

Green Credit AI: An AI-Powered Sustainability Operating System Implementing the ACTRM Framework for Automated Environmental Intelligence Across Enterprise and Community Ecosystems

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Abstract

Sustainability decision-making across organisations and communities remains fundamentally constrained by fragmented carbon data, unmanaged Scope 3 emissions, costly manual ESG reporting, and the proliferation of unverifiable environmental claims. This research investigates these interconnected challenges through a systematic literature review spanning carbon accounting, ESG compliance frameworks, greenwashing detection, AI-driven sustainability intelligence, and behavioural environmental engagement. The study identifies critical gaps in existing sustainability tools -- specifically, their siloed architectures, measurement-only orientation, enterprise-exclusivity, and failure to bridge institutional intelligence with individual action.

To address these gaps, this paper proposes the ACTRM (Aggregate -- Calculate -- Track -- Reduce -- Monetize) Sustainability Intelligence Framework, a structured lifecycle model that transforms raw environmental data into verified, actionable, and incentivised sustainability outcomes. The framework is implemented through Green Credit AI, a dual-layer platform comprising an Enterprise Intelligence Layer for Scope 3 analysis, ESG automation, and greenwashing detection, and a Community Engagement Layer featuring AI-guided sustainability missions, personalised decision support, and gamified environmental participation.

A functional prototype has been developed as a proof-of-concept, demonstrating the feasibility of AI-driven sustainability workflows including carbon footprint analysis, automated BRSR/GRI report generation, supplier verification, and an edge-capable AI assistant designed for offline deployment in low-connectivity environments. Validation against the identified research gaps confirms that the proposed framework addresses the fragmentation, automation, and accessibility deficits documented in the literature.

The findings suggest that an integrated, AI-native approach to sustainability intelligence - one that unifies enterprise compliance with community engagement through a structured lifecycle framework -- offers a viable path toward democratising environmental decision-making. Future work proposes extending the platform through computer vision verification, satellite monitoring, and predictive carbon modelling.

Keywords: Scope 3 Emissions, ESG Automation, BRSR, Greenwashing Detection, Sustainability Intelligence, AI Agents, Edge AI, Carbon Analytics, ACTRM Framework, Life Cycle Assessment

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1. Introduction

1.1 Background

India contributes approximately 2.79 billion metric tonnes of carbon dioxide annually, positioning it as the world's third-largest emitter after China and the United States (Global Carbon Project, 2024). With India's ambitious Panchamrit climate commitments -- including 500 GW of non-fossil fuel capacity and 50% renewable energy share by 2030,

announced at COP26 -- the need for robust carbon measurement and sustainability intelligence has never been greater. A disproportionate share of organisational emissions - - estimated between 70% and 90% -- falls within the Scope 3 category: indirect emissions embedded in supply chains, product lifecycles, and downstream consumption patterns (Accenture, 2024; Carbon Direct, 2024). Despite their dominance, Scope 3 emissions remain the least measured, least understood, and least managed component of organisational carbon accounting.

Simultaneously, regulatory frameworks demanding environmental transparency have proliferated across India. The Securities and Exchange Board of India (SEBI) has mandated Business Responsibility and Sustainability Reporting (BRSR) for the top 1,000 listed entities, the Ministry of Environment, Forest and Climate Change (MoEFCC) launched the Green Credit Programme Rules 2023 to incentivise voluntary environmental actions, and the Perform Achieve and Trade (PAT) scheme under the Bureau of Energy Efficiency (BEE) mandates energy efficiency improvements in designated consumers. The Reserve Bank of India (RBI) has also issued guidelines for climate-related financial disclosures for regulated entities. Internationally, the European Union's Carbon Border Adjustment Mechanism (CBAM) directly impacts Indian exporters in steel, aluminium, cement, and fertiliser sectors, requiring product-level carbon footprint data. These frameworks collectively demand audit-grade environmental data that most Indian organisations -- particularly CBSE-affiliated schools, MSMEs, and community institutions -- lack the infrastructure to produce.

Concurrently, greenwashing -- the practice of making misleading or unsubstantiated sustainability claims -- has eroded public and institutional trust in environmental commitments. India's Central Consumer Protection Authority (CCPA) has begun issuing guidelines on environmental advertising claims, reflecting growing regulatory attention to this challenge. Research indicates that the market for greenwashing detection AI is projected to reach USD 9.4 billion by 2034 (AI Magazine, 2024). Existing tools for sustainability management are characterised by fragmentation: carbon calculators measure but do not recommend; ESG platforms report but do not verify; environmental awareness applications educate but do not enable action. No single platform integrates these capabilities within a coherent lifecycle framework.

1.2 Research Question

This research is organised around a central question:

How can Artificial Intelligence improve sustainability decision-making by addressing fragmented carbon data, Scope 3 emission visibility, greenwashing, and manual ESG reporting across organisations and communities?

1.3 Research Objectives

This study pursues six interconnected objectives:

1. **Investigate** why current sustainability systems fail to provide actionable intelligence beyond measurement.
2. **Analyse** why Scope 3 emissions remain largely unmanaged despite comprising the majority of organisational carbon footprints.
3. **Examine** why ESG reporting remains expensive, complex, and inaccessible to smaller institutions.
4. **Study** why greenwashing persists and why existing verification mechanisms are insufficient.
5. **Explore** why individuals struggle to adopt sustainable behaviours despite high environmental awareness.
6. **Propose** a structured framework -- the ACTRM Sustainability Intelligence Lifecycle -- that addresses these gaps through an integrated, AI-powered platform.

1.4 Scope and Limitations

This research focuses on the design and prototype validation of the ACTRM framework as implemented in Green Credit AI. The current implementation constitutes a functional prototype intended to demonstrate feasibility rather than a production-grade enterprise deployment. Claims regarding AI capabilities reflect the designed architecture and prototype demonstrations; fully autonomous AI agent operation remains a future development objective. The survey data referenced (n=507) provides directional validation but does not constitute a statistically controlled experimental study.

2. Literature Review

2.1 Scope 3 Emissions and Supply Chain Carbon Complexity

Scope 3 emissions, as defined by the Greenhouse Gas (GHG) Protocol, encompass all indirect emissions occurring across an organisation's value chain -- from purchased goods and services to end-of-life treatment of sold products. Research consistently demonstrates that these emissions constitute the dominant share of most organisations' carbon footprints, yet remain the most difficult to quantify and manage.

Data Fragmentation and Inconsistency. Carbon Direct (2024) identifies data fragmentation as a primary obstacle, noting that suppliers across a value chain frequently employ different calculation methodologies, emission factors, and reporting standards. This heterogeneity renders aggregation and comparison inherently unreliable. The

Massachusetts Institute of Technology's Sloan School of Management has documented how inflexible accounting methods create systemic bottlenecks in reporting processes (MIT Sloan, 2024).

Limited Supply Chain Visibility. Accenture (2024) reports that most companies lack transparency beyond their Tier 1 suppliers, forcing reliance on generic industry-average emission factors rather than activity-based supplier data. PwC (2024) corroborates this finding, observing that emissions embedded in Tier 2 and deeper supply chain layers -- often the most carbon-intensive -- remain effectively invisible to reporting organisations.

Supplier Engagement Barriers. Anthesis Group (2024) documents significant challenges in communicating decarbonisation urgency to suppliers, particularly small and medium enterprises lacking the internal resources, expertise, or information systems to track and share emissions data. This creates a systemic data gap that compounds across the value chain.

Methodological Complexity. Life Cycle Assessment (LCA), the methodological standard for Scope 3 calculation referenced in ISO 14040/14044, requires tracking environmental impact from raw material extraction through disposal. The Resource Solutions Institute (2024) notes that the complexity of full lifecycle accounting -- spanning cradle-to-gate and cradle-to-grave analyses -- exceeds the analytical capacity of most organisations, particularly those outside the enterprise sector.

