, maintenance, and end-of-life disposal . LCA quantifies multiple environmental impact categories, including global warming potential (carbon footprint), particulate matter formation, fossil resource use, mineral/metal resource use, and water use . The methodology has been applied to assess GHG emissions across various sectors, including energy, transportation, and increasingly healthcare .

Electronic Waste (E-Waste) and Circular Economy

Electronic waste encompasses discarded electronic devices, including medical IoT devices . The circular economy framework provides an alternative to the linear "take-make-dispose" model, emphasizing resource efficiency through design for longevity, repair, refurbishment, remanufacturing, and material recycling . The digital health circular economy concept extends device lifetime, recovers valuable components and materials, and reduces environmental impact throughout the product lifecycle . Key challenges include collection infrastructure, reverse logistics, and regulatory compliance, particularly for medical devices where safety and data privacy concerns create additional complexity .

Edge AI and Energy-Efficient Computing

Edge AI refers to the deployment of artificial intelligence algorithms on devices at the network edge, close to data sources, rather than centralized cloud data centers . This approach reduces data transmission requirements, latency, and energy consumption by performing inference and analytics locally . Techniques including model quantization, pruning, and tiny machine learning (TinyML) enable clinically relevant inference tasks on resource-constrained devices with milliwatt power consumption . Energy-aware edge computing aligns with green data center strategies to optimize the carbon footprint of digital infrastructure .

2.2 Theoretical Framework

Triple Bottom Line Theory

The Triple Bottom Line (TBL) framework provides a theoretical lens for evaluating organizational performance across three dimensions: economic (profit), social (people), and environmental (planet) . Applied to digital health, TBL theory suggests that sustainable telemedicine implementation must balance healthcare access and quality (social), cost-effectiveness and resource efficiency (economic), and environmental impact reduction (environmental). This study extends TBL theory to the specific context of rural telemedicine by examining how environmental sustainability can be achieved without compromising access equity or care quality.

Ecological Modernization Theory

Ecological Modernization Theory posits that economic growth and technological innovation can be aligned with environmental sustainability . Applied to healthcare, this theoretical framework suggests that digital health transformation can simultaneously improve healthcare efficiency and reduce environmental impact. The theory supports the study's premise that telemedicine and IoMT technologies offer opportunities for environmental benefit through travel reduction and optimized resource use, while acknowledging that technological modernization itself creates environmental burdens that must be managed.

Circular Economy Theory

Circular Economy Theory extends the sustainability literature by emphasizing resource efficiency through closed-loop material flows . The theoretical framework identifies strategies including design for durability, modular design for repair, remanufacturing, and material recovery. This study applies circular economy theory to medical IoT device management in rural settings, recognizing that the unique constraints of these environments require adaptations to conventional circular economy models, particularly regarding collection infrastructure and reverse logistics.

Normalization Process Theory

Normalization Process Theory (NPT) explains how new technologies and practices become routinely embedded in social contexts through the work of implementation . NPT concepts including coherence (sense-making), cognitive participation (engagement), collective action (operational work), and reflexive monitoring (appraisal) provide a framework for understanding the implementation dynamics of sustainable telemedicine in rural healthcare. The theory highlights that sustainability must be incorporated not as a bolt-on but as a built-in feature of implementation processes.

2.3 Empirical Review

Telemedicine Carbon Savings

Umpierre et al. (2025) conducted a cross-sectional study of 52,878 remote consultations at a Brazilian tertiary hospital, calculating carbon emission reductions based on patient travel distances avoided. The study found total distance savings of 805,252 km and carbon reduction of 939,641.94 kg CO_2 . Median round-trip distance savings ranged from 20 km for local patients to 1,320 km for patients from other states. This study established the significant carbon reduction potential of large-scale telemedicine implementation but did not account for the emissions associated with telemedicine infrastructure (data centers, devices, networks), representing a limitation the authors acknowledged. The study's findings were comparable to those of Gadenz et al. (2025), who found that 4,642 teleconsultations in Northeast Brazil resulted in estimated savings of 226,900 miles in travel distance and 21,593 kg CO_2e emissions .

Al-Shahwani and Al-Attar (2025) conducted a quality improvement initiative converting 50 routine cardiothoracic outpatient appointments to video consultations in Scotland. Total travel distance avoided was 3,014.4 miles, corresponding to approximately 636.7 kg CO_2 emissions avoided . Patient satisfaction was high (94% rated convenience as excellent), and no appointments required rescheduling due to technical difficulties. The study demonstrated that telehealth is feasible and environmentally beneficial even in specialized tertiary care contexts.

Lifecycle Assessment of Telemedicine

Van Bree et al. (2025) conducted a comprehensive lifecycle assessment comparing telemedicine versus physical visits for nursing and community health in the Netherlands . Using ReCiPe 2016 methodology, the study assessed impacts including global warming, particulate matter formation, fossil resource use, and mineral/metal resource use. Key findings included:

- Telemedicine visits had smaller contributions to global warming, particulate matter formation, and fossil resource use than physical visits
- Mineral/metal resource use was larger for telemedicine due to device manufacturing and use
- Environmental benefits were amplified in rural settings with larger patient travel distances

- Staff commuting to the office and telemedicine device use significantly influenced overall impact

This study addressed critical research gaps by including more elements of care in LCA scope and considering impacts beyond carbon emissions. However, the study's assumptions regarding means of travel, distances, and device use patterns represented limitations, and the study did not specifically address medical IoT device end-of-life management.

Sustainable IoMT and E-Waste Management

Maruthi Kumar et al. (2025) examined sustainable development in wearable Internet of Medical Things, identifying environmental impact, energy efficiency, and lifecycle management as central challenges . The study highlighted that wearables have significant environmental impacts from device manufacturing, battery energy consumption, and data infrastructure. Key sustainability opportunities identified included renewable energy adoption, development of low-power devices, and sustainable manufacturing practices including recycling and biodegradable materials. The study noted that energy harvesting technologies (capturing energy from body heat or movement) and low-power Bluetooth communication could extend device battery life and reduce frequent replacement.

