Robotic Systems for Sidewalk Maintenance

Why aren't robots shoveling the snow?

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Abstract

Sidewalk snow removal in the United States is mandated by law, underserved by equipment, and hemorrhaging labor. ADA compliance, municipal ordinance, and tort liability require cleared paths. The machines that clear roads cannot fit. The workers who could clear by hand are seasonal, expensive, and increasingly unavailable. Municipalities respond with overtime, contractors, and deferred maintenance. The gap persists.

This paper presents a robotic system designed to close it: a 600mm x 600mm rover platform with modular attachments for snow clearing, sweeping, and brine application, operated remotely over LTE by a single supervisor monitoring multiple units. Fleet coordination integrates with existing municipal GIS and work order systems. The platform is currently deployed in pilot configuration under direct human supervision.

Under supervised autonomy (1:10 operator-to-unit ratio), five-year total cost of ownership drops approximately 70% versus manual labor and 50% versus contractors. At current 1:1 teleoperation, TCO reduction still exceeds 50% versus manual and 20% versus contract crews. These figures exclude avoided slip-and-fall liability and eliminated worker injury costs. Specifications reflect current hardware and software constraints.

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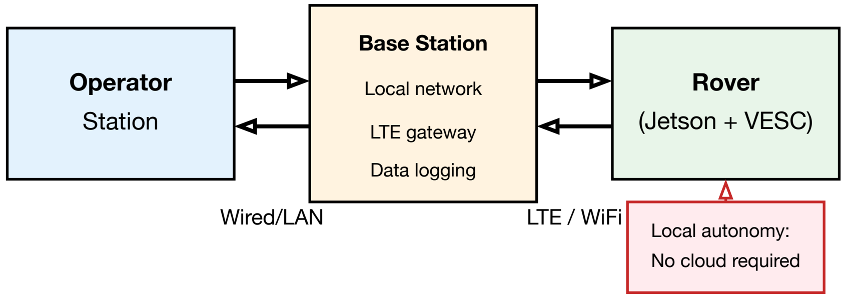


Figure 1: System architecture: local-first SCADA model with no cloud dependency

1 Introduction

The intended audience for this paper is municipal public works departments, university facilities managers, and commercial property operators evaluating alternatives to manual sidewalk maintenance.

The system described in this paper is operational. Specifications reflect current hardware and software constraints.

Figure 1 shows the high-level system architecture. The system follows a SCADA-like model: the operator station connects directly to rovers via the local network or LTE, with no cloud dependency. Each rover operates independently with local safety systems that halt the vehicle without network connectivity. Rovers continue autonomous operation during network outages and sync when connectivity is restored.

2 Why Now: The Hardware Inflection Point

This system would not have been economically viable five years ago. Several technology trends have converged to create an inflection point for low-cost outdoor robotics.

48V ecosystem standardization. The electric bicycle and personal mobility industry has driven massive production scale for 48V lithium-ion batteries, motor controllers, and hub motors. Components that cost $500+ in 2018 now cost under $100 at retail. More importantly, this ecosystem has standardized on common form factors, connectors, and protocols. The BVR0 prototype uses an off-the-shelf e-bike battery ($200), hoverboard hub motors ($80 each), and VESC motor controllers ($60 each). Total drivetrain cost: under $500 for a platform capable of moving 50kg payloads at walking speed.

Edge compute cost collapse. The NVIDIA Jetson Orin NX delivers 100 TOPS of AI inference at 15W for under $500. Five years ago, equivalent compute required $5,000+ in hardware and 10× the power budget. This enables onboard perception, mapping, and decision-making without cloud connectivity. The Raspberry Pi 5 and similar single-board computers now provide sufficient compute for teleoperation and basic autonomy at $100.

Sensor commoditization. The Livox Mid-360 solid-state LiDAR costs $1,000 and provides 360° coverage with 40m range. Consumer 360° cameras like the Insta360 X3 ($400) provide sufficient resolution for remote operation and machine vision. Recent research has demonstrated practical calibration methods for fusing these sensors into coherent spatial representations [1]. Five years ago, this sensor suite would have cost $20,000+.

Open-source software maturity. ROS2, OpenCV, PyTorch, and related tools have matured to production quality. Pre-trained models for common perception tasks (pedestrian detection, path segmentation, obstacle classification) are freely available and run efficiently on edge hardware. Projects like comma.ai's openpilot demonstrate what is possible: an open-source driver assistance system with over 300×10^6 miles driven, 325+ supported vehicle models, and contributions from over $1{,}000$ developers [2]. The entire perception and control stack runs on a $500 device.

Proven autonomous navigation at scale. The question of whether robots can navigate shared pedestrian spaces has been answered. Starship Technologies' delivery robots have logged over 12×10^6 autonomous miles on sidewalks worldwide [3]. Waymo's robotaxi fleet has driven 96×10^6+ fully driverless miles with demonstrated safety improvements: 79% fewer injury-causing crashes than human drivers [4]. These are not research prototypes; they are commercial services operating daily. The perception, planning, and safety systems required for sidewalk navigation exist and work.

The result: a complete sidewalk-clearing robot can be built for under $5,000 in hardware, using components available from consumer electronics suppliers. The software stack to operate it

Figure 2: Aerial view of Lakewood, Ohio showing dense residential grid with continuous sidewalk network. Lake Erie and downtown Cleveland visible in background.

autonomously has been proven at scale in adjacent domains. This is below the threshold where municipalities can experiment without major capital approval processes.

3 Public Works as an Optimization Problem

3.1 The Optimization Problem

Municipal public works departments solve a recurring constrained optimization problem. The objective is to maintain public rights-of-way to a defined service level, subject to fixed annual budgets (typically set 18 months in advance), hard service-level agreements requiring snow clearance within a specified number of hours after snowfall ends, seasonal demand spikes with 10× variance in labor need between summer and winter, an adversarial environment of weather, vandalism, equipment failure, and political pressure, asset lifetime requirements of 15–25 years for equipment, and public accountability where every failure is photographed and posted.