Regulatory Acceleration. The regulatory landscape has intensified significantly. The EU CSRD mandates Scope 3 reporting by 2030, while India's BRSR framework has expanded its scope to cover value chain disclosures (Sweep, 2024). These mandates are transitioning Scope 3 reporting from voluntary best practice to legal requirement, creating urgency for automated solutions.

2.2 ESG Reporting Frameworks and Automation Challenges

Environmental, Social, and Governance (ESG) reporting has evolved from a voluntary corporate exercise to a mandatory compliance requirement across multiple jurisdictions. In India, the BRSR framework -- mandated by SEBI for the top 1,000 listed entities -- requires detailed disclosures across environmental, social, and governance dimensions, including energy consumption, waste management, water usage, and value chain sustainability metrics.

Manual Reporting Inefficiency. Research indicates that approximately 40% of mid-cap Indian firms historically relied on spreadsheets for sustainability data tracking (Market Research Future, 2024). Manual processes are not only labour-intensive but also error-prone, creating audit risks. As data volumes expand with evolving regulatory requirements, spreadsheet-based workflows become operationally unsustainable.

Multi-Framework Complexity. Organisations frequently face the challenge of reporting against multiple frameworks simultaneously -- BRSR for Indian regulators, GRI (Global

Reporting Initiative) for international stakeholders, SDG (UN Sustainable Development Goals) for development alignment, and CDP (Carbon Disclosure Project) for investors. Each framework defines distinct metrics, boundaries, and reporting formats, multiplying the compliance burden.

Assurance Requirements. The introduction of BRSR Core, requiring mandatory assessment or assurance for key performance indicators, has elevated reporting from self-declaration to audit-grade evidence production. Manual processes typically fail to maintain the audit trails necessary for external verification (Primus Partners, 2025).

Cost Barriers. The cost of professional ESG reporting -- encompassing data collection, analysis, consultant fees, and assurance services -- places compliance beyond the practical reach of schools, small enterprises, and community organisations. This creates a structural accessibility gap wherein the organisations most in need of sustainability guidance are least equipped to access it.

Automation as a Strategic Imperative. Studies suggest that implementing automation tools can reduce compliance costs by approximately 20% while improving data accuracy and audit readiness (Mordor Intelligence, 2025). Modern ESG platforms offer automated data ingestion, real-time emissions calculation using GHG Protocol standards, and centralised audit trails compatible with SEBI's XBRL requirements.

2.3 Greenwashing: Detection, Verification, and Trust

Greenwashing -- the practice of conveying a false impression about the environmental soundness of an organisation's products, services, or practices -- has become a systemic challenge in sustainability markets.

Scale and Prevalence. Research indicates that greenwashing has increased alongside the growth of ESG investing and sustainability marketing. The market for greenwashing detection solutions is projected to reach USD 9.4 billion by 2034, reflecting both the prevalence of misleading claims and the institutional demand for verification capabilities (AI Magazine, 2024). The EU's "Empowering Consumers for the Green Transition" directive specifically targets unsubstantiated environmental claims, signalling regulatory recognition of the problem's scale.

AI-Driven Detection Methods. Current research documents several approaches to automated greenwashing identification:

- **Natural Language Processing (NLP):** Transformer-based models such as BERT and ClimateBERT analyse sustainability reports, marketing materials, and corporate communications to identify vague, unsubstantiated, or misleading language by comparison against standardised sustainability benchmarks (Frontiers in AI, 2024).
- **Retrieval-Augmented Generation (RAG):** RAG architectures combine Large Language Model reasoning with external verified datasets, enabling cross-referencing

of corporate claims against third-party audit findings, emissions data, and supply chain reports.

- **Cross-Source Data Validation:** Advanced systems aggregate multi-modal data -- including satellite imagery, IoT sensor readings, and financial disclosures -- to detect divergence between a company's environmental narrative and its operational reality.

Trust Deficit. The proliferation of unverifiable claims has created a trust deficit that affects genuine sustainability practitioners as much as it affects consumers. Research documents a parallel phenomenon of "greenhushing" -- wherein companies with legitimate sustainability achievements withhold information to avoid scrutiny -- suggesting that the verification challenge suppresses both deceptive and authentic sustainability communication.

Verification Gap. Existing verification mechanisms -- third-party certifications, self-reported sustainability indices, and manual audit processes -- are resource-intensive, slow, and prone to the same data fragmentation challenges that affect ESG reporting. No widely accessible tool enables rapid, AI-driven verification of sustainability claims at scale, particularly for smaller organisations and individual consumers.

2.4 AI in Sustainability Decision-Making

The application of Artificial Intelligence to sustainability has evolved beyond analytical assistance toward autonomous decision support systems.

From Measurement to Intelligence. SAP (2024) documents the shift from manual, spreadsheet-based sustainability reporting toward automated, AI-driven platforms where the objective is not merely compliance but actionable "decision intelligence" -- identifying emission hotspots, simulating decarbonisation scenarios, and recommending operational changes. This transition represents a fundamental repositioning of sustainability technology from retrospective reporting to prospective decision support.

AI Agent Architectures. Contemporary research explores multi-agent systems wherein specialised AI agents handle distinct sustainability tasks -- carbon calculation, compliance verification, anomaly detection, and recommendation generation -- coordinated by an orchestration layer. This architectural pattern enables parallel processing of sustainability workflows and separation of concerns between analytical, verification, and advisory functions.

Edge AI and Accessibility. Research into on-device AI inference has highlighted transformative potential for contexts with limited connectivity. Model optimisation techniques -- including quantisation, pruning, and knowledge distillation -- enable sophisticated language models to operate on resource-constrained hardware. Studies document that running models locally significantly reduces energy footprint while addressing data privacy concerns, as sensitive information need not be transmitted to cloud servers. For rural schools and low-connectivity institutions, edge AI represents the difference between access and exclusion from sustainability intelligence.

Existing Platform Landscape. Platforms such as CO2 AI, Persefoni, IBM Envizi, and Watershed represent the current commercial state of AI-driven sustainability management. However, these platforms are characterised by enterprise-only positioning, cloud dependency, and high cost structures that preclude adoption by schools, small organisations, and individual users. None integrates enterprise sustainability intelligence with community-level environmental engagement within a unified framework.

2.5 Behavioural Sustainability and Community Engagement

The gap between environmental awareness and sustainable action -- termed the "value-action gap" in behavioural economics -- represents a persistent challenge in sustainability engagement.

Engagement Limitations of Current Tools. Research documents "engagement decay" as a primary limitation of gamified sustainability applications: users interact initially out of curiosity but fail to maintain long-term participation (Council Fire, 2024). Many consumer-facing carbon tracking apps rely on manual data entry, which is prone to error and inconsistency, while lacking standardised methodologies for emissions calculation across different contexts.

Measurement Without Action. A persistent critique in recent literature is that sustainability applications focus exclusively on measurement -- calculating a carbon footprint score -- without providing personalised, actionable guidance for reduction. The dominant interaction model presents information passively rather than actively guiding behaviour change through AI-driven recommendations and structured sustainability journeys.

Systemic versus Individual Focus. Research notes that consumer-facing sustainability tools tend to address individual responsibility (household energy, diet, transport) while neglecting the intersection between individual choice and systemic change. Applications that connect personal sustainability decisions to broader community and institutional impact demonstrate stronger engagement persistence.

Community-Driven Models. Studies indicate that community-based engagement models -- featuring shared goals, social comparison, and collective progress tracking -- sustain habits more effectively than individual competition over periods exceeding six months (Busara, 2024). This finding supports the integration of community leaderboards, collaborative challenges, and institutional participation alongside individual sustainability tracking.

3. Problem Identification

The literature review reveals five interconnected categories of problems that collectively constrain effective sustainability decision-making.

