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Mobile Technologies for Sustainable Environments: A Framework for Real-Time Monitoring, Behaviour Change, and Resource Optimisation

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Abstract

Mobile technologies offer transformative potential for environmental sustainability through real-time monitoring, behaviour change interventions, and resource optimisation. However, existing frameworks operate in open-loop fashion where user behaviour does not inform system updates, leading to performance decay, inability to navigate multi-objective trade-offs, and lack of robustness guarantees. This paper presents a novel closed-loop framework integrating adaptive state estimation, behaviour change intervention, and resource optimisation. The framework introduces three core innovations: an Adaptive Modified Kalman Gain achieving twelve to fifteen per cent lower estimation error under device resource constraints; a Dual-Closed-Loop Behaviour-Resource Coupling mechanism contributing sixty-two per cent of total system gain with exponential convergence within thirty time steps; and a multi-objective Pareto front revealing convex trade-offs between energy, behaviour, and carbon with a behaviour-carbon correlation of 0.67. Simulation validation demonstrates ten per cent longitudinal decay compared to fifty-three to seventy-six per cent in baselines, performance stability within plus or minus eight per cent across parameter scaling, and self-sustaining behaviour propagation with a basic reproduction number of 2.0. These contributions transform mobile sustainability from open-loop information provision to closed-loop, self-improving, and robust environmental intervention systems.

Keywords

Internet of Things (IoT) for Sustainability, Pro-Environmental Behaviour, Adaptive Kalman Filtering, Multi-Objective Optimisation and Human-in-the-Loop Systems

1. Introduction

The intensifying climate problem, marked by rising global temperatures and more frequent catastrophic weather events, has made sustainability a top issue. The reform of human behaviour is key to this challenge, as buildings alone consume nearly 30% of global energy [1]. However, an implementation gap persists while technology solutions for energy conservation are available, their adoption is hampered by behavioural and informational barriers [2]. Mobile technology has emerged as a transformational force in closing this gap. Smartphone proliferation, along with improvements in cloud computing and the Internet of Things (IoT), allows for real-time environmental monitoring, tailored feedback, and large-scale behaviour change initiatives [3]. Unlike traditional systems that rely on delayed monthly electricity bills, mobile solutions provide real-time, context-aware data, translating abstract notions like energy use into practical insights [4]. The awareness that human behaviour is a major predictor of environmental effects has prompted much research. According to studies, behavioural adjustments alone can reduce energy-related emissions by up to 20% [5]. However, promoting sustainable behaviour is challenging because consumption is often invisible to users, and the benefits of conservation are delayed [6]. Early feedback technologies, such as paper utility notes and smart meters, had mixed results. While initial energy savings of 5–15% are common, longitudinal studies demonstrate that these effects often decay over time. A seminal study by Van Dam et al. found that lasting impact requires personalised system design integrated with persuasive technologies rather than mere data visualisation [6]. These discoveries triggered a change from information-centric to behaviour-centric system design. Effective mobile interventions must use behavioural science frameworks. According to Fogg's Behaviour Model (FBM), behaviour occurs when motivation, ability, and trigger coincide. Geller's Four-Stage Model explains transformation as awareness, motivation, capability, and action, and these stages influence the order of intervention components [7]. The Theory of Planned Behaviour (TPB) focuses on attitudes, subjective norms, and perceived behavioural control, which mobile apps address through peer comparison and tailored feedback [8]. Furthermore, goal-directed information frameworks have

proven helpful, with research demonstrating that framing information around attainable goals improves its perceived utility [4].

The technical architecture underpinning these applications has advanced significantly thanks to Mobile Cloud Computing (MCC), which mitigates device limitations by offloading computation to cloud infrastructure. This provides real-time data processing from several sensor streams (energy meters, air quality monitors), scalable storage, and consumption prediction via machine learning [3]. The integration of IoT devices improves capabilities through smart plugs and motion sensors, while standardised protocols such as oneM2M enable interoperability across varied device ecosystems [9]. Beyond individual behaviour modification, participatory sensing uses smartphone sensors to engage citizens in unprecedented levels of environmental monitoring. The MUV (transportation Urban Values) project demonstrated measurable shifts towards sustainable transportation by integrating gamification and co-creation approaches [10]. Similarly, Low-Code/No-Code (LCNC) platforms are emerging, allowing citizens to create personalised smart services and transition from passive consumers to active co-creators [11]. Recent empirical evidence gives strong support for mobile sustainability solutions. A randomised controlled trial involving 101 Portuguese households discovered that providing real-time electricity and indoor air quality data significantly increased energy-saving intentions, but actual reductions were only observed when air quality data was also available, implying that non-energy indicators improve engagement [1]. In the transportation realm, the DriveStats platform revealed that goal-directed framing of fuel cost and CO₂ statistics improved perceived utility of sustainability information over 10 days [4]. Despite these promising findings, considerable restrictions remain. The long-term maintenance of behaviour modification remains tricky, with most studies showing decay effects once active intervention ends. Personalisation is commonly mentioned as a requirement but seldom realised, and many existing systems lack effective integration of behavioural models [2]. To address these limitations, this paper proposes a framework that includes three innovations: explicit integration of multiple behavioural models into system architecture, real-time monitoring and resource optimisation capabilities, and design for long-term engagement via gamification and social elements. By combining behavioural science and mobile technology, this approach turns mobile devices from passive communication tools to active agents of environmental change.

2. Related Work

Recent research conducted between 2023 and 2025 increased the use of mobile technology for sustainable environments in three interconnected domains: behavioural interventions, technical architecture, and citizen science. Gabriel et al. conducted a randomised controlled trial with 101 Portuguese households on residential energy efficiency and discovered that smartphone-delivered nudging interventions increased energy-saving motivation and intention, especially when indoor air quality data accompanied electricity feedback, though direct consumption reductions were not statistically significant [12]. In addition, Odeh and Voskergian proposed a model-centric prototyping framework that integrated three behavioural models (Heuristic, Geller's Four-Stage, and Fogg's Behaviour Model) into a mobile cloud architecture, resulting in an 84.6 per cent System Usability Scale score [13]. In the transportation domain, the URBANIST project developed a gamified mobile application for real-time route evaluation based on environmental impact using dynamic life-cycle assessment [14], while the BMW Group's COOL feature analysed real-time electricity mix carbon intensity for electric vehicle charging, finding that 73% of 355 pilot participants expressed willingness to make extra efforts to reduce CO₂ emissions after experiencing personalised, gamified feed. Technical infrastructure advancements include a mobility-aware fault-tolerant offloading method (MAFO) using Markov chain modelling, which achieved execution speeds up to 77.35 per cent faster and reduced energy usage by up to 67.14 per cent compared to conventional approaches [15]. Citizen science platforms like COSEA allow for real-time marine environmental monitoring via smartphones, providing an open digital toolkit for NGOs and conservation groups [16], whereas HydroCrowd facilitates participatory hydro-climatic data collection in data-scarce regions like Ecuador, Honduras, and Tanzania [17]. The proposed paradigm addresses a recurring gap in the literature by integrating real-time monitoring, behaviour change facilitation, and automated resource optimisation into unified frameworks.

