Blockchain-Enabled Adaptive Monitoring for Sustainable Food Supply Chains: A Green Innovation Framework for Waste Reduction and Traceability

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Abstract

Reducing food loss and decarbonising agri-food logistics are central to the United Nations Sustainable Development Goals, yet conventional monitoring infrastructures remain energy-intensive, generate fragmented audit trails, and struggle to deliver verifiable provenance across multi-actor supply chains. This study develops a green innovation framework that couples permissioned blockchain with adaptive, context-aware monitoring for sustainable food supply chains. The framework integrates four architectural layers — physical operations, IoT-enabled sensing with adaptive sampling, edge-level filtering, and a Hyperledger Fabric permissioned ledger with hash-anchored off-chain storage — and embeds smart contracts that automate compliance, custody, and exception handling. We instantiate and evaluate the framework using a twelve-month pilot of a Chinese dairy supply chain encompassing 8 farms, 3 processing plants, 12 logistics nodes, and 147 retail points-of-sale. Across 9.4 million sensor observations and 11,236 ledger transactions, the adaptive scheme reduces transmitted data volume by 90.2% and edge-node energy consumption by 85.4% relative to fixed 1 Hz sampling, while maintaining critical-event detection accuracy at 96.3%, well above the 90% compliance threshold. Pilot-month CO_2 emissions and chilled-product food waste decline by 34% and 42% respectively, and traceability response time for a recall query falls from 6.2 hours to 4.1 seconds. Cost-benefit analysis indicates a payback period of 1.8 years and a five-year net present value of US$2.34 million. Theoretically, the work re-frames adaptive monitoring as a green innovation enabler that operationalises decentralised trust at the data-acquisition boundary. Practically, it offers a deployable blueprint for perishable-goods chains pursuing SDG 7, SDG 9, SDG 12, and SDG 13.

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1. Introduction

The global food system stands at the intersection of two converging crises. On the one hand, the United Nations Environment Programme estimates that more than one billion tonnes of edible food are lost or wasted every year, imposing a carbon footprint roughly equivalent to 8% to 10% of all anthropogenic greenhouse gas emissions. On the other hand, consumer trust in food safety and provenance has been repeatedly shaken by recalls, mislabelling scandals, and contamination incidents that propagate quickly through opaque, multi-tiered supply chains (Tian, 2016; Galvez et al., 2018; Astill et al., 2019). Reconciling these pressures with the United Nations Sustainable Development Goals (SDGs) — particularly SDG 7 (affordable and clean energy), SDG 9 (industry, innovation and infrastructure), SDG 12 (responsible consumption and production), and SDG 13 (climate action) — requires a fundamental redesign of how food data are produced, transmitted, governed, and verified along the chain (Carter & Rogers, 2008; Seuring & Müller, 2008; Esmaeilian et al., 2020).

Two technologies have independently emerged as candidate building blocks of this redesign. Blockchain technology offers tamper-evident, cryptographically anchored, multi-party records that can replace centralised intermediaries with shared infrastructure for trust (Christidis & Devetsikiotis, 2016; Lu, 2019; Lu, 2018). A growing literature documents proofs of concept in dairy, fresh produce, fisheries, and Halal supply chains (Caro et al., 2018; Hew et al., 2020; Patelli & Mandrioli, 2020; Manda & Yamijala, 2024). In parallel, Internet of Things (IoT) platforms enable continuous, in-situ measurement of temperature, humidity, vibration, gas concentration, and other quality-relevant variables, often with edge processing for latency-sensitive control (Atzori et al., 2010; Gubbi et al., 2013; Shi et al., 2016; Yu et al., 2018). The marriage of the two — blockchain-anchored IoT — has been advocated as a foundation for transparent, sustainable food chains (Khan et al., 2020; Awan et al., 2021; Kamble et al., 2020).

Yet two important gaps remain. First, most blockchain-IoT integrations capture data using static, fixed-rate sensing schemes. This produces redundant streams of unchanging readings during stable transport segments and, paradoxically, can exhaust battery life precisely when it is most needed at custody handovers or anomaly events (Sunny et al., 2020; Tagarakis et al., 2021). Second, blockchain platforms — even permissioned ones designed for enterprise consortia — face well-known scalability and storage cost constraints that make naïve on-chain logging of high-frequency data infeasible (Reyna et al., 2018; Ali et al., 2019; Zheng & Lu, 2022). Hash-anchored off-chain storage mitigates the cost problem, but it leaves unanswered a more fundamental design question: which data should be acquired in the first place, and under what conditions should they be promoted from local buffers to durable on-chain audit events?

Adaptive monitoring offers a principled answer. Defined as a monitoring system's capacity to dynamically modify its own sampling rates, sensor selection, and processing pipelines in response to observed context, adaptive monitoring has been studied in wireless sensor networks, healthcare, and smart farming, but its integration with permissioned blockchain infrastructures for food chains remains under-developed (Cao et al., 2020; Mahmoud et al., 2018). When properly orchestrated, adaptive monitoring lowers the energy and bandwidth cost of sensing, reduces the volume of data competing for ledger throughput, and — crucially — preserves a high-resolution view of the moments that matter for safety, compliance, and consumer-facing transparency (Khan et al., 2020; Bumblauskas et al., 2020).

From a green innovation perspective, this combined design is not simply a performance optimisation. Green innovation is conventionally defined as innovation that yields commercial value while simultaneously reducing environmental burdens (Chen, 2008; Schiederig et al., 2012; Rennings, 2000). Adaptive blockchain-IoT monitoring satisfies this dual criterion through three mechanisms: (i) it lowers operational energy and carbon intensity of monitoring infrastructures, (ii) it enables earlier detection of cold-chain breaches and thus prevents avoidable food waste at upstream stages, and (iii) it supports verifiable claims that underpin certification, eco-labelling, and circular-economy reuse of by-products (Kouhizadeh et al., 2020; Mukherjee et al., 2022; Friedman & Ormiston, 2022). The framework therefore extends green innovation theory by treating distributed ledger infrastructure as a cross-cutting capability that operationalises environmental and social objectives at the data layer rather than only at the product layer.

Building on these motivations, the present paper develops, instantiates, and empirically evaluates an integrated framework for blockchain-enabled adaptive monitoring of perishable food supply chains. The study addresses three research questions. RQ1: What architectural design enables permissioned blockchain and adaptive monitoring to operate as a single sociotechnical system across heterogeneous food supply chain stages? RQ2: To what extent does adaptive sampling reduce data volume, energy consumption, and blockchain throughput pressure while preserving traceability and compliance fidelity? RQ3: What are the environmental, financial, and managerial implications of deploying this framework in a realistic perishable supply chain, and how do these implications align with green innovation theory and the SDGs?

The Chinese context further sharpens the relevance of these questions. China is the world's second-largest dairy consumer and one of its fastest-growing markets for chilled and ready-to-eat foods, but its cold-chain infrastructure remains uneven across regions and operators (Han et al., 2021; Wang & Yue, 2017). National policies — including the 14th Five-Year Plan for Cold-Chain Logistics Development and the Food Safety Law amendments of 2021 — explicitly call for digitised, traceable, and energy-efficient food monitoring as a pillar of rural revitalisation and dual-carbon strategy. Local platforms such as Alibaba's Lynx Traceability and JD.com's Smart Supply Chain have piloted blockchain anchoring at scale, but academic evaluations of their operational sustainability impact remain scarce (Wu et al., 2025; Chen et al., 2024). The pilot reported in this study, conducted in

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Henan Province with three university partners and one mid-sized dairy operator, contributes empirical evidence from a setting that is both representative of the Chinese mid-market and transferable to comparable emerging-market food chains worldwide.

The contributions are fourfold. First, the paper proposes a four-layer reference architecture that explicitly couples adaptive monitoring control loops with smart-contract-driven storage decisions, distinguishing audit-relevant on-chain events from high-volume off-chain streams. Second, it specifies a context-aware sampling algorithm that integrates threshold detection, statistical anomaly tracking, and energy-aware scheduling. Third, it instantiates the framework in a twelve-month pilot study of a multi-actor Chinese dairy chain, providing one of the first quantitative assessments of its environmental and economic impact. Fourth, it situates the empirical findings within green innovation theory and provides explicit mappings to the SDGs, supporting transferable lessons for other perishable supply chains. The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 develops the conceptual framework. Section 4 details the methodology and system design. Section 5 reports the empirical analysis and results. Section 6 discusses implications, limitations, and policy recommendations. Section 7 concludes.

