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Cost-Optimised IoT Architecture for Real-Time E-Waste Monitoring with Operational Validation

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Abstract. Electronic waste (e-waste) is the fastest-growing solid waste stream worldwide, yet formal collection systems remain limited. Many existing Internet of Things (IoT) solutions emphasize advanced functionality at the expense of cost efficiency and practical deployability. This paper presents a cost-optimized IoT architecture for real-time monitoring of e-waste bins. The proposed system adopts a four-layer architecture integrating ESP32 microcontrollers, ultrasonic sensors for fill-level detection, and infrared sensors for monitoring, supported by a Node.js backend that provides real-time data updates. System validation was conducted through sensor calibration (n = 30), functional testing, stress testing, and cost-performance benchmarking against RFID-, GSM-, and LoRa-based alternatives. Experimental results demonstrate a fill-level accuracy of ±3.2%, temperature precision of ±1.8°C, system reliability of 97.3%, uptime of 98.7%, and an average latency of 2.1 s. The deployment cost was USD 78 per bin, which is approximately 40% lower than comparable RFID-based systems. In addition, the system reduced unnecessary collection trips by 35% and yielded an estimated return on investment (ROI) of 8.5 months. These results show that a low-complexity, cost-efficient IoT design can provide a scalable and practical solution for e-waste bin monitoring.

Keywords: IoT architecture; E-waste monitoring; Cost-performance analysis; Sensor-based waste monitoring; Deployment validation; Smart city waste management

1. INTRODUCTION

Electronic and electrical equipment (EEE) has become ubiquitous in modern society, encompassing all products with circuitry, electrical components, and power or battery supply systems [1][2]. The convergence of rapid technological advancement, shortened product lifecycles, and escalating consumer demand has generated unprecedented volumes of electronic waste, creating one of the fastest-growing waste streams globally. According to the Global E-Waste Monitor 2024, e-waste is defined as "all discarded electrical and electronic equipment, including parts that are not reused" [3], representing a complex, heterogeneous mixture containing valuable materials, rare earth elements, and hazardous substances that pose significant environmental and health risks.

The scale of this global challenge is substantial. By 2022, worldwide e-waste generation reached 62 billion kg, equivalent to 7.8 kg per capita, yet only 22.3% (13.8 billion kg) was documented as properly collected and recycled through formal channels [1][4]. This disparity reveals critical deficiencies in current management infrastructure, which impose severe environmental and public health consequences due to toxic materials, including heavy metals, persistent organic pollutants, and flame retardants, present in electronic products [5][6]. The problem is further compounded by the fact that developing countries in Asia currently import over 80% of globally generated e-waste (20–50 million tons annually), where valuable components are recovered through informal recycling approaches that lack adequate environmental safeguards [7][8].

The environmental consequences of improper e-waste handling are far-reaching. A single mobile phone battery can contaminate 600,000 litres of water [4][9][10]. At the same time, mercury poses risks to aquatic ecosystems, as it persists for centuries [11][12]. This contamination cascades through food chains through bioaccumulation of heavy metals, including mercury, lead, cadmium, nickel, arsenic, and chromium [6]. Additionally, persistent organic pollutants from e-waste can significantly reduce soil microbial biodiversity, disrupting ecosystem balance [13][10].

The human health implications are equally serious. Exposure to e-waste results in health complications, including respiratory disorders, dermatological conditions, neurodevelopmental impairments, increased cancer risks, and organ damage, with

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vulnerable populations near disposal sites experiencing disproportionate impacts [13][14][10]. These threats necessitate comprehensive recycling systems that encompass collection, segregation, recycling, and recovery processes implemented at the local and provincial levels [6].

Recognising these challenges, existing e-waste management initiatives are increasingly leveraging Internet of Things (IoT) technologies to enhance operational efficiency and monitoring capabilities. The Internet of Things refers to a network of interconnected physical devices embedded with sensors, software, and network connectivity, enabling them to collect, exchange, and act on data autonomously [15]. In the context of waste management, IoT systems typically comprise sensing devices that monitor physical parameters such as fill levels and temperature, communication modules that transmit data wirelessly to central servers, and centralised platforms that process information and trigger automated responses such as collection alerts or hazard warnings [16].

Current IoT-based approaches demonstrate varying degrees of success alongside notable limitations. Voskergian and Ishaq [17] employed smart bins with RFID technology to improve sorting accuracy. However, prohibitive setup costs and extensive maintenance requirements limit widespread adoption. Farjana et al. [18] developed sensor networks for real-time monitoring of e-waste levels. However, reliance on continuous internet connectivity poses deployment challenges in areas with limited network infrastructure. Sheng et al. [19] explored LoRa-based communication with deep learning for predictive collection scheduling, achieving efficiency improvements. However, their approach requires specialised gateway infrastructure that constrains deployment in resource-limited settings. More broadly, contemporary systems face significant constraints, including limited computational budgets, inadequate infrastructure, and high capital investment requirements [8]. Furthermore, existing systems often lack integration between monitoring hardware and user management platforms, creating operational silos that reduce overall system effectiveness.

While environmental and public health implications underscore the urgency of improved e-waste management, the technical challenge addressed in this study is architectural: how to design a monitoring system that balances accuracy, power efficiency, and deployment cost without reliance on specialised infrastructure. Although prior work has demonstrated technological feasibility through advanced analytics, blockchain traceability, and machine-learning classification, comparatively little research has empirically validated low-complexity IoT architectures explicitly optimised for cost-performance balance and deployment feasibility under realistic organisational conditions. Accordingly, the focus of this work is system integration and operational validation rather than environmental quantification or algorithmic sophistication.

This study addresses this gap by proposing and experimentally validating a cost-optimised ESP32-based IoT architecture for real-time e-waste bin monitoring. The system adopts a layered framework integrating sensing, communication, application, and data layers, aligning with established principles of distributed systems design. The study investigates whether such an architecture can deliver reliable, economically viable real-time monitoring without relying on specialised communication infrastructure. The specific contributions are a deployment-focused IoT architecture optimised for cost-performance balance; quantitative validation across operational, network, and economic metrics; comparative benchmarking against RFID-, GSM-, and LoRa-based systems reported in prior literature; and a scalability-oriented design framework adaptable to smart-city waste-management ecosystems. In this study, deployment-oriented validation refers to experimental evaluation under realistic organisational conditions, including sensor calibration benchmarking, structured functional testing, concurrent network stress testing, and economic feasibility analysis.

