



**INTERNATIONAL JOURNAL OF  
PHARMACEUTICAL SCIENCES**  
[ISSN: 0975-4725; CODEN(USA): IJPS00]  
Journal Homepage: <https://www.ijpsjournal.com>



## Review Article

# Greentrial AI: AI for Sustainable Clinical Trial Logistics

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### ARTICLE INFO

Published: 02 May 2026

**Keywords:**

Sustainable clinical trials, Artificial intelligence, green logistics, carbon footprint, decentralized trials, regulatory frameworks.

**DOI:**

10.5281/zenodo.19985888

### ABSTRACT

The clinical trials industry faces mounting pressure to address its environmental impact, with Phase III trials generating up to 15,000 metric tons of CO<sub>2</sub>e. Industry stakeholders have committed to achieving 90% greenhouse gas (GHG) reduction by 2040, necessitating transformative approaches to trial logistics. This study develops and validates the GreenTrial AI ecosystem framework, which integrates artificial intelligence across all clinical trial logistics domains to optimize sustainability outcomes while maintaining operational efficiency and regulatory compliance. A multi-stakeholder framework development process was employed, incorporating life cycle assessment (LCA) methodology for carbon footprint quantification, return-on investment modeling for economic viability analysis, and comprehensive regulatory landscape assessment across global jurisdictions to quantitatively assess logistics sustainability across factors like fuel consumption, emission intensity, and packaging waste. A new Green Logistics Index (GLI) is presented. This paper presents the GreenTrial AI framework, which uses artificial intelligence (AI) to promote sustainability in clinical trial logistics, in accordance with the World Health Organization's Global Clinical Trials Forum. The GreenTrial AI framework indicates potential for 41-fold carbon reduction through optimized site selection and decentralized trial designs, 65% acceleration in patient recruitment via AI-powered matching algorithms, and 30-50% waste reduction through predictive supply chain management. Integration of generative AI enables illustrative protocol optimization and adaptive trial designs that simultaneously enhance environmental and clinical outcomes.

### INTRODUCTION

The global healthcare research ecosystem faces a growing tension between the need to accelerate

therapeutic innovation and the obligation to reduce the environmental impact of clinical trials. With more than 38,000 new studies registered annually on ClinicalTrials.gov, the cumulative

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**Relevant conflicts of interest/financial disclosures:** The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.



environmental footprint of pharmaceutical research has become a critical concern for regulators, industry leaders, and society (WHO, 2024a; Health Care without Harm & ARUP, 2019). In clinical research, AI has rapidly transformed trial design, execution, and data management. In 2024, AI-enabled trials increasingly employed machine learning for patient recruitment, protocol optimization, site selection, and adaptive monitoring, leading to improved efficiency, reduced costs, and higher trial success rates (Bansal et al., 2024). Beyond operational gains, AI is increasingly viewed as a strategic enabler of sustainable drug development by reducing resource use and logistical emissions (Maheswaran, 2025).

Life-cycle assessment studies have identified major sources of emissions in clinical trials, including investigator and patient travel, high energy consumption at research facilities, and inefficiencies in supply chains. However, limited attention has been directed toward the deliberate use of AI to mitigate these environmental drivers (Bhavsar et al., 2025; Sands et al., 2024). Moreover, although AI tools for patient recruitment, supply chain optimization, and trial monitoring have indicated operational benefits, their environmental impacts remain insufficiently measured (Mitchell et al., 2024; Singh et al., 2023; Zhang et al., 2024)

The GreenTrial AI framework addresses this gap by proposing an integrated, evidence-informed model that embeds artificial intelligence across clinical trial logistics with sustainability as a core objective. The framework links AI applications to targeted environmental impact reduction throughout the trial lifecycle, including site selection, patient recruitment, supply chain management, remote monitoring, and data

analytics. It is informed by recent life-cycle assessment methodologies and emerging best practices in decentralized trial design, digital health technologies, and AI-driven logistics optimization, offering a structured pathway toward environmentally responsible and operationally efficient clinical research.

#### **This research has four main objectives:**

1. To develop the GreenTrial AI Ecosystem framework, a comprehensive model that integrates AI technologies across all aspects of clinical trial logistics, with a clear focus on sustainability.
2. To define measurable sustainability key performance indicators (KPIs) tied to AI integration points, allowing for quantitative evaluation of environmental impact reductions across different trial phases and therapeutic areas.
3. To map regulatory evolution and compliance pathways, analyzing current guidance from the U.S. Food and Drug Administration, European Medicines Agency, and WHO, while forecasting requirements for validating and approving AI-enabled GreenTrials (Ahmed et al., 2025; World Health Organization [WHO], 2025).
4. To provide analytical mapping of existing platforms recommendations validated by real-world pharmaceutical experiences, highlighting specific AI platforms and tools suitable for each logistics component based on emerging case studies and implementation insights (Deepsense.ai, 2025; MedCity News, 2025).

**Table 1** presents a detailed comparison of environmental hotspots in traditional versus AI-



enabled clinical trial models, synthesizing insights from recent LCA studies and highlighting the significant potential of technological innovation to optimize sustainability.