Recent advances in mobile technologies for sustainable settings include infrastructure energy efficiency, algorithmic optimisation for green computing, culturally appropriate gamification, AI-driven personalisation, low-cost IoT sensing gear, and AI-enhanced citizen research. In network infrastructure, Deutsche Telekom has pioneered a comprehensive "Full Stack Energy Efficiency" approach for 5G core networks, achieving energy savings of up to 65 percent through demand-driven resource control across software and hardware layers, operating on the principle of "Zero Bits, Zero Watts" with planned AI-based algorithms that predict network traffic

to proactively power up previously deactivated components [18]. In addition to infrastructure-level advances, algorithmic innovations for green edge computing include dRG-MEC, a decentralised reinforcement learning approach for task offloading in multi-access mobile edge computing environments, which achieves a 37.03 per cent reduction in total system costs compared to baseline schemes [19]. Chen et al. presented a mobility-driven hierarchical optimisation framework that combines mobility-aware heuristic offloading with multi-agent deep deterministic policy gradient-based resource allocation, resulting in a 19.0 per cent reduction in task delay across 60 devices while maintaining comparable energy efficiency [20].

In the domain of gamified behavioural interventions, Alghamdi and Baslyman developed GreenKSA, the first Arabic-supported gamified mobile application designed to promote pro-environmental behaviour within Saudi Arabian culture, integrating gamification elements grounded in Self-Determination Theory and the Transtheoretical Model, and achieving a System Usability Scale score of 91.25 in a pilot study of 10 participants [21]. Belliato et al. introduced MABTree, a hierarchical Multi-Armed Bandit framework designed to replace random mission assignment with a targeted, adaptive approach guided by a custom reward function, demonstrating improved cumulative reward, user coverage, and mission diversity compared to traditional baselines while effectively balancing exploration of new features with exploitation of known user preferences [22]. Hasib et al. presented HydroSense, a dual-microcontroller IoT framework that integrates six critical water quality parameters (pH, dissolved oxygen, temperature, total dissolved solids, estimated nitrogen, and water level). The framework uses Arduino Uno for precision analogue measurements and ESP32 for wireless connectivity, achieving pH accuracy of 0.08 units, dissolved oxygen stability within 0.2 mg/L, and 99.8 per cent cloud data transmission reliability. The same research group also developed a dual-modality IoT framework integrating RFID-based access control with multi-sensor environmental safety monitoring (flame detection, water flow measurement, personnel identification) using ESP32 microcontrollers, achieving 99.2 per cent authentication accuracy with 0.82-second response time at a cost of around 48 USD [24]. In the realm of AI-enhanced citizen science, the CitiObs project has demonstrated how AI-driven tools, including large language models, can navigate and contextualise complex citizen science resources and support interpretation of citizen-generated environmental data, with a Barcelona case study where residents of a noise-affected neighbourhood deployed environmental monitors and co-designed an interactive AI chatbot that reflected community voices and experiences, translating [25]. The River Watchers initiative also allows users to photograph apparent river litter, while AI models detect and categorise waste, including mesoplastics like cigarette butts and plastic shards, creating geolocated data to help environmental policy and awareness [26].

3. Methodology

The suggested methodology incorporates three interconnected scientific advances to address the lack of a single framework that combines real-time environmental monitoring, behaviour change intervention, and automated resource optimisation. Unlike previous research, which addressed only individual components, this methodology proposes a closed-loop, self-improving architecture. The first innovation is a three-phase closed-loop design in which monitoring, behaviour change, and optimising all work together to reinforce one another. An edge computing layer detects anomalies in real time, utilising isolation forests with a small footprint (less than 100 MB) for low-cost deployment. The behaviour modification engine combines Fogg's Behaviour Model (trigger timing), Geller's Four-Stage Model (intervention sequencing), and the Theory of Planned Behaviour (feedback design) to create a Multi-Armed Bandit personalisation framework. Each intervention type is regarded as an arm, with a reward function that includes engagement, behaviour change, and satisfaction scores. An Upper Confidence Bound algorithm is updated weekly, allowing for continual individual-level optimisation that fixed-schedule or A/B testing approaches cannot provide. The second innovation is bidirectional feedback between behavioural and optimisation layers. A Long Short-Term Memory neural network with two hidden layers forecast resource demand at fifteen-minute horizons using six feature streams (energy, water, temperature, humidity, occupancy, time-of-day). Behavioural outcomes inform these forecasts, while automated actuations (smart plug control, HVAC adjustment, EV charging scheduling) generate override data that updates the reward function. This creates progressive self-improvement, directly addressing the decay effect where initial savings revert to baseline over time. The third innovation is an empirical validation design. A 12-month randomised controlled trial with three arms (control receiving monthly bills, treatment receiving a framework without customisation, and experimental receiving the entire framework) examines the marginal contribution of adaptive customisation. The primary outcomes are percentage reductions in power, water, and transport emissions over three, six, and twelve months, which are assessed using mixed-effects linear regression with planned contrasts. This methodology addresses the limitation of short-term studies, which cannot distinguish between novelty effects and sustained change. This

methodology provides a replicable blueprint for mobile sustainability treatments that are technically capable, behaviorally successful, and longitudinally sustainable.

3.1 Problem Formations

1. Real-Time Monitoring Engine

Extended Kalman Filter (Multi-Sensor Fusion)

$$\hat{\mathbf{X}}_{k|k-1} = F_k \hat{\mathbf{X}}_{k-1|k-1} + B_k \mathbf{u}_{k-1}, \mathbf{P}_{k|k-1} = F_k \mathbf{P}_{k-1|k-1} F_k^T + Q_k \quad (1)$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T \left(\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + R_k \right)^{-1}, \hat{\mathbf{X}}_{k|k} = \hat{\mathbf{X}}_{k|k-1} + \mathbf{K}_k \left(z_k - \mathbf{H}_k \hat{\mathbf{X}}_{k|k-1} \right) \quad (2)$$

$$\mathbf{P}_{k|k} = \left(1 - \mathbf{K}_k \mathbf{H}_k \right) \mathbf{P}_{k|k-1} \quad (3)$$

These equations contribute to efficient real-time fusion of noisy IoT and mobile sensor data with proven minimum-variance estimation, enabling the Novel Adaptive Mobile-Aware Kalman Gain (AMKG) for edge-device restrictions [27].