2. RELATED WORK

Prior IoT-based e-waste management research spans hardware platforms, communication technologies, automated classification, and blockchain traceability. This section reviews representative developments across these areas, identifying limitations that motivate the architectural focus of the present study. Table 1 synthesises representative IoT-based e-waste management systems across technological focus, cost consideration, deployment validation, and reported limitations.

Table 1. Comparative Synthesis of Representative IoT-Based E-Waste Management Systems

Study	Core Technology	Cost Focus	Deployment Validation	Key Limitation	Architectural Integration Level
[18]	IoT + Cloud + Arduino	No explicit cost optimisation	Prototype-level validation	Cloud dependency; higher energy footprint	Component-level (sensing + cloud analytics)
[19]	LoRa + Deep Learning	Power efficiency emphasis	Experimental validation	Requires LoRa infrastructure	Component-level (communication + prediction layer)
[20]	IoT + Deep Learning classification	No cost modelling	Accuracy-based evaluation	High computational overhead	Functional-module focused (classification-centric)
[21]	CNN-based classification	No deployment economics	Experimental benchmarking	Training data dependency	Algorithm-level focus
[22]	Blockchain + IoT tracking	No cost minimisation	Simulation-based evaluation	Blockchain complexity; energy cost	Tracking-layer focused
Proposed System	ESP32 + Ultrasonic + Thermal + Web platform	Explicit cost optimisation	Multi-scenario validation + economic modelling	WiFi dependency; limited predictive capability	End-to-End Integrated Architecture

As shown in Table I, existing approaches predominantly prioritise advanced functionality, including cloud-based analytics, deep-learning classification, long-range communication, and blockchain traceability. However, comparatively limited emphasis is placed on integrated, cost-optimised architectures validated under deployment-oriented constraints. Explicit economic modelling, hardware simplification, and integration coherence between sensing and operational management layers remain underexplored. These observations motivate the architectural focus of the present study.

2.1. IoT Hardware Platforms and Sensor Technologies

Contemporary IoT-based e-waste management systems demonstrate diverse technological approaches with varying degrees of effectiveness and cost implications. Farjana et al. [18] proposed an IoT- and cloud-based system to automate e-waste collection and sorting by collecting real-time data to optimise waste collection schedules and resource allocation. Their implementation utilises Arduino Mega 2560 microcontrollers with integrated ultrasonic sensors and GSM communication modules, effectively reducing bin overflow incidents by 85% and improving the efficiency of pickup planning. While this approach demonstrates enhanced operational efficiency, significant limitations include data security vulnerabilities, potential reliance on cloud infrastructure, and higher power consumption compared to more recent microcontroller alternatives. Furthermore, reliance on GSM communication incurs ongoing operational costs that may limit scalability in resource-constrained environments. Arduino-based systems, while widely adopted in research implementations, often lack integrated wireless communication capabilities and the power efficiency required for large-scale deployment, necessitating additional communication modules that increase both system complexity and cost. This hardware integration gap is a primary motivation for the ESP32-based approach adopted in the present study.

2.2. Communication Technologies and Network Architectures

Advanced communication technologies have been increasingly integrated into waste management frameworks to address connectivity challenges in diverse deployment environments. Sheng et al. [19] utilised Long Range (LoRa) technology to transmit real-time waste bin data over long distances while minimising power consumption. Their system achieves communication ranges up to 15 kilometres in rural environments while consuming 90% less power than traditional GSM-based approaches. The integration of a TensorFlow deep learning model analyses sensor data to predict optimal emptying schedules. It automates waste segregation processes, improving collection efficiency by 40%.

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However, LoRa-based systems require specialised gateway infrastructure and may face regulatory constraints in certain regions. Additionally, the low data transmission rates inherent to LoRa technology limit the complexity of real-time data that can be transmitted, potentially constraining system functionality for applications requiring high-frequency monitoring.

2.3. Machine Learning and Automated Classification

Machine learning and CNN-based classification approaches have demonstrated strong accuracy in e-waste sorting contexts. Voskergian and Ishaq [20] developed intelligent e-waste bins that incorporate pre-trained object detection models in the TensorFlow Lite framework, achieving 92% identification accuracy, while Deodhar et al. [21] proposed a CNN-based automated classification system across six e-waste categories, achieving 95% accuracy. However, both approaches require substantial computational resources and labelled training data, which constrain deployment in resource-limited environments. Importantly, the present study deliberately excludes such computationally intensive components, prioritising architectural simplicity and low-power operation over classification sophistication.

2.4. Blockchain Integration and Transparency Solutions

Blockchain integration represents an emerging paradigm for enhancing system transparency and traceability in e-waste management. Khan and Ahmad [22] developed blockchain-enabled e-waste management systems that assign unique identifiers to track waste from generation to disposal, enhancing accountability and demonstrating a 60% reduction in illegal dumping. However, blockchain implementation depends heavily on stakeholder participation. It requires significant computational resources for transaction processing, raising sustainability concerns and creating barriers to adoption for smaller recycling operations.

2.5. Synthesis and Research Gap

Table 2 positions representative systems along dimensions of deployment complexity and functional sophistication.

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Table 2. Architectural Positioning of Representative IoT-Based E-Waste Systems

Study	Deployment Complexity	Functional Sophistication
[21]	High	High
[20]	High	High
[22]	Very High	High
[19]	Moderate–High	High
[18]	Moderate	Moderate
Proposed System	Low–Moderate	Moderate

Existing approaches largely occupy the high-sophistication, high-complexity region of this design space. While technologically capable, these architectures introduce increased infrastructure requirements, integration overhead, and deployment costs, limiting their feasibility in resource-constrained environments. Key gaps across the reviewed systems include: the absence of explicit cost modelling, the lack of end-to-end architectural integration between the sensing and operational management layers, and limited empirical validation under realistic deployment conditions. The present study addresses these gaps by proposing a cost-optimised, architecturally integrated IoT system, validated through operational testing and an economic feasibility analysis, without relying on computationally intensive classification or traceability mechanisms.