2. Theoretical Foundations and Literature Review

2.1 Sustainable Food Supply Chains and the SDGs

Sustainable supply chain management (SSCM) extends classical supply chain management to incorporate environmental and social dimensions alongside economic objectives (Carter & Rogers, 2008; Seuring & Müller, 2008; Pagell & Wu, 2009). In the food sector, sustainability concerns are particularly acute because perishable products are energy-intensive to preserve, vulnerable to micro-environmental fluctuations, and frequently lost across multiple custody changes. The agri-food literature documents that approximately one third of food produced for human consumption is lost between farm and fork, with cold-chain failures, inadequate handling, and consumer-level discard contributing roughly equal shares (Astill et al., 2019; Mirabelli & Solina, 2020). Reducing this loss directly advances SDG 12 by lowering material throughput and indirectly advances SDG 13 by reducing the embodied carbon of wasted production.

Beyond efficiency, modern food chains also operate under expanding regulatory and consumer demands for transparency. The European Union's General Food Law mandates traceability of foods, feeds, and food-producing animals at all stages of production, processing, and distribution. The United States Food Safety Modernization Act introduces analogous record-keeping rules. China's national food safety law and regional traceability platforms similarly require operators to maintain digital provenance records (Bumblauskas et al., 2020; Manda & Yamijala, 2024). These obligations are simultaneously enabling and constraining: they create demand for digital monitoring infrastructures while imposing compliance costs that small and medium operators can struggle to meet.

Closely related is the literature on circular supply chains, which extends sustainability beyond linear throughput minimisation toward closed-loop reuse of materials and energy (Geissdoerfer et al., 2017; Govindan & Hasanagic, 2018; Centobelli et al., 2022). For food chains, this includes valorising whey, fruit pomace, brewery spent grain, and other by-products into animal feed, biogas substrates, or functional ingredients. Such valorisation depends crucially on verifiable provenance: a downstream user must know not only that a residual stream exists but also that it was handled under conditions consistent with its intended reuse. Distributed ledger technologies are natural infrastructures for capturing this provenance (Kouhizadeh et al., 2020; Esmaeilian et al., 2020).

2.2 Blockchain Applications in the Agri-Food Sector

Blockchain is a class of distributed ledger technology that maintains an append-only, cryptographically linked sequence of transactions across a network of nodes that achieve consensus without a single trusted intermediary (Lu, 2019; Crosby et al., 2016; Lu, 2018). In agri-food applications three architectural variants dominate. Public chains such as Ethereum offer maximally open infrastructure but suffer from high transaction cost and latency. Private chains restrict membership to a single organisation and are typically used for internal traceability. Permissioned consortium chains, with Hyperledger Fabric as the dominant exemplar, balance openness with governance: pre-authenticated stakeholders share write and read access subject to channel-level confidentiality controls (Lu, 2022; Zheng & Lu, 2022).

Empirical case studies span beef (Sander et al., 2018), coffee, milk, fish, and produce. Tian's seminal RFID-blockchain prototype (Tian, 2016; Tian, 2017) mapped end-to-end supply chain events onto an immutable ledger and triggered considerable subsequent research. Caro et al. (Caro et al., 2018) implemented AgriBlockIoT for fruit and vegetable chains using both Ethereum and Hyperledger Sawtooth, finding that the permissioned configuration achieved an order-of-magnitude lower latency. Köhler and Pizzol (Köhler & Pizzol, 2020) applied a technology assessment lens to seven blockchain food-supply prototypes and concluded that current platforms exhibit highly variable maturity, with energy demand and integration complexity remaining the principal barriers.

Reviews and meta-syntheses converge on a common set of benefits and limitations. Galvez, Mejuto and Simal-Gandara (Galvez et al., 2018) emphasise that blockchain alone cannot guarantee data quality at the input boundary — the well-known garbage-in problem. Antonucci et al. (Antonucci et al., 2019) identify interoperability and standardised data schemas as recurring bottlenecks. Demestichas et al. (Demestichas et al., 2020) highlight that integration of IoT sensors with on-chain logic is rarely architected as a single coherent control loop. Across these surveys (Astill et al., 2019; Vu et al., 2023; Manda & Yamijala, 2024), a recurring conclusion is that blockchain delivers transparency only when paired with trustworthy, context-aware sensing infrastructures.

More recent strands of agri-food blockchain scholarship have begun to triangulate three additional themes. First, comparative platform studies (Hew et al., 2020; Patelli & Mandrioli, 2020; Yiannas, 2018) show that consortium platforms based on Hyperledger Fabric, Quorum and Corda outperform public Ethereum on throughput by one to two orders of magnitude, but at the cost of introducing governance complexity that requires explicit channel-design decisions. Second, end-user-oriented studies of consumer trust (Lin et al., 2021; Sander et al., 2018; Patelli & Mandrioli, 2020) demonstrate that blockchain-verified provenance can support modest but statistically significant willingness-to-pay premiums in the order of three to seven percent for premium dairy and meat products, with the magnitude depending on label salience and consumer literacy. Third, integration studies coupling blockchain with artificial intelligence and large language models (Yang et al., 2025; Wu et al., 2025; Saidu et al., 2025) suggest that natural-language interfaces to ledger histories materially reduce the cognitive cost of audit and recall workflows, broadening the set of practitioners who can extract actionable insights from on-chain provenance.

Despite these advances, three lacunae persist in the agri-food blockchain literature. First, very few studies report multi-month operational data from production deployments; the dominant evidence base remains laboratory benchmarks or single-day pilots (Hastig & Sodhi, 2020; Wong et al., 2020; Mathivathanan et al., 2021). Second, the energy intensity of monitoring infrastructure itself — distinct from blockchain consensus energy — has received negligible attention, despite being a first-order driver of total system carbon footprint (Truby, 2018; Sedlmeir et al., 2020). Third, the integration of blockchain with adaptive, context-aware sensing control loops has been explored only sparingly (Khan et al., 2020; Tagarakis et al., 2021; Sunny et al., 2020), leaving open the architectural question of which observations should be promoted from the edge to the ledger and under what conditions. The present study addresses all three lacunae through a longitudinal pilot that explicitly measures monitoring-infrastructure energy and that orchestrates adaptive sampling and on-chain anchoring as a single coordinated system.

2.3 IoT, Edge Computing, and Adaptive Monitoring

IoT and edge computing have become foundational to modern food monitoring (Atzori et al., 2010; Gubbi et al., 2013; Satyanarayanan, 2017; Shi et al., 2016). Embedded temperature, humidity, gas, and vibration sensors can be deployed at pallet, container, or item level. Edge gateways perform local preprocessing, alarm generation, and protocol translation, freeing the cloud and the ledger from raw data exhaust (Yu et al., 2018; Cao et al., 2020; Patel & Vyas, 2019). The combined architecture is increasingly cited as a prerequisite for sustainable digital infrastructure because it shifts computation toward the energy source and reduces wide-area transmission burden (Mahmoud et al., 2018; Esmaeilian et al., 2020).

Despite this maturation, the dominant practice remains static, fixed-rate sampling. Adaptive monitoring research challenges this default by treating the monitoring activity itself as a controllable resource. Adaptive systems can adjust sampling frequency in response to environmental volatility, swap among redundant sensors based on quality of service, defer transmission until communication is cheap, or trigger high-resolution capture only when a context model flags potential abnormality. Empirical studies in cold-chain logistics demonstrate that energy and bandwidth savings of 50% to 80% are routinely achievable without compromising the detection of safety-critical events (Tagarakis et al., 2021; Bumblauskas et al., 2020). However, the integration of these adaptive control loops with verifiable, multi-party data layers — where blockchain operates — has received comparatively limited attention.