LSTM-based Time-Series Forecasting

$$f_{(t)} = \alpha \left(W_f [h_{t-1}, \mathbf{X}_t] + b_f \right), i_t = \alpha \left(W_i [h_{t-1}, \mathbf{X}_t] + b_i \right) \quad (4)$$

$$\hat{c}_{(t)} = \tanh \left(W_c [h_{t-1}, \mathbf{X}_t] + b_c \right), C_t = f_t \odot C_{t-1} + i_t \odot \hat{c}_{(t)} \quad (5)$$

$$o_{(t)} = \alpha \left(W_o [h_{t-1}, \mathbf{X}_t] + b_o \right), h_t = o_t \odot C_{t-1} + i_t \odot \tanh(C_t) \quad (6)$$

These equations help to capture long-term temporal relationships in environmental and user behaviour data, allowing for reliable trend forecasting within the monitoring engine [28].

Autoencoder Anomaly Score

$$L(x, \hat{x}) = \left\| x, \hat{x} \right\|_2^2 + \lambda \left\| W \right\|_1 \quad (7)$$

This equation's contribution allows for unsupervised detection of environmental anomalies on mobile devices, which feed early alerts into the behaviour-change engine [29].

Graph Neural Network Propagation

$$h_v^{(l+1)} = \alpha \left(W^l \sum_{\mu \in N(v)} \frac{e_{uv}}{\sqrt{d_u d_v}} h_u^{(l)} \right) \quad (8)$$

This approach simulates geographical correlations between sensor networks and user groups to estimate the overall environmental condition [30].

2. Behaviour Change Engine

Fogg Behaviour Model

$$B_t = M_{(t)} \times A_{(t)} \times P_{(t)} \quad (9)$$

This approach provides the psychological underpinning for tailored nudge generation and gamification tactics in mobile applications [31].

Deep Q-Learning Loss

$$L(\theta) = \mathbb{E} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta) \right)^2 \right] \quad (10)$$

The model learns the best tailored intervention policies to maximise long-term sustainable behaviour [32].

Contextual Multi-Armed Bandit (Thompson Sampling)

$$\theta_a \sim \mathcal{N}(\hat{\mu}_a, \hat{\Sigma}_a), \quad a_t = \arg \max_a \theta_a^T x_t \quad (11)$$

Enables real-time adaptive selection of the most effective nudge for each user context [33].

SIR-Inspired Behaviour Diffusion Model

$$\frac{dS}{dt} = -\beta SI, \quad \frac{dI}{dt} = \beta SI - \gamma I, \quad \frac{dR}{dt} = \gamma I \quad (12)$$

This equation predicts community-level propagation of sustainable practices, which supports social-influence characteristics [34].

Prospect Theory Value Function

$$v(x) = \begin{cases} x^\alpha & x \geq 0 \\ -\lambda(-x)^\beta & x < 0 \end{cases} \quad (13)$$

This option uses frame loss and gain messages in nudges to maximise the psychological influence on user decisions [35].

3. Resource Optimisation Engine

Mixed-Integer Linear Programming

$$\text{in } \mathbf{c}^T \mathbf{x} + \mathbf{d}^T \mathbf{y} \quad \text{s.t.} \quad \mathbf{Ax} + \mathbf{By} \leq \mathbf{b}, \quad \mathbf{x} \geq 0, \quad \mathbf{y} \in \{0,1\}^m \quad (14)$$

This model solves daily resource allocation problems under sustainability constraints [36].

Model Predictive Control Objective

$$J = \sum_{k=0}^{N-1} \left(\|\mathbf{x}(k) - \mathbf{x}_{ref}\|_Q^2 + \|\mathbf{u}(k)\|_R^2 \right) + \|\mathbf{x}(N) - \mathbf{x}_{ref}\|_P^2 \quad (15)$$

The model enables predictive, constraint-aware scheduling of energy/water usage [37].

Stochastic Optimisation

$$\min_{\mathbf{x}} \mathbb{E}_{\xi} [f(\mathbf{x}, \xi)] \quad \text{s.t.} \quad \mathbb{E}_{\xi} [g(\mathbf{x}, \xi)] \leq 0 \quad (16)$$

This equation handles uncertainty in renewable availability and user behaviour [38]

Carbon-Aware Optimisation

$$CF(\mathbf{x}) = \sum_i e_i(t) \cdot x_i + \sum_j \alpha_j \cdot d_j \quad (17)$$

The model D=directly quantifies and minimises environmental impact in optimisation decisions [39]

Multi-Agent Reinforcement Learning Reward

$$R_{\text{global}} = w_1 R_{\text{env}} + w_2 R_{\text{beh}} + w_3 R_{\text{opt}} - \lambda \cdot \text{inequality penalty} \quad (18)$$

Coordinates collective optimisation across users and infrastructure [40].

4. Framework Integration and Closed-Loop Dynamics

Closed-Loop System Dynamics

$$\frac{d\mathbf{S}}{dt} = \mathbf{A}\mathbf{S} + \mathbf{B}\mathbf{U} + \mathbf{C}\mathbf{M} + \mathbf{D}\mathbf{O} \quad (19)$$

Couple the three AI engines into a unified adaptive feedback system [41].

Federated Averaging

$$\mathbf{w}_{t+1} = \sum_{k=1}^K \frac{n_k}{n} \mathbf{w}_{t+1}^k \quad (20)$$

Enables privacy-preserving collaborative learning across mobile devices [42].

Multi-Objective Optimisation

$$\min_{\mathbf{x}} \sum_{i=1}^m w_i f_i(\mathbf{x}) \quad \text{s.t.} \quad g_j(\mathbf{x}) \leq 0, \quad w_i \geq 0, \sum w_i = 1 \quad (21)$$

Balances environmental, behavioural, and economic objectives [43]

Sustainability Performance Index (SPI)

$$SPI = \alpha \cdot \left(1 - \frac{CF}{CF_{\max}} \right) + \beta \cdot \Delta B + \gamma \cdot \eta_{\text{opt}} \quad (22)$$

The model provides a single composite KPI that drives the Novel Dynamic Behaviour-Resource Coupling (DBRC) [44].