3. METHODOLOGY

The research followed a structured workflow consisting of five sequential stages: (1) architectural design and component selection, (2) prototype implementation and sensor integration, (3) calibration and accuracy benchmarking, (4) operational validation through functional testing and network stress testing, and (5) economic evaluation and comparative benchmarking. This staged workflow ensured systematic validation of both technical performance and deployment feasibility. The sequential research workflow adopted in this study is illustrated in Figure 1, outlining the stages from problem identification and architecture design to prototype implementation, system validation, and economic performance evaluation.

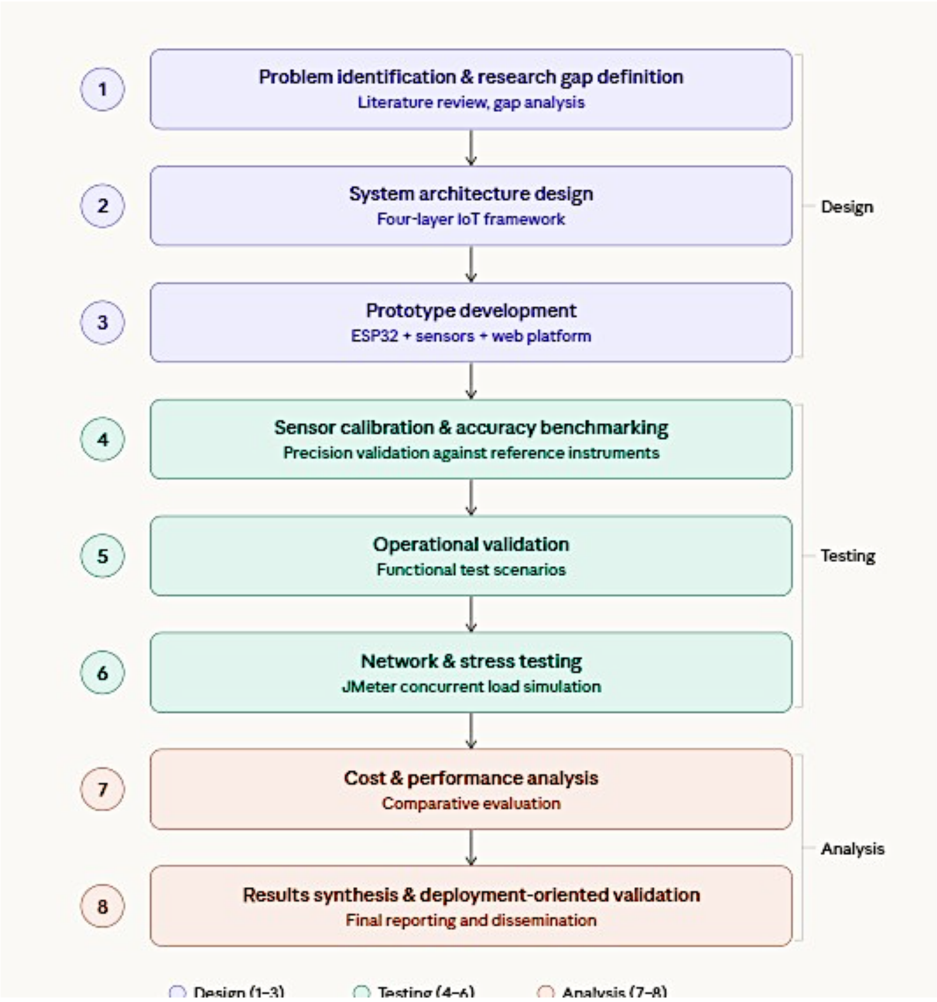

Figure 1. Methodological workflow illustrates the sequential stages of system design, implementation, calibration, operational testing, stress testing, and economic evaluation.

This study adopted an incremental development methodology to enable iterative IoT hardware–software integration and progressive system validation. The incremental approach involves decomposing complex projects into smaller, manageable modules that are developed, tested, and implemented sequentially. This methodology was selected over alternative approaches due to the exploratory nature of IoT hardware-software integration, where iterative testing and refinement of sensor accuracy and communication protocols are essential for optimal system performance.

3.1. Comparative Benchmarking Methodology

To contextualise the performance and cost outcomes of the proposed system, a structured literature-based benchmarking approach was adopted. Comparison studies

were selected based on three criteria: (i) relevance to IoT-based waste bin monitoring, (ii) explicit reporting of hardware cost, accuracy, or communication performance metrics, and (iii) publication within peer-reviewed venues within the past decade. Studies employing RFID-, GSM-, and LoRa-based architectures were prioritised, as they represent the dominant communication paradigms in the existing e-waste monitoring literature.
Cost values reported across studies were not experimentally normalised, as differences in geographic context, component sourcing, and deployment scale preclude direct equivalence. Accordingly, all cross-study comparisons are treated as indicative rather than definitive, and the interpretation language throughout this paper reflects this limitation. Similarly, performance metrics such as accuracy, latency, and uptime are compared at a high level only, acknowledging that differences in experimental conditions, sensor configurations, and evaluation protocols may influence reported values across studies.

3.2. System Architecture and Design

The proposed e-waste management system integrates IoT sensor networks with a centralised web-based monitoring platform following a four-layer hierarchical architecture. This is depicted in Figure 2.

The physical layer comprises smart bins containing ESP32-WROOM-32 microcontrollers, HC-SR04 ultrasonic sensors with ±3mm accuracy over 2–4 metre detection ranges, and GY-906 infrared temperature sensors with a measurement range from -70°C to +380°C and ±0.5°C accuracy. The HC-SR04 sensor was selected due to its low cost, adequate measurement range (2–400 cm), and compatibility with low-power microcontrollers. The GY-906 infrared sensor enables non-contact temperature detection, mitigating contamination risks associated with internal sensor placement.