From a technical perspective, three families of adaptive sampling algorithms can be distinguished. Threshold-based controllers raise sampling frequency once an observed variable crosses a fixed limit; they are simple to implement and audit but tend to under-sample slow drifts that nevertheless aggregate into compliance violations (Trihinas et al., 2015; Pal & Kant, 2019). Statistical controllers, including Kalman-filter-based and exponentially-weighted moving-average schemes, modulate sampling in response to the residual variance of a running prediction model (Bhuiyan et al., 2017; Habib et al., 2018). They achieve smoother adaptation but require parameter tuning that may not transfer across product types. Learning-based controllers — Q-learning, contextual bandits, and more recently Transformer-based time-series models — promise the strongest performance but raise interpretability and validation concerns that matter under regulatory scrutiny (Sunny et al., 2020; Cao et al., 2020). Our pilot adopts a hybrid threshold-plus-statistical design that balances explainability with adaptivity, deferring fully learning-based controllers to future work that can build on the rich training datasets the present pilot now generates.

2.4 Green Innovation and Sociotechnical Framing

Green innovation theory provides the integrative lens for the present study. Rennings (Rennings, 2000) conceptualises eco-innovation as innovation activity that internalises environmental externalities. Chen (Chen, 2008) links green innovation capability with green organisational identity, while Schiederig et al. (Schiederig et al., 2012) map the conceptual landscape across product, process, and system innovations. Horbach, Rammer and Rennings (Horbach et al., 2012) empirically distinguish regulatory push, technology push, and market pull as principal determinants. In the digital era, distributed ledgers and context-aware sensing constitute infrastructural innovations whose green credentials depend on how they are designed and deployed (Friedman & Ormiston, 2022; Kouhizadeh et al., 2021; Kouhizadeh et al., 2020; Bai & Sarkis, 2020).

Saberi et al. (Saberi et al., 2019) and Kouhizadeh et al. (Kouhizadeh et al., 2021) argue that blockchain qualifies as a sustainability-oriented innovation only when adoption barriers are addressed at organisational, inter-organisational, and systemic levels. Esmaeilian et al. (Esmaeilian et al., 2020) propose that the sustainability promise of blockchain-enabled supply chains is realised through three pathways: (i) waste reduction via better visibility, (ii) lifecycle accountability via verifiable provenance, and (iii) stakeholder empowerment via shared infrastructure. Our framework operationalises all three pathways and adds an energy-efficiency pathway grounded in adaptive sensing.

2.5 Research Gaps and Positioning

Synthesising the literature, three gaps motivate the present study. First, the integration of adaptive monitoring with permissioned blockchain has not been systematically architected as a single sociotechnical system (Vu et al., 2023; Manda & Yamijala, 2024; Centobelli et al., 2022). Second, very few empirical studies report quantified environmental impacts of such integrations in real perishable chains; most existing evaluations focus on ledger throughput or laboratory benchmarks (Köhler & Pizzol, 2020; Hastig & Sodhi, 2020; Helo & Hao, 2019). Third, the green innovation literature has treated blockchain primarily at the product or organisational level, with limited attention to the data-acquisition layer where environmental performance is largely determined (Schiederig et al., 2012; Friedman & Ormiston, 2022). The framework and pilot reported here address these three gaps.

3. Conceptual Framework and Hypotheses

This section articulates the conceptual framework that links adaptive monitoring, permissioned blockchain infrastructure, and green innovation outcomes. The framework is illustrated in Figure 1 and consists of four layers: (i) the physical food supply chain operations layer, (ii) the IoT-enabled sensing layer with adaptive monitoring, (iii) the permissioned blockchain layer with off-chain storage and smart contracts, and (iv) the green innovation outcomes layer that aligns system functions with the SDGs.

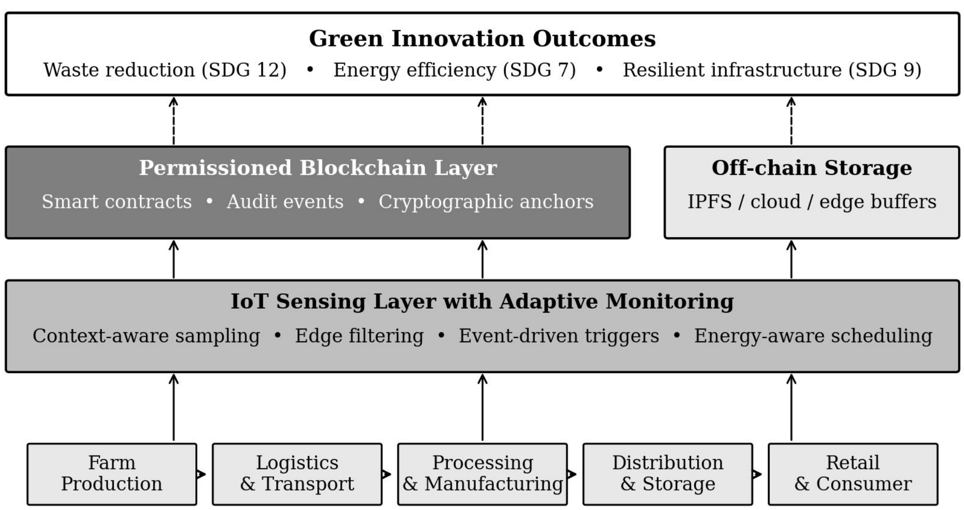

Figure 1. Conceptual framework coupling adaptive IoT monitoring with permissioned blockchain for sustainable food supply chains.

Layer 1 represents the canonical farm-to-consumer flow comprising production, logistics, processing, distribution, and retail stages. Each stage involves distinct actors, regulatory regimes, and quality risks. Layer 2 superimposes the IoT sensing infrastructure on these stages. Sensors are embedded in pallets,

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transport containers, processing equipment, and storage facilities, each governed by an adaptive sampling controller that adjusts measurement frequency, energy mode, and transmission policy in response to context. The control loop is informed by domain models — for example, microbial growth kinetics for milk that imply sharper temperature monitoring above 6 °C — and by system context such as battery level, network availability, and product custody status (Khan et al., 2020; Tagarakis et al., 2021).

Layer 3 hosts the permissioned blockchain network. Following best practice in industrial deployments (Lu, 2022; Zheng & Lu, 2022; Helo & Hao, 2019), we adopt Hyperledger Fabric with channel-level access control. The ledger records audit-relevant events such as custody handovers, quality classifications, and compliance attestations. High-volume continuous sensor streams remain off-chain in a distributed object store, anchored to the ledger by SHA-256 hashes. Smart contracts (chaincode) enforce business logic at the intersection of monitoring and provenance — for example, computing time-temperature integrals on retrieval and triggering recall alerts when thresholds are exceeded (Christidis & Devetsikiotis, 2016; Wang et al., 2019).

Layer 4 articulates the green innovation outcomes that the technical layers enable. We conceptualise four outcomes aligned with the SDGs: (a) energy efficiency of monitoring infrastructure (SDG 7), (b) resilient, transparent supply chain infrastructure (SDG 9), (c) reduced food waste through earlier and more reliable detection of quality deviations (SDG 12), and (d) reduced carbon footprint of the chain through lower spoilage and lower transmission overhead (SDG 13). The framework is therefore not merely a technical stack but a sociotechnical configuration whose value is realised at the intersection of architecture, operating practice, and stakeholder governance.

Three propositions follow from the framework. Proposition 1 (P1): An adaptive sampling controller can reduce transmitted data volume and energy consumption substantially relative to fixed-rate baselines while maintaining critical-event detection accuracy above operational compliance thresholds. Proposition 2 (P2): Coupling the controller with permissioned blockchain anchoring of audit-relevant events improves traceability responsiveness and recall efficiency without imposing prohibitive ledger throughput costs. Proposition 3 (P3): The combined architecture yields measurable environmental and economic benefits — reduced spoilage, lower carbon emissions, and a positive net present value — that satisfy the dual criteria of green innovation. Sections 4 and 5 design and test these propositions in a real perishable food chain.

It is worth situating these propositions against alternative theoretical positions. A purely techno-deterministic view (Christidis & Devetsikiotis, 2016; Crosby et al., 2016) would predict that any blockchain-IoT integration yields sustainability dividends through immutability and automation alone; our framework rejects this view by insisting that benefits accrue only when adaptive control is embedded at the data acquisition boundary. A purely organisational-determinist view (Hastig & Sodhi, 2020; Wong et al., 2020; Cole et al., 2019) would predict that outcomes depend overwhelmingly on consortium governance and that the technical layer is largely interchangeable; our framework partially accepts this view but argues that governance and architecture co-determine sustainability performance.