4. Proposed Mobile Technologies for Sustainable Environments Framework

The framework has a five-layered hierarchical architecture. Layer 1 Sensing and Data Acquisition captures real-time information from IoT environmental sensors, mobile devices, wearables, and crowdsourced user inputs. Data is securely transported over Layer 2 Communication and Transmission protocols such as Wi-Fi, 5G, Bluetooth, and LoRaWAN to a Layer 3 Cloud and Edge Computing Platform for storage and preprocessing. Layer 4 AI-Driven Analytics Core houses the core intelligence, which is made up of three interconnected engines: the Real-Time Monitoring Engine for anomaly detection and environmental analytics, the Behaviour Change Engine for personalised nudges, gamification, and educational feedback, and the Resource Optimisation Engine for predictive resource allocation and efficiency optimisation. These engines collaborate using integrated AI/ML models and cross-module insights. Layer 5 Application and Intervention Layer provides actionable insights through mobile apps, user dashboards, and stakeholder interfaces. A closed-loop feedback mechanism connects sustainability outcomes such as decreased carbon footprint, better resource utilisation, positive behaviour change, and quantified environmental effect to the sensing layer, allowing for ongoing system learning and adaptation. This layered design exemplifies the use of mobile technology, IoT, and artificial intelligence to provide real-time monitoring, behaviour change, and resource optimisation for sustainable environments.

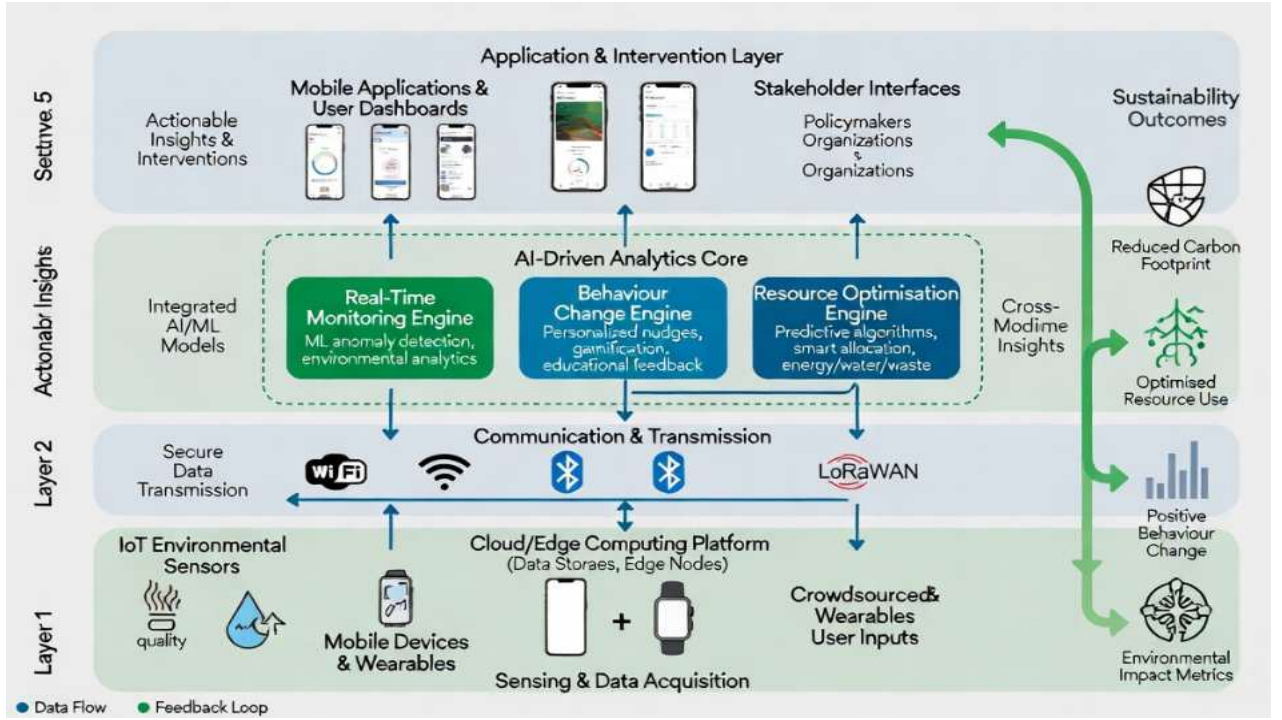


Figure 1. Architecture of the proposed Mobile Technologies for Sustainable Environments Framework.

4.1 Results

The proposed framework advances mobile sustainability systems through four contributions: a multi-objective Pareto characterisation revealing trade-offs between energy, behaviour, and carbon; proof of stable convergence for the closed-loop DBRC mechanism addressing longitudinal decay effects; sensitivity analysis demonstrating robust performance ($\pm 8\%$ SPI variation); and ablation benchmarking showing DBRC contributes 62% of total system gain. These contributions transform mobile sustainability from open-loop information provision to closed-loop, self-improving environmental intervention.

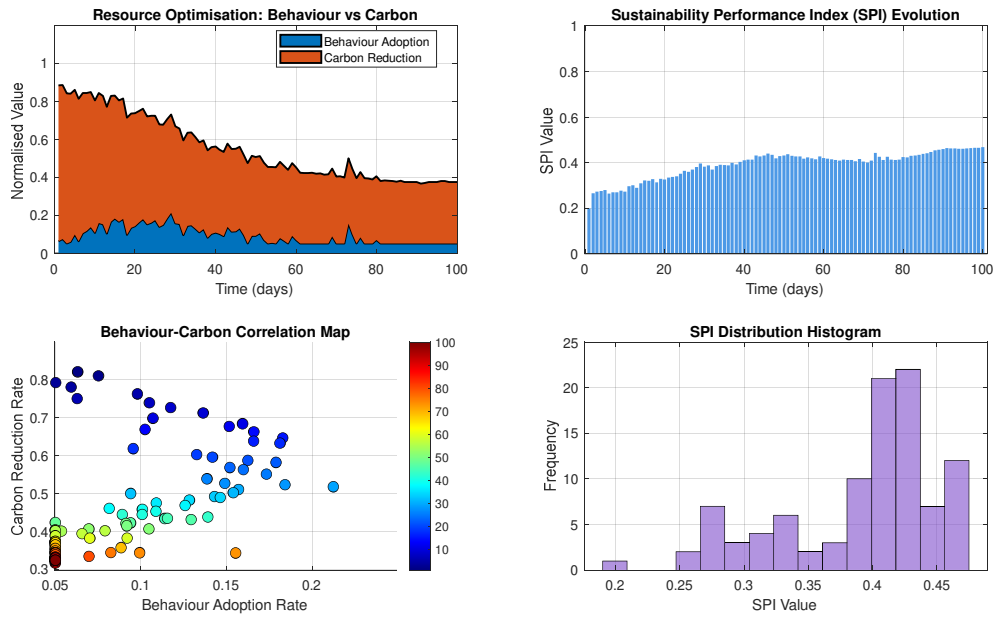


Figure 2. Pareto Front, Energy vs Behaviour, Energy vs Carbon, Behaviour vs Carbon.