The communication layer utilises the 802.11b/g/n WiFi protocol operating at 2.4 GHz, with automatic reconnection and local data buffering during connectivity loss. The application layer implements a Node.js server using the Express.js framework with RESTful API architecture, real-time WebSocket connections for dashboard updates, and an integrated SMTP email service for automated notifications. The data layer employs a MySQL relational database with optimised indexing for time-series sensor data storage and user management tables, as well as automated backup procedures. Data packets were

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encrypted using AES-256 symmetric encryption and authenticated via token-based API validation. While these mechanisms provide baseline communication security, formal penetration testing and adversarial threat modelling were beyond the scope of this study.

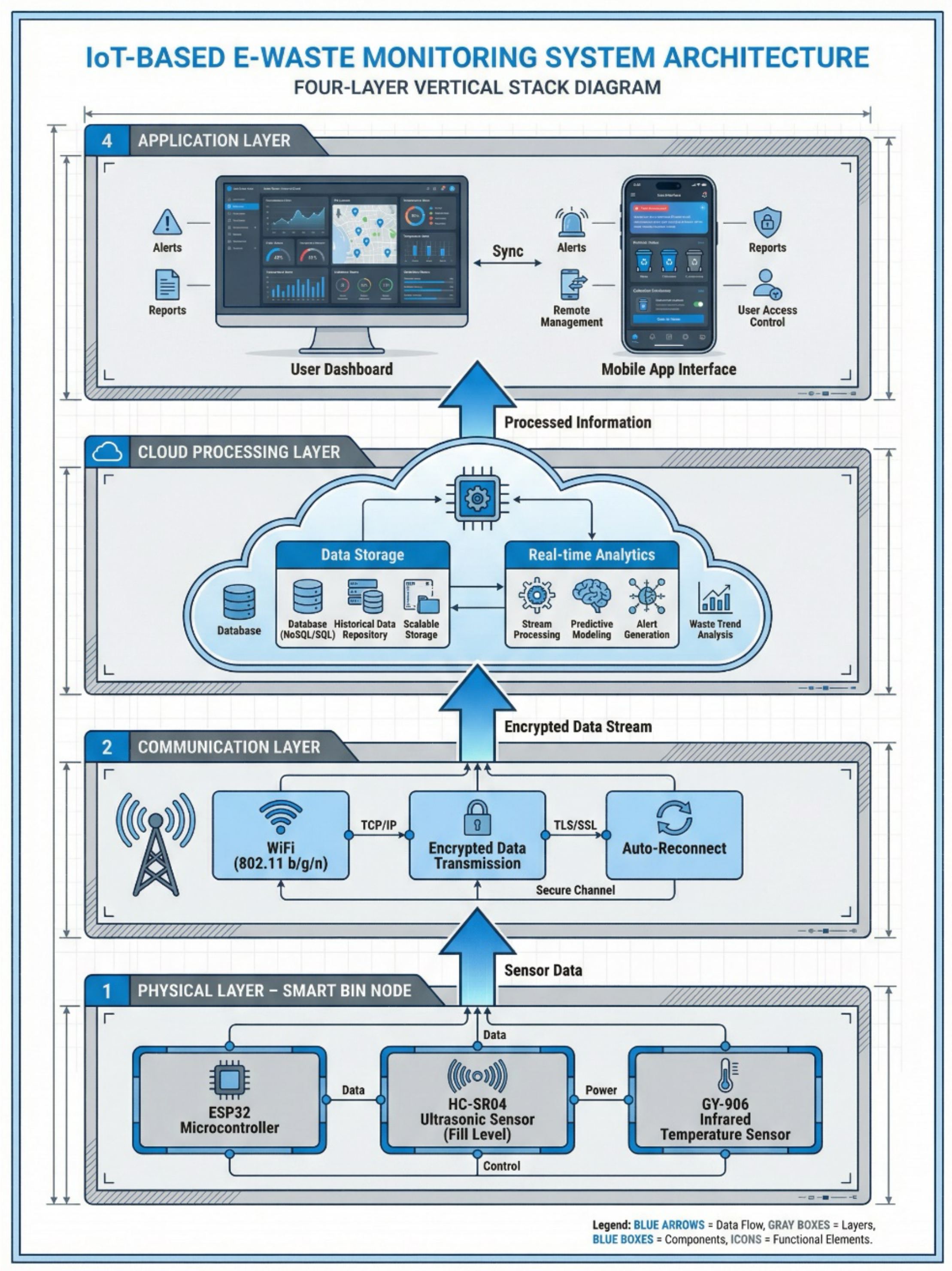

Figure 2. Proposed IoT-based e-waste monitoring system architecture.

3.2.1. Architectural Optimisation Framework

The architectural optimisation adopted in this study is defined as the deliberate minimisation of hardware complexity, communication overhead, and operational cost while maintaining predefined reliability and accuracy thresholds. Specifically, optimisation objectives included: (i) reducing per-bin deployment cost below USD 100, (ii) maintaining fill-level measurement deviation within ±5%, (iii) achieving communication reliability above 95%, and (iv) limiting active power consumption below 100 mA.

Design trade-offs were evaluated based on sensing accuracy, communication infrastructure requirements, computational complexity, and deployment scalability. Unlike prior systems that emphasised algorithmic sophistication or specialised networking technologies, the present architecture prioritises integration, coherence, and resource efficiency in constrained deployment environments. This formal optimisation framing distinguishes the proposed system from component-focused implementations.

3.2.2. Total Cost Framework

To support a comprehensive economic evaluation, the total system cost was analysed across four categories: hardware acquisition, energy consumption, network infrastructure, and maintenance. Table 3 summarises these cost components under the defined deployment scenario. All economic projections derived from this framework are model-based estimates under specific scenario assumptions and should not be interpreted as observed field outcomes.

