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A COMPREHENSIVE REVIEW OF IOT-BASED SMART WASTE MANAGEMENT SYSTEMS: SENSING, SEGREGATION, AND COMMUNICATION ARCHITECTURES

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Abstract: Municipal solid waste management has become one of the most pressing infrastructural challenges of rapid urbanisation, and the last decade has produced a large and fragmented body of research on Internet of Things (IoT)-enabled smart bins and collection networks. This paper presents a comprehensive review of IoT-based smart waste management research published between 2014 and 2026, synthesising findings from thirty-four primary technical sources spanning sensing hardware, automated segregation, wireless notification, collection-route optimisation, and system security. A five-branch taxonomy is proposed that classifies the surveyed literature by the function each system performs within the sense-segregate-communicate-route-secure pipeline. The review finds that fill-level monitoring through ultrasonic ranging is now a mature, near-universal capability, whereas gas- or odour-based sensing appears in only a small minority of designs, vision-based segregation remains largely confined to laboratory-scale datasets, and long-range low-power communication technologies such as LoRaWAN are gaining adoption without yet displacing cellular SMS gateways in cost-sensitive deployments. A comparative feature matrix and a capability-prevalence analysis across the reviewed systems are presented, together with a discussion of recurring barriers: per-unit hardware cost, sensor drift, limited validation beyond bench testing, and the absence of standardised evaluation protocols. The review concludes by identifying multi-modal sensor fusion, edge-deployed adaptive classifiers, and decomposition-aware priority alerting as the directions most likely to shape next-generation smart-bin design.

***Index Terms* -** Internet of Things, smart waste management, literature review, waste segregation, bin monitoring, gas sensing, route optimisation, smart cities.

I. INTRODUCTION

Solid waste generation has outpaced the institutional capacity to manage it in almost every rapidly urbanising region of the world. [1] projects that municipal solid waste generation will climb from roughly 2.1 billion tonnes in 2023 to 3.8 billion tonnes by 2050, and notes that a substantial share of this volume, on the order of a third, is still openly dumped or burned rather than collected and treated. In India specifically, [2] places daily municipal solid waste generation above 160,000 tonnes, a large fraction of which accumulates in roadside bins between collection rounds. The consequences are not purely aesthetic: [3] documents that prolonged exposure to the byproducts of uncollected organic decomposition, including ammonia and hydrogen sulphide, is associated with respiratory irritation in nearby residents. These pressures have made municipal waste handling one of the most active application domains for the Internet of Things (IoT), and the resulting research output has grown quickly enough that [4] needed to screen 3,732 candidate records down to 173 primary studies for a single systematic review covering only one slice of the field.

Three operational shortcomings recur across this literature with enough consistency that they can be treated as the defining problems of the domain. The first is the absence of source-level segregation: recyclable, organic, and inert material is typically deposited into a single container, which raises downstream sorting cost and contaminates otherwise recoverable streams. The second is the lack of a reliable, low-latency channel for reporting how full a bin actually is, which forces collection fleets to choose between wasteful fixed schedules and reactive, complaint-driven visits. The third, addressed by a smaller and more recent slice of the literature, is the chemistry of decomposition: organic waste left in a sealed or semi-sealed compartment for more than a day begins to release ammonia and other malodorous compounds well before a human observer would necessarily notice the bin is full. Individually, each of these three problems has an established line of corrective research; the contribution of this review is to organise, compare, and critically assess that research as a connected whole rather than as three independent literatures.

This review addresses three questions that, to the best of our knowledge, have not been jointly answered in a single concise survey targeted at practitioners building bin-level (rather than fleet- or city-level) smart waste hardware. First, which sensing modalities have matured to the point of routine adoption, and which remain experimental? Second, how do the communication architectures reported in the literature trade off range, power, and infrastructure dependency, and which are best suited to regions with intermittent broadband coverage? Third, what evaluation gaps recur across the reviewed systems, and what would closing them require? The remainder of the paper is organised as follows. Section II describes the review methodology. Section III proposes a taxonomy used to structure the remaining discussion. Section IV reviews sensing technologies. Section V reviews automated segregation approaches. Section VI reviews communication and notification architectures. Section VII reviews collection-route optimisation. Section VIII reviews security and data-integrity considerations. Section IX reviews citizen-facing platforms. Section X presents a comparative analysis across the surveyed systems. Section XI discusses open challenges. Section XII proposes future research directions, and Section XIII concludes.

II. REVIEW METHODOLOGY

This review is a narrative synthesis rather than a formally registered systematic review; no PRISMA protocol was pre-registered, and the searches described below were conducted by a single reviewing team rather than independently duplicated. Within that scope, the selection process followed a deliberate and repeatable procedure, illustrated in Fig. 1. Candidate records were identified through IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Google Scholar using combinations of the terms "smart bin", "smart dustbin", "IoT waste management", "waste segregation IoT", "gas sensor waste bin", "LoRaWAN waste", "vehicle routing waste collection", and "waste classification deep learning", restricted to material published between 2017 and 2026, with a small number of foundational technical references (notably sensor datasheets and early characterisation studies) cited from before this window where they provide the only citable source for a specific technical parameter.

Records were retained for full review if they (a) described a bin-level or fleet-level technical system rather than a purely policy, economic, or behavioural study; (b) reported at least one IoT-connected sensing, actuation, or communication component; and (c) were published in an indexed, citable venue (journal, conference proceedings, or a recognised technical report from a standards or international body). Records were excluded if they addressed only post-collection processing (landfill engineering, incineration, or material-recovery-facility operations) without a bin- or vehicle-side IoT component, or if they were superseded by a later, more complete version of the same study from the same authors. The search returned approximately 210 candidate records; after removing duplicates across databases, 158 unique records remained. Title-and-abstract screening against the criteria above retained 89 records for full-text assessment, and full-text eligibility checking yielded the final working corpus of thirty-four primary technical sources, supplemented by three contextual references covering global waste statistics and health guidance. This corpus is necessarily a sample rather than an exhaustive census of the field; it is best read as a representative cross-section spanning low-cost microcontroller prototypes, peer-reviewed sensor and communication studies, and recent deep-learning and blockchain-augmented designs, rather than as a complete bibliography of every published smart-bin paper.