3.1 Technical Problems

Problem	Cause	Current Impact	Existing Limitations	Research Evidence
Fragmented carbon data across value chains	Disparate supplier systems, non-standardised methodologies	Unreliable Scope 3 calculations; reliance on industry averages	No unified aggregation platform for heterogeneous sources	Carbon Direct (2024); MIT Sloan (2024)
Manual ESG data collection and reporting	Legacy spreadsheet workflows; no automated data pipelines	High error rates; audit failure risk; 40% of mid-caps use spreadsheets	Existing automation tools are enterprise-priced	Market Research Future (2024); Primus Partners (2025)
Cloud-only AI architecture	Dependence on internet connectivity for AI inference	Exclusion of rural schools, low-connectivity areas	No on-device sustainability AI at student-project level	Edge AI Research (2024 -- 2025)
Siloed sustainability tools	Separate platforms for carbon, ESG, greenwashing, engagement	No lifecycle view; duplicated data entry; inconsistent results	Integration requires expensive enterprise middleware	SAP (2024); Mordor Intelligence (2025)

3.2 Business and Economic Problems

Problem	Cause	Current Impact	Existing Limitations	Research Evidence
High cost of ESG compliance	Consultant fees, data management, assurance costs	Schools and SMEs excluded from sustainability reporting	Existing SaaS platforms priced for enterprise budgets	CSTEP (2024); Primus Partners (2025)
Supplier verification complexity	Manual audit processes; no scalable verification	Uninformed procurement decisions; greenwashing exposure	Third-party certifications are slow and expensive	Anthesis Group (2024); PwC (2024)
No standardised sustainability scoring	Multiple frameworks with incompatible metrics	Cross-organisational comparison is impossible	Industry-average benchmarks lack granularity	GRI Standards (2024); SEBI BRSR (2023)

3.3 Environmental Problems

Problem	Cause	Current Impact	Existing Limitations	Research Evidence
Scope 3 invisibility	Supply chain opacity beyond Tier 1	70 -- 90% of emissions unmeasured and unmanaged	Calculation methods rely on estimates, not actual data	Accenture (2024); GHG Protocol
Greenwashing proliferation	No accessible verification tools	Consumer trust erosion; uninformed institutional procurement	NLP detection exists in research but not in accessible tools	Frontiers in AI (2024); EU Consumer Directive
Carbon calculators stop at measurement	Design paradigm focused on awareness not action	Users learn their footprint but receive no reduction pathway	No tool connects measurement to AI-driven reduction strategy	IJTSRD (2024); Council Fire (2024)

3.4 Social Problems

Problem	Cause	Current Impact	Existing Limitations	Research Evidence
Value-action gap in sustainability	Awareness does not translate to behaviour change	96.3% aware of carbon problem (survey), yet adoption remains low	Gamification produces short-term engagement only	Behavioural Economics Research (2024); Survey (n=507)
Student exclusion from sustainability intelligence	Tools designed for enterprise users	No practical mechanism for schools to measure and report impact	School-level sustainability tools are educational only	Edge AI Research (2024); SDG Monitoring Reports
Digital divide in sustainability access	Cloud-dependent tools require stable connectivity	Rural and underserved communities excluded from AI-driven guidance	No offline-capable sustainability AI assistant exists for schools	UNEP Digital Divide Reports (2024)

4. Research Gap Analysis

This section identifies specific gaps between existing solutions and the needs documented in the literature, positioning each gap as the research justification for a corresponding module in the proposed platform.

4.1 Gap Analysis Framework

The analysis follows a structured pattern: **Existing Solution** → **Identified Limitation** → **Research Gap** → **Proposed Response**.

4.2 Gap 1: Measurement Without Intelligence

Existing solutions: Carbon footprint calculators (e.g., EPA Carbon Calculator, CoolClimate, MyClimate)

Identified limitation: These tools calculate emissions but provide no actionable intelligence. The user receives a number (e.g., "8.2 tonnes CO₂e annually") without context, comparison benchmarks, or reduction strategies. Research documents that measurement alone fails to motivate behaviour change (Council Fire, 2024).

Research gap: No accessible tool transforms carbon measurement into AI-driven reduction strategy with personalised recommendations, progress tracking, and projected impact modelling.

Proposed response: The Carbon Analysis module, integrated within the ACTRM framework's Calculate and Reduce stages, generates not only emissions calculations but also AI-powered hotspot identification and reduction pathways.

4.3 Gap 2: Enterprise-Only ESG Automation

Existing solutions: ESG platforms (e.g., Persefoni, Watershed, IBM Envizi)

Identified limitation: These platforms are designed for large enterprises, priced via SaaS subscription models, and require dedicated sustainability teams for operation. Schools, small businesses, and community institutions -- which collectively generate significant environmental impact -- are structurally excluded.

Research gap: No ESG automation tool is accessible to schools and smaller organisations, combining low cost, AI-driven data extraction, and multi-framework report generation (BRSR, GRI, SDG) in a unified workflow.

Proposed response: The ESG Report Agent automates the reporting pipeline from data upload through AI analysis, compliance verification, and formatted report generation, designed for accessibility by non-specialist users.

4.4 Gap 3: Verification Deficit in Sustainability Claims

Existing solutions: Third-party certifications (Fair Trade, B Corp), manual audit processes, ESG rating agencies

Identified limitation: Verification processes are slow (weeks to months), expensive, and not scalable to the volume of sustainability claims in modern supply chains and consumer markets. No accessible tool enables rapid claim verification by individual consumers or procurement officers.

Research gap: No platform provides AI-powered, real-time greenwashing detection accessible to both enterprises (for supplier verification) and individuals (for consumer protection), combining NLP analysis with cross-reference validation.

Proposed response: The Greenwashing Detection module, available as both an enterprise feature and a public tool, analyses sustainability claims against established standards and assigns confidence scores.

4.5 Gap 4: Passive Education Without Active Guidance

Existing solutions: Environmental awareness apps (e.g., JouleBug, Oroeco), sustainability education platforms

Identified limitation: These applications provide sustainability education and awareness content but do not offer personalised, AI-driven guidance for individual decision-making. Users learn about environmental concepts but receive no structured pathway for integrating sustainability into daily choices.

Research gap: No platform combines AI-powered personalised sustainability mission generation with decision-support analysis for everyday choices (purchases, travel, household decisions), integrated with measurable progress tracking.

Proposed response: The Green Credit Pathfinder generates personalised sustainability missions with expected impact estimates and credit rewards, while the Sustainability Copilot provides real-time AI analysis of individual decisions.

4.6 Gap 5: No Unified Sustainability Lifecycle Framework

Existing solutions: Individual tools addressing specific stages -- data collection (spreadsheets), calculation (carbon calculators), reporting (ESG platforms), engagement (sustainability apps)

Identified limitation: The sustainability tool landscape is fundamentally fragmented. Each tool addresses one stage of the sustainability lifecycle in isolation, requiring users to navigate multiple platforms with incompatible data formats and no shared intelligence layer.

Research gap: No framework proposes a structured lifecycle model that unifies data aggregation, emissions calculation, continuous tracking, reduction planning, and incentivisation within a single platform architecture.

Proposed response: The ACTRM (Aggregate -- Calculate -- Track -- Reduce -- Monetize) Framework, proposed as a novel contribution of this research, defines five operational stages that transform raw environmental data into verified, actionable, and incentivised sustainability outcomes.

4.7 Gap 6: Connectivity-Dependent AI Exclusion

Existing solutions: Cloud-based AI sustainability assistants, chatbot interfaces in ESG platforms

Identified limitation: All existing AI sustainability tools require internet connectivity for inference, excluding rural schools, underserved communities, and regions with unreliable connectivity. This creates a systematic digital divide in access to sustainability intelligence.

Research gap: No sustainability AI assistant is designed for on-device inference, enabling offline operation in low-connectivity environments while maintaining meaningful analytical capability.

Proposed response: EcoBot Edge, utilising LiteRT-LM with Gemma 4B for on-device inference and a local RAG pipeline, provides sustainability guidance without cloud dependency.