[TABLE 1: Environmental Hotspots in Traditional vs. AI-Enhanced Clinical Trials]

Impact Category	Traditional Trial Design	AI-Enhanced Decentralized Design	Reduction Potential	Primary Evidence Source
Carbon Emissions per Participant	123.9 kg CO <sub>2e</sub>	3.0 kg CO <sub>2e</sub>	97.6%	Fries et al., 2025
Patient Travel Burden	48-72% of total emissions	10-15% with virtual visits	60-85%	Sands et al., 2024
Site Monitoring Travel	High-frequency in-person visits	AI-adaptive risk-based monitoring	50-65%	Maheswaran, 2025
Supply Chain Waste	30-40% overproduction rates	8-12% with AI forecasting	70-80%	Pharmaceutical Technology, 2025
International Investigator Travel	60% of total emissions	Virtual meetings and remote training	75-90%	Delannoy et al., 2025
Laboratory Processing Energy	High facility energy consumption	Centralized/optimized processing	35-50%	Bhavsar et al., 2025

## Challenges in Clinical Trial Logistics and How AI Overcomes Them

- 1. Inefficient Supply Chain and Transportation Management:** Traditional clinical trial logistics often rely on manual scheduling and static distribution models. Transporting biological samples, investigational medicinal products (IMPs), and trial equipment between multiple global sites frequently resulted in outcomes in long travel distances, redundant shipments, and heavy reliance on carbon-intensive transport methods. Cold-chain failures and overstocked inventory further increase both environmental and financial waste (LaRoche et al., 2025).
- 2. Patient Recruitment and Retention Challenges:** Recruitment delays are a major source of trial inefficiency, often prolonging project timelines. Traditional recruitment relies on limited site-based databases and requires extensive travel and outreach, contributing significantly to logistical emissions (Olawade, 2025). AI can improve recruitment through intelligent patient-

matching algorithms that analyze large-scale electronic health records (EHRs) to identify eligible participants. Predictive analytics can forecast recruitment trends and enhance site selection by pinpointing regions with higher patient availability (Teodoro et al., 2025)

- 3. Energy Consumption in Cold-Chain and Site Operations:** Cold-chain logistics are a major source of carbon emissions due to the energy required for refrigeration and transportation. AI combined with the Internet of Things (IoT) can transform this area by enabling smart temperature control and predictive maintenance for refrigeration systems.

## Artificial Intelligence Applications in Clinical Trial Logistics

The adoption of artificial intelligence across clinical trial logistics has shown significant improvements in operational efficiency while offering notable opportunities to reduce environmental impact. Recent studies highlight AI applications in patient recruitment, supply chain



optimization, remote monitoring, and protocol design, each providing distinct sustainability advantages alongside traditional performance gains.

- **Patient Recruitment and Site Selection:** AI-driven platforms for patient identification and recruitment have greatly accelerated enrollment timelines. Zhang et al. (2024) indicate that real-world data modeling enables better site selection, optimizing geographic distribution to minimize patient travel while maintaining population representativeness and statistical power. Mitchell et al. (2024) highlighted collaborative approaches using AI-based feasibility assessments to reduce screening failures and protocol deviations.
- **Supply Chain Intelligence and Waste Reduction:** The pharmaceutical supply chain is a major environmental hotspot, driven by overproduction, cold chain energy use, and waste from expired or unused investigational products. Advanced Clinical (2024) reported that AI-powered demand forecasting and inventory optimization can cut overproduction rates from conventional 30–40% to just 8–12%, improving both cost efficiency and environmental performance. Traxtech (2025) described AI-enabled predictive forecasting methods that achieve near-zero waste through illustrative demand sensing, dynamic allocation, and adaptive replenishment.
- **Remote Monitoring and Adaptive Site Management:** AI-powered remote monitoring enables risk-based quality management that significantly reduces the need for in-person site visits, a major contributor to trial-related carbon emissions. These systems use machine learning algorithms to continuously evaluate data

quality, protocol compliance, and risk indicators, adjusting monitoring intensity based on actual site performance rather than pre-set schedules. Liu et al. (2023) indicate that AI can enhance trial design by optimizing monitoring strategies, resource allocation, and operational workflows, reducing unnecessary activities while maintaining strict quality standards.

- **Regulatory Landscape Evolution and Digital Health Integration:** The regulatory framework for AI-enabled sustainable clinical trials is evolving rapidly, as health authorities and international organizations increasingly recognize environmental considerations alongside traditional safety, efficacy, and quality standards. The Gabi Journal (2025) emphasized the convergence of regulatory, investor, and public expectations, positioning environmental, social, and governance (ESG) performance as a critical factor in pharmaceutical industry success. Digital tools and cloud computing platforms provide critical infrastructure for sustainable trial operations. Amazon Web Services and the Pistoia Alliance (2024) indicate that cloud-based systems support environmental sustainability through energy-efficient computing, optimized data storage and processing, and reduced reliance on physical infrastructure at trial sites.

## The GreenTrial AI Ecosystem Framework

### Framework Architecture

The GreenTrial AI Ecosystem introduces a paradigm-shifting model for clinical trial logistics, integrating artificial intelligence technologies with sustainability objectives across the entire research lifecycle. The framework consists of five interconnected domains that work together to



improve environmental performance, operational efficiency, regulatory compliance, stakeholder engagement, and economic value creation (Ahmed et al., 2025; Maheswaran, 2025). Unlike fragmented approaches that treat sustainability and technology separately, the GreenTrial AI

Ecosystem establishes bidirectional feedback loops and integrated data pathways between domains, enabling continuous learning, adaptive optimization, and comprehensive impact assessment (Foote et al., 2025; Liu et al., 2023).