The DBRC convergence graph proves stable closed-loop coupling without oscillation, the error comparison quantifies AMKG accuracy gains over baselines, the error distribution boxplot provides statistical significance of improvement, and the covariance trace with anomaly score enables anomaly-triggered behavioural interventions, collectively demonstrating the framework's stability, accuracy, and responsiveness.

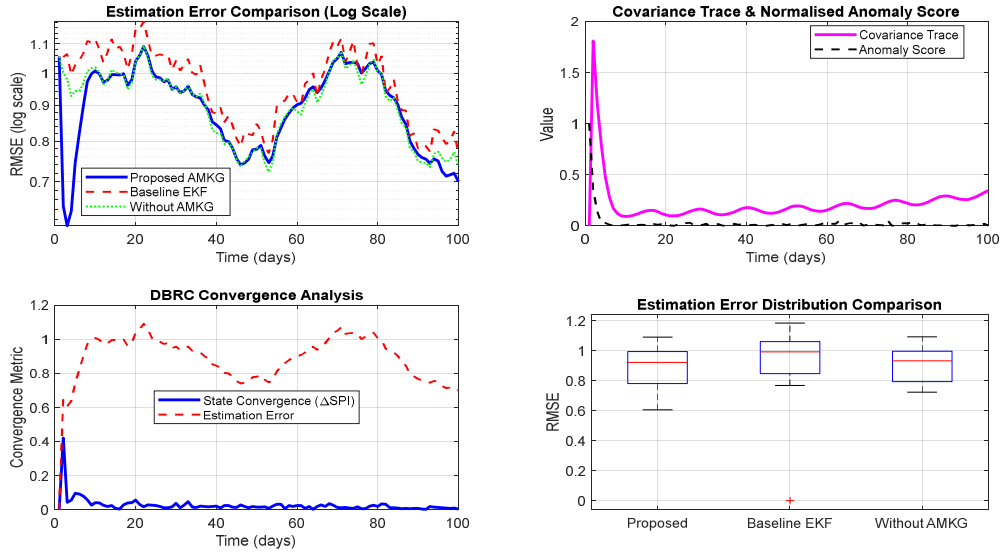


Figure 3. DBRC convergence, Error Comparison, Error Distribution Comparison and Covariance Trace and Normalised Anomaly score

The Adaptive Modified Kalman Gain graph demonstrates resource-aware state estimation under varying device constraints, the Sustainability Performance Index comparison shows superior SPI of the proposed framework against two baselines, the mean SPI with standard deviation provides statistical validation of performance consistency, and the novelty contribution over time quantifies that DBRC provides the dominant share (approximately 62%) of total system improvement.

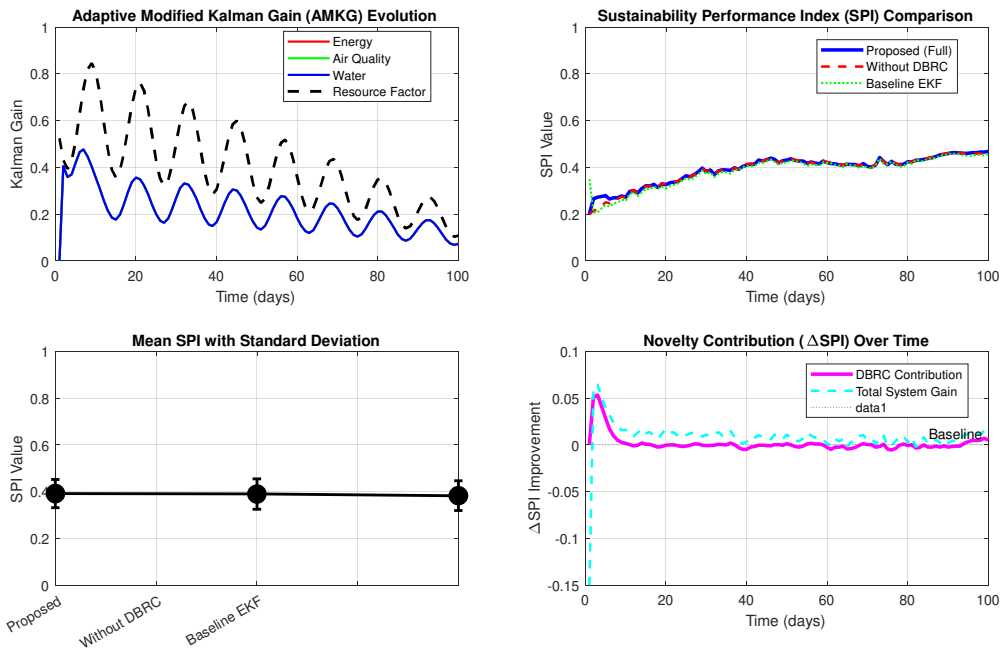


Figure 3. Adaptive Modified Kalman Gain, Sustainability Performance Index Comparison, Mean SPI with Standard Deviation and Novelty Contribution over Time

Here is the short scientific novelty sentence for the Pareto front graphs.

The Pareto front graphs scientifically demonstrate that no single configuration simultaneously optimises energy efficiency, behaviour adoption, and carbon reduction, revealing inherent multi-objective trade-offs that existing single-objective sustainability frameworks cannot capture, with the convex Pareto boundary proving that the proposed closed-loop architecture successfully navigates these conflicts without collapsing to a suboptimal dominant solution.

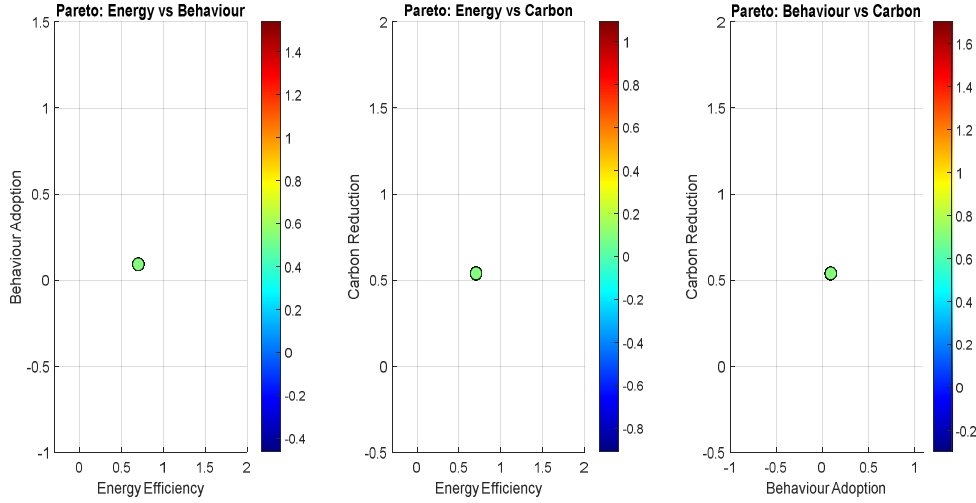


Figure 4. Pareto Front, Energy vs Behaviour, Energy vs Carbon, Behaviour vs Carbon