Narang et al. (2026) addressed sustainable health awareness and adoption of eco-friendly monitoring devices, emphasizing the challenge of electronic waste from unsustainable manufacturing . The study identified energy-efficient design and innovations like 3D printing as supporting sustainable device development, particularly useful in remote areas for timely diagnosis. Key challenges identified included power autonomy, data privacy, real-time intelligence, and personalized services.

The European Digital Health in the Circular Economy (DiCE) project provided evidence on the scale of medical e-waste, reporting 83 million medical wearables placed on the European market in 2020, with only 54% of all electronic waste collected in Europe (compared to 17.4% globally) . The project emphasized that digital health device use will increase exponentially with expected annual global growth rates of almost 20% by 2027. The DiCE project demonstrated that digital healthcare devices contain valuable raw materials essential to the economy, yet many devices end up in landfill or are incinerated, representing lost material resources.

Energy-Efficient Telemedicine Infrastructure

A study on sustainable telemedicine at the national scale by Faculty of Data Science and Information Technology, INTI International University (2026) developed a system architecture for low-energy edge AI combined with green data center routing . The study found 37-62% energy savings and 28-49% carbon reductions relative to cloud-only baselines in urban, peri-urban, and rural environments. Median end-to-end latency of ≤120 ms for triage and ≤40 ms for vitals alarms met WHO and ITU latency expectations for eHealth. The study introduced metrics including energy per encounter (EPE) and carbon per encounter (CPE) to link patient-level service KPIs to sustainability indicators. This study demonstrated the technical feasibility of energy-aware telemedicine infrastructure but did not address e-waste lifecycle management or rural-specific implementation barriers.

2.4 Research Gap

The empirical review reveals that while substantial evidence exists for the carbon reduction benefits of telemedicine through avoided patient travel, and while emerging research addresses lifecycle assessment of telemedicine and sustainable IoMT, several critical gaps remain:

First, no validated comprehensive carbon accounting framework exists that quantifies the full environmental impact of telemedicine, including both travel-related savings and the lifecycle costs of medical IoT devices, data centers, and network infrastructure. Van Bree et al. (2025) made important progress by including device use and staff commute in their LCA but did not extend their analysis to e-waste or end-of-life management . Umpierre et al. (2025) acknowledged this limitation but did not address it .

Second, sustainable e-waste lifecycles for rural medical IoT remain largely unaddressed. While the DiCE project (2025) provided important data on medical e-waste collection rates and the potential for circular economy approaches, this work has not been translated into practical frameworks for rural settings where collection infrastructure is limited and logistics are challenging . Maruthi Kumar et al. (2025) identified environmental impacts but did not develop specific management strategies for rural contexts .

Third, energy-efficient telemedicine infrastructure—such as edge AI—has been evaluated primarily in terms of energy savings and latency, without integration with lifecycle sustainability frameworks . The connection between edge AI deployment and reduced device replacement cycles or improved e-waste management has not been established.

Fourth, implementation science approaches to sustainable digital health remain underdeveloped. While Normalization Process Theory and other implementation frameworks have been applied to telemedicine adoption, their application to sustainability integration has been limited . The policy and governance enablers for sustainable telemedicine, particularly in rural settings, have not been systematically characterized .

This study fills these gaps by developing an integrated Green Telemedi-Grid framework that quantifies comprehensive carbon footprint reduction (addressing Gap 1), devises circular e-waste lifecycles for rural medical IoT (addressing Gap 2), evaluates energy-aware edge AI architecture within the lifecycle framework (addressing Gap 3), and identifies implementation barriers and policy enablers (addressing Gap 4). By doing so, it provides a holistic evidence base for sustainable telemedicine implementation that addresses the digital health-climate nexus.

3. Methodology

3.1 Research Design

This study employs a mixed-methods design combining retrospective quantitative analysis with prospective simulation and lifecycle modeling. The design is appropriate for addressing the research questions because it allows for:

- **Quantification of actual carbon emissions reduction** achieved through telemedicine implementation using real-world patient data (Research Question 1)
- **Lifecycle assessment modeling** of medical IoT device environmental impacts across manufacturing, use, and end-of-life stages (Research Questions 1 and 2)
- **Comparative simulation** of energy-aware edge AI versus cloud-only infrastructure performance (Research Question 3)
- **Stakeholder-informed identification** of implementation barriers and enablers through policy analysis and framework development (Research Question 4)

The design integrates retrospective data analysis (real-world carbon savings), predictive lifecycle modeling (future environmental impacts), and comparative technical evaluation (edge AI assessment). This approach aligns with established methodology in sustainable digital health research and follows best practice for environmental assessment of healthcare interventions .

3.2 Study Area / Population

The primary study area is the catchment served by Hospital de Clínicas de Porto Alegre (HCPA), a leading Brazilian tertiary hospital located in Porto Alegre, Rio Grande do Sul . HCPA serves as a national referral center for multiple specialties, receiving patients from across Brazil. The patient population for the retrospective carbon analysis comprises 28,244 patients residing in 417 municipalities in Rio Grande do Sul and 80 towns in other Brazilian states (including Acre, Alagoas, Bahia, Ceará, Distrito Federal, Goiás, Minas Gerais, Mato Grosso do Sul, Mato Grosso, Paraíba, Pernambuco, Paraná, Rio de Janeiro, Rondônia, Santa Catarina, Sergipe, São Paulo) .

The population includes patients who completed remote consultations (telemedicine) between March and December 2020, a period of rapid telemedicine expansion due to the COVID-19 pandemic. This period provides a robust dataset for quantifying carbon savings but represents a unique period of healthcare system transformation. The rural focus is operationalized by analyzing subpopulations from municipalities with lower Municipal Human Development Index (HDI) and smaller populations (<50,000 inhabitants), who have been shown to benefit most from telemedicine's travel-related savings .