This is a control problem, not a technology problem. The question is not whether robots can clear snow. The question is whether a robotic system can meet service-level guarantees more reliably than the current approach, at equal or lower cost, without introducing new failure modes that the department cannot manage.

The control variables available to a public works director are labor hours allocated per event, fleet size, route sequencing and prioritization, response latency between snowfall end and clearing completion, and equipment availability as a percentage of fleet operational at any given time. Any proposed system must improve at least one of these variables without degrading the others.

3.2 Reference Case: Lakewood, Ohio

Lakewood is a first-ring suburb of Cleveland with a population of 49,517 [5] and over 180 miles of sidewalks [6]. It is the most walkable city in Ohio and the state's most densely populated municipality (~9,000 residents per square mile). The city experiences an average of 24 snow events per season requiring clearing [7].

Lakewood presents a compelling case study for several reasons. As a "streetcar suburb" developed in the early 20th century, the city was designed around pedestrian access to transit stops. This legacy produces an unusually complete and well-connected sidewalk network with high daily foot traffic: residents routinely walk to schools, commercial districts, and transit. Sidewalk accessibility is not optional infrastructure; it is the primary mobility layer for a significant portion of the population.

However, this same legacy produces challenges. Aging infrastructure (century-old water mains, overhead power lines, and narrow rights-of-way) creates maintenance complexity. In June 2022, a severe storm system spawned tornadoes that knocked out power across the city for up to two weeks. Cellular connectivity failed within days as tower batteries depleted without grid power. This event demonstrated both the fragility of communications infrastructure and the city's resilience requirements: any deployed system must degrade gracefully when connectivity is unavailable.

Currently, Lakewood does not clear sidewalks municipally. Property owners are required by ordinance to clear adjacent sidewalks within 24 hours of snowfall. Enforcement is handled by the Division of Housing and Building on a complaint basis. The city does not provide school busing, making sidewalk accessibility a student safety issue.

This profile (high density, extensive sidewalk network, heavy pedestrian reliance, aging infrastructure, demonstrated connectivity fragility, property-owner mandate with uneven compliance, and no current municipal clearing budget) represents a common pattern in Midwestern streetcar suburbs and makes Lakewood an ideal testbed for autonomous sidewalk maintenance.

3.3 Reference Case: Minneapolis, Minnesota

Minneapolis presents a contrasting case: a larger city actively grappling with the economics of municipal sidewalk clearing. With a population of 429,000 and approximately 1,910 miles of sidewalks, Minneapolis has 92% of streets with sidewalks on both sides and is recognized as a Gold-level Walk Friendly Community.

The city experiences an average of 54 inches of annual snowfall across approximately 23 snow events per season, with four typically triggering declared snow emergencies [8]. Current ordinance requires residential property owners to clear sidewalks within 24 hours of snowfall; commercial properties must clear within 4 daytime hours. Enforcement, as in most cities, is complaint-driven.

In 2023, Minneapolis commissioned a study of citywide municipal sidewalk clearing. The projected cost: $\$116.2 \times 10^6$ over the first three years, with annual operating costs of $\$40.6 \times 10^6$ thereafter [9]. At $1{,}910$ miles, this works out to approximately $\$21{,}250$ per mile per year, reflecting the full cost of equipment, labor, and overhead at municipal scale.

Rather than commit to this expense, the city launched a targeted pilot program in 2024-2025. The program focused on 66 miles of high-priority pedestrian sidewalks in South Minneapolis, deploying four "Snow Ambassador" staff to patrol, clear, and treat problem areas. The pilot also included a mobile response team for 311 requests and a senior assistance program partnering with neighborhood groups [10].

Results were striking: the pilot spent approximately $\$230{,}000$, less than half the budgeted $\$595{,}000$, while addressing 534 site clearings and 902 problem addresses [10]. The per-mile cost of $\$3{,}485$ for targeted intervention compares favorably to the $\$21{,}250$ per-mile estimate for comprehensive municipal clearing.

Minneapolis illustrates the cost cliff municipalities face: property-owner mandates are cheap but ineffective, while full municipal programs are effective but prohibitively expensive. The pilot suggests a middle path, targeted intervention on priority routes, but this approach still requires significant labor coordination and does not scale gracefully to full network coverage.

This gap between "complaint-driven non-enforcement" and "$40 million annual programs" is precisely where robotic systems can operate. A fleet of autonomous units could provide consistent coverage of priority routes at a fraction of the labor cost, while the logging and verification capabilities address the accountability gaps that plague contractor and property-owner models.

3.4 Current Approaches and Failure Modes

The consequences are measurable: in 2023, 65% of pedestrian fatalities occurred in locations without a sidewalk or where the sidewalk was obstructed [11]. Sidewalk coverage in major U.S. cities averages only 27–58% of road networks [12].

Most municipalities address sidewalk maintenance through one of three approaches:

1. Municipal crews with hand tools and small equipment

Typical configuration: seasonal workers with shovels, walk-behind snowblowers, and occasionally ATVs or Toolcats.

Failure modes: Labor availability (snowstorms do not schedule around shift changes), coverage rate (a worker with a shovel clears approximately 0.1 miles per hour), consistency (different workers clear to different standards), and injury (snow removal is

Figure 3: Minneapolis Snow Ambassadors clearing priority sidewalks during the 2024-2025 pilot program. Manual labor with shovels and walk-behind blowers remains the standard approach.

Figure 4: Uncleared sidewalks force pedestrians onto roads, creating safety hazards and liability exposure

among the leading causes of workers' compensation claims in public works [13]).