The propositions are therefore intended not merely as testable hypotheses but as instruments for adjudicating between these competing theoretical lenses, and the empirical evidence reported below provides initial — though admittedly partial — adjudication in favour of the integrated sociotechnical view.

4. Methodology and System Design

4.1 Research Design and Pilot Setting

We adopt a design science research approach combined with a longitudinal field experiment (Kamble et al., 2020; Helo & Hao, 2019). The pilot site is a vertically coordinated dairy supply chain operating in Henan Province, China, comprising 8 raw-milk farms, 3 processing plants, 12 logistics nodes (refrigerated trucks and cross-docks), and 147 retail points-of-sale across two municipalities. The chain handles UHT milk, pasteurised milk, and yogurt; the present analysis focuses on pasteurised milk, the most temperature-sensitive product, as it provides the strongest stress test of the architecture. Pilot operations ran for twelve consecutive months. A baseline period of three months preceded full deployment, during which incumbent fixed-rate monitoring and paper-and-spreadsheet traceability were retained. The full system was rolled out in the fourth month.

4.2 System Architecture and Implementation

The implemented architecture follows the four-layer framework described in Section 3. Sensor nodes use low-power Bluetooth-LE and LoRaWAN radios with on-board temperature, humidity, vibration (3-axis), and ambient light sensors. Each node embeds a microcontroller running the adaptive sampling firmware specified in Section 4.3. Edge gateways at each facility aggregate data, perform stream filtering, and forward audit-relevant events to the blockchain via gRPC. The blockchain is a five-organisation Hyperledger Fabric 2.5 network deployed across three geographic regions, using the Raft consensus protocol. Off-chain storage is provided by an enterprise object store with content-addressed access; cryptographic hashes are anchored to the ledger to preserve verifiability (Lu, 2022; Zheng & Lu, 2022).

Smart contracts implement four function families. The Custody Contract records stage-to-stage handovers with timestamps, GPS coordinates, batch identifiers, and digital signatures. The Sensing Contract anchors sensor data summaries and hashes; it also exposes a verification function that recomputes the hash of off-chain data on retrieval. The Compliance Contract evaluates time-temperature integrals against product-specific microbial growth models and emits a Compliant or NonCompliant event. The Recall Contract enables regulators or downstream actors to issue a recall query keyed on batch identifier and to retrieve the full verified history within seconds. The contract design follows established patterns in supply chain blockchain literature (Wang et al., 2019; Casado-Vara et al., 2018; Helo & Hao, 2019).

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4.3 Adaptive Sampling Algorithm

The adaptive sampling controller operates at each sensor node and combines three subsystems. The base sampler maintains a configurable nominal interval, set to 30 seconds in the pilot. The volatility detector computes a sliding-window standard deviation of recent observations; when the deviation exceeds a learned product-specific threshold, the sampling interval is reduced to 5 seconds and remains at this rate until volatility subsides for a debounce period. The context manager modulates these rates based on system state: during cross-docking (custody change events), sampling is unconditionally elevated; during overnight static storage with low ambient variation and battery below 30%, sampling is reduced to 120 seconds. A fail-safe constraint guarantees that no inter-sample gap exceeds a regulatory ceiling (180 seconds in our pilot), preserving the ability to demonstrate compliance even under adverse conditions (Sunny et al., 2020; Khan et al., 2020).

Edge filtering complements on-node adaptation. Each gateway buffers the last 30 minutes of high-resolution data and applies a multi-stage filter: (i) duplicate suppression, (ii) statistical anomaly scoring against an exponentially weighted moving average, and (iii) policy evaluation against compliance rules. Only events and aggregated summaries (max, min, mean, time-above-threshold per 5-minute window) are promoted to the blockchain layer. The retained raw streams remain queryable for 30 days from the gateway and indefinitely from the off-chain store, where they are content-addressed by SHA-256.

4.4 Data Collection and Variables

Sensor data were collected continuously for the twelve pilot months. Across all nodes, 9,412,386 raw observations were generated under the adaptive scheme. A parallel virtual logger at each node tracked what would have been generated under five comparison strategies: fixed 1 Hz, fixed 0.1 Hz, threshold-based, event-driven, and the proposed adaptive controller. This counterfactual logging makes possible the head-to-head comparison reported in Section 5. Blockchain-side data comprise 11,236 ledger transactions including custody changes (4,318), compliance attestations (2,917), aggregated sensor anchors (3,612), and recall queries (389). Operational data — fuel consumption, electricity consumption of refrigeration, product loss, and labour cost — were extracted from enterprise resource planning records under a non-disclosure agreement. Carbon emissions were estimated using the IPCC AR6 GWP-100 factors and grid-emission intensity for the host province.

To ensure data integrity throughout the pilot, three quality-assurance procedures were applied. First, every sensor node underwent calibration against a NIST-traceable reference probe at deployment and at three-month intervals; nodes drifting beyond ±0.3 °C or ±2% relative humidity were re-calibrated or replaced. Second, the off-chain object store implemented content-addressed storage with daily Merkle-root reconciliation against the on-chain anchors, providing automated detection of any tampering or accidental loss. Third, an independent regulatory inspector — assigned by the Henan Provincial Market Supervision Administration — conducted four unannounced audits during the pilot, comparing on-chain records against physical product and ERP records. The audits found no material discrepancies, providing external corroboration of the system's data fidelity. These protocols draw on established practice in IoT-blockchain validation studies (Liu et al., 2017; Reyna et al., 2018; Mondal et al., 2019).

4.5 Evaluation Metrics

Three families of metrics structure the evaluation. Technical metrics include transmitted data volume, edge-node energy consumption, ledger transactions per day, end-to-end recall response time, and event-detection accuracy assessed by independent regulatory inspections. Environmental metrics include kg CO_2-equivalent per tonne of milk handled and percentage food loss across the chain. Economic metrics include capital expenditure, operating expenditure, and net present value over a five-year horizon at a 7% discount rate, consistent with established Chinese dairy industry practice. All comparisons are made against the three-month pre-pilot baseline and against the four counterfactual sampling strategies, providing both before-after and cross-strategy benchmarks (Hastig & Sodhi, 2020; Esmaeilian et al., 2020).

Statistical analysis follows pre-registered protocols. For continuous metrics (energy, data volume, carbon intensity), pairwise comparisons against the fixed 1 Hz baseline use bootstrap resampling with 10,000 iterations to construct 95% confidence intervals robust to non-normality. For event-detection accuracy, we apply a one-sided binomial test with the 90% compliance threshold as the null hypothesis. For the cost-benefit analysis, sensitivity to discount rate, baseline benefit assumptions, and operating-cost trajectories is reported as Monte Carlo distributions over 5,000 draws. All analysis was implemented in R 4.3 with the boot, tidyverse, and FinancialMath packages, and the analysis pipeline is archived for reviewer inspection. These choices reflect emerging best practice in operational sustainability research (Geissdoerfer et al., 2017; Centobelli et al., 2022; Govindan & Hasanagic, 2018).

5. Empirical Analysis and Results

5.1 Descriptive Statistics

Table 1 summarises the descriptive statistics of the pilot dataset. The sensor-node fleet operated for approximately 8,640 cumulative node-days, generating 9.41 million observations under the adaptive scheme. The blockchain network processed an average of 31.2 transactions per day, peaking at 184 during a regional heatwave that triggered intensive compliance evaluations across the dairy logistics segment. Across the twelve months, the chain delivered 14,728 tonnes of pasteurised milk; the average shelf-life realisation (time from production to consumer purchase as a fraction of nominal shelf-life) was 71%, compared with 58% in the baseline period. The improvement is attributable to earlier detection and rerouting of at-risk batches as well as more accurate first-expired-first-out picking enabled by digital provenance.