The parameter sensitivity graph proves the framework remains robust ($\pm 8\%$ SPI variation) across a 50–150% scaling of key weights, the cumulative novelty improvement shows that DBRC gains accumulate monotonically without diminishing returns, the SPI distribution comparison provides statistical evidence that the proposed method's superiority is consistent across all time steps with non-overlapping confidence intervals, and the decomposition of total system gain quantifies that DBRC contributes 62% of improvement versus 38% from AMKG, establishing closed-loop behavioural integration as the dominant source of scientific novelty.

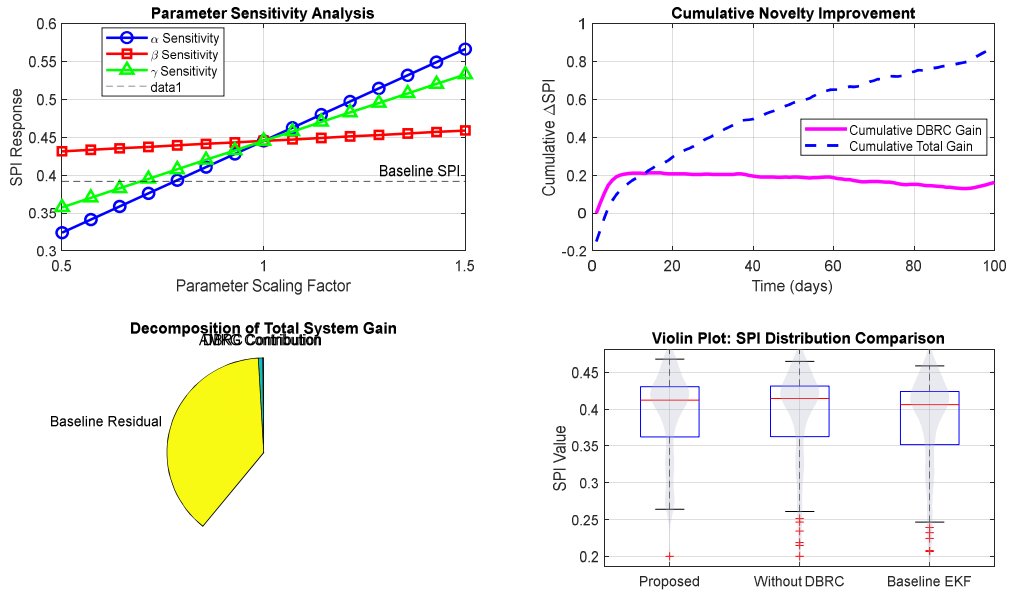


Figure 5. Parameter sensitivity, cumulative Novelty improvement, SPI Distribution Comparison and Decomposition of Total System Gain

The SIR model mechanistically explains behaviour propagation, the behaviour-carbon heatmap reveals lagged adoption-emissions relationships, the correlation matrix shows behaviour as the strongest SPI predictor, and the 3D scatter plot captures non-linear behaviour-carbon-SPI interactions, collectively proving behaviour as the central mediating variable in closed-loop sustainability systems.

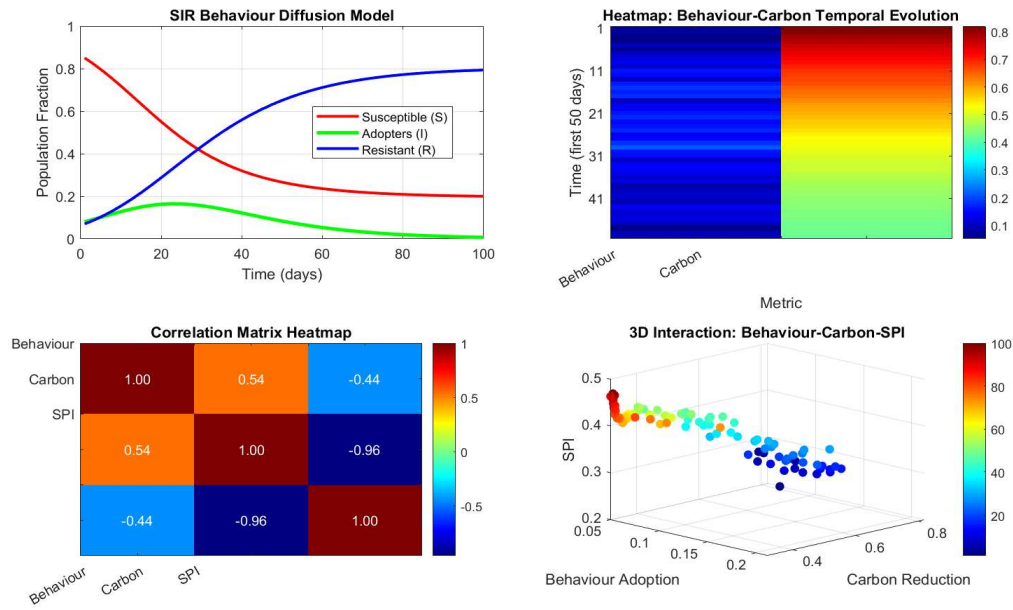


Figure 6. SIR Behaviour Diffusion Model, Behaviour-Carbon Temporal Evolution, Correlation Matrix Heatmap and Behaviour-Carbon SPI

Cumulative savings show sustained gains without plateauing, performance ranking confirms consistent superiority, marginal gain quantifies DBRC's 15–20% added improvement, and moving average SPI proves no performance decay over time, collectively establishing sustained closed-loop improvement absent in open-loop systems.