2. Contractor services

Typical configuration: Landscaping companies with plowing contracts.

Failure modes: Incentive misalignment (per-event contracts reward billing, not coverage), verification (municipalities rarely have real-time visibility into contractor operations), reliability (contractors serve multiple clients), and equipment mismatch (contractors use equipment sized for parking lots).

3. Property owner mandates

Typical configuration: Ordinances requiring property owners to clear adjacent sidewalks within N hours.

Failure modes: Enforcement cost, equity (elderly, disabled, and low-income residents cannot comply), and inconsistency (a

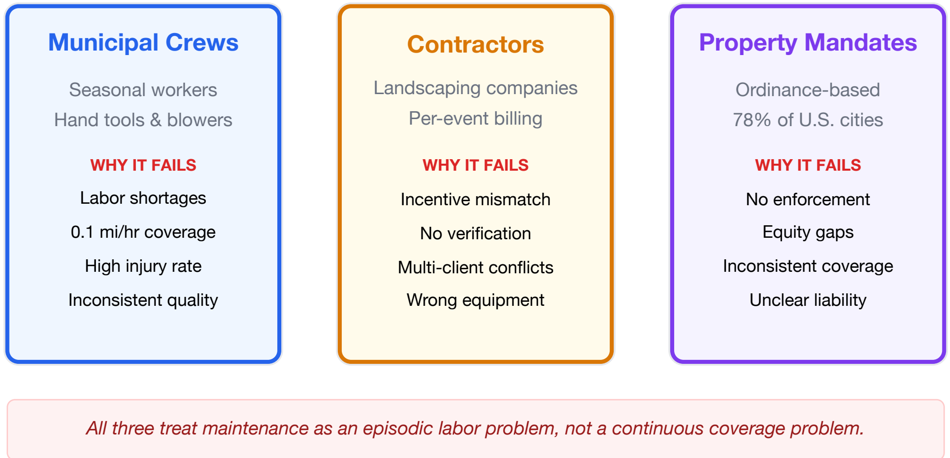


Figure 5: Current approaches to sidewalk maintenance share structural failure modes that prevent reliable service delivery.

Requirement	Threshold	Rationale
Width	≤ 30 in (762mm)	Operate within ADA minimum clear width
Clearing rate	≥ 0.5 mi/hr	5× hand labor productivity
Duty cycle	≥ 4 hrs continuous	Complete route without returning to base
All-weather	-20°F to 40°F	Operate when service is required
Remote operability	LTE or equivalent	Supervise from central location
Maintenance	Field-serviceable	Repair without factory return
Acquisition cost	< $30,000	Justify against labor savings

Table 1: Minimum thresholds for operational viability

cleared sidewalk next to an uncleared sidewalk is not a cleared route).

This is the dominant approach. A survey by the Institute of Transportation Engineers found that 78% of municipalities assign sidewalk snow removal responsibility to adjacent property owners [14]. The legal rationale is liability transfer: if the property owner is responsible, the city is not liable for slip-and-fall injuries.

In practice, enforcement is nearly nonexistent. A University of Delaware study found that 70% of surveyed municipalities did not enforce their sidewalk snow-removal ordinances [15]. Most cities enforce on a complaint basis only. The result is that **most sidewalks in most American cities are not reliably cleared**. The liability has been transferred on paper, but the service gap remains.

This creates a paradox: cities avoid clearing sidewalks to limit liability, but uncleared sidewalks generate liability anyway. The same study found that 58% of municipalities reported being sued for pedestrian accidents on improperly maintained sidewalks [15]. Zurich Insurance reserves approximately $\$1 \times 10^9$ annually for slip-and-fall claims, with sidewalk incidents averaging $\$19{,}776$ per claim [16]. The current equilibrium is unstable. It persists only because no cost-effective alternative has existed.

3.5 The Structural Problem

All three approaches share a common failure: they treat sidewalk maintenance as an episodic labor problem rather than a continuous coverage problem (like an indoor robotic vacuum).

The service requirement is spatial: every linear foot of sidewalk must be cleared. The labor model is temporal: workers clock in and clock out. The mismatch is fundamental.

Heavy equipment solves this mismatch for roadways. A plow truck clears miles per hour. A single operator covers an entire route. But heavy equipment cannot operate on sidewalks. The geometry does not permit it. ADA minimum clear width is 36 inches. A standard plow truck is 102 inches wide.

The result is that sidewalks, the most pedestrian-critical infrastructure, are maintained with the lowest-productivity methods.

3.6 Requirements for a Solution

Any system that claims to address this problem must satisfy the constraints shown in Table 1.

Failure Mode	Example	Root Cause
Integration collapse	Smart city dashboards	No connection to existing workflows
Vendor dependency	Proprietary fleet systems	Lock-in without exit strategy
Scaling cliff	Autonomous shuttle pilots	Works at demo scale, fails at city scale
Maintenance gap	Sensor networks	No plan for ongoing service
Political discontinuity	Multi-year IT projects	Leadership change kills funding

Table 2: Common failure modes in municipal technology pilots

3.7 What This Paper Does Not Claim

This paper does not claim that robotic sidewalk maintenance is superior to human labor in all circumstances. It claims that robotic systems can extend the coverage capacity of a fixed labor budget, reduce marginal cost per mile at scale, and provide consistent service levels that are difficult to achieve with variable labor.

The system described here is not autonomous in the consumer sense of that word. It requires human operators. It reduces the operator-to-asset ratio, not the operator count to zero.

The system does not eliminate the need for manual crews during extreme weather events. Blizzards, ice storms, and accumulations exceeding the system's clearing capacity (approximately 6 inches per pass) require conventional equipment and personnel. Robotic systems augment baseline capacity; they do not replace surge capacity.

4 Why Existing Solutions Fail

This section examines why previous attempts at municipal technology modernization have failed, and what distinguishes viable infrastructure from pilot-stage technology.