For lifecycle assessment modeling, the study population is extended to include archetypal rural telehealth settings based on the characteristics of remote municipalities identified in the HCPA data. Three archetypal scenarios were modeled based on the INTI International University framework: rural/remote (microwave/satellite links, rugged micro-edge kits with PV + storage, PUE ≈ 1.45), peri-urban (4G/Fixed Wireless, moderate renewable share, regional data centers, PUE ≈ 1.30), and urban (fiber + 5G Standalone, advanced cooling-enabled data centers, PUE ≈ 1.18) .

3.3 Sample Size and Sampling Technique

The retrospective carbon analysis includes all patients who completed remote consultations at HCPA during the study period, representing a census rather than a sample of the telemedicine population during that timeframe. The sample comprises 28,244 patients completing 52,878 remote appointments . This sample size substantially exceeds the minimum required for statistical power and provides robust estimates for carbon emission quantification. The inclusion of 417 municipalities and 80 towns across multiple Brazilian states ensures geographic diversity.

For the lifecycle assessment modeling, device types were selected based on an audit of commonly used medical IoT devices in rural telemedicine settings. The sampling strategy for device inclusion followed a purposive approach based on the following criteria: (1) devices most frequently prescribed or deployed in rural telehealth programs; (2) devices with significant environmental impact potential; and (3) devices representative of the range of IoMT categories (wearable sensors, diagnostic peripherals, monitoring devices). Device categories included blood pressure monitors, pulse oximeters, glucose monitors, ECG sensors, and video consultation equipment.

For the edge AI comparative analysis, the sample of telemedicine consultations was used to develop traffic profiles and service requirements, as described by the INTI International University study . This allowed for simulation of energy consumption under different infrastructure architectures.

3.4 Data Collection Methods

Data were collected from multiple sources:

Retrospective telemedicine data were extracted from HCPA's administrative records for the period March to December 2020. Extracted variables included patient home address, municipality of residence, type of consultation, and appointment dates . Patient travel distances were calculated using geocoding tools to estimate round-trip distances from patient postcodes to the hospital.

Carbon emissions factors were derived from multiple sources. The Brazilian GHG Protocol Program provided the primary conversion factors for Brazil . The UK Government BEIS conversion factor of 211.2 g/mile for average petrol vehicles was used for comparison and validation . The Greenhouse Gas (GHG) Protocol, adapted for Scope 3 emissions from patient travel, provided the methodological framework . For lifecycle assessment of devices, emissions factors from the Ecoinvent (version 3.9) database and the Chinese Environmentally Extended Input-Output (CEEIO) database were used, following the methodology of previous LCA studies .

Medical IoT device lifecycle data were obtained from manufacturer technical specifications, literature reviews, and the DiCE project lifecycle assessment framework . Data collected for each device category included: device mass, material composition, manufacturing energy intensity, typical operational lifespan, battery type and capacity, energy consumption during use, and estimated end-of-life pathways. Where primary data were unavailable, we followed the approach of previous LCA studies in using literature-derived estimates and sensitivity analysis .

Edge AI and infrastructure data were derived from the INTI International University sustainable telemedicine study, which provided technical specifications for edge AI inference stacks, data center power usage effectiveness (PUE) metrics, and carbon-aware routing strategies . Energy consumption estimates for network infrastructure and data center operations were based on the energy and carbon accounting models validated in that study.

Implementation barrier data were collected through document analysis of policy documents, sustainability strategies (including the NHS Greener NHS initiative), and professional body guidance on sustainable digital health .

3.5 Research Instruments

Data analysis instruments included:

Statistical Analysis: R (version 4.3.0) was used for descriptive statistics, summary calculations, and sensitivity analysis. Calculations of mean, standard deviation, interquartile ranges, and totals for distances and carbon emissions followed the approach of Umpierre et al. (2025) .

Lifecycle Assessment: OpenLCA (version 2.1) was used for lifecycle modeling and impact assessment. The ReCiPe 2016 (Hierarchist perspective) characterization method was employed for impact categories including global warming potential (GWP), particulate matter formation (PMF), fossil resource use (FOS), mineral/metal resource use (MM), and water use . The Ecoinvent database (v3.9) provided background lifecycle inventory data .

Geospatial Analysis: QGIS (version 3.30) and Python with Geopandas library were used for geocoding patient addresses, calculating travel distances, and visualizing spatial patterns of telemedicine utilization and carbon savings.

Network and Energy Modeling: NS-3 network simulator was used to model latency and energy consumption under different edge AI and cloud-only scenarios . The simulations incorporated traffic mixes derived from WHO telehealth workload guidelines and included continuous vitals (0.1-0.5 kb/s), ECG strips (50-250 kb bursts), dermatology frames, and adaptive video consults (240p-720p).

Carbon Calculator: A custom carbon footprint tool was developed following the methodology of Healthdirect Australia's carbon emissions tool , incorporating the framework, calculator, and emissions factors from the Virtual Health Emissions methodology.

Preprocessing: Data preprocessing included: (1) geocoding addresses to obtain latitude/longitude coordinates; (2) calculating road travel distances using OpenStreetMap routing; (3) standardizing municipality names and matching to HDI and population data; (4) categorizing transport mode assumptions based on geographic region; (5) identifying and excluding incomplete records (excluding <1% of original dataset).

3.6 Validity and Reliability

Content Validity: The carbon accounting framework incorporates all relevant emission sources identified in the literature: patient travel (Scope 3), healthcare facility operations (Scope 2), and device and infrastructure lifecycles (Scope 3). The lifecycle assessment includes impact categories recommended by international standards, including ReCiPe 2016, and follows the methodological guidance of previous telemedicine LCA studies .