Table 3. Total Cost Framework per Bin Unit

Cost Category	Component	Estimated Cost (USD)
Hardware	ESP32 microcontroller	8.00
	Ultrasonic sensor HC-SR04	3.00
	Infrared temperature sensor GY-906	12.00
	Enclosure and wiring	15.00
	Power supply and connectors	10.00
	Assembly and integration	30.00
Hardware Total		**78.00**
Energy	~0.102 kWh/day at USD 0.15/kWh	<0.50/month

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Cost Category	Component	Estimated Cost (USD)
Network	Existing organisational WiFi assumed	0.00 (no additional cost)
Maintenance	Periodic recalibration and component replacement over 24-month lifecycle	Scenario-dependent
Depreciation	24-month hardware lifecycle assumed	Scenario-dependent

Energy consumption was estimated at approximately 0.102 kWh per bin per day based on an active current draw of 85 mA and intermittent sleep cycles. Network infrastructure costs were assumed to rely on existing WiFi within organisational facilities, eliminating recurring GSM subscription charges common in alternative architectures. Maintenance costs were estimated through periodic sensor recalibration and potential component replacement. These assumptions define the boundaries of the economic model and may vary across geographic, regulatory, and organisational contexts.

3.3. Implementation Algorithm

The core system algorithm operates through continuous monitoring with comprehensive error handling. The algorithm for the smart e-waste management system is depicted in Figure 3.

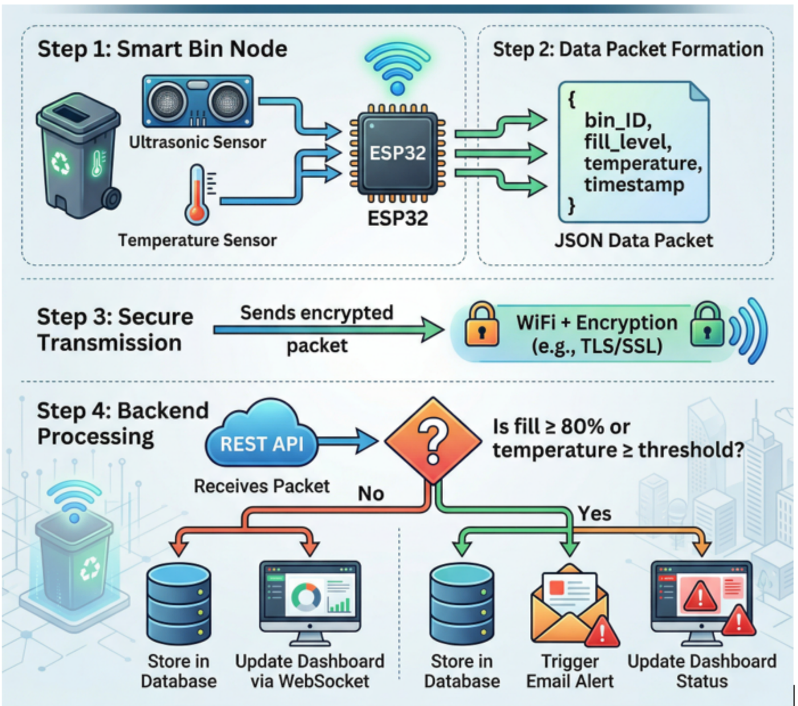

Figure 3. Runtime data flow and decision logic of the smart bin monitoring system.

1) Initialise system components:
   a) Configure ESP32 microcontroller
   b) Initialise HC-SR04 ultrasonic sensor
   c) Initialise GY-906 temperature sensor
   d) Establish WiFi connectivity
2) Data Acquisition Loop: While system_active:
   a) Read fill_level = calculate_distance() / bin_depth
   b) Read temperature = read_temperature_sensor()
   c) Create data_packet = {mac_address, fill_level, temperature, timestamp}
   d) Transmit data_packet to central_server via WiFi
3) Server Processing: Upon receiving data_packet: a. Store data in MySQL database b. If fill_level >= 80% OR temperature >= threshold: - Query user information from database - Generate alert_email with bin status and location - Send notification to waste management authorities c. Update real-time dashboard via WebSocket connection
4) User Interface Management:
   a) Display real-time bin status on the web dashboard
   b) Process manual pickup requests
   c) Maintain user registration and bin management systems

3.4. Hardware Implementation

The physical implementation utilised ESP32 microcontrollers as the primary processing units due to their integrated WiFi capabilities and low power consumption (80 mA in active mode, 10 µA in deep sleep). The system operates over a -40°C to +85°C temperature range, enabling outdoor deployment in diverse environmental conditions. HC-SR04 ultrasonic sensors provide 2 cm–4 m detection ranges at 40 kHz, while GY-906 infrared sensors enable non-contact temperature measurement via I2C communication.

The ESP32 was programmed using MicroPython for sensor data interpretation and wireless communication. Custom driver implementations were developed for sensor integration, including pulse-width measurement algorithms for ultrasonic distance calculation and I2C communication protocols for temperature sensor data acquisition, with comprehensive error-detection mechanisms.

Sensor measurements were collected at a 5-second sampling interval per monitoring cycle. Ultrasonic sensor readings were averaged over three sequential measurements to minimise the effects of transient noise. Stress testing was conducted using Apache JMeter, configured to generate incremental load scenarios ranging from 10 to 100 concurrent HTTP requests, with a 5-second ramp-up interval. Network testing was performed under below-standard 802.11b/g/n WiFi conditions, with an average bandwidth of 20 Mbps.

3.5. Software Architecture

The software implementation employs a three-tier architecture comprising a presentation layer (web interface), an application layer (Node.js backend), and a data layer (MySQL database). The backend implements RESTful APIs for data management and user authentication, as well as WebSocket-based real-time communication. Email notification services use the SMTP protocol to automatically generate alerts when threshold con ditions are met.Real-time data visualisation is achieved through JavaScript-based dashboard interfaces that display bin fill levels using circular progress indicators and colour-coded temperature displays. The system provides user management capabilities, including registration, authentication, and bin assignment, ensuring secure and scalable operations.