4.1 Taxonomy of Municipal Tech Failures

Over the past 15 years, municipal technology pilots have exhibited consistent failure patterns:

4.2 Why Contractors Underperform

Contractor relationships for sidewalk maintenance fail for structural reasons. Municipalities cannot observe contractor performance in real-time, creating verification asymmetry where quality is measured by complaint volume rather than coverage data. Per-event contracts reward billing frequency while seasonal contracts reward minimal effort per pass, creating incentive misalignment. Contractors serve multiple clients simultaneously, and commercial parking lots pay faster than municipalities. Finally, contractor equipment is sized for parking lots and driveways, not 36-inch sidewalks.

4.3 Why Consumer Robotics Fail in Municipal Applications

Consumer and commercial robots repurposed for municipal use fail on fundamental requirements. Consumer robots expect 1–2 hours of operation while municipal applications require 8+ hour shifts. Consumer IP ratings assume occasional rain, but municipal snow clearing requires operation in active precipitation at −20°F. Consumer products are designed for replacement rather than repair, yet municipal assets must be field-serviceable for 5–15 year lifetimes. Finally, consumer products lack incident logging while municipal operations require full audit trails.

4.4 Why Delivery Robots Don't Transfer

Autonomous delivery robots (Starship, Kiwibot, Serve, Amazon Scout) have logged millions of sidewalk miles. A reasonable question: why not repurpose these platforms for snow clearing?

The answer is that delivery and maintenance are different operational regimes:

Delivery robots optimize for navigation efficiency and payload capacity. Maintenance robots optimize for sustained mechanical work output in adverse conditions. A delivery robot's drivetrain, thermal management, and power system are undersized for snow clearing by factors of 2–5×.

Furthermore, delivery robot business models depend on per-delivery revenue with high utilization. Municipal contracts require guaranteed availability during unpredictable weather events. The operational and economic models are incompatible.

4.5 Competitive Landscape

Several companies have developed autonomous snow-clearing robots, though none has achieved significant municipal adoption.

Requirement	Delivery Robot	Maintenance Robot
Payload	Parcels (5-20 kg)	Snow auger, sweeper (15-30 kg)
Duty cycle	30-60 min round trips	4+ hours continuous
Surface contact	Passive wheels	Active tool engagement
Operating temp	Above freezing	-20°F to 40°F
Weather operation	Fair weather preferred	Operates during storms
Motor load	Light, variable	Continuous high torque
Maintenance interval	Depot service	Field-serviceable daily

Table 3: Delivery vs maintenance robot requirements

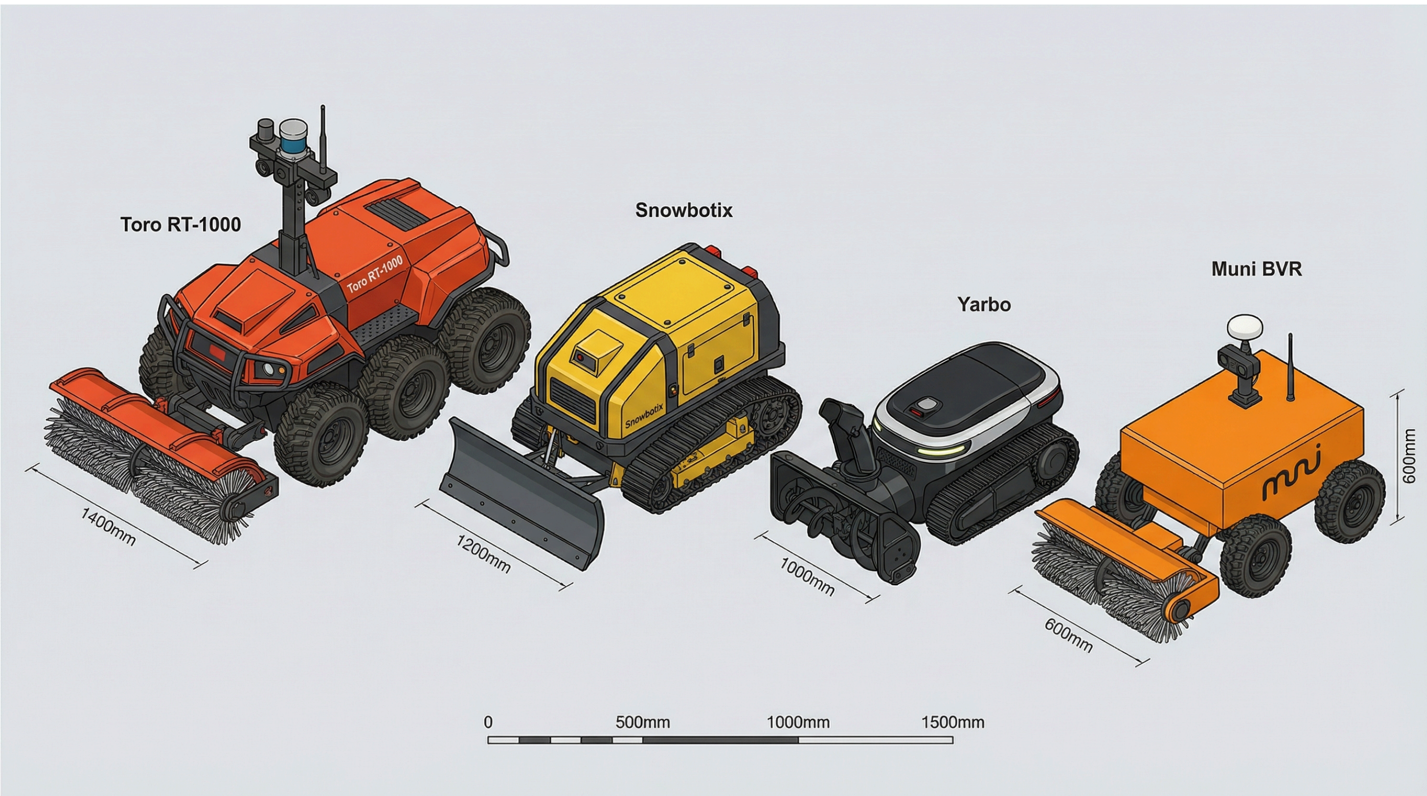


Figure 6: Competitive landscape: form factor comparison. Large-format platforms (Toro RT-1000, Snowbotix) target commercial properties; consumer products (Yarbo) target residential; the Muni BVR targets the underserved municipal sidewalk segment with a compact 600mm footprint.