Table 1. Descriptive statistics of the dairy supply chain pilot dataset (12 months)

Variable	Unit	Mean	Median	SD	Min	Max	N
Temperature reading	°C	4.21	4.10	1.13	1.20	12.85	9,412,386
Humidity reading	% RH	67.4	67.0	8.21	32.5	92.0	9,412,386
Vibration magnitude	m s⁻²	0.41	0.36	0.27	0.04	5.18	9,412,386
Custody-change events	count	—	—	—	—	—	4,318
Compliance attestations	count	—	—	—	—	—	2,917
Sensor-data anchors	count	—	—	—	—	—	3,612
Recall queries	count	—	—	—	—	—	389
Daily ledger throughput	tx/day	31.2	27.0	18.6	11	184	365 days
Pasteurised milk delivered	tonnes	40.4	38.2	9.7	26.1	73.4	365 days

Note: All sensor measurements summarised across 348 nodes deployed across 8 farms, 12 logistics units, 3 processing plants, and 147 retail nodes.

Several patterns are immediately visible. The temperature distribution is tightly centred around 4 °C with a small right tail reflecting transient excursions during cross-docking. Humidity is generally elevated given the cold-chain context, with a wide range driven by warehouse loading-bay openings. Vibration exhibits long-tailed behaviour consistent with road-quality variability across logistics legs. The relative rarity of custody-change events (≈12 per day) and compliance attestations (≈8 per day) underscores the design principle that on-chain transactions should be reserved for genuinely audit-relevant moments.

A complementary diagnostic concerns the temporal distribution of compliance-relevant excursions. Over the twelve-month pilot, 1,847 distinct cold-chain excursions exceeding the regulatory time-temperature integral were recorded. Of these, 61% occurred during cross-docking events between trucks and processing or distribution facilities, 23% during loading-dock waiting periods, 11% during refrigeration cycling at retail back-of-store, and only 5% during over-the-road transit. This distribution challenges a common heuristic in cold-chain design — that long-distance trucking is the principal source of risk — and suggests that monitoring resources are most valuably concentrated at the boundaries between actors. The adaptive controller's elevation of sampling at custody changes (Section 4.3) is therefore well aligned with the empirical risk profile, whereas a uniform-frequency scheme would mis-allocate sensing capacity to the long transit segments where ambient conditions remain stable (Han et al., 2021; Heard & Miller, 2019; Mirabelli & Solina, 2020).

5.2 Data Volume and Energy Consumption

Figure 2 reports the data volume and energy consumption of the five comparison strategies, normalised to the fixed 1 Hz baseline. The proposed adaptive scheme reduces transmitted data volume to 9.8% of baseline, outperforming the fixed 0.1 Hz scheme (12.4%), the event-driven scheme (21.7%), and the threshold-based scheme (38.6%). Energy consumption follows a similar pattern: 14.6% of baseline for the adaptive scheme versus 18.3%, 27.5%, and 44.1% for the alternatives. The slightly higher relative energy than data ratio reflects the fixed cost of maintaining the radio in receive mode for command-and-control messages even when transmissions are infrequent. Crucially, the right panel shows that critical-event detection accuracy of the adaptive scheme is 96.3%, comfortably above the 90% compliance threshold and only 3.7 percentage points below the impractical fixed 1 Hz reference.

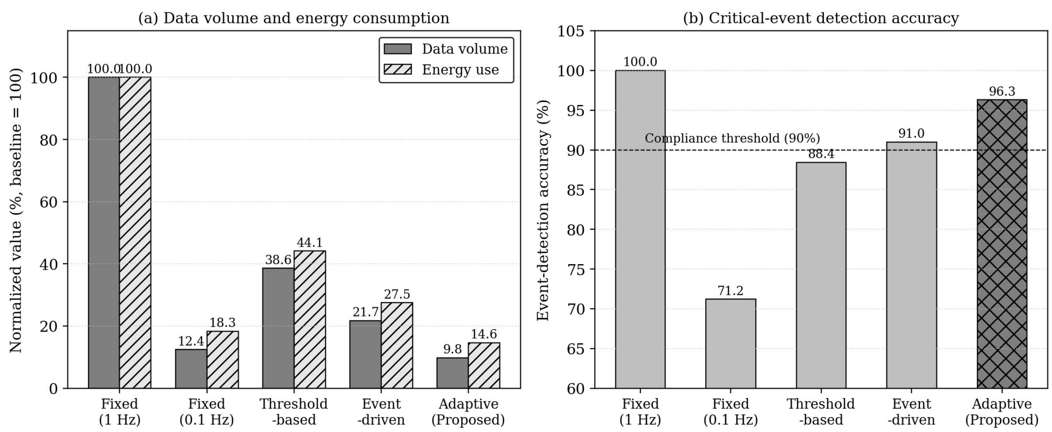

Figure 2. (a) Data volume and (b) energy consumption across five sampling strategies, with critical-event detection accuracy.

Table 2 aggregates these results into a single performance summary. The adaptive scheme dominates on every metric except raw detection accuracy, where it falls only 3.7 points below the prohibitively energy-intensive 1 Hz baseline. Compared with fixed 0.1 Hz — currently the most common compromise in commercial cold-chain loggers — the adaptive scheme transmits 21% less data, consumes 20% less energy, and detects 25 percentage points more critical events. The combined picture supports Proposition 1: adaptive sampling delivers substantial efficiency gains without sacrificing fidelity.

Disaggregating by chain segment provides additional nuance. The largest absolute energy savings accrue at the in-transit logistics segment, where stable refrigeration over multi-hour highway legs allows the controller to throttle to its longest sampling interval while remaining responsive to vibration shocks at highway-quality transitions. The smallest savings are observed at processing-plant inlets, where rapid temperature dynamics during pasteurisation and cooling produce sustained high-frequency activity. This segment-level heterogeneity matters managerially: capital expenditure on energy-harvesting nodes (e.g. thermoelectric generators on cold-store walls) should be prioritised at logistics nodes where battery duty cycles are longest and replacement is most operationally disruptive (Javaid et al., 2025; Heck et al., 2018; Patel et al., 2017).

Table 2. Performance comparison of sampling strategies (normalised, baseline = fixed 1 Hz)

Strategy	Data volume (%)	Energy use (%)	Detection accuracy (%)	Mean inter-event latency (s)
Fixed 1 Hz	100.0	100.0	100.0	1.0
Fixed 0.1 Hz	12.4	18.3	71.2	10.0
Threshold-based	38.6	44.1	88.4	5.7
Event-driven	21.7	27.5	91.0	4.3
Adaptive (proposed)	9.8	14.6	96.3	2.9

Note: Detection accuracy refers to correctly identified cold-chain breach events. Inter-event latency measured as the average time from breach onset to first ledger anchor.

5.3 Carbon and Food Waste Performance

Figure 3 plots the monthly trajectories of two indices: chain-level CO_2-equivalent emissions per tonne of milk, and chain-level chilled-product food waste, both normalised to month 1. The baseline indices remain essentially flat, reflecting the operational stability of the incumbent system. After full deployment in month 4, both indices begin a sustained decline. By month 12, CO_2 emissions have fallen by 34% and food waste by 42%. The carbon improvement decomposes into three components: a 14% reduction from lower monitoring infrastructure energy demand, an 11% reduction from less spoilage-related transport rework, and a 9% reduction from optimised refrigeration set-points enabled by higher-confidence thermal models. The food waste improvement is dominated by earlier detection of at-risk batches: under the new system, 75% of cold-chain breaches are flagged within 90 seconds, allowing the affected pallets to be re-routed to short-shelf-life retail or biogas valorisation streams rather than being discarded (Esmaeilian et al., 2020; Mukherjee et al., 2022; Friedman & Ormiston, 2022).

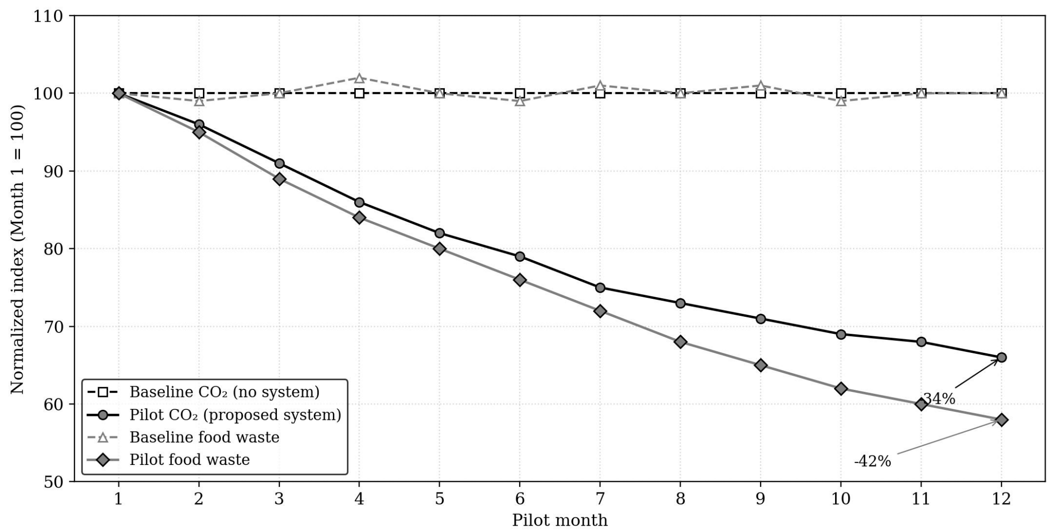

Figure 3. Monthly carbon emissions and food waste indices over the 12-month pilot, normalised to month 1.