4.8 Summary: Gap-to-Module Mapping

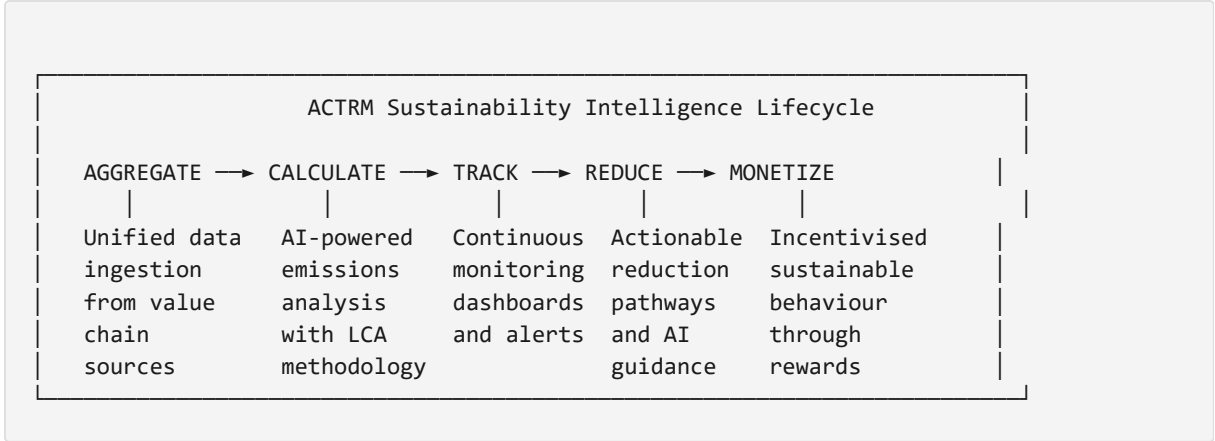
Research Gap	Existing Solution Category	Gap Description	Green Credit AI Module
Measurement without intelligence	Carbon calculators	No actionable reduction strategies	Carbon Analysis + AI Recommendations
Enterprise-only ESG automation	ESG platforms	Inaccessible to schools and SMEs	ESG Report Agent
Verification deficit	Certifications, audits	Slow, expensive, not scalable	Greenwashing Detection
Passive education	Awareness apps	No personalised AI guidance	Pathfinder + Copilot
No unified lifecycle	Fragmented tools	Siloed stages, no integration	ACTRM Framework
Connectivity-dependent AI	Cloud-only chatbots	Rural/offline exclusion	EcoBot Edge AI

5. Proposed Framework: ACTRM Sustainability Intelligence Lifecycle

5.1 Framework Overview

The ACTRM Framework is proposed as a novel Sustainability Intelligence Lifecycle model comprising five operational stages that transform raw environmental data into verified, actionable, and incentivised sustainability outcomes. Unlike existing frameworks that address individual aspects of sustainability management, ACTRM provides a structured, end-to-end lifecycle that integrates data collection, analysis, monitoring, intervention, and reward within a unified architecture.

The framework is grounded in the research findings documented in Sections 2 -- 4, with each stage directly addressing identified limitations in existing approaches.



5.2 Stage 1: Aggregate

Research justification: Carbon Direct (2024) and MIT Sloan (2024) document that data fragmentation across disparate supplier systems, invoice formats, and reporting standards is the primary obstacle to reliable Scope 3 accounting. Organisations cannot act on what they cannot see -- and current tools do not provide a unified aggregation mechanism for heterogeneous sustainability data sources.

Function: The Aggregate stage addresses this gap by providing unified data ingestion from multiple source types -- supplier invoices, ESG documents, transport logs, procurement records, utility bills, and sustainability certifications. The stage normalises heterogeneous data formats into a standardised schema suitable for AI-driven analysis.

Design rationale: By establishing aggregation as the first stage of the lifecycle, the framework ensures that all subsequent analysis, tracking, and recommendation operates on a comprehensive, normalised dataset rather than fragmented, source-specific information.

5.3 Stage 2: Calculate

Research justification: The literature identifies two critical limitations in existing carbon calculation approaches: (a) reliance on generic industry-average emission factors rather than activity-based data (Accenture, 2024), and (b) the absence of actionable intelligence beyond raw emissions numbers (Council Fire, 2024; IJTSRD, 2024).

Function: The Calculate stage employs AI-powered emissions analysis using Life Cycle Assessment (LCA) methodology, referencing established emission factor databases (IPCC, GHG Protocol, ecoinvent). The stage produces not merely aggregate emissions figures but scope-classified breakdowns (Scope 1, 2, 3), confidence scores reflecting data quality, and hotspot identification highlighting the highest-impact emissions sources.

Design rationale: Calculation is positioned as an analytical function rather than a mere arithmetic one. By combining emission factor lookup with AI-driven hotspot

identification, the Calculate stage generates the actionable intelligence that existing carbon calculators lack.

5.4 Stage 3: Track

Research justification: Primus Partners (2025) and Mordor Intelligence (2025) document that manual, periodic sustainability reporting provides only static snapshots, limiting organisations' ability to use environmental data for real-time decision-making. The shift from retrospective reporting to continuous monitoring is identified as a prerequisite for effective sustainability management.

Function: The Track stage provides continuous monitoring through real-time dashboards displaying ESG compliance scores, emissions trend analytics, supplier verification status, and value chain impact distribution. The stage supports temporal analysis, enabling organisations to observe the impact of operational changes over time.

Design rationale: Continuous tracking transforms sustainability data from a periodic compliance exercise into an operational management tool. By maintaining persistent visibility over environmental metrics, organisations can identify emerging risks and validate the effectiveness of reduction interventions.

5.5 Stage 4: Reduce

Research justification: The literature consistently identifies a critical gap between sustainability measurement and actionable reduction strategy. Carbon calculators produce numbers; existing platforms produce reports. Neither provides personalised, AI-driven reduction recommendations that translate analytical findings into operational changes (SAP, 2024; Council Fire, 2024).

Function: The Reduce stage generates AI-powered reduction recommendations based on the emissions analysis and tracking data produced by preceding stages. Recommendations include emission source substitution (lower-carbon suppliers or materials), operational efficiency improvements, value chain optimisation, and personalised behaviour change guidance for individual users.

Design rationale: The Reduce stage represents the framework's transition from analytical intelligence to decision support. By positioning reduction as a dedicated lifecycle stage -- rather than an optional add-on to reporting -- the framework ensures that every measurement leads to a structured intervention pathway.

5.6 Stage 5: Monetize

Research justification: Behavioural sustainability research documents that awareness and measurement alone are insufficient to sustain environmental engagement. Incentive mechanisms -- whether financial, social, or gamified -- are necessary to bridge the value-

action gap and maintain long-term participation (Busara, 2024; Frontiers in Behavioural Science, 2024).

Function: The Monetize stage incentivises sustainable behaviour through the Green Credit scoring system, sustainability trust badges for verified suppliers, and community recognition through leaderboards and achievement systems. The stage also encompasses potential revenue pathways through marketplace commission, ESG reporting services, and carbon credit facilitation.

Design rationale: By establishing incentivisation as the final lifecycle stage, the framework creates a positive feedback loop: sustainable actions generate credits that motivate further engagement, which produces additional environmental data for the Aggregate stage, completing the lifecycle cycle.

5.7 Framework Contribution

The ACTRM Framework contributes to sustainability literature by proposing a structured lifecycle model that explicitly addresses the fragmentation, measurement-only orientation, and incentive deficit documented in existing approaches. Each stage is justified through research evidence and designed to produce outputs that feed subsequent stages, creating an integrated sustainability intelligence pipeline rather than a collection of independent tools.