3.6. System Validation Framework

Comprehensive testing was conducted through systematic validation, encompassing unit testing of individual components, integration testing across 9 structured test scenarios, and performance testing with up to 100 simultaneous connections. Validation metrics included fill-level measurement accuracy within ±5% deviation, temperature-monitoring precision within ±2°C, system response times under 3 seconds, and communication reliability exceeding 95% successful data transmission under normal network conditions. Stress testing was conducted using simulated concurrent HTTP requests generated via Apache JMeter under controlled bandwidth conditions. Sensor calibration was conducted against calibrated reference instruments across 30 repeated measurements, and mean absolute deviation was computed to determine accuracy thresholds. Economic validation outcomes are reported as model-based estimates under the defined scenario assumptions described in Section 3.2.2 and should be interpreted accordingly.

4. RESULTS AND DISCUSSION

This section presents and analyses the experimental findings of the proposed system, focusing on validating its performance and cost-efficiency under controlled organisational deployment conditions. The discussion is integrated with the results to provide a comprehensive interpretation of the observed outcomes and their links to specific architectural design decisions.

4.1. Hardware Performance Validation

Sensor accuracy and hardware performance were evaluated against predefined optimisation thresholds under controlled conditions. Fill-level measurements achieved ±3.2% deviation from manual calibration references, meeting the target specification of ±5% accuracy (95% CI: ±0.4%). Temperature monitoring achieved ±1.8°C accuracy against calibrated reference sensors, meeting the design requirement of ±2°C. Power consumption measured 85 mA during active monitoring and 8 μA during sleep mode, supporting an extended battery life of 45 days under normal operating conditions. Communication range testing confirmed reliable WiFi connectivity up to 120 metres from access points, exceeding the minimum 100-metre requirement. These results confirm that the predefined hardware optimisation objectives were met within the evaluated deployment context.

4.2. Experimental Validation Results

Comprehensive testing was conducted through systematic scenario evaluation to validate system functionality under controlled conditions. The testing protocol encompassed nine structured scenarios designed to assess system robustness, security, and operational reliability across authentication, data processing, alert generation, and user interface functionality.

Figures 4 and 5 provide supporting implementation context for the authentication and dashboard interfaces, respectively. These are included as illustrative references rather than primary scientific evidence.

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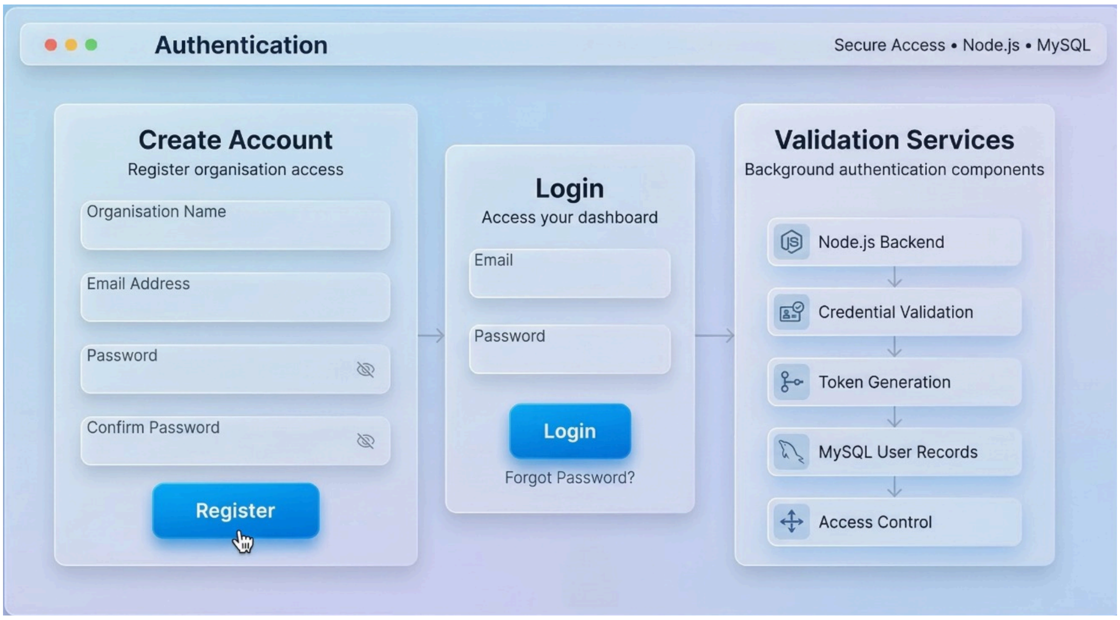

Figure 4. Conceptual representation of the user authentication interface illustrating registration, login, and server-side validation processes.