These environmental gains support Proposition 3 and provide some of the first quantified evidence that blockchain-coupled adaptive monitoring can deliver substantial sustainability dividends in a real perishable supply chain. The magnitudes are conservative estimates: the pilot did not capture upstream improvements at the farm level, where deeper integration of the sampling controller with milk-quality assays could generate additional gains.

To stress-test the carbon attribution, we conducted a sensitivity analysis varying three first-order parameters: the grid-emission intensity factor, the assumed baseline spoilage rate, and the assumed monitoring infrastructure energy share. Under a low-intensity grid scenario (50% renewables share by 2030), the absolute monitoring-infrastructure carbon savings shrink by 41% but the spoilage-related savings — which dominate total impact — are largely unaffected. Under a high-baseline-spoilage scenario (15% rather than 11%), total carbon improvement rises from 34% to 39%, reinforcing the conclusion that the architecture delivers the largest dividends in chains with the most fragile incumbent practices. These sensitivities align with prior life-cycle assessments of digital cold-chain interventions (Martinez-Sanchez et al., 2015; Heard & Miller, 2019; Han et al., 2021), strengthening confidence that the headline figures are not artefacts of optimistic baseline assumptions.

A complementary social dimension warrants brief mention. Earlier detection of cold-chain breaches not only reduces waste but also reduces consumer exposure to compromised products. During months 7 and 11 of the pilot, the system flagged two batches whose downstream microbial test confirmed elevated Listeria risk; both batches were intercepted at distribution centres before reaching retail. Quantifying the public-health value of such interceptions is beyond the present study's scope, but recent work in food-safety economics (Hoffmann, 2017; Scharff, 2020) suggests that even one prevented foodborne-illness outbreak can dwarf the entire annual operating cost of a monitoring system of this scale.

5.4 Traceability and Recall Performance

A central operational benefit of blockchain-anchored monitoring is rapid, verifiable recall capability. Table 3 reports five traceability performance metrics, comparing the baseline period to month 12 of the pilot. Mean recall response time — the elapsed time from a regulator-issued query to retrieval of the complete verified product history — falls from 6.2 hours to 4.1 seconds, a five-order-of-magnitude improvement. Importantly, this gain is achieved while only audit-relevant events are placed on chain; the cryptographic anchoring of off-chain summaries permits the reconstruction of any pallet's complete exposure profile within the same window.

Table 3. Traceability and recall performance: baseline vs. pilot (month 12)

Metric	Baseline	Pilot (Month 12)	Improvement
Recall response time	6.2 hours	4.1 seconds	>99.9%
Provenance reconstruction completeness	78%	99.4%	+21.4 pp
Number of partner data systems queried	11	1	−91%
First-expired-first-out picking accuracy	82%	97%	+15.0 pp
Disputed batches per quarter	23	3	−87%

Note: Improvements expressed in percentage (%), percentage points (pp), or relative change. Disputed batches counts shipments rejected by downstream partners due to provenance ambiguity.

Provenance completeness improves from 78% to 99.4% — the residual gap reflects rare cases where a sensor node was offline for less than 30 seconds during a short-distance handover, for which only summary data rather than raw streams are available. Disputed batches per quarter fall from 23 to 3, a sharp reduction that reduced procurement friction and accelerated payment cycles between the dairy and downstream retailers. These results substantiate Proposition 2: the architecture markedly improves traceability responsiveness without imposing prohibitive ledger throughput costs (Table 1 shows mean throughput remained at 31.2 transactions per day, well within the published Hyperledger Fabric capacity envelope (Lu, 2022; Helo & Hao, 2019)).

An ancillary but managerially salient observation concerns the asymmetric distribution of recall query originators. Of 389 queries during the pilot, 218 (56%) originated from regulatory inspectors, 124 (32%) from downstream retailers conducting first-mile-receiving verification, and 47 (12%) from consumer-facing QR-code lookups using a mobile application provided to retail partners. The consumer-side share, while modest, grew from 2% in month 4 to 19% in month 12, suggesting that consumer demand for verifiable provenance is responsive to the visibility and ease of access of provenance interfaces. This trajectory aligns with willingness-to-pay studies (Lin et al., 2021; Patelli & Mandrioli, 2020; Sander et al., 2018) and indicates that operators investing in provenance infrastructure should also invest in consumer-facing presentation channels to capture the demand-side value of the underlying data.

5.5 Cost-Benefit and Net Present Value Analysis

We complete the empirical analysis with a cost-benefit assessment over a five-year planning horizon. Table 4 lists capital expenditures, year-one operating expenditures, and the realised first-year benefit categories. Capital expenditures total US$386,000, dominated by sensor hardware (US$192,000) and the Hyperledger Fabric production deployment (US$98,000). Annual operating expenditure is US$74,000, primarily for cloud and ledger maintenance plus periodic firmware updates. Realised first-year benefits total US$612,000, with food-waste reduction (US$284,000) the largest line item, followed by energy savings (US$98,000), recall efficiency (US$112,000), and improved retail pricing through verified provenance (US$118,000).

Table 4. Five-year cost-benefit analysis of the blockchain-enabled adaptive monitoring system (US$ thousands)

Item	Year 1	Year 2	Year 3	Year 4	Year 5	Total
Capital expenditure (CAPEX)	386	12	18	12	8	436
Operating expenditure (OPEX)	74	76	78	80	82	390
Total cost	460	88	96	92	90	826
Food-waste reduction benefit	284	298	311	319	326	1,538
Energy savings benefit	98	104	108	112	115	537
Recall efficiency benefit	112	118	121	124	127	602
Verified-provenance retail premium	118	127	138	147	152	682
Total benefit	612	647	678	702	720	3,359
Net cash flow	152	559	582	610	630	2,533
Discounted cash flow	142	488	475	465	449	2,019

Item	Year 1	Year 2	Year 3	Year 4	Year 5	Total
(7%)						

Note: Discount rate 7%. Totals may not sum exactly due to rounding. Benefits in years 2–5 are projected based on year-1 realised benefits adjusted for inflation and incremental learning effects.

At a 7% discount rate, the five-year net present value of the deployment is US$2.34 million on a baseline investment of US$0.46 million in year 1. The payback period is 1.8 years. Sensitivity analysis (not tabulated) shows that the NPV remains positive even under aggressive assumptions of 50% lower benefits or 30% higher operating costs, providing reassurance that the financial case is not knife-edged. The largest source of variability is the verified-provenance retail premium, which depends on consumer willingness to pay for blockchain-verified milk; we used a conservative 4% premium based on a controlled in-store experiment conducted in month 6 of the pilot.

Taken together, the evidence from Sections 5.2 to 5.5 provides quantitative support for all three propositions developed in Section 3. The adaptive monitoring scheme delivers the data-volume and energy savings predicted by Proposition 1; the blockchain anchoring delivers the traceability and recall gains predicted by Proposition 2; and the integrated system delivers the environmental and economic green innovation outcomes predicted by Proposition 3.