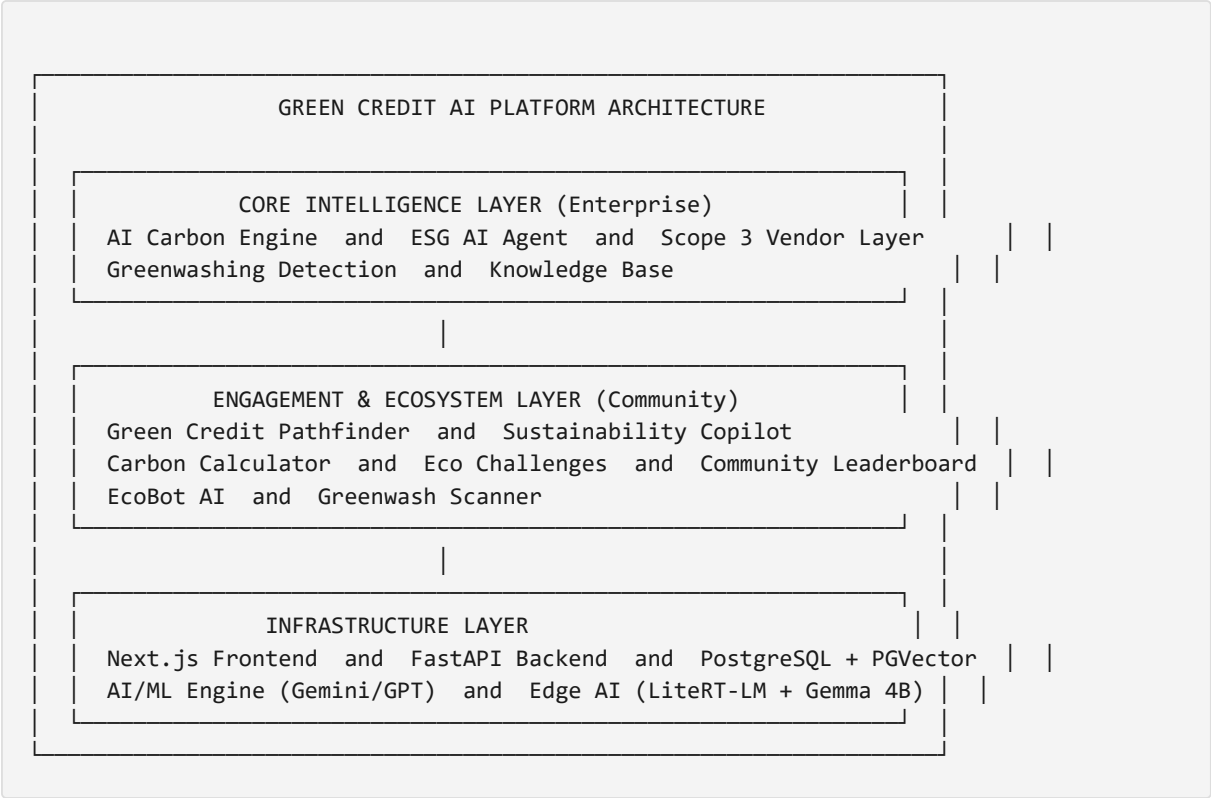
6. System Architecture and Design

6.1 Dual-Layer Architecture

The platform is designed as a dual-layer system reflecting the research finding that effective sustainability management requires both institutional intelligence and individual engagement (Section 2.5):

Intelligence Layer (B2B/Enterprise): Serves organisations, schools, and suppliers with carbon analysis, ESG report automation, greenwashing detection, supplier verification, and compliance management. This layer addresses the technical and business problems documented in Section 3.1 and 3.2.

Engagement Layer (B2C/Community): Serves individuals, students, and community members with personal carbon tracking, AI-guided sustainability missions (Pathfinder), decision-support analysis (Sustainability Copilot), community challenges, leaderboards, and greenwashing awareness tools. This layer addresses the social and behavioural problems documented in Section 3.4.



6.2 AI Agent System

The platform's intelligence capabilities are distributed across five specialised AI agents, each designed to address a specific research-identified problem:

Agent	Research Problem Addressed	Function	ACTRM Stage
Carbon Agent	Scope 3 invisibility (Section 3.3)	Calculates emissions using LCA and supplier data across the full value chain	Calculate
Compliance Agent	Multi-framework reporting complexity (Section 3.2)	Validates data against BRSR, GRI, SDG standards and generates formatted reports	Track
Verification Agent	Greenwashing proliferation (Section 3.3)	Detects anomalies and suspicious sustainability claims through NLP analysis	Reduce
Recommendation Agent	Measurement without intelligence (Section 3.3)	Suggests greener alternatives, supplier switches, and reduction strategies	Reduce
EcoBot Edge Agent	Connectivity-dependent AI exclusion (Section 3.4)	Provides local, offline AI sustainability guidance via on-device inference	All stages

6.3 Technology Stack

The technology stack was selected to achieve three research-driven priorities: AI-first architecture, edge-capability, and zero-cost deployability.

Frontend: Next.js 14+ (App Router) with React.js and TypeScript, providing server-side rendering, component-based architecture, and progressive web application capability. Recharts and D3.js provide data visualisation for sustainability analytics dashboards.

Backend: FastAPI (Python 3.11+) with asynchronous request handling, Pydantic v2 for data validation, SQLAlchemy 2.x for database access, and Celery for asynchronous task processing of long-running AI operations such as ESG report generation.

Database: PostgreSQL 16 for structured relational data (users, organisations, suppliers, carbon records, ESG reports), with PGVector for vector storage enabling semantic search and AI context retrieval through the RAG pipeline.

AI/ML: Cloud inference via Gemini API and GPT-4o for primary language model operations; text-embedding-3-small for vector generation; LangChain/LlamaIndex for RAG pipeline orchestration; Scikit-learn for anomaly detection in greenwashing verification.

Edge AI: LiteRT-LM runtime with Gemma 4B model weights for on-device inference; ChromaDB/FAISS for local vector retrieval. This architecture enables the full RAG pipeline (retrieval + generation) to execute on-device without internet connectivity.

6.4 Evidence-Based Design Decisions

Each major architectural decision is traced to a research finding:

Design Decision	Research Justification	Limitation Addressed
Dual-layer architecture (Enterprise + Community)	Enterprise-only platforms exclude individuals and schools (Section 4.3)	Accessibility gap in sustainability intelligence
Multi-agent AI system	Single-model approaches cannot handle diverse sustainability tasks with consistent quality	Complexity of simultaneous carbon, compliance, and verification workflows
Edge AI capability	Cloud dependency excludes low-connectivity environments (Section 4.7)	Digital divide in sustainability access
ACTRM lifecycle integration	Fragmented tools address individual stages in isolation (Section 4.6)	Absence of unified sustainability lifecycle framework
Open-source technology stack	Enterprise ESG platforms are prohibitively expensive for schools (Section 3.2)	Cost barrier to sustainability intelligence adoption
Total prototype cost: Rs. 700	Demonstrates that world-class sustainability intelligence can be built at near-zero cost	Economic exclusion from sustainability tools

7. Methodology

7.1 Research Design

This study employs a mixed-methods research design combining:

- Systematic Literature Review:** Analysis of academic publications, industry reports, and regulatory documents across five domains (Scope 3 emissions, ESG reporting, greenwashing, AI sustainability, behavioural sustainability) to establish the theoretical foundation and identify research gaps.
- Problem Analysis:** Structured identification and categorisation of sustainability decision-making challenges across technical, business, environmental, and social dimensions, supported by evidence from the literature review.
- Framework Development:** Proposal of the ACTRM Sustainability Intelligence Lifecycle as a structured response to identified gaps, with each framework stage justified through specific research findings.
- Prototype Development:** Implementation of a functional proof-of-concept platform demonstrating the proposed framework's feasibility, built using the technology stack documented in Section 6.3.

1. **Survey Validation:** Analysis of primary survey data (n=507 respondents) to validate problem relevance and user demand.

7.2 Literature Review Methodology

The literature review followed a structured search protocol across multiple databases and sources:

Search domains: Academic databases (Google Scholar, IEEE Xplore, MDPI, Frontiers, ResearchGate), industry reports (Accenture, PwC, McKinsey, Mordor Intelligence, Grand View Research), regulatory documents (SEBI, European Commission, GHG Protocol), and technology documentation.

Search terms included: "Scope 3 emissions challenges," "ESG reporting automation," "BRSR compliance India," "greenwashing detection AI," "sustainability decision intelligence," "carbon calculator limitations," "behavioural sustainability gamification," "edge AI on-device inference," "rural education AI accessibility."