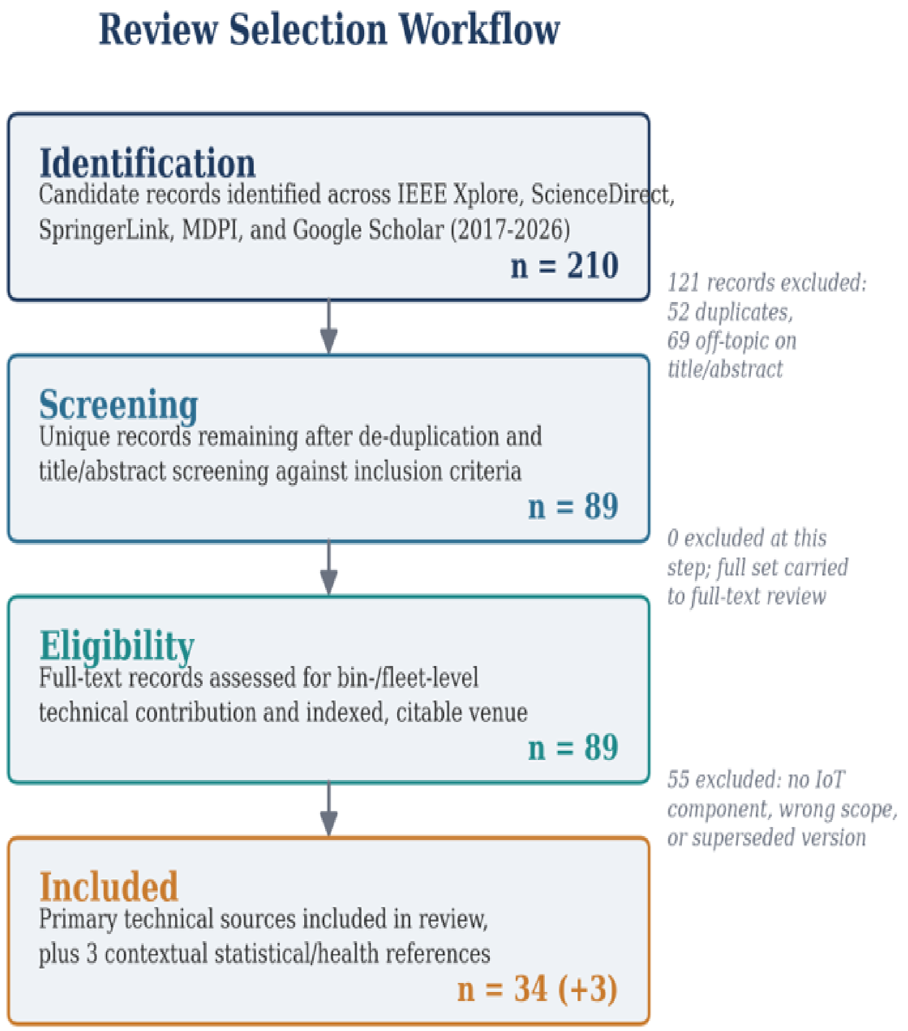

Fig. 1. Four-stage review selection workflow, from initial database identification (n=210) to the final included corpus (n=34 primary technical sources, plus 3 contextual references)

III. A TAXONOMY OF IOT-BASED SMART WASTE MANAGEMENT SYSTEMS

Prior reviews have proposed their own organising schemes for this literature; [5], for instance, classifies systems into five categories spanning automated collection and intelligent transportation, sorting and separation, smart garbage bins, citizen engagement, and integrated management platforms, while [6] organises its survey primarily around the sensing and deep-learning techniques used for waste identification, and the earlier survey by [7] groups solutions chiefly by the wireless technology used to report bin status. Building on these precedents but oriented specifically toward the bin-level engineering decisions practitioners must make, this review adopts a five-branch pipeline taxonomy, shown in Fig. 2, that mirrors the physical sequence of events a deposited item undergoes: sensing and monitoring, automated segregation, communication and notification, logistics and route optimisation, and a cross-cutting layer covering security, data integrity, and citizen-facing platforms. Sections IV through IX are organised according to this taxonomy, with each branch further divided into the sub-modalities most frequently reported in the surveyed corpus. The value of an explicit taxonomy here is partly diagnostic. Mapping the thirty-four reviewed systems onto these branches, summarised quantitatively in Section X, makes visible which combinations of capability are common (fill-level sensing paired with cellular or Wi-Fi notification), which are emerging (vision-based segregation paired with cloud inference), and which remain rare (odour or gas sensing paired with any form of automated, rather than purely informational, response). This last gap is returned to repeatedly in Sections IV, X, and XII, since it represents one of the more consistent blind spots across the corpus examined.

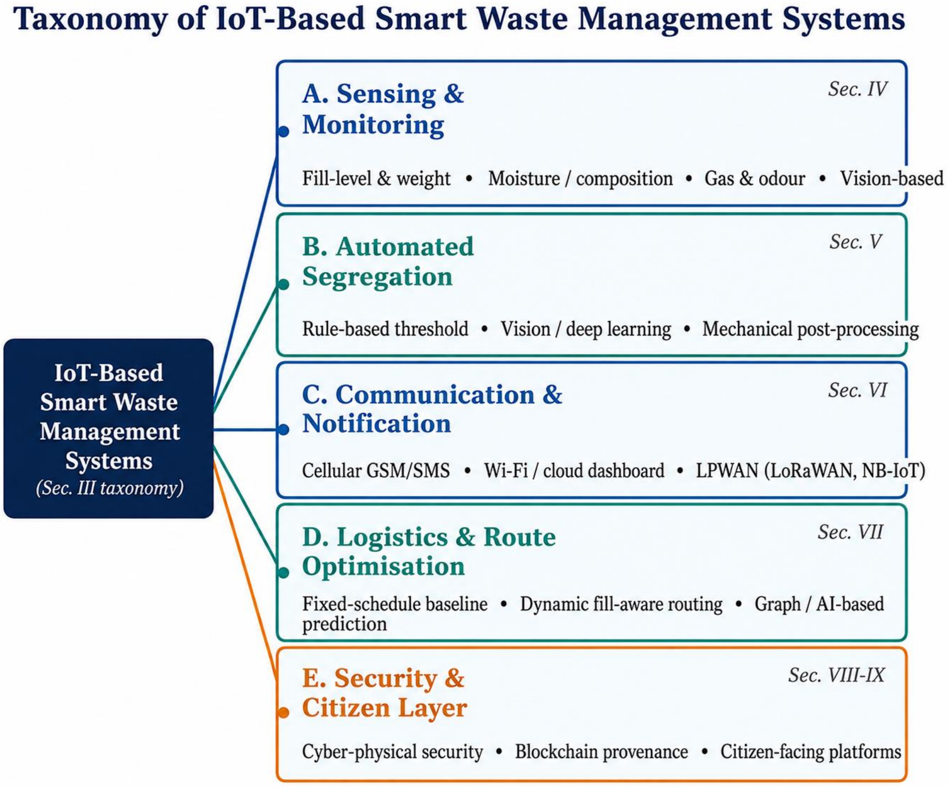

Fig. 2. Proposed five-branch taxonomy organising the reviewed literature into sensing and monitoring, automated segregation, communication and notification, logistics and route optimisation, and a cross-cutting security and citizen-engagement layer