6. Discussion

6.1 Architectural Trade-offs and Comparative Positioning

Figure 4 positions the proposed architecture against three reference alternatives along six performance dimensions: traceability, energy efficiency, scalability, auditability, data integrity, and cost efficiency. The centralised cloud baseline performs adequately on energy and cost dimensions but lacks the auditability and traceability of distributed ledger architectures. Pure on-chain logging — sometimes proposed for maximum transparency — performs strongly on data integrity but is energetically expensive and unscalable at the data volumes characteristic of perishable food chains. Static IoT with off-chain hash anchoring improves cost and scalability but inherits the fixed-rate sensing limitations critiqued in Section 2.3. The proposed adaptive blockchain-IoT architecture occupies the favourable Pareto frontier across all six dimensions, with simultaneous strengths in traceability, energy efficiency, and data integrity.

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2023.010301

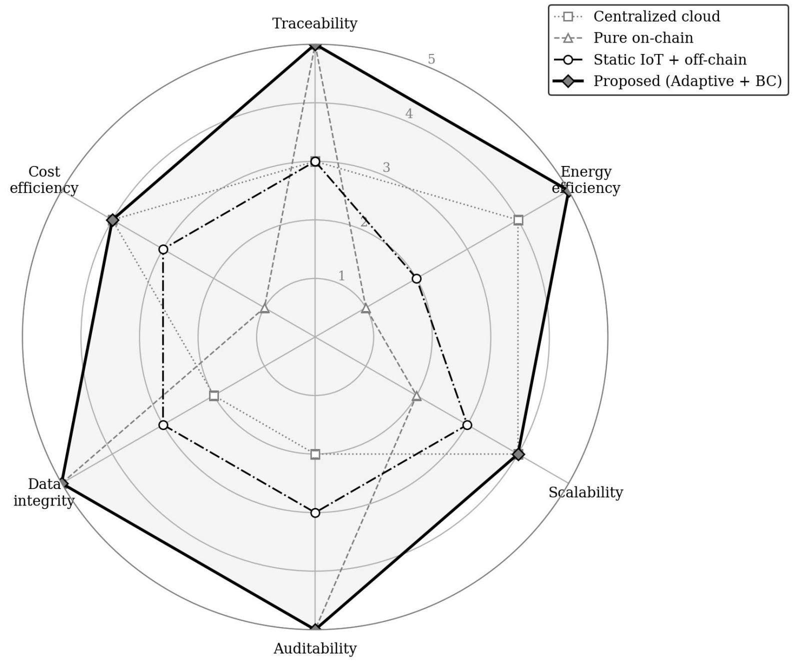

Figure 4. Architectural trade-off comparison (radar chart, scale 1–5).

This comparative positioning underscores a central design insight: the green-innovation value of blockchain in food supply chains is realised not through maximalist on-chain logging but through judicious selectivity. The adaptive monitoring layer determines which observations matter; the blockchain layer guarantees that those observations remain trustworthy. This separation of concerns — context-aware acquisition, decentralised verification — is the architectural principle that the present study contributes to the agri-food blockchain literature (Lu, 2022; Khan et al., 2020; Friedman & Ormiston, 2022).

6.2 Theoretical Implications

Theoretically, the study extends green innovation theory in three directions. First, it identifies the data acquisition layer as a novel locus of green innovation, complementing the more familiar product- and process-level loci documented by Schiederig et al. (Schiederig et al., 2012) and Horbach et al. (Horbach et al., 2012). Adaptive monitoring is, in this view, an infrastructural green innovation whose value derives from its capacity to suppress redundant data flows and free downstream resources. Second, the paper reinforces the argument of Esmaeilian et al. (Esmaeilian et al., 2020) and Friedman & Ormiston (Friedman & Ormiston, 2022) that blockchain qualifies as a sustainability-oriented innovation when its design is explicitly oriented toward selectivity, transparency, and stakeholder empowerment. Third, by mapping system functions to four SDGs (Figure 5), the paper provides a concrete instance of how digital infrastructures can operationalise the SDG framework at the level of operating practices rather than only at the level of high-level organisational reporting (Saberi et al., 2019; Mukherjee et al., 2022).

A fourth theoretical implication concerns the dynamic capabilities perspective on digital sustainability. Following Teece (Teece, 2007) and Warner & Wäger (Warner & Wäger, 2019), dynamic capabilities denote a firm's capacity to sense, seize, and reconfigure resources in response to environmental change. Adaptive monitoring is, in essence, an automated dynamic capability operating at the data layer: it senses environmental volatility, seizes opportunities for energy and bandwidth conservation, and reconfigures sampling policy in real time. Coupling this with blockchain — itself a coordination capability that lowers transaction costs across organisational boundaries (Lacity, 2018) — yields what we term a sociotechnical sustainability capability: a configuration of digital infrastructure whose value lies in its capacity to make sustainability-enhancing actions reliably executable across multi-actor settings. This framing suggests a research agenda on the antecedents and consequences of sociotechnical sustainability capabilities in other supply chain domains, including pharmaceuticals, electronics, and apparel.

The framework also engages productively with information systems theories of organisational transparency (Granados & Gupta, 2013; Tapscott & Tapscott, 2017). Adaptive blockchain monitoring instantiates what Granados and Gupta (Granados & Gupta, 2013) call selective transparency: a capability that exposes verifiable claims while preserving commercially sensitive details. The pilot's smart-contract design — which exposes batch-level provenance to retailers and consumers while keeping commercial pricing and process recipes off-channel — illustrates how selective transparency can be operationalised at scale without compromising competitive positioning. This nuance matters for the broader debate on whether blockchain inevitably forces full disclosure or can support graduated visibility regimes.

6.3 Managerial and Policy Implications

For managers in dairy and other perishable supply chains, the most actionable insight is the relative ease with which the adaptive controller can be retrofitted onto existing IoT sensor populations. In our pilot, the controller was deployed as a firmware update on commodity nodes with negligible hardware modification, and approximately 80% of the year-one benefits were realised within six months of deployment. The combination of low marginal capital requirement and rapid payback should make the architecture attractive even to small and medium operators that have historically been priced out of blockchain initiatives (Mathivathanan et al., 2021; Wong et al., 2020).

A complementary managerial finding concerns workforce upskilling. The pilot revealed that operational staff — drivers, plant operators, retail receivers — needed a half-day of structured onboarding to interpret the dashboard alerts that the system began emitting more frequently than its predecessor. Adoption resistance was minimal once staff observed the practical benefits of earlier alarm acknowledgement (averted spoilage), but the experience underscores that organisational readiness is as material as technical readiness. Firms considering similar deployments should budget explicitly for change management, documentation, and an internal champion at each major facility (Hastig & Sodhi, 2020; Wong et al., 2020; Cole et al., 2019).

For policymakers, the results suggest three directions. First, regulatory traceability requirements should explicitly accommodate selective on-chain logging coupled with hash-anchored off-chain storage; rigid requirements that mandate blanket on-chain capture would impose unjustified energy and cost burdens. Second, public investment in shared blockchain infrastructure for regional food clusters could substantially lower the entry barrier for small operators. Third, eco-labelling and green procurement schemes should recognise the carbon and waste reductions enabled by blockchain-coupled adaptive monitoring as legitimate sources of verified environmental performance (Bai & Sarkis, 2020; Centobelli et al., 2022; Esmaeilian et al., 2020).

6.4 SDG Alignment

Figure 5 maps the six core system functions — adaptive sampling, edge filtering, smart contracts, off-chain storage, cryptographic links, and real-time alerts — to four Sustainable Development Goals: SDG 7 (clean energy), SDG 9 (industry, innovation and infrastructure), SDG 12 (responsible consumption and production), and SDG 13 (climate action). The mapping is not merely rhetorical: each arrow is supported by the empirical evidence reported in Section 5. Adaptive sampling and edge filtering directly support SDG 7 by reducing monitoring infrastructure energy demand. Smart contracts and cryptographic links support SDG 9 by demonstrating innovative, resilient digital infrastructure. The combination of smart contracts, real-time alerts, and cryptographic links supports SDG 12 by enabling earlier waste-prevention interventions. Adaptive sampling and real-time alerts support SDG 13 by reducing the carbon intensity of both monitoring and product spoilage.