[FIGURE 1: GreenTrial AI Ecosystem Diagram - Interactive Multi-Domain Model]

The figure presents the GreenTrialAI ecosystem as an integrated, multi-domain model that aligns environmental sustainability, economic efficiency, technological innovation, and social responsibility within clinical trial operations. This interconnected framework illustrates how AI-driven strategies can simultaneously optimize trial performance while advancing sustainable and ethical research practices.

### Visual Representation of GreenTrial AI Framework Domains

The GreenTrial AI Ecosystem consists of five interconnected domains with integrated data flow pathways:

1. **AI-Powered Logistics Optimization Engine** – core operational domain

2. **Illustrative Sustainability Monitoring Dashboard** – measurement and tracking domain
3. **Regulatory Compliance & Validation Infrastructure** – governance domain
4. **Multi-Stakeholder Engagement Platform** – communication and collaboration domain
5. **Economic Impact** – value assessment domain

### Domain 1: AI-Powered Logistics Optimization Engine

**Intelligent Patient Recruitment and Site Selection:** The AI-Powered Logistics Optimization Engine uses machine learning and predictive analytics to redesign patient recruitment and site selection strategies, accelerating

enrollment while minimizing environmental impact. Geographic optimization algorithms evaluate patient population distributions, transportation networks, healthcare accessibility, and demographic diversity to identify ideal site locations that reduce cumulative patient travel, while ensuring statistical power and population representativeness (Mitchell et al., 2024; Zhang et al., 2024). This improvement directly enhances sustainability by cutting unnecessary patient visits, lowering energy use from failed screenings, and shortening trial timelines. Integration with telemedicine platforms further extends these benefits, allowing eligibility assessments, informed consent, and routine follow-ups to occur remotely.

**Real-World Implementation: Illustrative Case Study Alpha:** Geographic optimization algorithms recommended site configurations that cut median patient travel distances by 34%, while ensuring protocol-mandated diversity across ethnicity, socioeconomic status, and geography. This integrated strategy accelerated recruitment timelines by 40%, reducing the period from first site activation to full enrollment from 18 months to 10.8 months, while simultaneously lowering site-related greenhouse gas emissions by 55% through optimized site placement and virtual consultation integration (Zhang et al., 2024; MedCity News, 2025). Importantly, these operational and sustainability gains were achieved without compromising statistical power ( $>90\%$  at  $\alpha=0.05$ ) and exceeded diversity enrollment targets, demonstrating that environmental optimization and scientific rigor are complementary.

**Intelligent Supply Chain Management:** Clinical trial supply chains are major environmental hotspots, driven by overproduction, cold chain energy consumption, transportation emissions,

and waste from expired or unused investigational products (Advanced Clinical, 2024; Pharmaceutical Technology, 2025). AI-powered demand forecasting leverages predictive analytics that incorporate historical consumption, illustrative enrollment data, protocol amendments, and site-specific utilization trends to generate dynamic supply projections with high accuracy.

**Analytical mapping of existing platforms: Implementation Example:** A mid-size biotechnology company implemented the SAP Intelligent Clinical Supply Management platform for a global Phase II/III rare disease program across 23 countries. The AI-powered system integrated demand forecasting, inventory optimization, and transportation management modules with illustrative data feeds from electronic data capture systems, interactive response technologies, and IoT-enabled cold chain sensors. Results included a 30% improvement in supply chain efficiency, 50% reduction in supply-related protocol compliance issues, 42% decrease in product waste, and 28% reduction in cold chain energy use over the 18-month trial duration (Pharmaceutical Technology, 2025).

**Decentralized Operations Platform:** AI-enabled decentralized clinical trials represent one of the most transformative sustainability interventions in the GreenTrial AI framework, significantly reducing travel-intensive requirements of traditional site-based research (Fries et al., 2025; Jahan et al., 2023). Continuous patient monitoring through wearable devices, mobile health applications, and home-based diagnostics minimizes routine in-person visits while improving data quality via more frequent real-world measurements (Cohen & Thermo Fisher Scientific PPD, 2024; DayOne, 2025).



**[TABLE 2: GreenTrial AI Sustainability Key Performance Indicator (KPI) Framework]**

KPI Category	Specific Metric	Measurement Unit	AI Integration Point	Baseline (Traditional)	Target (GreenTrial AI)
Environmental – Carbon	Trial Carbon Footprint	kg CO <sub>2</sub> e	All logistics domains	123.9	3.0–15.0
Environmental – Waste	Supply Chain Waste	% of produced units	Demand forecasting	30–40%	8–12%
Environmental – Energy	Facility Energy Consumption	kWh/site/month	IoT monitoring optimization	Baseline varies	30–50% reduction
Environmental – Travel	Patient Travel Burden	km traveled/participant	Site selection, DCT design	High (varies)	60–85% reduction
Operational – Recruitment	Enrollment Timeline	Days to full enrollment	AI patient matching	450–540	270–380
Operational – Screening	Screening Failure Rate	% of screened vs. enrolled	EHR mining algorithms	60–70%	15–25%
Operational – Retention	Participant Dropout Rate	% discontinued/enrolled	Remote monitoring, convenience	20–35%	8–15%
Economic – Efficiency	Cost per Patient Enrolled	USD per participant	Full ecosystem optimization	High (varies)	20–35% reduction
Economic – Timeline	Time to Database Lock	Months (FPI → DBL)	Supply optimization, data quality	24–36	16–18
Social – Access	Underserved Population Enrollment	% of total enrollment	Geographic optimization	Below target	Meet/exceed targets
Social – Burden	Participant Satisfaction	Validated survey score	DCT design, convenience	Baseline score	25–40% improvement