IV. SENSING TECHNOLOGIES IN SMART BINS

Although the surveyed systems differ considerably in which sensors they include, almost all of them can be mapped onto a common three-layer reference architecture, shown in Fig. 3: a perception layer of heterogeneous transducers at the bin itself, a processing layer (typically a single low-cost microcontroller, occasionally a master-slave pair or a small edge-compute board) that fuses readings and applies decision logic, and an actuation-and-communication layer that drives any local actuator and forwards a decision to a human-facing channel. The remainder of this section works through the perception layer modality by modality; Sections V and VI then take up the processing-layer decision logic and the actuation-and-communication layer respectively.

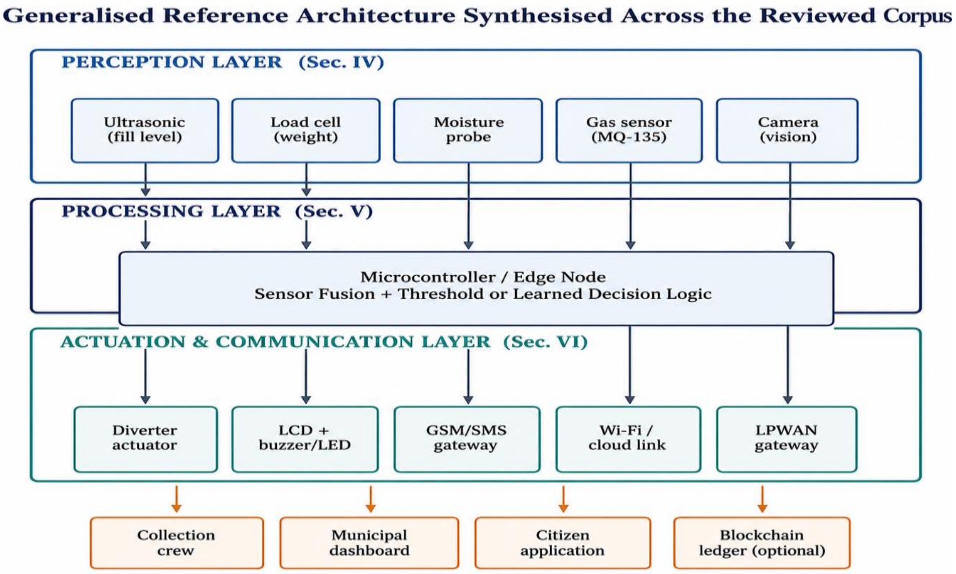

Fig. 3. Generalised three-layer reference architecture synthesised across the reviewed corpus: a perception layer of heterogeneous sensors, a processing layer that fuses readings and applies decision logic, and an actuation-and-communication layer that drives local actuators and forwards decisions to external stakeholders

A. Fill-Level and Weight Sensing

Fill-level sensing is the single most consistently reported capability in the corpus and is also the oldest: early systems such as [8] and [9] pair a single ultrasonic time-of-flight rangefinder with a microcontroller to estimate the empty headspace above the waste line, broadcasting the resulting percentage over Wi-Fi or a cellular uplink. The technique is attractive because HC-SR04-class ultrasonic modules are inexpensive, require only a digital trigger/echo pair, and are tolerant of the dust and humidity found inside a bin. Several later designs extend the single-sensor pattern to multiple compartments, using one rangefinder per stream so that dry and wet (or recyclable and organic) fill levels can be reported independently, and a small number, including [11], add a second physical quantity, weight, via a load cell, on the reasoning that mass and volume diverge for compacted or low-density waste and that a combined reading is more robust than either alone. [11] and [12] similarly combine ultrasonic and weight channels, framing the dual reading as a way to catch sensor faults: a bin reporting high fill by volume but negligible weight, or vice versa, is flagged for a maintenance check rather than treated as a genuine alert.

What is notable about this sub-literature is how little it has changed at the sensing-hardware level over the period reviewed. The HC-SR04 (or close clones) and resistive or strain-gauge load cells dominate low-cost designs from 2017 through 2023 with only incremental changes in calibration routine or sampling cadence; the more substantive evolution, discussed in Section VI, has occurred in how the resulting reading is transmitted rather than in how it is sensed.

B. Moisture and Composition Sensing

A second, smaller cluster of systems adds a capacitive or resistive soil-moisture probe to the deposition point, using the dielectric contrast between wet and dry material as a cheap proxy for organic-versus-recyclable classification. [13] and [14] both report this approach, typically thresholding a 0-1023 analogue-to-digital reading against an empirically chosen cut-off to drive a servo-actuated diverter. The appeal of moisture-based segregation is its simplicity: a single analogue pin and a few lines of threshold logic are sufficient, in contrast to the camera, inference hardware, and labelled training data required by the vision-based alternative described next. The corresponding limitation, acknowledged implicitly by the narrow scope of validation reported in most of these papers, is that moisture content correlates only loosely with true material category; a damp paper towel and a wrapped food scrap can present similar dielectric readings despite belonging to different disposal streams.