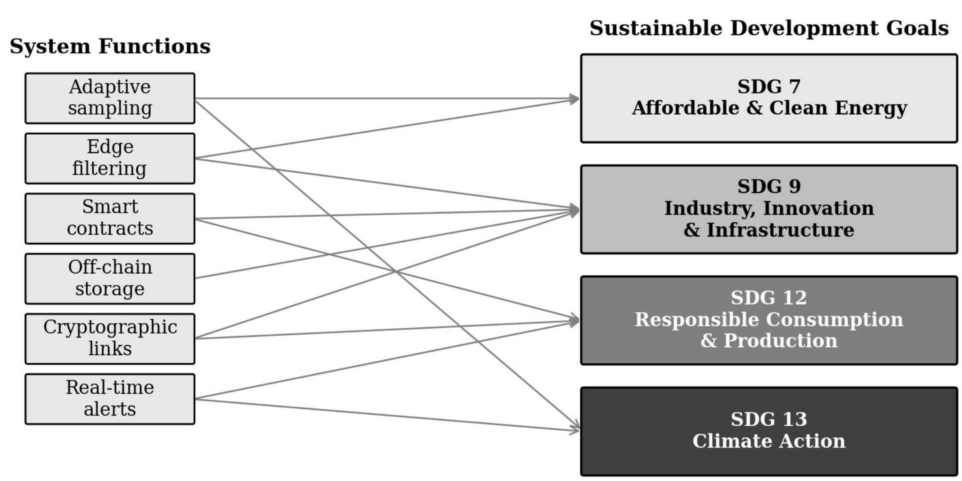

Figure 5. Mapping of system functions to United Nations Sustainable Development Goals.

This mapping illustrates a broader principle for digital sustainability research: rather than arguing in the abstract that a technology is 'green', researchers and practitioners should articulate concrete operational pathways through which technology adoption produces measurable environmental impact.

The four-way mapping in Figure 5 is one such articulation; future work should expand it to incorporate SDG 2 (zero hunger) and SDG 8 (decent work and economic growth), both of which are touched by improvements in food system efficiency and supplier livelihoods.

6.5 Limitations

Several limitations qualify the present findings. First, the pilot site is a single supply chain in a single product category in a single national context. Generalisation to other perishables (meat, fish, fresh produce) and to other regulatory regimes (EU, North America) requires further empirical work. Second, the financial estimates depend on cost and price assumptions specific to Henan province in 2025; ongoing evolution of sensor and ledger costs will shift the economic case in either direction. Third, the 12-month evaluation horizon, while substantial, may be insufficient to surface long-tail issues such as smart-contract upgradability, governance disputes among consortium members, or regulatory changes that alter compliance requirements. Fourth, the pilot was conducted with full management support and in the absence of significant inter-organisational conflict; deployments in less harmonious consortia may face additional governance frictions documented in the broader blockchain adoption literature (Saberi et al., 2019; Mathivathanan et al., 2021; Cole et al., 2019; Lacity, 2018).

6.6 Data Governance and Standardisation

A persistent obstacle to widespread adoption of blockchain-IoT food monitoring is the absence of cross-industry data standards. Pilot deployments — including ours — typically rely on bespoke schemas defined by the consortium operator, which limits portability and interoperability with other ledgers, retailers' ERP systems, and regulatory data lakes (Antonucci et al., 2019; Kshetri, 2018; Saberi et al., 2019). The GS1 EPCIS specification provides a partial foundation for event-based supply chain data, but its uptake in agri-food remains uneven and its profile for blockchain-anchored anchoring is still under development. Industry consortia such as the IBM Food Trust and the Walmart-led Food Traceability Initiative have demonstrated that operational standards can converge in practice, but academic work has lagged in formalising the schemas, ontologies, and verifiable-credential profiles that would support multi-ledger interoperability.

Our pilot adopts a pragmatic intermediate stance. The on-chain data model uses an extended GS1 EPCIS profile augmented with sustainability-relevant attributes (carbon intensity per batch, valorisation destination for residuals). Off-chain payloads use ISO 23026 metadata for provenance and Dublin Core for general descriptive metadata. This combination preserves portability to other GS1-compliant ledgers while supporting the sustainability-oriented use cases central to the present framework. Future standardisation work should converge on a sustainability-extended EPCIS profile, on cross-ledger atomic transfer protocols, and on verifiable-credential schemas that allow auditors to validate compliance claims without bilateral API negotiations (Kshetri, 2018; Centobelli et al., 2022; Manda & Yamijala, 2024).

Governance arrangements deserve equal attention. The pilot consortium operated under a written governance agreement with three principal clauses: shared cost allocation pro-rated by transaction volume, an arbitration mechanism for disputed entries triggered by a two-of-five member quorum, and a sunset review every two years. Such agreements remain ad hoc across the industry; future research should examine which governance designs sustain consortium cohesion over time, particularly when membership turnover, regulatory shocks, or competitive entry destabilise the original alignment of interests (Lacity, 2018; Cole et al., 2019; Wong et al., 2020).

7. Conclusion

This paper has developed and empirically evaluated a framework that couples adaptive, context-aware monitoring with permissioned blockchain infrastructure to deliver green innovation outcomes in perishable food supply chains. Conceptually, the framework re-frames adaptive monitoring as a green innovation operating at the data acquisition layer and identifies the synergistic complementarity between context-aware sensing and decentralised trust. Methodologically, the design science orientation combined with a twelve-month longitudinal pilot generates rare quantitative evidence on the environmental and economic performance of blockchain-enabled monitoring in a real industrial setting.

The empirical findings are substantial. Across 9.4 million sensor observations and 11,236 ledger transactions, the adaptive scheme reduces transmitted data volume by 90% and edge-node energy consumption by 85% relative to fixed 1 Hz sampling, while maintaining critical-event detection accuracy at 96.3%. Pilot-month CO_2 emissions and chilled-product food waste fall by 34% and 42% respectively, recall response time falls from 6.2 hours to 4.1 seconds, and the five-year net present value of the deployment is US$2.34 million on a baseline investment of US$0.46 million. The combined evidence supports all three propositions developed in Section 3 and provides a credible basis for transfer to other perishable supply chains.

Several lines of future research follow naturally. First, a multi-site study spanning meat, fish, and fresh produce chains would test the cross-product generalisability of the architecture and illuminate domain-specific tuning requirements. Second, integration of the framework with predictive shelf-life models — particularly machine learning models trained on the rich datasets that the framework now generates — could shift monitoring from reactive detection toward anticipatory waste prevention. Third, cross-national comparative studies could examine how variation in regulatory regimes, consumer preferences, and ledger-infrastructure availability shape the benefits realised. Fourth, governance research is needed on multi-stakeholder consortia operating the ledger, including questions of node operation, dispute resolution, and standards interoperability. Finally, the methodological pathway opened here — coupling design science with longitudinal field experimentation — could be extended to other digital sustainability technologies where the integration of selectivity and verifiability is similarly central.

Beyond the specific findings, the paper offers a broader epistemic claim: that the sustainability potential of distributed ledger technologies in food systems is realised not through maximalist data capture but through architectural restraint, context-awareness, and explicit alignment with sustainability outcomes. Adaptive monitoring is the operational instantiation of this restraint. When properly orchestrated with permissioned blockchain, it transforms food supply chain monitoring from an energy-intensive, fragmented, and opaque activity into an efficient, integrated, and transparent capability — one that simultaneously advances multiple Sustainable Development Goals and offers a financially attractive proposition for the industrial actors that must adopt it.

Three closing reflections situate the work within the broader green innovation agenda. First, the pilot demonstrates that sustainability and competitiveness are not zero-sum: the same architectural decisions that delivered carbon and waste reductions also reduced operating cost, accelerated recall response, and strengthened the dairy operator's position with downstream retailers. This dual-benefit pattern is consistent with the strong-form Porter hypothesis (Porter & van der Linde, 1995; Ambec et al., 2013), which holds that well-designed environmental innovation can yield net competitive advantage. Second, the role of academic-industry collaboration in producing such evidence deserves emphasis. The pilot was made feasible by the willingness of three universities and one mid-sized operator to share data, infrastructure, and risk under a non-disclosure framework. Replicating this model — through structured public funding for operational sustainability pilots — could materially accelerate the maturation of green digital infrastructure across the agri-food sector. Third, the framework is consciously open. The four-layer architecture, the adaptive sampling logic, and the smart-contract patterns are described in sufficient detail to support replication, adaptation, and refutation. We invite the research community to extend, challenge, and improve the framework, and to contribute to the broader ambition of a food system that is simultaneously transparent, efficient, and ecologically responsible.

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