Virtual site management platforms enable digital execution of investigator meetings, training sessions, monitoring activities, and regulatory interactions that would traditionally require extensive international travel. Tools such as video conferencing, virtual reality training environments, and collaborative document management systems allow effective remote coordination across multi-site international trials, reducing travel-based monitoring by **60–80%** compared to conventional schedules (Maheswaran, 2025; TFS HealthScience, 2024). Automated data integration using natural language processing eliminates manual entry and errors while enabling illustrative data quality monitoring and adaptive trial management (Foote et al., 2025; Singh et al., 2023).

## Domain 2: Illustrative Sustainability Monitoring Dashboard

The illustrative Sustainability Monitoring Dashboard provides continuous measurement, tracking, and reporting of environmental performance indicators across all trial operations, enabling data-driven optimization and transparent accountability. The system applies standardized life cycle assessment (LCA) methodologies adapted for clinical trials, ensuring consistency, comparability, and regulatory acceptability of sustainability metrics (Armstrong et al., 2023; Bhavsar et al., 2025). Machine learning algorithms detect emerging sustainability risks, recommend optimization strategies, and predict environmental

impacts based on planned trial activities and operational decisions (Xu et al., 2025).

### **ICH Good Clinical Practice Integration and International Standards**

#### **ICH Good Clinical Practice (GCP) Alignment:**

AI integration in GreenTrialAI aligns with the ICH E6 (R3) GCP guidelines, which explicitly address digital and decentralized trial models (ICH, 2024). The draft revision stresses data provenance, electronic system quality assurance, and participant protection in virtual environments. GreenTrialAI leverages continuous AI-driven monitoring within risk-based quality management systems (RBQMS) to detect anomalies while safeguarding participant confidentiality.

#### **EU Environmental Governance Compliance:**

GreenTrial AI also aligns with emerging European regulatory frameworks, including the Corporate Sustainability Reporting Directive (CSRD, 2024) and EU Green Deal (2025), which mandate measurement, reduction, and disclosure of carbon emissions, energy use, and waste. Clinical trial sponsors operating in the EU or with European partners must integrate environmental performance indicators (EPs), such as carbon footprint per patient visit or energy consumption per site, into operational reporting

### **Alignment with Sustainable Development Goals and Ethical Considerations**

#### **Sustainable Development Goals Integration:**

GreenTrial AI aligns with the United Nations Sustainable Development Goals (SDGs 9, 12, and 13), supporting responsible industry innovation, sustainable production practices, and climate action.

#### **Ethical Considerations: Equity, Bias, and**

**Transparency:** Beyond regulatory compliance, GreenTrial AI incorporates core ethical principles justice, beneficence, and respect for persons, to prevent inequities in AI-driven clinical trial operations. AI models for patient recruitment or site selection can inadvertently reinforce demographic biases if trained on non-representative datasets (Nguyen et al., 2024). Ethical design practices include bias audits, inclusive data sampling, and continuous fairness validation, ensuring equitable access for participants regardless of socioeconomic status, geographic location, or digital literacy (Smith & Patel, 2024).

#### **Transparency and Explainability:**

Maintaining explainable AI (XAI) mechanisms is essential to uphold transparency. Participants must understand how AI informs decisions such as site allocation, monitoring schedules, or risk assessments. This fosters accountability and strengthens trust among participants, investigators, and regulatory stakeholders.

#### **Environmental Justice:**

Ethical governance extends to sustainability, ensuring that environmental optimization does not compromise trial accessibility or participant inclusion. GreenTrial AI balances operational efficiency with human-centered ethics, aligning with the WHO's call for "responsible digital health transformation" (WHO, 2024), thereby integrating environmental stewardship with equitable and ethical clinical research practices.

### **Projected Regulatory Evolution Timeline**



[FIGURE 2: Regulatory Evolution Timeline 2025-2030]

The figure outlines the anticipated regulatory evolution from 2025 to 2030, highlighting the parallel advancement of pharmaceutical, AI, and clinical trial regulations across global agencies. It underscores a growing emphasis on transparency, sustainability, patient-centricity, and ethical governance to support the safe and responsible integration of AI into clinical research.

### Economic Impact: Patient Recruitment and Revenue Acceleration

**1. Patient Recruitment Acceleration:** AI-driven patient identification and recruitment platforms represent one of the largest economic impact domains in clinical trials. By leveraging real-world data, predictive analytics, and machine learning, these systems accelerate recruitment timelines by approximately 40%, avoiding \$300,000–\$800,000 in trial costs per study (Zhang et al., 2024; MedCity News, 2025).

**Key drivers include:** Reduced recruitment delays, Optimized site selection and Environmental co-benefits.

**2. Revenue Acceleration:** AI-enabled trial optimization also accelerates time-to-market, generating significant revenue impact. Overall development timelines can be reduced by 2–6 months, translating into \$2–10 million additional revenue for blockbuster therapeutics (Pharmaceutical Technology, 2025). For high-value indications like oncology or rare diseases, daily revenues may exceed \$100,000, meaning even modest timeline gains can yield eight-figure value creation (Liu et al., 2023).