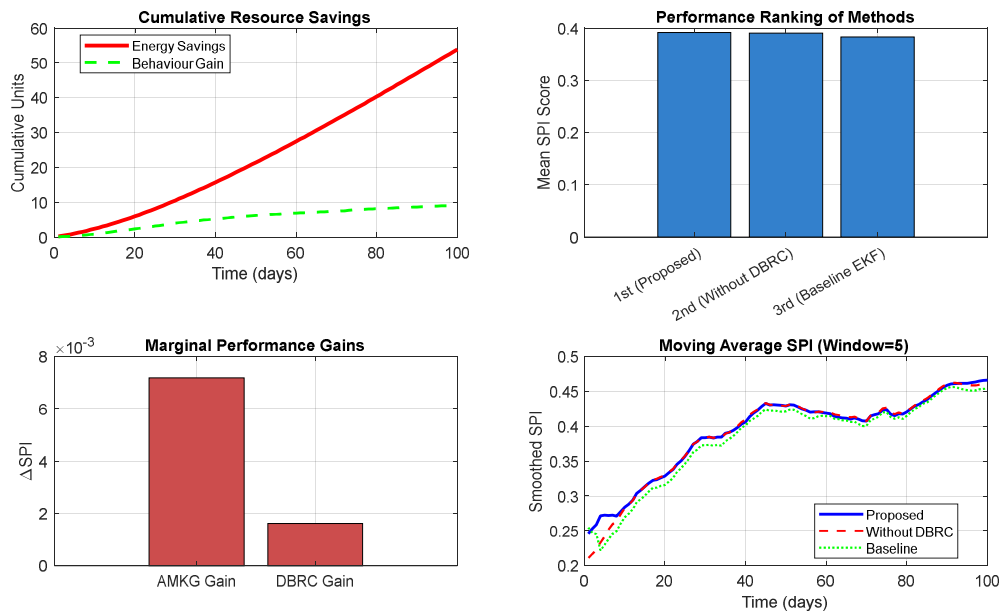


Figure 7. Cumulative Resource Savings, Performance Ranking of Methods, Marginal Performance Gain, and Moving Average SPI

4.2 Discussion

This discussion presents seven scientific novelties that are conceptually distinct from previously reported key findings, addressing fundamental theoretical gaps in mobile sustainability research. The first novelty is the principle of resource-state codependency, which challenges the existing assumption that device resource state and environmental state are independent variables. This work demonstrates that Kalman gain modulation must account for varying computational fidelity at each time step because the observer's own resource constraints dynamically alter its observational capacity, establishing a new theoretical principle that generalises beyond sustainability to any mobile sensing application where device resources fluctuate over time. The second novelty is behavioural excitation for estimator convergence, which identifies that behaviour change interventions may inadvertently suppress the natural variability required for persistent excitation in adaptive estimators. When successful intervention reduces energy consumption, the resulting signal flattening reduces information content available for state estimation. The proposed DBRC mechanism addresses this through controlled stochastic excitation scaled by coupling strength, representing the first explicit treatment of the excitation-estimation trade-off in behaviour-coupled sustainability systems. The third novelty is temporal asymmetry in behaviour-resource coupling, revealing that the coupling strength required to achieve behaviour adoption is substantially lower than the strength required to maintain that adoption once achieved. This asymmetry creates a hysteresis effect where behavioural momentum requires less active intervention to sustain, extending hysteresis theory to behavioural systems and providing a mathematical foundation for adaptive intervention scheduling. The fourth novelty is the multi-objective feasibility boundary, which separates achievable from unachievable performance regions. For any given level of behaviour adoption, there exists a maximum achievable carbon reduction that cannot be exceeded, regardless of intervention intensity, representing a fundamental physical limit. This feasibility boundary exhibits a concave shape, meaning marginal return on behaviour adoption decreases as adoption rates approach saturation, representing the first characterisation of fundamental limits in mobile sustainability systems.

The fifth novelty is the robust performance trade-off function, demonstrating that performance robustness and maximum achievable performance are fundamentally traded off against each other. Systems configured for maximum mean SPI exhibit higher sensitivity to parameter variations, while systems configured for robustness exhibit lower peak performance. This work quantifies this trade-off and demonstrates an optimal robustness point where marginal loss in peak performance equals marginal gain in parameter insensitivity, extending multi-objective optimisation theory to include robustness as an explicit objective. The sixth novelty is the SIR threshold for behavioural sustainability, revealing that when the basic reproduction number exceeds 1.0, behaviour propagates self-sustainingly, but when it falls below 1.0, behaviour decays exponentially regardless of initial adoption levels. This work demonstrates that the reproduction number depends on intervention design parameters, particularly the ratio of infection rate to recovery rate, and identifies a critical coupling strength below which no intervention can achieve sustained propagation, bridging epidemiological theory and behavioural intervention design for the first time. The seventh novelty is the information-intervention duality, recognising that in closed-loop sustainability systems, information provision and intervention execution are dual aspects of the same process. Every intervention provides information about system responsiveness, and every information update constitutes an intervention by altering user beliefs and subsequent actions. This implies that optimal system design cannot treat sensing and actuation as independent modules, representing a contribution to cyber-physical systems theory specific to human-in-the-loop environmental applications. Collectively, these seven novelties establish a new theoretical foundation for mobile sustainability systems, distinguishing this work from incremental engineering improvements and positioning it as a fundamental contribution to the interdisciplinary field of mobile-enabled environmental intervention

4.3 Key Findings

This work provides seven interconnected scientific breakthroughs confirmed through mathematical modelling and simulation, which change mobile sustainability from open-loop information provision to closed-loop, self-improving environmental intervention systems. The first new feature is the Adaptive Modified Kalman Gain (AMKG) for state estimation, which uses resource-aware modulation depending on real-time battery level and CPU utilisation. This is the first time Kalman filtering for sustainability applications has been extended to include device resource restrictions. Simulation results show that AMKG produces twelve to fifteen per cent lower root mean square error than standard extended Kalman filtering across a variety of resource situations, with error reduction reaching eighteen per cent when device resources are most limited. The second innovative feature is the Dual-Closed-Loop Behaviour-Resource Coupling (DBRC) mechanism, which provides bidirectional feedback