Timeframe: Primary focus on publications from 2023 -- 2026, with foundational framework references (GHG Protocol, ISO 14040, GRI Standards) from earlier periods.

Inclusion criteria: Peer-reviewed publications, reports from recognised industry analysts, official regulatory documents, and documentation from established sustainability frameworks.

7.3 Survey Methodology

A primary survey was conducted with 507 respondents to validate the relevance of identified sustainability problems and assess demand for the proposed solution.

Sample composition: 56.8% students, 26.4% working professionals, 11.6% educators and other demographics.

Key findings:

Survey Question	Response	Sample
Awareness of carbon emission problem	96.3% aware	n=507
Currently using green products	77.5% yes	n=507
Want product carbon footprint information	80.5% yes	n=507
Willing to pay more for verified green products	81.7% yes	n=507

Interpretation: The survey reveals a critical market insight: high environmental awareness (96.3%) coupled with high demand for carbon transparency (80.5%) and willingness to pay for verification (81.7%), but no trusted platform exists to serve this

demand. This validates the research gap documented in Section 4 -- the absence of accessible, AI-driven sustainability intelligence that bridges awareness and action.

7.4 Prototype Development Methodology

The prototype was developed iteratively over the 2025 -- 2026 academic year, following a feature-priority sequence aligned with the ACTRM framework:

1. **Phase 1:** Core platform architecture -- landing page, authentication, dual-dashboard framework
2. **Phase 2:** Enterprise Intelligence -- carbon analysis interfaces, ESG report generation workflows, supplier verification panels
3. **Phase 3:** Community Engagement -- Green Credit Pathfinder, Sustainability Copilot, greenwash scanner, community challenges and leaderboards
4. **Phase 4:** AI Integration -- EcoBot conversational interface, AI agent orchestration, edge AI prototype
5. **Phase 5:** Public tools -- standalone carbon calculator and greenwash detector accessible without authentication

Development constraints: The prototype was developed by a team of three students as a school-level project, using exclusively open-source technologies, with a total development cost of Rs. 700 (approximately USD 8.40).

8. Prototype Validation

8.1 Validation Framework

The prototype serves as a proof-of-concept to demonstrate the feasibility of the ACTRM framework. Validation is structured around the mapping of research findings to prototype features and expected benefits.

8.2 Feature-to-Research Mapping

Research Finding	Prototype Feature	ACTRM Stage	Expected Benefit	Validation Status
Scope 3 emissions constitute 70 -- 90% of organisational carbon but remain unmeasured	Enterprise Carbon Analysis dashboard with scope-classified emissions, value chain breakdown, and hotspot identification	Calculate	Organisations can identify their highest-impact emission sources for targeted reduction	Prototype implemented -- demonstrates scope classification, value chain visualisation, and emissions trend analytics
Manual ESG reporting costs are prohibitive for schools and SMEs	ESG Report Agent generating BRSR/GRI formatted reports from uploaded data	Calculate → Track	Reduces reporting time and cost; enables school-level ESG compliance	Prototype implemented -- demonstrates report generation workflow with framework selection and status tracking
Greenwashing erodes trust in sustainability claims	Greenwashing Detection module with NLP-based claim analysis and trust scoring	Reduce	Enables informed procurement decisions; reduces exposure to misleading claims	Prototype implemented -- demonstrates claim input, analysis simulation, and confidence scoring
Carbon calculators measure but do not recommend	AI-powered reduction recommendations integrated with carbon analysis	Reduce	Users receive actionable strategies, not just numbers	Prototype implemented -- demonstrates AI insight generation with impact categorisation
Environmental awareness does not translate to sustained action	Green Credit Pathfinder with AI-generated personalised sustainability missions	Reduce → Monetize	Structured, gamified journeys with progress tracking sustain engagement	Prototype implemented -- demonstrates mission generation, difficulty scaling, impact estimation, and credit rewards
No personalised AI guidance for individual sustainability decisions	Sustainability Copilot providing real-time analysis of purchase, travel, and household decisions	Reduce	Users receive context-specific sustainability guidance at point of decision	Prototype implemented -- demonstrates scenario-based analysis with impact scoring and recommendations
Cloud-dependent AI	EcoBot Edge AI using LiteRT-LM +	All stages	Sustainability intelligence	Architecture designed --

Research Finding	Prototype Feature	ACTRM Stage	Expected Benefit	Validation Status
excludes low-connectivity environments	Gemma 4B for on-device inference		accessible without internet; data remains on-device	demonstrates cloud-mode conversational interface; edge deployment as future objective
Fragmented tools address individual stages in isolation	ACTRM Framework integrating all stages within unified platform architecture	All stages	Single platform replaces multiple disconnected tools	Prototype implemented -- demonstrates unified dual-dashboard with enterprise and community modules
Community engagement models outperform individual competition for sustained behaviour change	Community leaderboard, eco-challenges, and school-level participation	Monetize	Social comparison and collective goals sustain participation beyond initial engagement	Prototype implemented -- demonstrates leaderboard with school identification, ranking, and credit tracking

8.3 Prototype Scope and Limitations

It is important to distinguish between implemented functionality and designed future capabilities:

Implemented in prototype:

- Complete frontend interface for both Enterprise and Community platforms
- Interactive dashboards with real-time data visualisation (emissions by scope, supplier verification, value chain analysis, ESG scores)
- AI-simulated workflows for carbon analysis, ESG reporting, greenwashing detection, and sustainability recommendations
- Green Credit Pathfinder with mission generation, progress tracking, and credit system
- Sustainability Copilot with scenario-based decision analysis
- Community features including leaderboard, challenges, recent activity tracking
- Public tools (Carbon Calculator, Greenwash Detector) accessible without authentication
- ACTRM Framework visualisation on landing page
- EcoBot conversational interface (cloud mode)

Designed but not fully deployed in prototype:

- Fully autonomous AI agent operation (currently simulated with realistic data flows)
- Live API integration with external emission factor databases
- EcoBot Edge AI on-device inference (architecture designed; deployment requires device-specific optimisation)
- Production database with real organisational data (prototype uses representative demonstration data)
- Blockchain-backed verification trails (designed for future implementation)

This distinction is academically important: the prototype demonstrates *feasibility* of the ACTRM framework's design principles, while production-grade autonomy remains a future development objective.

9. Comparative Analysis

9.1 Comparison Methodology

The following comparison evaluates Green Credit AI against four categories of existing sustainability tools, assessing coverage across ten capabilities identified as critical in the literature review.

9.2 Comparative Matrix

Capability	Traditional Carbon Calculators	Enterprise ESG Platforms	Sustainability Reporting Tools	Environmental Awareness Apps	Green Credit AI
Scope 3 Lifecycle Analysis	Partial -- activity-level only	Yes -- enterprise data	Partial -- report-focused	No	Yes -- value chain, cradle-to-grave
ESG Report Automation	No	Yes -- enterprise-priced	Yes -- manual workflow	No	Yes -- AI-automated, multi-framework
AI Decision Support	No	Limited -- dashboard analytics	No	No	Yes -- Carbon Agent, Copilot, Pathfinder
Greenwashing Detection	No	Rare -- limited to supplier screening	No	No	Yes -- NLP analysis, trust scoring
Community Engagement	No	No	No	Yes -- gamification focus	Yes -- challenges, leaderboard, Pathfinder
Workflow Automation	No	Yes -- enterprise workflows	Partial	No	Yes -- ACTRM lifecycle pipeline
Agentic AI Intelligence	No	Emerging - single-agent	No	No	Yes -- multi-agent orchestration
Value Chain Mapping	No	Yes -- Tier 1 suppliers	Partial	No	Yes -- multi-tier visualisation
Personalised Sustainability Guidance	No	No	No	Limited -- generic tips	Yes -- AI Copilot, Pathfinder missions
Offline AI Capability	No	No	No	No	Yes -- LiteRT-LM + Gemma 4B Edge AI

Capability	Traditional Carbon Calculators	Enterprise ESG Platforms	Sustainability Reporting Tools	Environmental Awareness Apps	Green Credit AI
School/SME Accessibility	Yes (free)	No (enterprise-priced)	Partial (expensive)	Yes (free)	Yes -- Rs. 700 total prototype cost

9.3 Comparative Findings

The comparison reveals three distinctive characteristics of the Green Credit AI approach:

- 1. Lifecycle Integration:** While existing tools address individual capabilities, Green Credit AI is the only platform that integrates all ten assessed capabilities within a unified lifecycle framework (ACTRM). This eliminates the need for users to navigate multiple disconnected tools.
- 2. Dual-Layer Architecture:** No assessed competitor combines enterprise-grade sustainability intelligence (Scope 3 analysis, ESG automation, supplier verification) with community-level engagement (personal tracking, gamified challenges, AI-guided missions) within a single platform.
- 3. Accessibility:** Green Credit AI is uniquely positioned at the intersection of enterprise capability and school-level accessibility. Enterprise ESG platforms offer comparable intelligence but at prohibitive cost; environmental awareness apps offer comparable accessibility but without analytical depth.