C. Gas and Odour Sensing

Gas sensing is the least common of the four sensing sub-modalities in the reviewed corpus, despite being directly relevant to the decomposition-odour problem identified in Section I. Outside the waste-management literature specifically, the MQ-135 tin-dioxide metal-oxide sensor has been characterised extensively for ammonia, carbon dioxide, and benzene sensitivity; its manufacturer-published load-resistance curve [15] underlies most of the ppm-conversion models used in downstream applications, and its accuracy at sub-100 ppm ammonia concentrations has been independently corroborated in an agricultural research context by [16]. Within general air-quality monitoring, [17] and [18] both deploy the MQ-135 on Raspberry Pi and Arduino platforms respectively to track ambient pollution rather than bin-specific odour. What is comparatively rare is the integration of this class of sensor directly into a waste bin's decision logic, a gap explicitly noted by [4], whose review of seventy or more IoT waste studies found gas sensing present in only a small minority of designs. Adjacent to single-sensor approaches, the electronic-nose literature, recently surveyed by [19], demonstrates that arrays of multiple gas-sensitive elements combined with pattern-recognition models can discriminate between odour sources far more specifically than a single MQ-135 channel, at the cost of greater hardware and calibration complexity; this body of work is presently under-exploited by the smart-bin literature reviewed here and is revisited as a future direction in Section XII.

D. Vision-Based Sensing

The most active sensing sub-literature by publication volume over the past five years is camera-plus-deep-learning material classification. [20] trains a convolutional network to discriminate organic from recyclable waste from camera images feeding an IoT-connected bin controller; [21] reports an earlier convolutional architecture evaluated on a curated waste-image dataset; and [22] applies a YOLOv3 object detector to localise and classify multiple waste items within a single frame rather than assuming one item per image, which is closer to the messy, multi-item reality of an actual bin opening. [23] extends the same family of techniques to electronic waste specifically, using a learned classifier to plan e-waste collection logistics rather than in-bin sorting. Reported classification accuracies in this sub-literature are frequently high, often exceeding 90% on the authors' own held-out test sets, but, as discussed further in Section X and Section XI, the great majority of this accuracy is measured on curated, well-lit, single-item or few-item images rather than on the occluded, soiled, and variably lit conditions found inside a deployed bin, which leaves an open question about how much of the reported performance would survive field deployment.

V. AUTOMATED SEGREGATION APPROACHES

A. Rule-Based Segregation

The simplest and most field-proven segregation strategy in the corpus is a single-threshold rule applied to one sensor channel, almost always the moisture probe described in Section IV-B, driving a servo or solenoid-actuated diverter flap. Both [13] and [14] implement this pattern, and its principal advantage is determinism: the decision boundary is fixed at deployment time, requires no training data, and runs comfortably within the timing budget of an 8-bit microcontroller. Its principal weakness is the same one noted in Section IV-B: a single scalar threshold cannot capture the many ways waste composition can confound a moisture reading.

B. Vision and Deep-Learning-Based Segregation

A second, more recent segregation strategy delegates the classification decision to a trained model rather than a fixed threshold. Beyond the sensing-side papers already discussed in Section IV-D, two recent works extend this idea toward traceability: [24] couples an AI-based waste classifier with a blockchain ledger so that each classified item's provenance and disposal path can be audited after the fact, and [25] proposes a multi-agent architecture in which several low-cost classification nodes coordinate over a blockchain-secured channel, explicitly targeting deployments where a single centralised classifier would be too expensive. Both works illustrate a broader trend: as classification moves from a single threshold to a learned model, the literature increasingly treats the resulting label as a data asset worth securing and auditing, not merely as an actuation trigger, a theme revisited in Section VIII.

C. Mechanical Post-Segregation Processing

A small number of designs in the broader IoT waste literature go beyond binary stream separation to address contamination within a single stream, for example using vibration or rotation to separate fine particulate contaminants (soil, dust, grit) from bulkier recyclable material before it reaches a collection vehicle. This sub-category is the least populated of the three segregation strategies reviewed here; most of the corpus stops at the diverter-flap decision and does not attempt any further mechanical conditioning of the separated streams, leaving in-bin contamination removal as a comparatively open niche, returned to in Section XII.

VI. COMMUNICATION AND NOTIFICATION ARCHITECTURES

A. Cellular/GSM-SMS Gateways

Where connectivity cannot be assumed, the most consistently reported notification path is a GSM modem dispatching SMS messages directly to a collection crew or supervisor, bypassing any requirement for a continuously available internet connection. This pattern appears across cost-sensitive prototypes throughout the review period and is explicitly motivated in several papers, including [26], by deployment contexts where broadband coverage cannot be guaranteed. A particularly clear illustration of the value of this channel comes from outside conventional municipal collection: [27] applies the same SMS-alert pattern to biomedical waste bins in healthcare facilities and reports that prompt notification measurably shortened the time infectious refuse was left unattended, suggesting that the latency benefit of direct SMS alerting generalises beyond the household-waste context in which most of this sub-literature is framed. [28] proposes an energy-aware variant of the same general notification pattern, arguing that the comparatively infrequent, short-burst nature of SMS transmission is well matched to battery- or solar-powered nodes that cannot sustain a continuously open data connection.

B. Wi-Fi and Cloud-Connected Dashboards

Where reliable broadband or campus-style Wi-Fi is available, a second cluster of systems instead streams sensor readings to a cloud backend and exposes the result through a web or mobile dashboard, trading the simplicity of SMS for richer visualisation, historical logging, and the ability to aggregate many bins into a single fleet-level view. [8] and [9] both follow this pattern at city scale, and [26] formally evaluates the operational benefit of such a deployment using the SQERT model, reporting double-digit reductions in vehicle-kilometres travelled relative to fixed-schedule collection.

C. Low-Power Wide-Area Networks (LPWAN)

A third communication family, more prominent in work published from 2018 onward, uses a low-power wide-area network protocol, most commonly LoRaWAN, to achieve multi-kilometre range on a fraction of the energy budget required by cellular or Wi-Fi radios. [10] reports a LoRaWAN-connected bin-level monitoring deployment explicitly targeting the energy constraints of battery-powered nodes, and [29] combines low-power LoRaWAN sensing nodes with a route-optimisation layer, demonstrating that the same radio link can support both the fill-level telemetry and the routing decision it ultimately informs. Table I summarises the principal trade-offs among the cellular/SMS, Wi-Fi/cloud, and LPWAN families as characterised across the reviewed corpus; no single technology dominates on every axis, which helps explain why all three remain active in current research and deployment rather than one having displaced the others.