4.5.1 Toro / Left Hand Robotics

The Toro Company acquired Left Hand Robotics in 2021, gaining the RT-1000 autonomous platform [17]. The RT-1000 is a multi-purpose robot capable of mowing and snow clearing, using RTK GPS, LiDAR, radar, and six cameras for navigation. It clears approximately 2 miles of sidewalk per hour with a 56-inch brush attachment.

The RT-1000 has seen limited municipal deployment, notably in Grande Prairie, Alberta for trail maintenance. However, its form factor (ATV-sized, 1,250 lbs) limits sidewalk applicability: it cannot navigate narrow passages, ADA ramps, or constrained urban sidewalks common in older cities.

Toro's likely strategy: Toro is the dominant player in commercial grounds equipment ($4B+ revenue). Their acquisition of Left Hand signals intent to lead in autonomous outdoor equipment. However, Toro's core business is selling equipment to landscaping contractors and grounds managers, not operating municipal services. They will likely pursue an equipment-sales model (sell RT-1000 units to municipalities or contractors) rather than a service model. This creates an opening for service-oriented approaches that align incentives with municipal outcomes rather than equipment purchases.

Toro's installed base and dealer network give them distribution advantages, but their large-format approach leaves the narrow-

Segment	Form Factor	Business Model	Players
Large commercial	ATV-sized	Equipment sales	Toro, Snowbotix
Residential	Walk-behind	Consumer purchase	Yarbo
Municipal sidewalk	Compact	Service/RaaS	?

Table 4: Competitive landscape segmentation

sidewalk segment underserved. A 600mm-wide rover can access infrastructure that a 1,400mm-wide RT-1000 cannot.

4.5.2 Snowbotix

Snowbotix offers multi-utility robots with 48–72 inch clearing widths, operating in temperatures as low as −40°F [18]. Their robots can clear up to 5 acres per charge and include solid/liquid deicing capability. Like the RT-1000, these are large-format machines designed for parking lots, campuses, and wide pathways rather than constrained urban sidewalks.

4.5.3 ASV.ai

ASV.ai (Canada) offers a Robotics-as-a-Service model for autonomous snow removal, targeting both municipal and commercial customers [19]. Their approach emphasizes fleet management and centralized monitoring rather than individual unit sales. This service model is closer to our approach, though their platform details and municipal deployment track record are limited.

4.5.4 Yarbo

Yarbo produces a consumer/prosumer autonomous snow blower with 24-inch clearing width and 12-inch depth capacity [20]. It features weather-triggered scheduling and operates in temperatures as low as −13°F. Yarbo targets residential customers and small commercial properties rather than municipal infrastructure.

4.5.5 Nivoso

Nivoso is a University of Minnesota spinout founded by Max Minakov that developed an autonomous snow-clearing robot. The company won the Student Division of the Minnesota Cup in 2023, earning $26,000 in seed funding [21]. As of early 2025, Nivoso began selling robots to residential customers and piloting with large snow-clearing companies and senior living facilities. The company represents an emerging competitor in the residential/light commercial segment.

4.5.6 Municipal Pilots

- **Innisfil, Ontario (2021):** Partnered with Swap Robotics for a sidewalk-clearing pilot, using a v-plow and onboard salt with human chaperones during initial deployment. The pilot led to further development: Swap Robotics received $790K from the Ontario government in 2023 and expanded to other Ontario locations.
- **Grande Prairie, Alberta (2019):** Deployed Toro RT-1000 for autonomous trail maintenance around Bear Creek Reservoir, later relocated in 2021 for improved operational efficiency.

These pilots demonstrate municipal interest but have not scaled beyond single-unit demonstrations.

4.5.7 Market Gap

The competitive landscape reveals a clear gap:

No established player offers a compact, sidewalk-optimized platform with a municipal service model. Toro's equipment-sales approach requires municipalities to build operational capability internally. Consumer products like Yarbo lack the durability and fleet management for municipal scale. The narrow-sidewalk, service-oriented segment remains open.

4.6 Why This System Is Different

The system described in this paper is designed around municipal constraints from inception, addressing gaps left by existing competitors:

Form factor optimized for urban sidewalks. At 600mm × 600mm, the rover navigates narrow passages, ADA ramps, and constrained infrastructure that larger platforms cannot access. This is not a downsized lawn tractor; it is purpose-built for the 4-foot sidewalk envelope.

Service model aligned with municipal outcomes. Unlike Toro's equipment-sales approach (which transfers operational risk to the municipality), this system can operate as a managed service where the vendor is accountable for cleared miles, not units sold. Municipalities pay for outcomes, not assets.

Teleoperation-first autonomy progression. Competitors like Snowbotix and the RT-1000 emphasize autonomous operation from day one. This system starts with human operators, building reliability data and public trust before autonomy increases. The progression is: 1:1 teleop → 1:2 assisted → 1:10 supervised → eventual full autonomy. Each transition requires demonstrated reliability over a full season.

Integration-first architecture. Designed to connect to existing GIS, work order, and complaint systems rather than replace them. Municipal IT departments can integrate telemetry into existing dashboards without new software platforms.