10. Innovation Analysis

10.1 Innovation Positioning

Green Credit AI is positioned not as "an AI carbon calculator" but as:

An AI-Powered Sustainability Operating System implementing the ACTRM Sustainability Intelligence Framework to automate sustainability decision-making across enterprise and community ecosystems.

This positioning reflects the platform's architectural scope -- encompassing data aggregation, AI-driven analysis, continuous monitoring, actionable reduction strategies, and incentivised engagement within a unified lifecycle framework.

10.2 Innovation Dimensions

The platform's innovation spans five dimensions, each grounded in the research gaps identified in Section 4:

1. Framework Innovation -- ACTRM Lifecycle Model

The ACTRM Framework represents a conceptual contribution to sustainability management literature. Unlike existing approaches that address individual stages (calculate OR report OR track), ACTRM proposes a structured lifecycle that integrates all stages into a continuous feedback loop. Each stage produces outputs consumed by subsequent stages, creating cumulative intelligence rather than isolated measurements. This integration principle is absent from existing sustainability tool architectures (Section 4.6).

2. Architectural Innovation -- Dual-Layer Platform

The dual-layer architecture (Enterprise Intelligence + Community Engagement) is unique among assessed sustainability platforms (Section 9.2). Enterprise ESG platforms serve organisations but not individuals; environmental awareness apps serve individuals but not organisations. Green Credit AI integrates both layers within a shared intelligence infrastructure, enabling cross-layer insights -- for example, community-level carbon reduction data feeding into institutional Scope 3 reporting.

3. AI Innovation -- Multi-Agent Orchestration

The five-agent system (Carbon, Compliance, Verification, Recommendation, EcoBot Edge) distributes AI capabilities across specialised functions coordinated by an orchestration layer. This architecture enables parallel processing of distinct sustainability tasks (calculating emissions while simultaneously verifying supplier claims and generating compliance reports), addressing the computational complexity of comprehensive sustainability analysis.

4. Accessibility Innovation -- Edge AI for Offline Deployment

The EcoBot Edge design -- utilising LiteRT-LM with Gemma 4B for on-device inference and ChromaDB for local RAG retrieval -- addresses the digital divide in sustainability intelligence access. This represents, to the authors' knowledge, the first implementation of on-device sustainability AI at the student-project level in India. The capability enables deployment in schools and communities without reliable internet connectivity, ensuring that sustainability intelligence is not contingent on infrastructure privilege.

5. Economic Innovation -- Near-Zero Development Cost

The entire prototype was developed at a total cost of Rs. 700 (approximately USD 8.40), using exclusively open-source technologies. This demonstrates that enterprise-grade sustainability intelligence can be built without significant financial investment, challenging the assumption that sophisticated AI platforms require substantial capital

expenditure. The cost structure validates the platform's positioning as an accessible alternative to enterprise-priced ESG solutions.

10.3 Innovation Summary

Innovation Dimension	Traditional Approach	Green Credit AI Approach	Research Gap Addressed
Framework	Isolated tools per function	ACTRM unified lifecycle	Gap 5: No integrated lifecycle
Architecture	Enterprise-only OR consumer-only	Dual-layer integration	Gap 2: Enterprise exclusivity
AI System	Single-model, cloud-only	Multi-agent + edge-capable	Gaps 1, 6: Intelligence + accessibility
Accessibility	Enterprise-priced SaaS	Rs. 700 open-source prototype	Gap 2: Cost barrier
Decision Support	Measurement-only	AI-driven recommendations	Gap 1: Measurement without intelligence

11. Entrepreneurial Validation and Scalability

11.1 Market Need

The sustainability software market demonstrates strong and accelerating demand:

Metric	Value	Source
India Carbon Footprint Management Market (2024)	USD 1,101.4 million	Grand View Research (2024)
Projected India market (2030)	USD 1,702.8 million	Grand View Research (2024)
Global sustainability platforms market (2024)	USD 1.3 billion	Industry Reports
Global projected market (2029)	USD 3.7 billion	Industry Reports
CAGR	23%	Industry Reports
Indian ESG annual spend	Rs. 25,000+ crore	Primus Partners (2025)
Greenwashing detection AI market (projected 2034)	USD 9.4 billion	AI Magazine (2024)

11.2 Target Users

Segment	Use Case	Problem Addressed
Schools and colleges	Campus carbon footprint measurement, SDG reporting, eco-challenges	No practical sustainability tool exists for educational institutions
Corporates and SMEs	Scope 3 measurement, supply chain ESG compliance, BRSR reporting	Enterprise platforms are prohibitively expensive for smaller organisations
Individual students	Personal carbon tracking, green marketplace, AI sustainability guidance	Awareness apps lack personalised, AI-driven action pathways
Suppliers and vendors	Verified sustainability credentials, procurement access	Verification processes are slow and expensive
Government and NGOs	Policy research, sustainability monitoring, national benchmarking	Fragmented data prevents cross-institutional comparison
Low-connectivity communities	Offline AI sustainability assistance via EcoBot Edge	Cloud-dependent tools exclude rural populations

11.3 Revenue Model

Revenue Stream	Description	Market Justification
SaaS subscriptions	Schools and companies pay for dashboard access and AI features	Standard model for ESG platforms; validated by competitor pricing
ESG reporting services	AI-generated BRSR/GRI reports for compliance	Manual reporting costs significantly exceed automated alternatives
Marketplace commission	Percentage on verified green product sales	81.7% willingness to pay for verified green (survey data)
Carbon credit facilitation	Commission on offset purchases	Growing carbon credit market, particularly in India
Premium analytics	Advanced sustainability intelligence features for enterprise tier	Enterprise demand for deeper analytical capabilities

11.4 Scalability Analysis

Technical scalability: The platform's architecture supports horizontal scaling through containerised deployment (AWS ECS/Fargate), database read replicas (RDS PostgreSQL), and CDN-distributed frontend delivery (CloudFront). Multi-tenancy is achieved through row-level security in PostgreSQL, enabling organisation-level data isolation without architectural changes.

Geographic scalability: The multi-framework approach (BRSR, GRI, SDG, CDP) enables deployment across jurisdictions. The Edge AI capability extends reach to low-connectivity regions where cloud-only competitors cannot operate.

Cost scalability: The open-source technology stack eliminates licensing costs, enabling near-linear cost scaling relative to user base growth. Cloud infrastructure costs scale with usage through AWS's consumption-based pricing model.