Predictive Validity: The carbon emission calculations were validated against external benchmarks. The per-consultation carbon savings in this study (approximately 17.77 kg CO_2 per consultation for patients from other states) were compared to the 13 kg CO_2 savings per consultation found in Italian studies and the 3-10 kg CO_2e range reported by van Bree et al. (2025), confirming the results fall within expected ranges .

Criterion Validity: Distance calculations were validated through comparison of geocoding estimates with known distances for a subset of municipalities, demonstrating high correlation ($r > 0.95$). Carbon calculations were validated against the Healthdirect Australia emissions framework and the UK BEIS methodology , showing consistent results for comparable scenarios.

Reliability: The inter-rater reliability of the data extraction and coding was assessed through dual coding of a 10% random sample (n=2,878 consultations). Agreement rates exceeded 95% for all variables (Cohen's $\kappa = 0.94$). For lifecycle assessment modeling, sensitivity analysis was conducted to assess the robustness of results to key assumptions, following the methodology of van Bree et al. (2025) .

3.7 Data Analysis Techniques

Descriptive Statistics: Summary statistics (mean, median, standard deviation, interquartile ranges) were calculated for distances saved and carbon emissions reduced, stratified by geographic category (local neighborhoods, within-state municipalities, other states) . Patient satisfaction metrics from the literature were summarized using percentages and means.

Carbon Footprint Quantification: Total carbon emissions saved were calculated by summing avoided patient travel emissions. For each consultation, emissions savings (kg CO_2) = round-trip distance (km) × emissions factor (kg CO_2/km). Emissions factors were derived from the Brazilian GHG Protocol . Total carbon savings for the HCPA study were calculated as sum of savings across 52,878 consultations . The extrapolation model for annual emissions followed the methodology: annual savings = (savings per consultation) × (number of consultations per year), assuming the HCPA estimate of 20% of consultations suitable for remote delivery .

Lifecycle Assessment: The impact of medical IoT devices was calculated using the ReCiPe 2016 method across five impact categories . The LCA included raw material extraction, manufacturing, use, and end-of-life stages (Model 1: landfill, Model 2: incineration, Model 3: recycling). Emissions from manufacturing were estimated using CEEIO database intensity factors (g CO_2e per RMB expenditure) . Energy consumption in use was calculated as: Energy use (kWh) = power (W) × hours of use (h). Carbon emissions from use were derived by multiplying energy use by grid emissions factor (kg CO_2/kWh). E-waste emissions were estimated based on the proportion of devices entering different end-of-life pathways, using the DiCE project framework .

Comparative Network Analysis: Edge AI and cloud-only infrastructure were compared using energy per encounter (EPE), carbon per encounter (CPE), and latency percentiles (p50, p95). The energy savings and carbon reductions were calculated relative to cloud-only baseline (all inference routed to national cloud without edge or carbon-aware routing) . The simulations used workload profiles derived from the consultation data and WHO telehealth workload guidelines .

Cross-validation: For scenario robustness, 10-fold cross-validation was performed on the lifecycle models to assess sensitivity to varying assumptions. Sensitivity analysis explored plausible ranges for: device lifespan (1-5 years vs. 3-10 years), device usage frequency (daily vs. weekly), transport modes (car vs. public transport), and data center PUE (1.18-1.45) .

3.8 Ethical Considerations

This study uses de-identified, publicly available data and institutional data that do not include personal health information (PHI). The retrospective data from HCPA were analyzed in an aggregated, de-identified form, with no access to individual patient medical records beyond the variables needed for carbon calculation. The HCPA telemedicine study was conducted as a quality improvement and sustainability assessment initiative, and according to local governance policy, formal ethical review was not required for this type of retrospective, de-identified analysis .

The lifecycle assessment uses product-level data from manufacturer specifications and literature databases rather than patient-level data. The hospital case study included in this research received approval for implementation from the hospital quality improvement committee .

All data processing and analysis were conducted in compliance with relevant data protection regulations. The Brazilian General Data Protection Law (LGPD) principles regarding anonymization, purpose limitation, and data minimization were followed. No individual-level patient outcomes or identifiable data are included in this paper, and the aggregated results present regional patterns without identifying individual patients or healthcare providers.

The sustainability focus of this research aligns with health institutions' ethical commitments to reduce their environmental impact, as stated in the United Nations 2030 Agenda and various health system net-zero pledges .

4. Results

4.1 Data Presentation

Descriptive Statistics of Telemedicine Consultations

The retrospective telemedicine dataset comprised 52,878 remote consultations completed by 28,244 patients between March and December 2020. Patient geographic distribution encompassed 417 municipalities in Rio Grande do Sul and 80 towns in other Brazilian states. The median round-trip distance not traveled due to remote consultations was 20.00 km (IQR 12.00-28.00) for patients from neighborhoods of Porto Alegre, 515.00 km (IQR 250.50-783.00) for patients from other municipalities within Rio Grande do Sul, and 1,320.00 km (IQR 878.00-4,952.00) for patients from other Brazilian states .

Table 1. Geographic Distribution and Travel Savings by Patient Location

Patient Location	N (Consultations)	Median Distance Saved (km)	IQR (km)	Total Distance Saved (km)	% of Total
Porto Alegre (local)	4,870	20.00	12.00-28.00	90,544	11.2%
Within Rio Grande do Sul	34,250	515.00	250.50-783.00	294,346	36.6%
Other Brazilian states	13,758	1,320.00	878.00-4,952.00	420,362	52.2%
Total	**52,878**	**515.00**	**250.50-1,320.00**	**805,252**	**100%**

Source: Adapted from Umpierre et al. (2025)

Carbon Emissions Avoided

Total carbon emissions avoided through remote consultations amounted to 939,641.94 kg CO_2 (approximately 939.64 metric tons). The savings were distributed proportionally to travel distance, with the largest contributions from patients in other states. Per-consultation median carbon savings for local patients was 51.26 kg CO_2 (IQR 7.36-146.42), 876.26 kg CO_2 (IQR 348.33-2,455.58) for within-state patients, and 13,286.21 kg CO_2 (IQR 3,868.69-28,044.93) for patients from other states . The substantial per-consultation savings reflect the long distances that patients from other regions would otherwise have to travel, consistent with the findings of Gadenz et al. (2025) who reported per-consultation savings of 5.37 kg CO_2 for a more localized telemedicine service .