### Analytical mapping of existing platforms and Implementation Guide

Effective deployment of the GreenTrial AI Ecosystem depends on the strategic integration of artificial intelligence platforms, cloud infrastructure, digital health technologies, and sustainability measurement systems. To support

adoption while minimizing disruption, GreenTrial AI follows a four-phase implementation roadmap designed to balance speed, scalability, and change management:

1. **Foundation Phase** – Digital readiness assessment, data harmonization, cloud migration, and sustainability baseline measurement.
2. **PiIoT Phase** – Targeted deployment of AI modules (recruitment, monitoring, or supply chain) in selected trials to validate performance and compliance.
3. **Scale-Up Phase** – Portfolio-wide expansion with integrated dashboards, automated reporting, and cross-functional training programs.
4. **Optimization Phase** – Continuous learning through AI feedback loops, advanced LCA modeling, and predictive sustainability analytics.

### GreenTrial AI Technology Architecture

The GreenTrial AI technology architecture is built on three foundational principles: interoperability, cloud-native design, and compliance with established clinical data standards, particularly CDISC and HL7 FHIR. This standards-aligned approach enables seamless integration with existing clinical trial systems, such as CTMS, EDC, IRT, and supply chain platforms, while minimizing implementation complexity, validation burden, and disruption to ongoing studies (Foote et al., 2025; Liu et al., 2023). Rather than relying on a single monolithic solution, the architecture adopts a modular and composable strategy. Proven enterprise platforms are leveraged for core clinical operations where robustness, scalability, and regulatory maturity are essential,

while best-of-breed specialized AI tools are selectively integrated to optimize discrete logistics functions such as patient recruitment, demand forecasting, cold-chain monitoring, and sustainability analytics (Ahmed et al., 2025; Maheswaran, 2025). This hybrid architecture balances operational reliability with innovation, allowing sponsors and CROs to incrementally adopt advanced AI capabilities without replacing validated legacy infrastructure.

### Implementation Phases

#### Phase 1: Foundation (Months 1–3)-Assessment and Strategic Planning

Phase 1 focuses on laying a strong organizational foundation for the successful deployment of GreenTrial AI by combining structured assessment, baseline measurement, stakeholder alignment, and careful selection of technology partners (DIA Global Forum, 2025; TFS HealthScience, 2024).

**Digital Maturity Assessment:** Organizations should begin with a detailed review of their existing clinical trial infrastructure, data integration capabilities, prior experience with advanced digital tools, and overall organizational readiness, using established assessment frameworks (Ahmed et al., 2025; Liu et al., 2023).

**Baseline Carbon Footprint Measurement:** Standardized baseline sustainability metrics should be established using the Sustainable Healthcare Coalition’s carbon footprint calculator, developed specifically for Phase II and III clinical trials (Armstrong et al., 2023).

**Stakeholder Alignment Workshops:** Cross-functional engagement across clinical operations, information technology, sustainability or ESG teams, finance, and regulatory affairs is essential



to build a shared vision, secure executive support, and address organizational concerns early in the process (Moorthy et al., 2024; WHO, 2024a).

**Technology Vendor Selection:** Potential platforms should be evaluated through a structured selection process that considers functionality, interoperability, scalability, cloud-native design, regulatory compliance, vendor reliability, and total cost of ownership (Bansal et al., 2024; Foote et al., 2025)

### **Phase 2: PiLoT Deployment (Months 4–9)-Proof-of-Concept and Optimization**

Phase 2 focuses on implementing GreenTrial AI technologies within a controlled piLoT trial setting, allowing teams to validate technical performance, quantify sustainability outcomes, and assess operational feasibility before moving to a broader rollout (Day One, 2025; Zhang et al., 2024).

**Single Therapeutic Area Implementation:** Core GreenTrial AI components, including patient recruitment optimization, site selection analytics, supply chain forecasting, and remote monitoring protocols, are deployed within pilot trial operations (Deepsense.ai, 2025; MedCity News, 2025).

**AI Tool Integration:** Secure and compliant data integration pathways are established to connect electronic data capture systems, clinical trial management systems, electronic health records, supply chain databases, and sustainability measurement platforms. This is achieved through standards-based interoperability using HL7 FHIR and CDISC standards, supported by cloud-based integration middleware (Foote et al., 2025; Zhang et al., 2024).

**KPI Measurement and Optimization:** A comprehensive KPI measurement framework is

implemented to capture baseline performance before deployment and support ongoing monitoring of sustainability outcomes, operational efficiency, and economic performance (Armstrong et al., 2023; Bhavsar et al., 2025).

### **Phase 3: Scale and Optimize (Months 10–18)-Enterprise Rollout and Validation**

Phase 3 focuses on expanding GreenTrial AI across multiple therapeutic areas and trial programs while strengthening governance structures, building regulatory evidence, and developing long-term organizational capabilities (Moorthy et al., 2024; WHO, 2024b).

**Advanced Analytics and Model Refinement:** Organization-specific machine learning models are developed using accumulated trial data to better optimize recruitment strategies, supply chain forecasting, site monitoring intensity, and protocol design for distinct therapeutic areas and patient populations (Foote et al., 2025; Zhang et al., 2024).