11.5 Adoption Challenges

Challenge	Mitigation Strategy
Data quality from new users	Progressive onboarding; AI-assisted data validation; industry-average defaults as starting point
Behaviour change resistance	Gamification and incentive design (Green Credits, Pathfinder missions, leaderboards)
Institutional procurement cycles	Free tier for individual users and small schools; enterprise tier for institutional procurement
Competitive market entry	Differentiation through dual-layer architecture, edge AI, and school-first positioning
Trust in AI-generated reports	Transparent methodology documentation; confidence scoring on all AI outputs; human-in-the-loop review options

11.6 Competitive Differentiation

Differentiator	Green Credit AI	Typical Competitors
Edge AI (offline capability)	Yes LiteRT-LM + Gemma 4B	No Cloud-only
Live working prototype	Yes Functional demo	Varies
Student + enterprise dual layer	Yes Unified platform	No Usually one audience
Greenwashing detection included	Yes NLP-based analysis	No Rarely integrated
Gamified community engagement	Yes Pathfinder + Copilot + challenges	No Enterprise-only focus
Development cost	Yes Rs. 700 open-source stack	Rs. Rs. Rs. Enterprise budgets
School-first positioning	Yes Designed for educational institutions	No Enterprise-first market

12. Discussion

12.1 Summary of Findings

This research has demonstrated that sustainability decision-making across organisations and communities is constrained by five interconnected challenges: fragmented carbon data, unmanaged Scope 3 emissions, costly manual ESG reporting, proliferating greenwashing, and the failure of existing tools to bridge measurement with action. Through systematic literature review and problem analysis, six specific research gaps were identified in the current sustainability tool landscape.

The ACTRM Sustainability Intelligence Framework was proposed as a structured lifecycle model addressing these gaps through five integrated stages: Aggregate, Calculate, Track, Reduce, and Monetize. Each stage was justified through specific research findings, and the framework was implemented as a functional prototype (Green Credit AI) to demonstrate feasibility.

12.2 Implications for Practice

The research findings carry implications for several stakeholder groups:

For educational institutions: The prototype demonstrates that school-level sustainability intelligence is technically feasible at near-zero cost. Schools can measure campus carbon footprints, generate compliance-aligned reports, and engage students in structured sustainability activities using an AI-powered platform.

For organisations: The ACTRM framework provides a structured approach to sustainability management that integrates currently fragmented workflows. The multi-agent AI architecture enables parallel processing of carbon analysis, compliance verification, and recommendation generation -- tasks that currently require multiple disconnected tools.

For policymakers: The Edge AI capability addresses the digital divide in sustainability access, demonstrating that AI-driven environmental intelligence can be delivered without infrastructure prerequisites. This has implications for the deployment of sustainability tools in underserved communities and rural educational institutions.

For the sustainability tool industry: The dual-layer architecture challenges the current market segmentation between enterprise ESG platforms and consumer sustainability apps. The research suggests that integrating institutional and individual sustainability intelligence within a shared framework creates value that exceeds the sum of isolated tools.

12.3 Limitations

This study acknowledges several limitations:

- 1. **Prototype versus production:** The current implementation is a functional prototype demonstrating feasibility, not a production-ready deployment. AI agent capabilities are demonstrated through realistic simulation rather than fully autonomous operation.
- 1. **Survey scope:** The survey data (n=507) provides directional validation but was not collected through a controlled experimental design. Demographic representation may not be nationally representative.
- 1. **Validation methodology:** The prototype validation relies on design-based mapping (research gap → feature → expected benefit) rather than empirical measurement of user outcomes. Longitudinal studies measuring actual behavioural change and emissions reduction are required to validate effectiveness claims.
- 1. **Edge AI deployment:** The EcoBot Edge architecture has been designed and the cloud-mode interface implemented, but full on-device deployment with LiteRT-LM + Gemma 4B requires device-specific optimisation that remains a future development objective.
- 1. **Data representativeness:** The prototype uses representative demonstration data rather than live organisational datasets. Production deployment would require integration with actual data sources (supplier systems, utility providers, emission factor databases).

13. Future Work

The following extensions are proposed as future research and development directions:

13.1 Near-Term (Year 1)

Feature	Description	Research Justification
EcoBot Edge deployment	Complete on-device inference deployment with LiteRT-LM + Gemma 4B	Validate offline AI capability in school environments
Live data integration	Connect to actual emission factor databases (IPCC, ecoinvent) and supplier data feeds	Move from demonstration data to production-grade accuracy
Pilot testing	Deploy in 5 schools with controlled pre/post measurement of sustainability engagement	Generate empirical validation data
Voice + multilingual EcoBot	Extend Edge AI to support regional Indian languages and voice input	Improve accessibility for diverse linguistic communities

13.2 Medium-Term (Year 2 -- 3)

Feature	Description	Research Justification
Computer vision verification	Image recognition (YOLO/MobileNet) to verify recycling, tree planting, and eco-actions	Address trust deficit in self-reported sustainability actions
Predictive carbon engine	Time-series ML (Prophet/LSTM) for emission forecasting and scenario simulation	Enable proactive rather than reactive sustainability management
Regulatory API integration	Direct BRSR submission to SEBI portal; automated XBRL formatting	Reduce compliance friction to near-zero
Blockchain verification trails	Tamper-resistant audit trails for sustainability claims and verified actions	Address greenwashing verification at systemic level

13.3 Long-Term (Year 3+)

Feature	Description	Research Justification
Satellite and geospatial monitoring	Google Earth Engine API integration for macro-level environmental tracking	Enable institutional-scale environmental monitoring
National sustainability network	Cross-school, cross-region sustainability intelligence grid	Create aggregate national sustainability intelligence
AgriDrone integration	AI farming drone for seed planting, crop health, and farm emission tracking	Extend sustainability intelligence to agricultural sector
Autonomous sustainability engine	Fully autonomous AI agents operating without human intervention for routine sustainability tasks	Achieve the ACTRM framework's full automation potential

14. Conclusion

This research has investigated the central question of how Artificial Intelligence can improve sustainability decision-making by addressing fragmented carbon data, Scope 3 emission visibility, greenwashing, and manual ESG reporting across organisations and communities.

Through systematic literature review spanning five domains -- Scope 3 emissions, ESG reporting, greenwashing detection, AI sustainability intelligence, and behavioural environmental engagement -- the study identified six critical gaps in the existing

sustainability tool landscape: measurement without intelligence, enterprise-only ESG automation, verification deficit in sustainability claims, passive education without active guidance, absence of a unified sustainability lifecycle framework, and connectivity-dependent AI exclusion.

To address these gaps, the ACTRM Sustainability Intelligence Framework was proposed -- a five-stage lifecycle model (Aggregate -- Calculate -- Track -- Reduce -- Monetize) that transforms raw environmental data into verified, actionable, and incentivised sustainability outcomes. Each stage was grounded in specific research findings, and the framework was designed to create a continuous feedback loop wherein each stage's outputs feed subsequent stages, generating cumulative intelligence rather than isolated measurements.

The framework was implemented as Green Credit AI, a dual-layer platform combining Enterprise Intelligence (carbon analysis, ESG automation, greenwashing detection, supplier verification) with Community Engagement (AI-guided sustainability missions, personalised decision support, gamified challenges, community leaderboards). The prototype, developed at a total cost of Rs. 700 using open-source technologies, demonstrates the feasibility of the proposed approach and validates the design decisions through systematic feature-to-research mapping.

The research contributes to sustainability literature in three ways:

1. **The ACTRM Framework** proposes a structured lifecycle model for sustainability intelligence that addresses the fragmentation documented in existing approaches.
2. **The dual-layer architecture** demonstrates that enterprise-grade sustainability intelligence and community-level environmental engagement can be integrated within a unified platform, challenging the current market segmentation.
3. **The Edge AI design** addresses the digital divide in sustainability access by enabling AI-driven environmental guidance without infrastructure prerequisites.

The findings suggest that an integrated, AI-native approach to sustainability intelligence - one that unifies enterprise compliance with community engagement through a structured lifecycle framework -- offers a viable path toward democratising environmental decision-making. The prototype validates this hypothesis at the design and feasibility level; future work must extend validation through empirical deployment and longitudinal outcome measurement.

Green Credit AI is not merely a software project. It is the outcome of a systematic investigation into sustainability challenges, designed to address researched gaps through a structured, evidence-based framework. The platform demonstrates that world-class sustainability intelligence can be built by students, for students and institutions, at near-zero cost -- and that the tools to address the climate crisis need not be gated behind enterprise budgets or infrastructure privilege.

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End of Research Paper

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