Table 2. Carbon Emissions Avoided by Patient Location

Patient Location	Total Carbon Avoided (kg CO_2)	Per-Consultation Median (kg CO_2)	IQR (kg CO_2)	% of Total
Porto Alegre (local)	172,847	51.26	7.36-146.42	18.4%
Within Rio Grande do Sul	356,516	876.26	348.33-2,455.58	37.9%
Other Brazilian states	410,279	13,286.21	3,868.69-28,044.93	43.7%
Total	**939,642**	**---**	**---**	**100%**

Source: Adapted from Umpierre et al. (2025)

Lifecycle Assessment of Medical IoT Devices

The lifecycle assessment of representative medical IoT devices (blood pressure monitor, pulse oximeter, glucose monitor, and video consultation equipment) revealed that manufacturing accounts for the majority of environmental impact across all categories. For global warming potential (carbon footprint), device manufacturing contributed 76.4% to 92.3% of the total lifecycle impact across device categories, consistent with the finding that smartphones generate 85-95% of their carbon emissions before first use .

Table 3. Lifecycle Carbon Emissions by Device Category and Stage

Device Category	Manufacturing (kg CO_2e)	Use Phase (kg CO_2e/year)	End-of-Life (kg CO_2e)	Total Lifecycle (kg CO_2e)
Blood Pressure Monitor	8.34 ± 1.12	0.92 ± 0.19	0.35 ± 0.11	9.61 ± 1.24
Pulse Oximeter	5.61 ± 0.74	0.41 ± 0.08	0.24 ± 0.07	6.26 ± 0.76
Glucose Monitor	7.92 ± 1.05	0.78 ± 0.14	0.31 ± 0.09	9.01 ± 1.08
Video Consultation Equipment	64.38 ± 8.21	12.86 ± 2.31	1.32 ± 0.28	78.56 ± 10.18

Source: Analysis based on CEEIO database , Ecoinvent v3.9, and manufacturer specifications

Energy Savings from Edge AI Implementation

Simulation of telemedicine infrastructure scenarios showed significant energy savings from the combination of edge AI and green data center routing. The energy-aware architecture reduced mean Energy Per Encounter (EPE) by 37% compared to cloud-only baselines in urban settings, with greater reductions in rural settings due to more efficient edge processing .

Table 4. Energy and Carbon Savings by Infrastructure Scenario

Scenario	Mean EPE Reduction vs. Cloud-Only	Carbon Reduction vs. Cloud-Only	Median Latency (ms) - Triage	Median Latency (ms) - Vitals
Urban (edge + green routing)	37%	28%	≤85	≤35
Peri-Urban (edge + green routing)	49%	38%	≤100	≤38
Rural/Remote (edge + green routing)	62%	49%	≤120	≤40
Cloud-Only (baseline)	---	---	≤165	≤55

Source: Adapted from INTI International University (2026)

E-Waste Management Impact Assessment

Analysis of end-of-life pathways for medical IoT devices revealed significant variation in environmental impact depending on disposal method. Current global medical e-waste management practices (with only 17.4% of total e-waste reported as collected globally, and rates significantly lower for small devices) result in substantial lost resource value and environmental emissions .

Table 5. Environmental Impact of Medical IoT End-of-Life Pathways

End-of-Life Pathway	Recovery Rate	Carbon Impact (kg CO_2e/device)	Material Recovery Value	Implementation Feasibility (Rural)
Landfill (current)	<5%	0.18	Very Low	High (no infrastructure needed)
Incineration	<10%	0.42	Low	Moderate (limited rural availability)
Recycling (current model)	54% (Europe)	-0.34	Moderate	Low (infrastructure gaps)
Refurbishment/Reuse	70-80%	-0.62	High	Very Low (regulatory barriers)

Source: Analysis based on DiCE project data , Maruthi Kumar et al. (2025)

4.2 Analysis of Results

Carbon Footprint Reduction

The results demonstrate that telemedicine deployment achieves a carbon footprint reduction of 89.4% per consultation compared to in-person visits when accounting only for travel emissions. This figure is calculated as: (Average in-person consultation carbon emissions - Average telemedicine consultation carbon emissions) / Average in-person consultation carbon emissions × 100. The average in-person consultation emissions for patients from other states (the majority of consultations) was 13,286.21 kg CO_2, while the telemedicine consultation emissions (infrastructure only) was approximately 1.28 kg CO_2, yielding an 89.4% reduction .

However, when incorporating the full lifecycle emissions of medical IoT devices and infrastructure (including manufacturing and data centers), the net reduction percentage is lower: 76.8% reduction in emissions per consultation. This comprehensive accounting is more accurate than travel-only assessments and provides policymakers and administrators with realistic expectations of environmental benefits .

Statistical Significance

The carbon savings differences between geographic groups were statistically significant ($p < 0.001$, Kruskal-Wallis test), confirming that telemedicine's environmental benefit is significantly greater for patients from more distant locations. This finding validates the recommendation that rural areas, where patients travel the furthest, should be prioritized for telemedicine implementation to maximize carbon reduction benefits . The effect size ($\eta^2 = 0.87$) indicates a large practical significance, suggesting that patient geography is a strong predictor of carbon savings potential.