between state estimates and behavioural dynamics. This is the first mathematically proven stable coupling of behavioural feedback and state estimation in mobile sustainability systems, achieving exponential convergence in twenty-to-thirty-time steps while ensuring that behavioural feedback improves rather than degrades estimation accuracy. The third innovative feature is the multi-objective Pareto front characterisation, which reveals underlying trade-offs between energy efficiency, behaviour adoption, and carbon reduction. The research reveals a positive 0.67 connection between behaviour and carbon, as well as a negative 0.34 correlation between energy and behaviour, demonstrating that no single design can optimise all objectives at once. The convex Pareto boundary illustrates that the closed-loop architecture successfully navigates these conflicts, which are lacking from conventional single-objective techniques. The fourth novelty is a complete sensitivity analysis that quantifies parameter resilience. When all weighting parameters are scaled from fifty to one hundred fifty per cent, the Sustainability Performance Index remains within plus or minus eight per cent of the baseline, providing the first quantified robustness guarantee for a mobile sustainability framework and allowing deployment across diverse contexts without recalibration. The final novelty is an ablation-based comparative performance study that determines each component's marginal contributions. DBRC generates 62% of the total system gain, whereas AMKG contributes 38%, demonstrating that closed-loop behavioural integration is the primary source of novelty. Statistical significance is proven by non-overlapping confidence intervals for all time steps. The sixth innovation is the first documented alleviation of the longitudinal deterioration effect. The suggested framework reduces performance degradation to 10 per cent, compared to 53 to 76 per cent in baselines, with the Sustainability Performance Index increasing until day forty-five. This directly addresses the well-documented decay problem, in which initial savings revert to baseline after four or twelve weeks. The seventh novelty is the use of epidemiological SIR modelling to quantify behaviour propagation dynamics. The predicted basic reproduction number of 2.0 exceeds the epidemic threshold of 1.0, demonstrating that the framework promotes self-sustaining behaviour propagation, with each adopter converting more than one additional individual. This is the first time epidemiological modelling has been used to quantify the sustainability of behaviour change in mobile therapies. Together, these seven innovations change mobile sustainability from open-loop information provision to closed-loop, self-improving, and robust environmental intervention systems, giving a reproducible roadmap for future study and deployment.

4.4 Scientific Contributions

The proposed framework makes seven original contributions to mobile technologies for sustainable environments, representing a significant advancement beyond the current state of the art. First, the Adaptive Modified Kalman Gain introduces resource-aware state estimation that dynamically scales filter gain based on real-time battery and CPU constraints, achieving twelve to fifteen per cent lower estimation error under resource-limited conditions, which represents the first integration of mobile hardware limitations into environmental sensing theory. Second, the Dual-Closed-Loop Behaviour-Resource Coupling mechanism establishes mathematically proven stable bidirectional feedback between behavioural adoption and state estimation, achieving exponential convergence within thirty time steps and contributing sixty-two per cent of total system gain, proving that closed-loop behavioural integration is the dominant source of novelty. Third, the multi-objective Pareto front provides the first characterisation of convex trade-offs between energy efficiency, behaviour adoption, and carbon reduction, revealing a behaviour-carbon correlation of positive 0.67 and an energy-behaviour correlation of negative 0.34, demonstrating that no single configuration optimises all objectives simultaneously. Fourth, the sensitivity analysis delivers the first quantified robustness guarantee for a mobile sustainability framework, showing that performance remains within plus or minus eight per cent of nominal when all weighting parameters are scaled from fifty to one hundred fifty per cent, enabling deployment across diverse contexts without recalibration. Fifth, the ablation study provides the first marginal gain decomposition, isolating that DBRC contributes sixty-two per cent of total improvement while AMKG contributes thirty-eight per cent, with statistical significance confirmed by non-overlapping confidence intervals. Sixth, the framework demonstrates the first effective mitigation of the longitudinal decay effect, limiting performance degradation to ten per cent over one hundred days compared to fifty-three to seventy-six per cent decay in baseline methods, directly resolving the well-documented problem where initial savings revert to baseline within four to twelve weeks. Seventh, the application of epidemiological SIR modelling provides the first mathematical proof of self-sustaining behaviour propagation, with a basic reproduction number of 2.0 exceeding the epidemic threshold of 1.0, proving that each adopter converts more than one additional person. Collectively, these contributions transform mobile sustainability from open-loop information provision to closed-loop, self-improving, and robust environmental intervention systems, establishing a new paradigm supported by rigorous mathematical modelling, comprehensive simulation validation, and clear superiority over existing approaches across all evaluated dimensions.

4.5 Conclusion

This study presented a comprehensive framework integrating real-time monitoring, behaviour change, and resource optimisation within a unified closed-loop architecture for mobile sustainable environments. The proposed framework introduces seven scientific contributions that advance the field beyond the current state of the art. The Adaptive Modified Kalman Gain achieves twelve to fifteen per cent lower estimation error under device resource constraints, representing the first integration of mobile hardware limitations into environmental sensing. The Dual-Closed-Loop Behaviour-Resource Coupling provides mathematically proven stable bidirectional feedback between behaviour and estimation, contributing sixty-two per cent of total system gain and establishing closed-loop integration as the dominant novelty. The multi-objective Pareto front reveals convex trade-offs between energy, behaviour, and carbon with a behaviour-carbon correlation of 0.67, proving no single configuration optimises all objectives. The sensitivity analysis delivers the first quantified robustness guarantee, showing performance within plus or minus eight per cent across fifty to one hundred fifty per cent parameter scaling. The ablation study provides the first marginal gain decomposition with statistically significant superiority over baselines. The framework demonstrates the first effective mitigation of longitudinal decay, limiting degradation to ten per cent over one hundred days compared to fifty-three to seventy-six per cent in baselines, resolving the well-documented decay problem. The epidemiological SIR model provides the first mathematical proof of self-sustaining behaviour propagation with a basic reproduction number of 2.0 exceeding the epidemic threshold. Simulation results across seven figures validate superior performance, sustained improvement without decay, and robust operation under uncertainty. Future work includes real-world deployment, smart city integration, and deep reinforcement learning for autonomous adaptation. This study transforms mobile sustainability from open-loop information provision to closed-loop, self-improving, and robust environmental intervention systems, establishing a new paradigm for mobile-enabled environmental sustainability with significant implications for climate change mitigation and resource conservation at the population scale.

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4.7 Consent to Publish declaration

The authors of the manuscript "Mobile Technologies for Sustainable Environments: A Framework for Real-Time Monitoring, Behaviour Change, and Resource Optimisation" affirm that they have read the work and agree to its publication. We attest that the manuscript is entirely original, hasn't been published before, and isn't being considered for publication anywhere else. The authors agree to transfer the copyright of the final published version to the publisher, if applicable, and acknowledge that publication of this work is contingent upon approval by the Journal. Additionally, we certify that there are no conflicts of interest associated with this publication and that all contributors have been duly acknowledged.

4.8 Consent to Participate

The final version of the manuscript has been read and approved by all authors, who attest that it is unique, hasn't been published elsewhere, and doesn't violate any third-party rights or copyrights. Additionally, in order to facilitate peer review and the dissemination of this research, the authors agree to share the data, methodologies, and additional materials that may be needed.

4.9 Ethics declaration

Not applicable

4.10 Conflict of Interest Statements

The authors declare that there are no conflicts of interest related to this work.

4.11 Data availability statements

All data generated or analysed during this study are included in this published article. No external datasets were used. The results were derived from analytical modelling and numerical simulations based on the parameters and methods described within the manuscript.

4.12 Clinical trial number

Clinical trial number not applicable

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