TABLE I
COMMUNICATION TECHNOLOGY COMPARISON ACROSS THE REVIEWED CORPUS

Technology	Typical Range	Power Profile	Infrastructure Dependency	Relative Cost	Best-Fit Scenario
Cellular GSM/SMS	City-wide (operator coverage)	Moderate; short burst transmission	Needs cellular signal; no local gateway required	Low hardware; recurring SIM/airtime cost	Coverage areas with unreliable broadband
Wi-Fi / Cloud	Tens of metres (AP range)	Continuous; comparatively higher draw	Needs local Wi-Fi AP plus stable internet backhaul	Low hardware; cost tied to broadband access	Campuses, malls, well-networked sites
LoRaWAN	Up to several km (gateway-dependent)	Very low, duty-cycled transmission	Needs a LoRaWAN gateway within range	Low per-node cost; one-time gateway cost	Dense bin networks on battery/solar power
NB-IoT	City-wide (operator coverage)	Low to moderate	Needs an NB-IoT-enabled cellular operator	Moderate; module cost plus data plan	Wide-area deployment without a private gateway

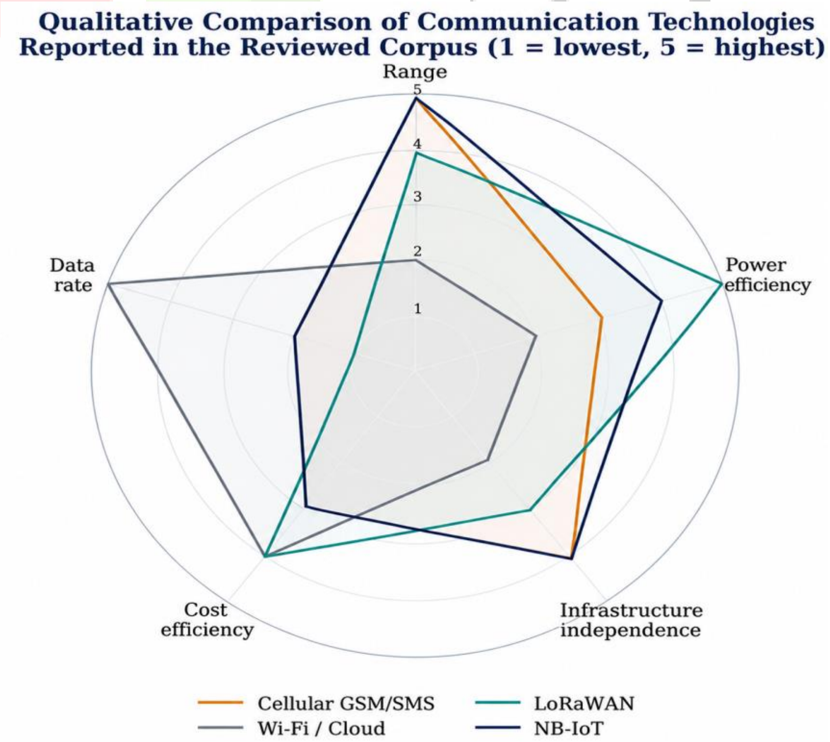

Fig. 4. Qualitative comparison of four communication technologies reported in the reviewed corpus across five evaluation axes (1=lowest, 5=highest); compare Table I

VII. COLLECTION-ROUTE OPTIMISATION AND FLEET MANAGEMENT

A distinct but closely related strand of the literature treats the bin-level fill or odour signal not as an end in itself but as an input to a vehicle-routing decision. [30] frames the problem at a higher level still, formulating a two-stage sustainable network-design model in which facility location and vehicle routing are optimised jointly, and noting explicitly that the credibility of the model's tracing and allocation logic depends on accurate upstream segregation, the same dependency on sensing quality that motivates Sections IV and V of this review. [29] frames its LoRaWAN deployment explicitly around route optimisation, recomputing collection sequences as new fill-level telemetry arrives rather than following a static round. [31] compares several waste-management models under IoT-enabled conditions using multi-agent simulation, finding that dynamically triggered, fill-aware routing consistently outperforms fixed-interval collection across the scenarios tested. [32] extends this idea further by combining graph-based route representations with AI-driven prediction, reporting a deployment-scale case, drawn from a large European city's published sensor-network experience, in which IoT-guided routing across roughly eighteen thousand bin-level sensors was associated with annual operating-cost savings in the hundreds of thousands of euros. Collectively, this sub-literature suggests that the marginal value of an individual bin's sensing accuracy is partly a function of how that reading is consumed downstream: a moderately noisy fill estimate feeding a well-designed routing layer can still yield substantial fleet-level efficiency gains.

VIII. SECURITY, PRIVACY, AND DATA INTEGRITY

As smart-bin deployments have grown from single-prototype demonstrations to city-scale sensor networks, a parallel literature has begun examining the resulting attack surface. [33] provides the most direct treatment found in this review, analysing smart waste management specifically from a cyber-physical-systems security perspective and observing that SMS-based command and notification paths are, in general, harder to compromise remotely than backends reachable over open Wi-Fi or public internet endpoints, precisely because they do not expose an internet-facing service to probe. This observation sits in some tension with the routing and dashboard literature reviewed in Sections VI and VII, which generally favours internet-connected backends for their richer functionality; the practical implication is that security posture is not a fixed property of “IoT waste management” as a category but depends heavily on which communication family, per Section VI, a given deployment chooses. On the data-integrity side, [24] and [25] both propose blockchain-backed ledgers as a way to make classification and disposal records tamper-evident after the fact, a direction that trades additional computational and storage overhead for auditability, and one that remains comparatively rare outside these two recent papers.

IX. CITIZEN ENGAGEMENT AND CROSS-CUTTING PLATFORMS

A final cluster of systems treats the public, rather than only the municipal collection crew, as a stakeholder in the sensing loop. [11] explicitly frames its design around citizen-facing feedback, arguing that visibility into bin status can shift public perception of waste services from purely reactive complaint-handling to a more collaborative model. [34] similarly proposes an IoT architecture explicitly framed around “waste management 2.0,” emphasising integration between bin-level sensing and city-level open data so that third-party applications, including citizen reporting tools, can be built on top of the same sensor feed. [12] reports a related real-time bin-mechanism design that exposes its status through a simple web interface intended for both operational staff and the public. Although still a minority strand relative to the sensing- and communication-focused literature reviewed in Sections IV and VI, this citizen-facing direction is one of the more consistent threads connecting otherwise disparate papers' stated motivations, and is returned to as a future direction in Section XII.