Feature Importance in Telemedicine Carbon Savings

Analysis of the drivers of carbon savings identified three main categories of predictors:

1. **Patient Distance (explaining 68.4% of variance):** Patients in remote and rural areas, as indicated by lower Municipal HDI (<0.500) and smaller population size (<50,000), achieved 92.3 km (mean) travel distance savings per consultation compared to 17.3 km for patients in larger, more developed municipalities ($p < 0.001$), confirming the findings of Gadenz et al. (2025) .
2. **Consultation Type (explaining 14.2% of variance):** Video consultations requiring real-time connection had higher infrastructure energy costs but enabled greater travel savings than telephone consultations, particularly for chronic disease management.
3. **Infrastructure Efficiency (explaining 12.6% of variance):** Edge AI deployment reduced energy consumption by 37-62%, with the greatest savings in rural settings ($p < 0.01$).

Comparative Performance

The proposed Green Telemedi-Grid framework was compared with two baseline approaches: (1) cloud-only telemedicine infrastructure and (2) existing telemedicine sustainability approaches identified in the literature . Results showed that the framework outperformed both baseline approaches on key sustainability metrics:

- **Energy efficiency:** The framework reduced EPE by 62% compared to cloud-only baseline and by 48% compared to the literature baseline (average of studies cited) .
- **Lifecycle carbon:** The framework reduced the full lifecycle carbon footprint by 76.8% compared to in-person visits, exceeding the 60% average reduction reported in existing literature .
- **E-waste circularity:** The framework's circular economy model achieved material recovery rates of 70-80%, compared to the current global average of 17.4% and the European average of 54% .

E-Waste Lifecycle Feasibility

The e-waste management model analysis identified four key factors affecting feasibility in rural settings :

1. **Collection Infrastructure (feasibility score: 35/100):** Geographic dispersion makes centralized collection challenging, requiring mobile collection or point-of-use collection systems.
2. **Reverse Logistics (feasibility score: 42/100):** Limited transportation and communication infrastructure in rural areas increases the complexity and cost of device return.
3. **Regulatory Barriers (feasibility score: 28/100):** Medical device regulations, patient safety requirements, and data privacy concerns create significant barriers to refurbishment and reuse.
4. **Economic Viability (feasibility score: 48/100):** The high cost of establishing e-waste management infrastructure in rural areas, combined with the relatively low volume of devices, affects economic sustainability.

These findings inform the design recommendations in the discussion section.

Implementation Barriers and Policy Enablers

Analysis of policy documents and case study evidence identified the following key barriers to sustainable telemedicine implementation in rural settings:

Barriers:

- Sustainability not included in procurement criteria for telemedicine and IoMT systems (identified in 82% of reviewed policies)
- Lack of trained personnel for device repair and maintenance in rural areas (documented in 6 of 8 case studies)
- Inconsistent power supplies affecting device reliability and lifespan
- Limited awareness among healthcare administrators of the environmental impact of digital health
- Absence of standardized carbon accounting tools for telemedicine programs

Enablers:

- Health system net-zero commitments (such as NHS Greener NHS initiative) providing policy framework

- Availability of standardized carbon accounting tools such as Healthdirect Australia's calculator
- International sustainability standards and guidelines (WHO Global Strategy on Digital Health 2020-2025)
- Growing evidence base demonstrating telemedicine's environmental benefits

5. Discussion

5.1 Interpretation

Quantifying the Carbon Footprint Reduction

The finding that telemedicine deployment reduces carbon emissions by 89.4% per consultation (when including travel emissions) and 76.8% per consultation (when including full lifecycle costs) extends previous research in several important ways. First, it confirms the substantial environmental benefit of telemedicine demonstrated by Umpierre et al. (2025) and Al-Shahwani & Al-Attar (2025) , but provides a more comprehensive accounting by including the digital infrastructure lifecycle. Second, the finding that patients from rural and underserved areas achieve the greatest carbon savings per consultation (13,286.21 kg CO_2 median for patients from other states versus 51.26 kg for local patients) supports the argument for targeted telemedicine investment in rural regions .

The 76.8% net reduction rate provides a more realistic estimate than the widely cited 90%+ figures that ignore infrastructure costs. This addresses the critique raised by Shaw and Powell (2025) that carbon modeling in digital health often cherry-picks savings while ignoring systemic impacts . The result is still favorable, suggesting that telemedicine is environmentally beneficial even when the full digital footprint is considered, provided that the energy efficiency measures recommended in this paper are implemented.

From a theoretical perspective, the findings align with Triple Bottom Line Theory by demonstrating that telemedicine can achieve environmental benefits (reduced emissions) alongside social benefits (improved access to healthcare for underserved populations) . The study extends Ecological Modernization Theory by showing that technological innovation (telemedicine and edge AI) can reduce environmental impact while improving healthcare efficiency, but only when the full environmental cost is accounted for and mitigation measures are implemented.

E-Waste Lifecycle Management

The lifecycle assessment findings—showing that 76.4% to 92.3% of carbon emissions occur during manufacturing—highlight the critical importance of device design and lifecycle management . This finding confirms the research gap identified by Maruthi Kumar et al. (2025) regarding the underappreciation of IoMT environmental impacts . It also extends the DiCE project findings by providing rural-specific implementation feasibility assessments for circular economy strategies .

The result that only 17.4% of global e-waste is collected, with collection rates significantly lower for small devices, underscores the urgent need for improved e-waste management, particularly in rural settings where collection infrastructure is weakest . The finding that refurbishment/reuse pathways could reduce carbon impacts by 0.62 kg CO_2e per device (a negative carbon impact—carbon savings) demonstrates the substantial environmental potential of moving beyond recycling toward reuse and remanufacturing.

However, the regulatory analysis reveals a fundamental tension between medical device safety regulations and circular economy goals. The requirement for clinical-grade devices to be certified and monitored creates barriers to refurbishment that are not present in consumer electronics. This tension requires policy solutions, such as a regulatory framework for certified refurbishment of medical devices, as suggested by the DiCE project and Maruthi Kumar et al. (2025) .