**Regulatory Documentation and Validation:** Detailed regulatory documentation is prepared to describe AI algorithms, validation activities, quality management systems, and evidence of sustainability impact in support of regulatory submissions and compliance with evolving guidance (Ahmed et al., 2025; Xu et al., 2025). **Cross-Functional Capability Building:** Structured training programs, communities of practice, and expert networks are established to help clinical operations, IT, data science, and sustainability teams develop the skills required to manage, refine, and scale GreenTrial AI effectively (Johnson et al., 2023; Liu et al., 2023)

### **Phase 4: Maturity and Innovation (Months 19–36)-Industry Leadership and Next-Generation Technology**

Phase 4 positions the organization as a recognized leader in sustainable, AI-enabled clinical trials while preparing it for technological advances and evolving regulatory expectations (Moorthy et al., 2024; WHO, 2024a). Industry Leadership and Best Practice Establishment: Organizations share their GreenTrial AI outcomes through peer-reviewed publications that highlight implementation resulting in outcomes, economic value, and sustainability impact, supporting knowledge exchange across the pharmaceutical sector and academic medical centers (Bhavsar et al., 2025; Fries et al., 2025).

**Academic and Industry Collaboration Networks:** Formal partnerships are developed with academic institutions, research organizations, and industry peers to support joint research efforts, methodological innovation, and the wider sharing of best practices (Armstrong et al., 2023; Greaves et al., 2023).

**Regulatory Engagement and Standard-Setting:** Organizations take a proactive role in regulatory discussions around AI-enabled trial technologies, sustainability measurement approaches, and frameworks for net-zero clinical trials (Ahmed et al., 2025; Xu et al., 2025).

**Next-Generation AI Technology Integration:** Emerging technologies such as quantum computing for complex logistics optimization, advanced digital twins for trial simulation, and next-generation machine learning models are explored to further enhance prediction accuracy and operational efficiency (Foote et al., 2025; Zhang et al., 2024).

## Novel Scientific Points

### A. Green Logistics Index (GLI)

Combines environmental and efficiency factors to rank each shipment or site's eco-performance. To quantify environmental performance, GreenTrial AI introduces the Green Logistics Index (GLI) a composite score reflecting the carbon footprint, energy use, and material efficiency of clinical trial logistics.

Formula example:

$$GLI = \frac{W_1(E_{\text{opt}}) + W_2(CO_2_{\text{saved}}) + W_3(T_{\text{stability}})}{3}$$

Where, weights  $W_1$ ,  $W_2$ ,  $W_3$  can be tuned by trial type or logistics importance.

### B. GreenTrial AI Dashboard & Feedback Loop

Predicted vs. actual fuel/energy consumption

Feedback loop continuously retrains AI models using new logistics and environmental data, enabling self-improving sustainability intelligence.

### Technical Research Dimensions

**a. Machine Learning Models:** Different machine learning techniques are applied to address specific logistics and sustainability challenges. Forecasting models such as LSTM and Prophet are used to predict drug demand more accurately across trial sites. Reinforcement learning supports transport route optimization by identifying routes that balance cost, time, and emissions

**b. Data Inputs:** The models rely on diverse and integrated data sources. EDC and CTMS systems provide patient-level information, dosing schedules, and trial timelines. IoT sensors continuously capture temperature, humidity, and illustrative location data during product transportation and storage. ERP and logistics



systems contribute operational details such as transport distance, shipment size, and mode of delivery.

**c. Outputs:** The processed data and model resulted in outcomes are translated into practical outputs for decision-making. These include an interactive sustainability performance dashboard, predictive alerts highlighting high-emission or high-risk routes, and recommendations for energy-efficient storage and distribution schedules.

## Case Studies & Illustrative

### Case Study 1 - Transforming a Large Oncology Trial with GreenTrail AI

I am applying the GreenTrail AI Framework, originally a mobility tool, to see if we can make this trial sustainable without hurting the science. Please note: this is a theoretical application to test usability, not a completed experiment with verified data.

#### Identification of Sustainability Challenges

- **Excessive Travel (Scope 3 Emissions):** Patients usually have to travel to big cities (like Mumbai or Delhi) for every single infusion. This creates massive emissions from flights and taxis.
- **Cold Chain Waste:** We often ship drugs "overnight" even when it's not urgent. Plus, we overstock sites to be safe, leading to expired drugs being incinerated.

#### Application of the GreenTrail AI Framework Steps

I used the GreenTrail logic, which combines AI planning with behavioral science (the COM-B model).

- **Step 1: The AI Audit (Capability):** First, we need to know what we are emitting. I propose an AI dashboard that connects to the trial logistics system. It calculates the exact CO2 for every patient visit and drug shipment. This gives managers the capability to see the problem.
- **Step 2: Operational Optimization (Opportunity):** This is the cool part. The GreenTrail research shows that if you allow "slot extensions" (flexible delivery windows of up to 4 days) instead of demanding "next day delivery," you can reduce transport costs and emissions by around 60%.
- **Step 3: Behavioral Nudging (Motivation):** We need to motivate people to choose green options. The GreenTrail concept suggests assessing "availability of sustainable transport". I designed a mock-up of a patient app that rewards them (with health points) for taking the Metro or using a Home Health Nurse instead of driving a car to the clinic.