X. COMPARATIVE ANALYSIS

To make the qualitative discussion of Sections IV through IX comparable across sources, each system-level paper in the reviewed corpus was coded against the capability branches defined in Section III, based on the sensing, segregation, communication, and logistics functionality reported in its own abstract and results. Table II reports this coding for eighteen representative bin- or fleet-level systems spanning the full review period; the complete thirty-four-source corpus, including survey, sensor-characterisation, and policy-context papers not themselves describing a deployable system, informs the discussion throughout the paper but is not repeated row-by-row in the table.

TABLE II
FEATURE MATRIX OF REPRESENTATIVE BIN- AND FLEET-LEVEL SYSTEMS

Ref.	Year	Primary Sensing	Segregation / Decision Logic	Communication	Route / Fleet Layer	Reported Focus
[8]	2023	Ultrasonic (fill)	—	Wi-Fi	No	Early detect-and-notify baseline
[9]	2023	Ultrasonic (fill)	—	Cloud, GPS-tagged	Yes (city-scale)	City-scale GPS-tagged deployment
[10]	2022	Ultrasonic (fill)	—	LoRaWAN	No	Low-power long-range bin telemetry
[11]	2020	Ultrasonic + load cell	—	IoT + citizen app	Citizen-facing	Citizen-oriented status sharing
[12]	2021	Ultrasonic + load cell	—	Web / cloud	No	Real-time public-facing bin status
[13]	2020	Ultrasonic + load cell	Moisture threshold	IoT / cloud	No	Moisture-based segregation with fill alert
[14]	2021	Ultrasonic + load cell	Moisture threshold	IoT / cloud	No	Moisture-based segregation with fill alert
[20]	2022	Camera	CNN (organic / recyclable)	IoT / cloud	No	Deep-learning waste classification
[22]	2021	Camera	YOLOv3 (multi-item)	—	No	Multi-item in-frame detection
[23]	2020	Camera	CNN classifier	—	Yes (e-waste planning)	E-waste collection-route planning
[24]	2025	Camera / sensor	AI classifier	Blockchain ledger	No	Tamper-evident classification record
[25]	2025	Camera / sensor (multi-agent)	AI classifier	Blockchain + multi-agent	No	Low-cost distributed classification
[26]	2023	Ultrasonic (fill)	—	Cloud	Yes (SQERT-evaluated)	Vehicle-km reduction via dynamic collection
[27]	2023	Ultrasonic (fill)	—	GSM / SMS	No	Biomedical-waste alert-latency reduction
[28]	2023	Ultrasonic (fill)	—	Energy-aware radio	Partial	Energy-aware notification variant
[29]	2018	Ultrasonic (fill)	—	LoRaWAN	Yes	Joint sensing and route optimisation
[30]	2022	— (network-level)	Segregation-dependent tracing	—	Yes (two-stage design)	Sustainable two-stage logistics model
[34]	2024	Ultrasonic (implied)	—	IoT + open-data API	Citizen-facing	Open-data “waste 2.0” architecture

Two patterns stand out from this coding exercise, visualised in Fig. 5. Ultrasonic fill-level sensing, alone or paired with a load cell, is present in twelve of the twenty-one bin-level and fleet-level systems examined in depth, confirming its status as the closest thing to a default sensing choice in this literature. Vision- or deep-learning-based segregation appears in six of the twenty-one, a share that has grown almost entirely within the last five years of the review window and that, per Section IV-D, is concentrated in papers reporting laboratory rather than field accuracy. Route- or fleet-level optimisation logic, present in seven of the twenty-one, is more common than gas- or odour-aware decision logic, which appears in none of the twenty-one bin-level systems coded for Table II; where gas sensing does appear in the broader thirty-four-source corpus, it is in general ambient air-quality studies rather than in bin-integrated designs, consistent with the minority-status finding reported for the wider literature by [4].

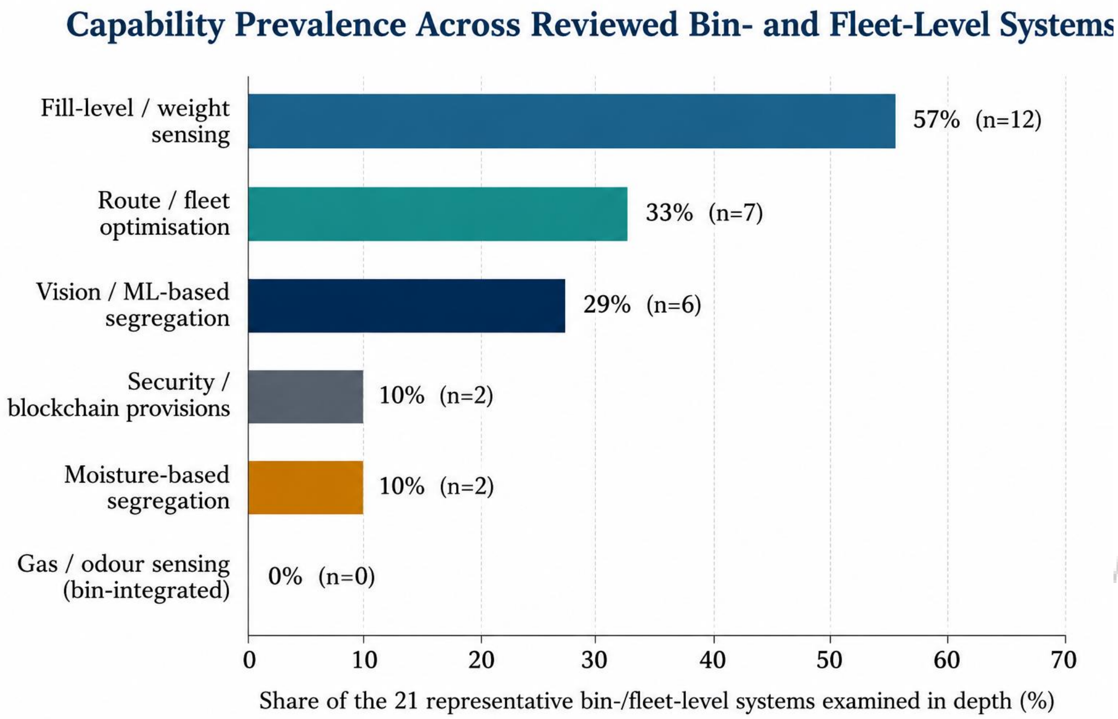

Fig. 5. Prevalence of six representative capabilities across the 21 bin- and fleet-level systems examined in depth in Section X, expressed as the percentage of systems coded as including each capability.