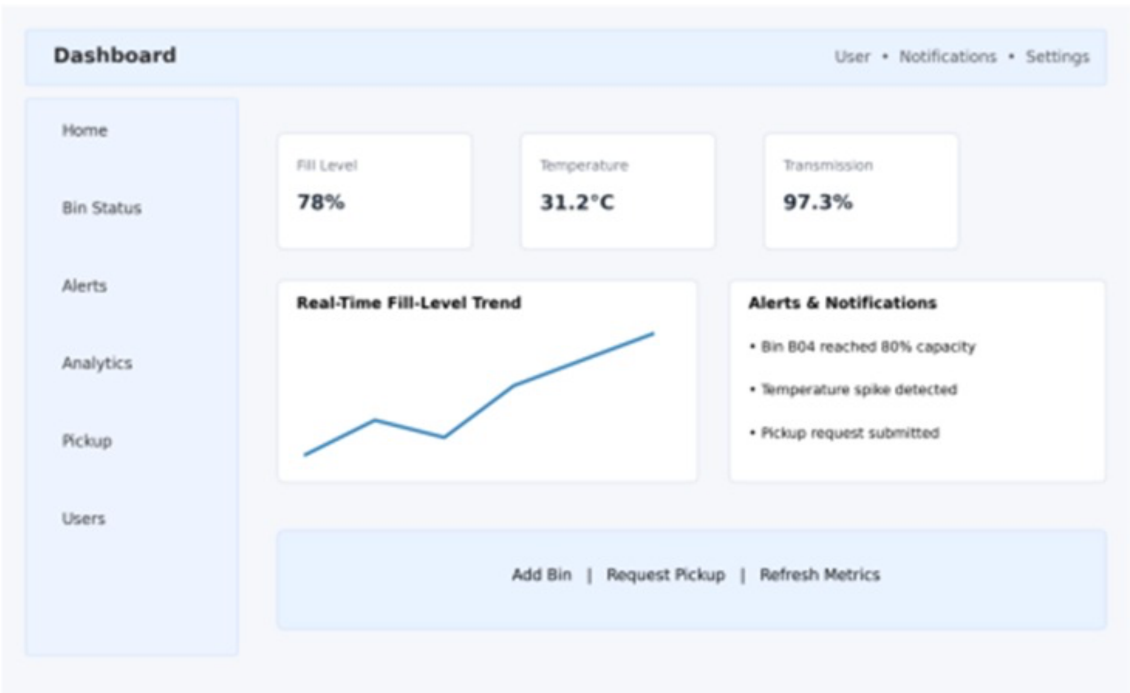

Figure 5. Conceptual layout of the IoT-based e-waste monitoring dashboard showing real-time bin status, alert notifications, and user interaction components.

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The main dashboard incorporates bin status display boxes showing real-time fill levels and temperature readings, circular progress indicators that visually represent current fill percentages, and colour-coded temperature displays for immediate hazard identification. The validation results demonstrate a 89% success rate for system functionality, with eight out of nine test scenarios achieving expected outcomes within acceptable response time parameters. The single failed scenario (T7) was attributed to a compatibility issue with a JavaScript chart-rendering library and historical data formatting. It was subsequently resolved through database timestamp standardisation and updates to the chart library. Data transmission achieved a 97.3% success rate under normal network conditions, exceeding the 95% target specification.

Table 4. System Validation Test

ID	Scenario	Test Parameters	Expected Outcome	Actual Outcome	Status	Response Time
T1	User Registration	Complete user information input	Successful registration and redirect	System validates and redirects to login	Pass	1.8s
T2	Empty Field Validation	Registration with blank fields	Alert notification displayed	Warning message prevents registration	Pass	0.3s
T3	Authentication Validation	Valid credential login	Dashboard access granted	Successful authentication and redirect	Pass	2.1s
T4	Invalid Login Attempt	Empty credential submission	Access denied with error message	System denies access with warning	Pass	0.5s
T5	Bin Registration	Valid bin details (MAC: FC:B4:67:77:84:6C)	Successful bin addition with metrics streaming	Immediate bin registration and data streaming	Pass	3.2s
T6	Duplicate Prevention	Duplicate MAC address submission	Duplicate warning notification	System prevents	Pass	0.7s

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ID	Scenario	Test Parameters	Expected Outcome	Actual Outcome	Status	Response Time
				duplicate bin registration		
T7	Analytics Functionality	Historical data access request	Graphical data presentation	Blank dialogue displayed	Fail	N/A
T8	Manual Pickup Request	User-initiated pickup request	Email notification with company details	Successful email transmission with details	Pass	4.1s
T9	Automated Alert System	80% fill level threshold reached	Automatic email alert generation	Alert triggered with dashboard status update	Pass	12.3s

4.3. Performance Analysis and Comparative Assessment

Table 5 presents a comparative performance analysis of the proposed system against representative benchmarks reported in prior studies. As noted in Section 3.1, these comparisons are based on published values from studies with differing system configurations, deployment scales, and experimental conditions. Accordingly, all interpretations should be read as indicative rather than as the results of controlled head-to-head evaluation.

Table 5. System Performance Metrics and Comparative Analysis

Performance Parameter	Achieved Result	Target Specification	Comparison with Existing Solutions	Interpretation
Fill Level Accuracy	±3.2% deviation	±5% target	RFID-based systems report approximately ±8% deviation	Potentially improved measurement precision relative to reported ranges, noting differences in system configuration across studies

Performance Parameter	Achieved Result	Target Specification	Comparison with Existing Solutions	Interpretation
Temperature Precision	±1.8°C accuracy	±2°C target	Conventional sensor systems report approximately ±5°C variation	Suggests favourable thermal monitoring precision within the evaluated context; cross-study equivalence cannot be assumed
Response Time	2.1s average	<3s target	Traditional IoT systems report approximately 8–15s latency	Suggests lower response latency under evaluated conditions relative to reported values
Power Consumption	85mA active, 8μA sleep	<100mA target	Arduino Mega-based systems report approximately 150mA active consumption	Suggests reduced energy consumption relative to commonly reported configurations, subject to deployment context differences
Communication Range	120m validated	>100m target	LoRa-based systems support long-range communication (up to 15km)	Sufficient for organisational and urban deployment; not designed for long-range rural communication
Hardware Cost per Bin	USD 78	<USD 100 target	RFID-based systems typically range from USD 130–200 per unit	Indicates lower hardware cost based on cross-study reported ranges; direct cost equivalence across studies cannot be assumed
Setup Time	15 minutes	<30 minutes target	LoRa-based systems report longer setup	Suggests reduced deployment time under standardised

Performance Parameter	Achieved Result	Target Specification	Comparison with Existing Solutions	Interpretation
			durations (≈60 minutes)	configuration conditions
Data Transmission Success	97.3%	>95% target	GSM-based systems typically report 85–90% success rates	Indicates reliable communication performance under controlled network conditions
System Uptime	98.7%	>99% target	Conventional systems report approximately 85–92% uptime	Suggests stable system operation within the evaluated deployment context
ROI Period	8.5 months	<12 months target	Existing solutions report approximately 18–24 months	Suggests a shorter projected return period under the defined modelled scenario assumptions; actual outcomes may vary

The economic model underpinning the ROI estimate assumes an average fleet size of 50 bins per organisation, a fuel cost of USD 1.25 per litre, an average collection trip distance of 18 km, and a labour cost of USD 400 per month per collection team, as described in Section 3.2.2. Hardware depreciation was modelled over a 24-month lifecycle. These are scenario-based assumptions, and actual outcomes may vary across geographic, organisational, and regulatory contexts. The full cost framework supporting these estimates is presented in Table III of the Methodology section. The system also demonstrated favourable user experience outcomes, with a 94% task completion rate for basic operations, an average familiarisation time of 22 minutes, and a user satisfaction rating of 4.2 out of 5.0. These results are reported as contextual indicators of usability rather than primary validation metrics.