Attachment	Season	Function
Snow auger	Winter	Snow/ice clearing
Brine sprayer	Winter	Pre-treatment, de-icing
Rotary sweeper	Spring/Fall	Debris, leaves
Inspection camera	Year-round	Sidewalk condition assessment

Table 5: Modular attachment system

Commodity components, field-serviceable. Built from off-the-shelf parts (VESC motor controllers, Jetson compute, commodity LiDAR) with documented repair procedures. A municipal fleet technician can replace components without specialized training or vendor lock-in.

Full accountability. Complete telemetry logging with 90-day retention, geo-stamped work verification, and incident replay capability. When a resident complains their sidewalk wasn't cleared, the system provides timestamped evidence of what actually happened.

The competitive moat is not technology: the components are available to anyone. The moat is operational fit: a system designed for how municipalities actually work, not how robotics companies wish they worked.

5 Design Principles

This section describes the engineering principles that guide system design. These principles encode operational constraints that distinguish infrastructure from demonstration technology.

5.1 Service Reliability Over Peak Autonomy

The system is designed to maximize uptime, not autonomy level. A rover that operates reliably at 1:1 teleoperation is more valuable than one that operates autonomously 80% of the time and fails unpredictably 20% of the time.

Autonomy is increased only when reliability at the current level exceeds 95% over a full season.

5.2 Incremental Deployment, Not Citywide Rollouts

Pilot deployments start with 2–3 rovers on 5–15 miles of sidewalk. Expansion occurs only after one full season of validated performance. This approach limits capital risk, allows operational learning, and builds institutional knowledge before scale.

5.3 Human Override as First-Class System

The operator can always take direct control. Override is not an emergency fallback; it is a normal operating mode. The system is designed assuming operators will intervene frequently during early deployment.

5.4 Modular Attachments Instead of Specialized Vehicles

A single rover platform supports multiple attachments:

This approach reduces capital cost (one platform, multiple uses) and increases utilization (year-round operation).

5.5 Spatial Redundancy Over Mechanical Complexity

Instead of building one highly reliable rover, deploy $N+2$ rovers for an N-rover workload. The probability that at least N rovers are operational is:

$$P_{\text{fleet}} = \sum_{k=N}^{N+2} \binom{N+2}{k} p^k (1-p)^{N+2-k}$$

where p is single-rover reliability. For $N = 10$ and $p = 0.9$ (90% individual reliability):

$$P_{\text{fleet}} \approx 0.89$$

The N+2 configuration achieves 89% fleet reliability from 90%-reliable individual units, a significant improvement over 35% reliability with no redundancy ($p^N = 0.9^{\{10\}}$). Higher redundancy or improved individual reliability further increases fleet availability.

5.6 Fleet Learning Without Centralized Fragility

Rovers share operational data (route timing, obstacle locations, surface conditions) through the fleet management system. However, each rover can operate independently if network connectivity is lost. There is no single point of failure in the fleet coordination layer.

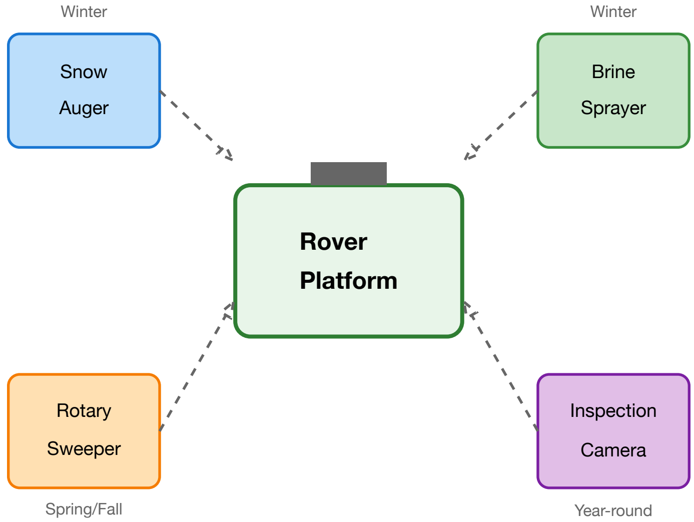


Figure 7: Modular attachment system: single platform supports seasonal tool changes, maximizing asset utilization

Component	Specification
Dimensions	600mm × 600mm × 400mm (without attachment)
Weight	35 kg base platform
Drivetrain	4-wheel skid-steer, hub motors
Power	48V Li-ion, 20Ah (960Wh)
Compute	NVIDIA Jetson Orin NX
Connectivity	LTE Cat-4 modem
Sensors	LiDAR (Livox Mid-360), 360° camera

Table 6: Platform specifications

Figure 8: BVR0 engineering prototype: ultra-low-cost, field-repairable. Pavement testing (left), mid-drift maneuver on grass (center), hoverboard hub motor after snow operation showing acceptable winter traction (right)

6 System Architecture

This section describes the technical architecture at a level appropriate for IT staff and systems integrators. Detailed specifications are provided in the appendices.

6.1 Platform Overview

6.2 Communications Stack

The system uses a layered communications architecture. Transport uses QUIC over UDP for low-latency command and telemetry. Video streams use H.265 RTP at 720p, 30 fps,

Figure 9: Left: BVR0 disassembled for maintenance: aluminum extrusion frame, hoverboard hub motors, e-bike battery, and modular plow attachment. All components replaceable with hand tools in under 30 minutes, with parts generally available from big box stores. Right: BVR1 (rendering), precision-engineered production unit shipping to pilot customers, featuring enclosed weatherproof chassis, integrated plow, RTK GPS, and stereo vision.

requiring approximately 2 Mbps. The base station maintains direct connections to rovers via LTE or local WiFi mesh. No cloud services are required for operation. Rovers fail safe on connectivity loss by stopping, holding position, or continuing autonomous waypoint following depending on mode. Typical end-to-end latency from operator input to rover response is 50–150ms over local network, 100–250ms over LTE.