Fig. 6 plots the thirty-four primary technical sources in the corpus by publication year. Output in this area was modest before 2019, accelerated through 2020-2022 alongside the broader maturation of low-cost IoT hardware and the publication of [4]'s systematic review, and has remained at an elevated, still-growing level through 2025-2026, with deep-learning- and blockchain-augmented designs accounting for a growing share of the most recent entries. This trend is consistent with the framing in Section I: the domain is not short of activity, but the activity has been concentrated on individual sub-problems (sensing, segregation, communication, routing, security) studied largely in isolation from one another, which is precisely the fragmentation this review has attempted to organise.

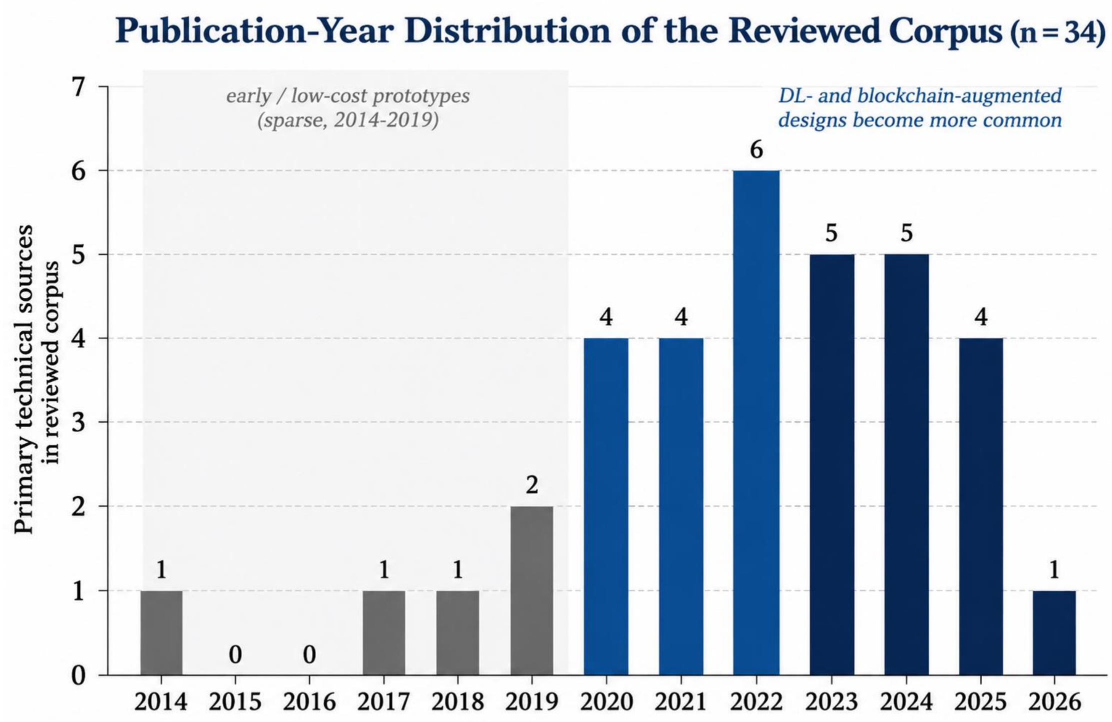

Fig. 6. Publication-year distribution of the 34 primary technical sources in the reviewed corpus (2014-2026)

A further observation from Table II concerns reporting practice rather than engineering content: the systems reviewed use a wide variety of outcome metrics, including classification accuracy, vehicle-kilometres travelled, mean collection latency, and qualitative case-study cost savings, with very little overlap in which metric any two papers report. This heterogeneity, discussed further as a challenge in Section XI, is itself a finding: it means that head-to-head numerical comparison across most pairs of systems in this corpus is not presently possible without re-implementation, and that the comparative claims in Table II should be read as qualitative capability coverage rather than as a performance ranking.

XI. OPEN CHALLENGES

A. Per-Unit Hardware and Deployment Cost

[35] surveys adoption barriers for smart-bin deployment specifically within Indian smart-city programmes and identifies per-unit cost as the dominant impediment to scaling beyond pilot deployments, ahead of technical or organisational barriers. Every additional sensing modality discussed in Section IV, and particularly the camera and inference hardware required for vision-based segregation in Section V-B, adds to this per-unit cost, creating a direct tension between capability breadth and the deployability that [35] identifies as the binding constraint in practice.

B. Limited Field Validation Beyond Bench Testing

With few exceptions, the systems reviewed in Sections IV through IX report results from controlled bench or laboratory testing rather than sustained outdoor deployment. Vision-based classifiers in particular are typically evaluated on curated, single- or few-item images rather than the occluded, soiled, and variably lit conditions of an in-use bin, a gap also noted by [36] in its own comparative analysis of smart-bin literature. The handful of papers that do report city-scale or multi-month field data, including [26] and [32], are consequently disproportionately influential in shaping confidence about which capabilities actually deliver real-world benefit.

C. Sensor Drift and Calibration

Metal-oxide gas sensors of the MQ-135 class, characterised in Section IV-C, are well documented to drift in baseline resistance over weeks to months of continuous operation, requiring periodic recalibration against clean air; the electronic-nose literature surveyed by [19] identifies long-term drift as one of the central unsolved problems for any multi-sensor gas-detection array, not only single-channel designs. None of the gas-sensing papers reviewed in Section IV-C report a recalibration protocol suitable for unattended, multi-year field deployment, leaving this as an open implementation gap rather than only a research gap.

D. Absence of Standardised Benchmarks and Datasets

The vision-based segregation papers reviewed in Section V-B each evaluate against a different, self-curated image set, and the sensor-fusion and rule-based systems reviewed in Sections IV and V each choose their own threshold values empirically, with no shared benchmark dataset or evaluation protocol comparable to, for example, ImageNet in general computer vision. This absence compounds the metric-heterogeneity problem identified in Section X and makes it difficult for a new entrant to the field to determine which published technique would actually generalise best to a new deployment site.

E. Connectivity and Energy Constraints in Low-Resource Settings

The continued relevance of cellular SMS-based notification, discussed in Section VI-A, is itself evidence of a persistent constraint: a meaningful share of candidate deployment sites, particularly in the regions where [2] reports the largest absolute waste volumes, cannot assume continuously available broadband. [28]'s energy-aware notification design and the LoRaWAN-based systems reviewed in Section VI-C represent two different responses to the same underlying constraint, low and intermittent power and connectivity budgets, and neither has yet become a clearly dominant default choice across the corpus.