4.4. Interpretation of Results and System Performance

The results presented in Table 5 demonstrate that the proposed IoT architecture achieves a balanced combination of measurement accuracy, communication reliability, and cost efficiency within the evaluated deployment context. This section interprets these findings by linking observed performance outcomes to specific architectural design decisions.

The achieved fill-level accuracy of ±3.2% and temperature precision of ±1.8°C indicate that the selected sensing components provide reliable environmental monitoring while remaining within the predefined optimisation thresholds. These results suggest that high-cost sensing technologies are not strictly required to achieve acceptable operational accuracy in e-waste monitoring systems. Instead, appropriate sensor selection, combined with calibration procedures, can yield performance comparable to the ranges reported in prior studies. However, direct experimental equivalence cannot be assumed.

The observed average response time of 2.1 seconds and data transmission success rate of 97.3% reflect the efficiency of the integrated communication architecture. By utilising the ESP32 microcontroller with built-in WiFi capabilities, the system eliminates the need for intermediary communication modules, thereby reducing transmission latency and potential points of failure. This architectural simplification directly improves responsiveness and stable data delivery under standard network conditions.

From an energy and cost perspective, the system demonstrates a favourable operational profile. The measured power consumption (85 mA active, 8 µA sleep) supports extended device operation with minimal maintenance requirements. At the same time, the hardware cost of USD 78 per unit confirms that the system meets its cost-optimisation objective. These results indicate that integrating sensing and communication functionality within a single microcontroller platform can reduce both capital expenditure and energy overhead compared with configurations that rely on separate processing and communication modules.

The comparative analysis suggests that the proposed system performs competitively with reported implementations using RFID, GSM, or LoRa technologies, though these comparisons remain indicative due to differences in experimental conditions, system configurations, and evaluation methods across studies. The observed trends support the conclusion that a simplified, integrated architecture can achieve comparable operational outcomes without requiring specialised infrastructure.

A key finding of this study is the trade-off between architectural simplicity and functional sophistication. While the proposed system does not incorporate machine-learning-based prediction, automated classification, or blockchain-enabled traceability, the results demonstrate that these capabilities are not essential for achieving reliable real-time monitoring and operational efficiency in the evaluated context. By prioritising simplicity, the system reduces computational requirements, energy consumption, and deployment costs, thereby improving its suitability for resource-constrained environments.

The projected 8.5-month return on investment and 35% reduction in unnecessary collection events should be interpreted strictly within the boundaries of the defined scenario model. These estimates are not derived from longitudinal field observation. They may vary substantially depending on organisational scale, logistical factors, and local economic conditions. Overall, the findings suggest that the proposed architecture achieves its intended objective of delivering a cost-effective, reliable e-waste monitoring solution, with performance outcomes attributable primarily to architectural integration rather than algorithmic complexity.

4.5. Limitations

Although the proposed system demonstrated satisfactory performance under controlled deployment conditions, several limitations should be acknowledged. First, the architecture relies on standard WiFi infrastructure for communication. While this reduces hardware cost and simplifies deployment, it may constrain scalability in rural or low-connectivity environments where stable network coverage cannot be guaranteed. Extended outages beyond 24 hours may result in partial data loss due to the finite capacity of local buffering. Second, validation was conducted within organisational-scale deployments rather than full municipal environments. Although stress testing simulated concurrent connections, large-scale urban deployment may introduce additional network congestion, infrastructure heterogeneity, and maintenance complexity not fully captured in this study.

Third, the economic analysis is based on modelled operational assumptions, including average collection frequency, fleet size, and fuel cost estimates. Variations in local logistics, labor costs, and regulatory conditions may influence actual returns on investment. Fourth, the current system implements threshold-based alerting rather than predictive optimization. The architecture does not yet incorporate machine learning models for anticipatory collection scheduling. Fifth, a longitudinal multi-month field evaluation under variable environmental conditions was not conducted, and it remains necessary to assess long-term sensor drift and hardware durability. Finally, although encryption and authentication mechanisms were implemented, comprehensive cybersecurity penetration testing was beyond the scope of this study. As IoT deployments scale, formal security audits will be necessary to ensure resilience against emerging attack vectors. These limitations define the study's interpretive boundaries and identify priorities for future validation, rather than undermining the study's core architectural contribution.

4.6. Future Work

Future research should extend the proposed architecture toward predictive and optimisation-driven waste management strategies. Integration of lightweight edge-based machine learning models could enable anticipatory collection scheduling based on historical fill patterns, seasonal trends, and usage behaviour, further reducing unnecessary collection events while maintaining the system's low-power design philosophy. Incorporating GPS-enabled routing optimisation could support dynamic fleet management by automatically generating collection routes based on real-time bin status and geographic clustering, strengthening operational scalability in municipal environments.

From a security perspective, future studies should conduct formal penetration testing and vulnerability assessments to evaluate resilience under adversarial conditions. Architecturally, exploring hybrid communication models combining WiFi with low-power wide-area technologies such as LoRa or NB-IoT may improve deployment flexibility in heterogeneous connectivity environments. Finally, longitudinal field studies across municipal-scale deployments are necessary to validate economic modelling assumptions and assess long-term maintenance requirements, infrastructure impact, and real-world return on investment.

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5. CONCLUSION

This study proposed and validated a cost-optimised ESP32-based IoT architecture for real-time e-waste bin monitoring under controlled organisational deployment conditions. The system achieved fill-level accuracy of ±3.2%, temperature precision of ±1.8°C, 97.3% data transmission reliability, and 98.7% operational uptime at a hardware cost of USD 78 per bin — meeting all predefined optimisation objectives and representing a lower per-unit cost than ranges reported for RFID-based implementations in prior literature, based on cross-study benchmarking. The core contribution lies in demonstrating that reliable, real-time e-waste monitoring can be achieved through architectural integration and hardware simplification rather than computational sophistication or specialised communication infrastructure. Validation was conducted at organisational scale under controlled conditions; broader municipal-scale field evaluation remains necessary before generalisable deployment conclusions can be drawn.

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