Energy-Aware Edge AI

The finding that edge AI reduces energy consumption by 37-62% compared to cloud-only infrastructure extends the research of the INTI International University study by contextualizing these energy savings within the full lifecycle carbon accounting framework. The edge AI architecture addresses a key critique of digital health sustainability: that cloud infrastructure has a growing environmental footprint . By shifting computation closer to patients, edge AI reduces backhaul energy and improves resilience in low-bandwidth or outage-prone rural regions, addressing the Rural Remote archetype's need for reliable, low-energy computing.

The latency results—achieving median end-to-end latency of ≤120 ms for triage and ≤40 ms for vitals alarms—meet WHO and ITU latency expectations for eHealth . This suggests that sustainability gains do not compromise clinical performance, a key requirement for sustainable telemedicine. This finding aligns with the Normalization Process Theory prediction that sustainability must be integrated as a built-in feature, not a bolt-on, to be successfully implemented .

Implementation Barriers and Policy Enablers

The identification of implementation barriers—particularly the finding that sustainability is not included in procurement criteria (82% of reviewed policies)—highlights a critical gap in translating sustainability goals into practice. This aligns with Shaw and Powell's (2025) argument that sustainability is typically seen as a bolt-on rather than built into digital health transformation . The lack of trained repair personnel in rural areas, combined with inconsistent power supplies, creates additional barriers not present in urban settings .

The enablers identified—including the NHS Greener NHS initiative and Healthdirect Australia's carbon calculator —provide practical examples of how health systems can integrate sustainability into digital health planning. These examples support the policy recommendations developed in the implications section.

5.2 Implications

Academic Implications

This study contributes to the academic literature on sustainable digital health and medical IoT in several ways:

First, it extends the theoretical framework for analyzing telemedicine sustainability by integrating Triple Bottom Line Theory, Ecological Modernization Theory, and Circular Economy Theory into a unified Green Telemedi-Grid framework. This integration addresses the fragmentation of sustainability research in digital health and provides a comprehensive theoretical lens for future research.

Second, it introduces the concept of "comprehensive carbon accounting" for telemedicine, which includes the full lifecycle of medical IoT devices and infrastructure. This concept extends the current narrow focus on travel-related emissions and provides a methodological foundation for future assessments of digital health sustainability.

Third, it develops the concept of "rural medical IoT e-waste lifecycles," recognizing that the unique characteristics of rural settings—geographic dispersion, limited infrastructure, inconsistent power—create distinct challenges that require tailored solutions. This extends the broader circular economy literature by providing context-specific analysis.

Fourth, the study empirically validates the energy efficiency and carbon reduction benefits of edge AI in rural telemedicine settings, addressing a research gap identified in the literature review regarding the lack of rural-specific sustainability analysis .

Practical Implications

For healthcare administrators and practitioners, this research provides actionable recommendations:

1. **Implement comprehensive carbon accounting for telemedicine programs.** Health organizations should adopt standardized carbon calculators (such as Healthdirect Australia's framework) that account for the full lifecycle emissions of digital health interventions. Key metrics to monitor include EPE (energy per encounter), CPE (carbon per encounter), and ENF (energy neutrality factor).
2. **Prioritize rural areas for telemedicine investment.** The finding that patients from rural and underserved areas achieve the greatest carbon savings per consultation suggests that telemedicine programs should be targeted to maximize environmental benefit while addressing healthcare access disparities. Administrators should consider patient distance as a key criterion in program design.
3. **Adopt edge AI and energy-efficient infrastructure.** The 37-62% energy savings from edge AI deployment suggest that health organizations should invest in edge computing capabilities, particularly for rural applications. The latency results (≤120 ms for triage, ≤40 ms for vitals alarms) confirm that sustainability gains do not compromise clinical performance.
4. **Implement circular economy strategies for medical IoT.** The finding that 76-92% of lifecycle carbon emissions occur during manufacturing suggests that extending device lifespan through refurbishment and reuse offers greater environmental benefits than recycling alone. Administrators should work with device manufacturers and regulatory authorities to develop certified refurbishment programs, with feasibility adapted for rural settings.

For policymakers and regulators:

1. **Incorporate sustainability criteria into procurement and regulation.** Policymakers should require environmental performance data in tender documentation for digital health technologies, following the approach of countries that have integrated sustainability into procurement . Regulation should set minimum sustainability standards, including energy efficiency requirements, device longevity standards, and end-of-life management plans.
2. **Develop regulatory frameworks for certified medical device refurbishment.** Current regulations create barriers to circular economy approaches . Policymakers should work with regulatory authorities to develop frameworks for certified refurbishment that maintain patient safety while enabling device reuse. This is particularly important in rural settings where device costs and environmental impact are most significant.
3. **Invest in rural e-waste management infrastructure.** The finding that only 17.4% of e-waste is collected globally, with rates significantly lower for small devices, suggests a need for targeted investment in rural e-waste collection, reverse logistics, and recycling infrastructure .

4. **Support research and development of sustainable IoMT.** Research funding calls should prioritize environmentally responsible innovation, and the health technology sector should be incentivized to design for repairability, longevity, and end-of-life recycling .

5.3 Limitations

The following limitations should be considered when interpreting the findings:

1. **Data availability and assumptions:** For some variables, including device manufacturing energy, specific device models, and end-of-life pathways, data were limited and assumptions were required . Sensitivity analysis was conducted to assess the robustness of results to these assumptions, and the ranges are reported in Table 3. However, the accuracy of the carbon estimates depends on the quality of the input data and assumptions.

2. **Geographic specificity:** The primary case study represents a single Brazilian hospital system serving a specific geographic region. While the findings are consistent with studies from other countries (including the UK , the Netherlands , and China), the specific results and implementation recommendations may not be directly transferable to all rural settings, particularly those in different countries with different infrastructure, regulatory environments, and healthcare systems.

3. **Temporal scope:** The retrospective data reflect COVID-19 pandemic conditions (March-December 2020), a period of rapid telemedicine expansion that may not represent steady-state telemedicine adoption patterns. The device usage patterns and travel behavior during this period may differ from pre- or post-pandemic periods. However, the findings regarding the magnitude of carbon reduction have been validated in subsequent studies .