XII. FUTURE RESEARCH DIRECTIONS

A. Multi-Modal Sensor Fusion

The capability-prevalence finding in Section X, that fill, weight, moisture, vision, and gas sensing are each reported mostly in isolation from one another, points toward multi-modal fusion as the most direct unexploited opportunity in the corpus. A bin that combines weight, moisture, and a gas channel, for instance, can in principle distinguish a momentarily noisy single-channel reading (a freshly deposited item) from a sustained multi-channel signature consistent with ongoing decomposition, a distinction no single-sensor system reviewed here is positioned to make reliably.

B. Edge-Deployed Adaptive Classifiers

Most of the rule-based systems reviewed in Section V-A rely on thresholds fixed at deployment time and tuned to the specific waste stream observed during initial testing. [6]'s survey of deep-learning approaches to smart-dustbin classification, together with the early but promising results reported by [32] for graph- and AI-based predictive routing, suggest that lightweight, locally-trained classifiers, retrained periodically on a given bin's own historical readings rather than a fixed global threshold, are now computationally feasible even on inexpensive edge hardware and would likely generalise better across the seasonal and locational variation in waste composition than the fixed thresholds used throughout Sections IV and V.

C. Multi-Gas and Electronic-Nose Profiles

Building on the gap identified in Section IV-C and Section XI-C, extending single-channel MQ-135 designs toward a small multi-gas array, drawing on the broader electronic-nose design principles surveyed by [19], would allow a bin to move from a binary “odour present or absent” signal toward a coarse attribution of which decomposition pathway, or which contaminant, is driving a given reading, which in turn could support more targeted maintenance or collection responses than a single ammonia-equivalent ppm value permits.

D. Standardised Open Benchmarks

A shared, openly published benchmark, covering both labelled waste-image data for the vision-based systems of Section V-B and a common reporting template for the outcome metrics discussed in Section X, would directly address the cross-paper comparability gap identified in Section XI-D and would make future review work of the kind undertaken here considerably less dependent on heterogeneous, self-reported metrics.

E. Deeper Citizen-Facing and Open-Data Integration

The citizen-engagement strand reviewed in Section IX remains comparatively small relative to the sensing- and communication-focused literature. Extending the open-API framing proposed by [34] and the citizen-visibility framing proposed by [11] into a standard, reusable interface, rather than each project's own bespoke dashboard, would let third-party applications, including the citizen-facing odour maps and predictive route-planning tools that several of the reviewed papers mention only as aspirational future work, be built once and reused across deployments.

F. Auditable, Blockchain-Secured Provenance at Scale

[24] and [25] demonstrate that blockchain-backed classification records are technically feasible at small scale; the open question, not yet addressed by either paper, is whether the computational and storage overhead of a distributed ledger remains acceptable when scaled to the thousands of bins and continuous sensor streams characteristic of the city-scale deployments reviewed in Section VII. The continued growth of AI-focused municipal waste research generally, reflected in the very recent survey by [37], suggests this question will receive direct empirical attention within the next review cycle for this literature.

Table III summarises the mapping between each open challenge identified in Section XI and the most relevant future research direction proposed above, providing a consolidated reference for practitioners planning next-generation system designs.

TABLE III

MAPPING OF OPEN CHALLENGES TO PROPOSED FUTURE DIRECTIONS

Open Challenge (Sec. X)	**Root Cause**	**Most Relevant Future Direction (Sec. XII)**
A. Per-unit hardware / deployment cost	Each additional sensing modality raises per-unit cost, in tension with deployability at scale	B. Edge-deployed adaptive classifiers reduce reliance on costly dedicated inference hardware
B. Limited field validation beyond bench testing	Most systems report only controlled bench/lab results rather than sustained outdoor deployment	D. Standardised benchmarks and reporting templates enable rigorous, comparable field trials
C. Sensor drift and calibration	Metal-oxide gas sensors drift over weeks to months; no recalibration protocol is reported	C. Multi-gas / electronic-nose profiles with built-in drift compensation
D. Absence of standardised benchmarks or datasets	Each vision-based study evaluates against its own curated dataset with no shared protocol	D. Standardised open benchmarks and shared reporting templates
E. Connectivity and energy constraints in low-resource settings	Many candidate deployment regions cannot assume continuous broadband or grid power	A. Multi-modal sensor fusion designed around low-power, LPWAN-first communication budgets
Fragmented evaluation metrics (Sec. X)	Papers report incomparable outcome metrics (accuracy, vehicle-km, latency, cost), limiting comparison	D. Standardised open benchmarks and a shared outcome-reporting template

XIII. CONCLUSION

This review has synthesised thirty-four primary technical sources, supplemented by three contextual references on global and Indian waste statistics and on the health implications of ambient pollution, into a five-branch taxonomy covering sensing, segregation, communication, logistics, and the cross-cutting security and citizen-engagement layer of IoT-based smart waste management research published between 2017 and 2026. Across the systems examined in depth, ultrasonic fill-level sensing is essentially ubiquitous, vision- and deep-learning-based segregation is a fast-growing but still largely laboratory-validated capability, route- and fleet-level optimisation is moderately well represented, and gas- or odour-aware decision logic remains rare despite a well-established underlying sensor technology and a clear motivating health and nuisance rationale. Communication architecture choices, cellular SMS, Wi-Fi/cloud, and LPWAN protocols such as LoRaWAN, trade off range, power, infrastructure dependency, and security posture in ways that make each suitable for a different deployment context rather than any one being a universal default. The principal barriers limiting translation from prototype to sustained municipal deployment are per-unit hardware cost, the scarcity of multi-month field validation, sensor drift in gas-sensing channels, and the absence of standardised benchmarks or reporting metrics across the literature. Multi-modal sensor fusion that combines fill, weight, moisture, vision, and gas channels within a single decision pipeline; edge-deployed classifiers that adapt to a bin's own historical readings; multi-gas electronic-nose profiles for odour-source attribution; and standardised, openly published benchmarks together represent the directions most likely to close the gap between the fragmented, single-capability prototypes that dominate the present literature and the integrated, field-validated systems that municipal-scale deployment will ultimately require.

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