Safety implications of latency: At 250ms round-trip latency and maximum speed of 1.5 m/s, a rover travels 375mm before an operator's reaction reaches it. This is well within the 500mm obstacle detection margin. However, latency directly affects operator situational awareness and reaction time. The system compensates by: (1) running obstacle detection locally with zero network dependency, (2) applying velocity limits proportional to latency, and (3) providing latency indicators in the operator UI. If latency exceeds 500ms, the rover automatically reduces speed; above 1000ms, it stops and awaits reconnection.

6.3 Onboard Compute Philosophy

Processing is distributed between edge (rover) and base station. Figure 11 shows this division.

Onboard processing handles real-time, safety-critical functions: the motor control loop at 100 Hz, obstacle detection and emergency stop, watchdog and heartbeat monitoring, telemetry collection, and autonomous waypoint following. The base station handles fleet coordination, dispatch, route optimization, historical data analysis, and incident review. All data remains on-premises. This division ensures rovers operate fully during network outages: they continue clearing assigned routes and sync when connectivity is restored.

6.4 Fleet Coordination Model

The fleet management system provides a dashboard showing real-time status of all rovers including position, battery level, and operational state. Dispatch functions assign routes based on weather conditions and network priority. Automated alerts notify operators of faults, low battery, and connectivity loss. Analytics capabilities generate coverage reports, performance metrics, and cost tracking. The system integrates with municipal GIS via standard formats (Shapefile, GeoJSON) and can export to work order systems via API or file export.

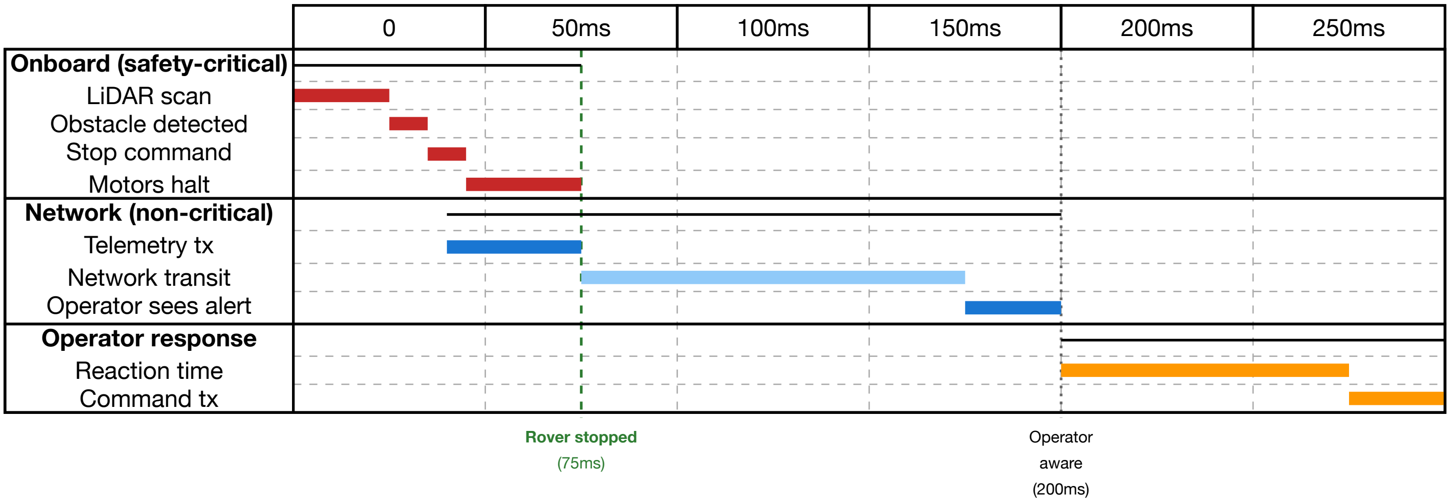


Figure 10: Safety response timeline: onboard obstacle detection and stop (red) completes in 75ms, independent of network path (blue). Operator notification is informational, not safety-critical.

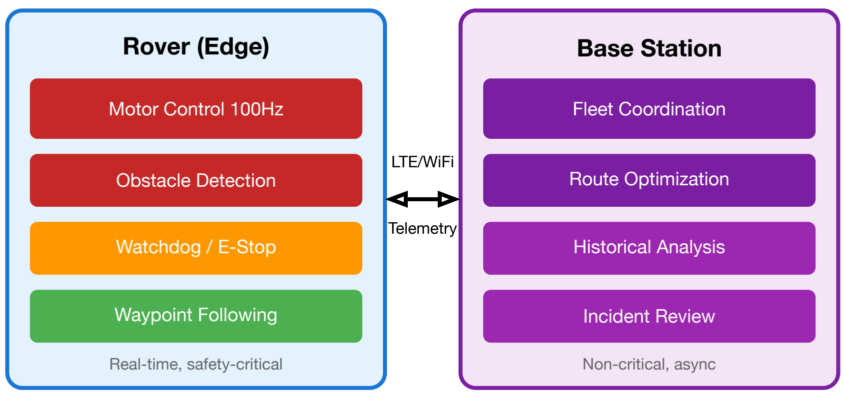


Figure 11: Compute distribution: safety-critical functions run onboard (left), fleet management runs on base station (right). Rovers operate independently during network outages.