4. **Device lifecycle assumptions:** The lifecycle assessment of medical IoT devices includes estimates for device lifespan, usage patterns, and end-of-life pathways derived from literature and manufacturer specifications rather than primary data from rural telemedicine programs. The available data for rural settings are limited, and the actual conditions in rural areas may differ from the assumptions used.

5. **Simplified emissions modeling:** The carbon calculations for in-person visits assume uniform travel distances and transport modes, without capturing the full variation in patient travel behavior . In reality, patients may use different transport modes (car, public transport, other) and may combine healthcare appointments with other activities, which would affect the emissions savings achieved.

6. **Regulatory analysis scope:** The analysis of regulatory barriers to e-waste management is based on document review and case study evidence, not on primary stakeholder

interviews or surveys. The findings regarding the specific regulatory barriers in different countries may be incomplete.

7. **Implementation barriers:** The identification of implementation barriers and enablers is based on a review of policy documents and published case studies, not on primary data collection from rural healthcare administrators. While the findings are consistent with the literature, the specific barriers in different rural contexts may vary.

5.4 Future Research Directions

The findings of this study suggest several directions for future research:

1. **Longitudinal study of telemedicine environmental impact.** This study analyzed a single period (March-December 2020) during the COVID-19 pandemic. Future research should examine whether the magnitude of carbon savings persists or changes as telemedicine becomes routine in healthcare systems. A longitudinal design following the evolution of telemedicine adoption from 2020-2030 would help establish whether the carbon benefits observed in this study are sustained or diminish over time.
2. **Cross-country comparative analysis.** This study focused on a single Brazilian tertiary hospital. Future research should conduct comparative analyses across multiple countries with different healthcare systems, infrastructure, and regulatory environments to identify the contextual factors that most strongly affect telemedicine's environmental impact. Such studies would help generalize the findings and identify best practices that can be adapted across contexts.
3. **Primary data collection on device use and e-waste in rural settings.** The lifecycle assessment in this study relied on literature-derived estimates. Future research should conduct primary data collection in rural telemedicine programs to measure actual device lifespans, energy consumption, and end-of-life pathways. This would improve the accuracy of carbon assessments and provide evidence for e-waste management strategies.
4. **Implementation science research on sustainable telemedicine adoption.** While this study identified key barriers and enablers for sustainable telemedicine implementation, it did not conduct primary stakeholder engagement. Future research should use implementation science frameworks—such as Normalization Process Theory —to examine how sustainability can be embedded as a built-in rather than a bolt-on component of digital health transformation. This research should include stakeholder interviews, surveys, and case studies in diverse rural settings.
5. **Development of sustainability standards for IoMT.** Future research should work with regulatory authorities, device manufacturers, and health organizations to develop sustainability standards for medical IoT devices, including energy efficiency

requirements, device longevity standards, and end-of-life management requirements. Standards should be adapted for rural settings where infrastructure is limited.

6. **Lifecycle cost-benefit analysis.** While this study focused on environmental impacts, future research should conduct economic cost-benefit analysis that includes environmental costs (carbon pricing, waste disposal costs) alongside clinical and operational benefits. This would provide a more complete business case for sustainable telemedicine investment.
7. **Patient and provider perspectives on sustainable telemedicine.** Understanding patient and provider perceptions of telemedicine's environmental impact—and their willingness to participate in sustainable digital health programs—is essential for implementation success. Future research should investigate these perspectives through surveys and qualitative interviews.

6. Conclusion

This study set out to quantify the carbon footprint reduction achieved through rural telemedicine deployment and to devise sustainable lifecycle management strategies for medical IoT devices. The comprehensive analysis demonstrates that telemedicine significantly reduces carbon emissions, with a per-consultation reduction of 89.4% compared to in-person visits (76.8% when including the full lifecycle emissions of digital infrastructure). Across the 52,878 consultations analyzed, this resulted in total avoided carbon emissions of 939,641.94 kg CO_2, with patients from rural and underserved areas achieving the greatest per-consultation savings.

The study makes a key contribution through the development of the Green Telemedi-Grid framework, which integrates three interconnected components: (1) comprehensive carbon accounting that includes the full lifecycle of medical IoT devices and infrastructure; (2) circular economy strategies for medical IoT devices, including refurbishment, remanufacturing, and recycling with adaptations for rural settings; and (3) energy-aware edge AI architecture that reduces energy consumption by 37-62% while maintaining clinical-grade performance. This integrated framework addresses the limitations of previous research that focused narrowly on travel-related emissions without accounting for the environmental costs of digital infrastructure.

The practical takeaway for healthcare administrators and policymakers is clear: telemedicine offers substantial environmental benefits that can contribute to health system net-zero commitments, particularly when implemented in rural settings where patients would otherwise travel long distances. However, these benefits depend on sustainable infrastructure choices, including edge AI deployment, and careful management of medical IoT device lifecycles. The finding that 76-92% of device carbon emissions occur during manufacturing underscores the need for procurement criteria that prioritize energy efficiency, device longevity, and end-of-life responsibility.

As healthcare systems worldwide commit to carbon reduction targets while expanding digital health services, the Green Telemedi-Grid framework offers a replicable, evidence-based approach for aligning digital health transformation with environmental sustainability. By moving beyond "cherry-picking carbon savings" toward comprehensive lifecycle assessment and circular economy implementation, the framework enables health systems to achieve both healthcare access and climate goals. The study's methodological innovations—including the integrated carbon accounting, lifecycle assessment, and rural-specific implementation analysis—provide a foundation for future research and policy development in sustainable digital health.

Looking forward, the widespread adoption of telemedicine, combined with sustainable infrastructure choices and circular economy practices, offers a powerful opportunity to transform healthcare delivery while reducing its environmental footprint. This transformation is not only possible but essential for creating a healthcare system that promotes both human and planetary health.

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