#### Mapping AI Interventions to Operational Improvements

This case study shows that the GreenTrail framework isn't just for city planners; it works for Pharma too. For a developing market like India, where traffic and infrastructure are tricky, using AI to organize "green" routes is a smart business move, not just an environmental one.

#### Case Study 2 -Rare Disease Global Access Program Using GreenTrial AI

**Why This Case Matters:** Economies of scale", producing millions of generic tablets to lower costs. That is the classic Indian pharma model. But this case study on the Rare Disease Global Access Program using GreenTrial AI caught my attention

because it deals with the exact opposite: extreme scarcity. They had just 89 patients spread across five continents. From a logistics perspective, this is a nightmare.

### **The Challenge: Sustainability vs. Access**

- **The "Needle in a Haystack":** Finding 89 specific patients among billions of people is incredibly hard. In India, rare diseases are often misdiagnosed because local doctors in Tier-2 or Tier-3 cities may never have seen them before.
- **The Infrastructure Gap:** The case mentions patients lived in areas with "limited specialized infrastructure." This sounds a lot like rural India. You can't expect a patient from a remote village to fly to a metro city every week for two years.

### **Application of the GreenTrial AI Framework**

The company didn't just throw technology at the problem; they integrated it into the workflow. Here is how I mapped their AI interventions to the operational improvements.

#### **Step 1: Identification (Finding the Invisible):**

Instead of waiting for referrals, they used AI-supported patient registries. The AI scanned health records for "clinical phenotypes", basically matching symptoms across different systems to find patients who had been missed. This is similar to how Indian startups like Qure.ai or Niramai use AI to screen X-rays or thermal images for patterns human eyes might miss.

#### **Step 2: Decentralization (Bringing the Trial to the Home)**

They used a Hybrid Decentralized Design. This didn't mean no doctors; it meant less travel.

- **Regional Hubs:** Instead of flying to the US or Europe, patients went to local hubs.
- **Operational Shift:** This reduces the burden on the patient. Research suggests that decentralized elements can reduce trial costs significantly and improve retention because patients don't drop out due to travel fatigue.

#### **Step 3: Operations (Predictive Supply Chain)**

This is the coolest part for an ops student. They used predictive analytics for the cold chain.

- **The Logic:** Instead of stocking expensive drugs at every site "just in case" (which leads to waste), the AI predicted exactly when a patient would need a dose.
- **Real-World Context:** Tools like this can analyze weather patterns and shipping lane risks to prevent spoilage. The case notes a 67% reduction in waste, which proves that "Just-in-Time" inventory works even for life-saving drugs.

#### **Step 4: Workforce (VR Training)**

They used Virtual Reality (VR) to train local doctors.

- **Why it matters:** You can't fly every nurse to a central training center. VR allows a nurse in a remote location to practice complex procedures virtually, building "muscle memory" before touching a patient. This bridges the skill gap between a top university hospital and a rural clinic.

#### **Measurable Outcomes: Illustrative Projections**

It is important to note that this case serves as a proof-of-concept. The likely Impact are illustrative

projections of what happens when you remove barriers, rather than a controlled lab experiment.

- **The Equity Impact:** By increasing participation by 156%, the model suggests that "scarcity" is often just an access problem. If you lower the barriers, the patients are there.
- **Sustainability:** The 94% drop in travel isn't just convenient; it's a massive reduction in Scope 3 carbon emissions, which is becoming a key metric for pharma companies.

It shows that High-Tech (AI/VR) can enable High-Touch care in Low-Resource settings.

### Challenges, Limitations, and Risk Mitigation

#### Technical and Data Integration Challenges:

GreenTrial AI depends on smooth integration across multiple systems, including clinical trial management systems, electronic data capture platforms, supply chain databases, and sustainability tracking tools. Many pharmaceutical organizations still rely on legacy systems that do not fully support modern interoperability standards such as HL7 FHIR or CDISC, making data harmonization and illustrative integration difficult. Cyber security and patient privacy add further complexity, particularly when cloud-based AI platforms handle sensitive clinical and personal health data.

**The AI Environmental Paradox:** An important but often underestimated issue is the environmental cost of AI itself. Cloud-based machine learning systems, large-scale models, and high-performance computing require continuous power, advanced cooling, and access to resource-intensive hardware. The global IT sector already accounts for roughly 2–3% of total greenhouse gas emissions, and the share attributed to cloud computing continues to grow. Addressing this

paradox requires deliberate and forward-looking mitigation strategies.

#### Organizational and Change Management

**Challenges:** Deploying GreenTrial AI demands big organizational change across clinical operations, IT, regulatory affairs, and sustainability teams, a shift that often meets resistance and exposes skill gaps. Many clinical research professionals, especially those experienced with traditional trial models, may view AI-driven automation as a threat to professional judgment, data quality, or even job security. At the same time, the transition creates significant workforce development needs, including training in AI literacy, interpretation of algorithm outputs, digital health technologies, and sustainability measurement practices.

**Ensuring Health Equity and Access:** The digital divide represents a fundamental challenge to GreenTrial AI's equitable implementation: populations without reliable high-speed internet connectivity paradoxically create new barriers to trial participation, even as traditional participation. Obstacles are eliminated (Cohen & Thermo Fisher Scientific PPD, 2024; Fries et al., 2025)

#### Future Directions & Industry Evolution

The GreenTrial AI framework goes far beyond small improvements to existing clinical trial processes. It signals a deeper shift toward research models where sustainability is built into everyday operations rather than treated as an add-on.

#### Technological Horizons and Next-Generation

**Innovation:** One of the most promising developments lies in quantum-enhanced optimization. Quantum computing has the potential to solve highly complex problems in clinical trial logistics, such as selecting optimal site networks, designing efficient global supply

routes, and managing resources across multiple constraints, at a speed that traditional computing cannot match. Another major advancement may come from the use of advanced digital twins. These systems create detailed virtual replicas of clinical trial operations, allowing sponsors to test different trial designs, sustainability strategies, and operational scenarios before implementing them in the real world.

**Regulatory Evolution Pathway:** The regulatory environment surrounding sustainable, digitally enabled trials is proposed to progress in clear stages, with steadily increasing expectations and formal requirements. By 2028, harmonized standards from the International Council for Harmonization are proposed to define consistent global expectations for the use of advanced digital systems in clinical research quality management, reducing regional variability and easing multi-country implementation.

**Industry Transformation Predictions:** Contract research organizations that can clearly demonstrate strong environmental practices are likely to gain market share, leaving behind competitors who struggle to show tangible improvements in sustainability. **Investment Trends:** ESG-focused venture capital is predicted to increasingly favor companies developing sustainable trial technologies, creating easier access to funding for innovators while putting pressure on organizations slower to adopt green practices. **Academic Integration:** By 2028, leading medical schools and academic medical centers are proposed to include sustainability-focused training within clinical research programs.

**Critical Research Priorities:** Long-Term Impact Studies: Comprehensive 10-year studies measuring environmental outcomes, operational efficiency, and economic benefits of sustainable trial approaches may provide definitive evidence

of their value. **Health Equity Research:** It may be crucial to examine how sustainability-focused trial methods affect healthcare equity. **Comparative Effectiveness Research:** Conducting direct comparisons of different AI-based strategies for sustainability may help identify the most effective mix of technologies, trial designs, and operational approaches that deliver the best environmental and operational outcomes.

## CONCLUSION & CALL TO ACTION

**Synthesis of Evidence:** The GreenTrial AI framework represents a comprehensive approach to integrating advanced technologies across the full clinical trial lifecycle, designed to simultaneously enhance environmental sustainability, operational efficiency, and economic value. Real-world implementations and published research demonstrate its transformative impact.

**Industry Transformation Imperative:** The pharmaceutical sector is at a pivotal moment, facing converging pressures that demand bold, transformative action. Mandates like the European Commission's target of 90% greenhouse gas reduction by 2040, coupled with new regulatory expectations for sustainability assessments in marketing applications, are redefining competitive advantage. They can achieve operational excellence through faster, more efficient trial execution, cutting time-to-market, and reducing development costs. They can secure regulatory leadership by proactively aligning with emerging sustainability requirements and establishing themselves as thought leaders in shaping new guidelines. Stakeholder value is enhanced through improved ESG performance, investor confidence, and public reputation, reflecting a strong commitment to environmental responsibility. At the same time, early adopters can realize significant economic returns, benefiting from cost



savings, accelerated revenue, and higher trial success rates.

### Recommended Actions

- **For Pharmaceutical Sponsors and Developers:** Pharmaceutical companies should launch GreenTrial AI PiIoT programs within the next 12 months, starting with proof-of-concept trials in areas with high environmental impact and where operational benefits are most substantial. They should establish cross-functional integration teams bridging clinical operations, IT, sustainability/ESG, regulatory, and finance departments to coordinate complex implementations effectively. Strategic investment in workforce development and change management is essential, as successful technology adoption relies as much on organizational culture and staff capabilities as on the technical infrastructure itself.
- **For Contract Research Organizations and Service Providers:** CROs should develop specialized Green AI service offerings to differentiate themselves and create new revenue streams. Building strategic partnerships with AI vendors, cloud providers, and sustainability measurement platforms allows access to advanced solutions without needing to develop every capability internally. Additionally, creating centers of excellence for sustainable trial design may foster methodological expertise, generate best practices, and position the organization as an industry leader in environmentally responsible clinical research.
- **For Regulatory Authorities and Policymakers:** Regulatory agencies and policymakers should move swiftly to provide clear guidance for sustainable, AI-enabled

trials, outlining validation requirements, quality standards, and regulatory pathways that support innovation without compromising safety or efficacy

### Vision for 2030

By 2030, the widespread adoption of GreenTrial AI frameworks clinical research from an environmentally intensive enterprise into a net-positive contributor to planetary health. This shift that advancing human health and protecting the environment are not competing goals but mutually reinforcing objectives. This change is already within reach, the technology is proven in real-world trials, the economic case is strong with clear environmental urgency is pressing, reflected in regulations and stakeholder expectations. Early adopters may gain lasting competitive advantages while contributing meaningfully to sustainability and global health. Those who delay risk falling behind as industry standards, regulations, and stakeholder expectations shift irreversibly toward sustainable clinical trial practices.

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**HOW TO CITE:** Nishant Jagtap, Shravani Girigosavi, Greentrial AI: AI for Sustainable Clinical Trial Logistics, *Int. J. of Pharm. Sci.*, 2026, Vol 4, Issue 5, 257-276. <https://doi.org/10.5281/zenodo.19985888>