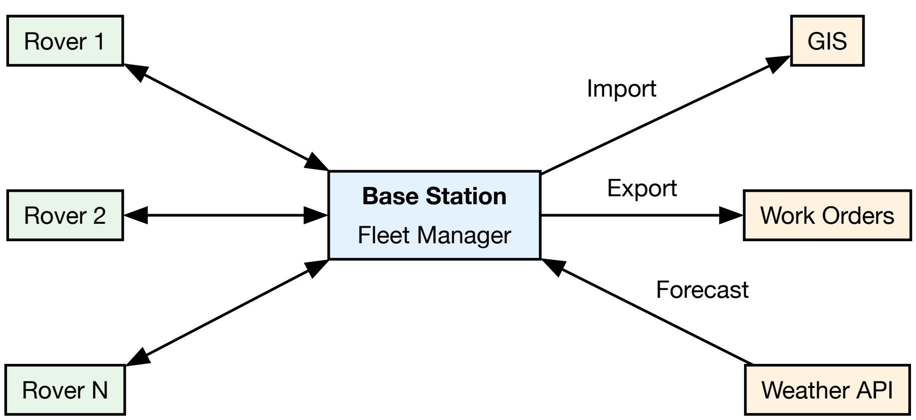


Figure 12: Fleet coordination architecture: rovers connect to base station via LTE; base station integrates with municipal GIS, work order, and weather systems.

7 Autonomy: What Is Automated, What Is Not

This section explicitly separates automated functions from human-controlled functions. This transparency builds trust with operators and regulators.

7.1 Deterministic Behaviors (Fully Automated)

These functions operate without human intervention. Motor control translates velocity commands to wheel speeds. The watchdog stops the rover if no command is received for 250ms. E-stop response immediately halts the rover on command. Low

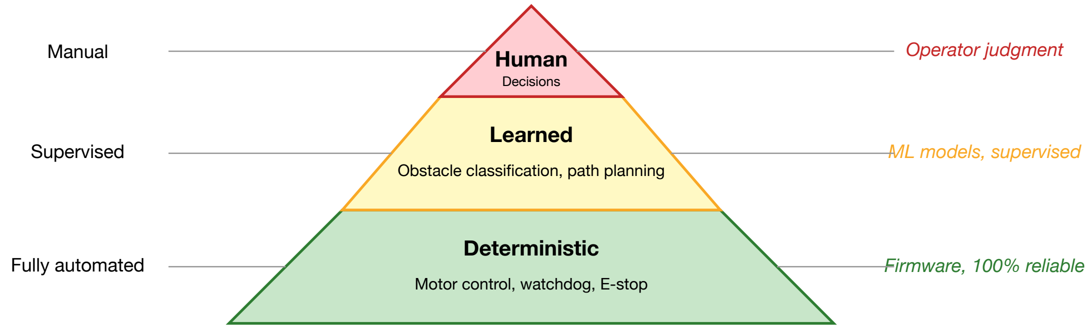


Figure 13: Autonomy pyramid: deterministic behaviors (base) are fully automated in firmware; learned perception (middle) uses ML with supervision; human judgment (top) handles exceptions and decisions.

battery response reduces speed and initiates return to base. Obstacle stop halts the rover when LiDAR detects an obstacle within 500mm. These behaviors are implemented in firmware and cannot be overridden by software.

7.2 Learned Perception (Automated with Supervision)

These functions use trained models and require validation before deployment. The key distinction from Layer 1 (deterministic safety) is that learned systems can fail in unexpected ways: a model may misclassify an obstacle, hallucinate a path, or degrade in conditions not represented in training data. Human supervision provides the safety net while models are validated.

7.2.1 Obstacle Classification

Task: Distinguish between obstacle types (pedestrian, vehicle, fixed object, animal) to enable appropriate responses. A pedestrian requires yielding and path deviation; a parked car requires routing around; a trash can may be passable.

Architecture: Two-stage approach combining LiDAR and camera:

1. **3D Detection (LiDAR):** PointPillars architecture converts sparse point clouds into a dense pseudo-image representation, then applies 2D convolutions for efficient processing [22]. On the Jetson Orin NX with TensorRT optimization [23], PointPillars achieves 20–40 FPS depending on scene complexity. The model outputs 3D bounding boxes with class predictions.
2. **2D Verification (Camera):** YOLOv8n runs on the 360° camera feed to verify and refine LiDAR detections [24]. With INT8 quantization, YOLOv8n achieves 60+ FPS on the Orin NX. Camera provides texture and appearance cues that LiDAR lacks (e.g., distinguishing a person from a mannequin).

Training data: Initial models use public datasets (nuScenes [25], KITTI, Waymo Open Dataset) for pretraining, then fine-tune on collected sidewalk data. The system logs all sensor data during teleoperation, building a dataset specific to sidewalk environments: pedestrians with strollers, dogs on leashes, delivery carts, snow-covered obstacles.

Failure modes: Novel objects not in training data, heavy precipitation degrading both sensors, reflective surfaces confusing LiDAR. Mitigation: conservative default behavior (stop and alert operator on low-confidence detections).

7.2.2 Surface Assessment

Task: Estimate surface conditions (snow depth, ice presence, wet pavement) to adapt clearing behavior and provide work verification.

Architecture: Semantic segmentation using a lightweight encoder-decoder network. The model classifies each pixel of the camera feed into categories: cleared pavement, snow-covered, ice/slush, grass, obstacle.

Candidate models:

- **SegFormer-B0:** Transformer-based segmentation [26], 3.8M parameters, 30 FPS on Orin NX
- **DDRNet-23-slim:** Designed for real-time segmentation, 60 FPS on Orin NX
- **BiSeNet V2:** Bilateral network for fast segmentation, 50 FPS on Orin NX

Snow depth estimation: Rather than absolute depth measurement (which requires stereo or structured light), the system estimates relative depth categories: trace (under 1 inch), light (1–3 inches), moderate (3–6 inches), heavy (over 6 inches). This is sufficient for operational decisions: trace requires no action, light uses standard clearing, heavy may require multiple passes or operator intervention.

Training approach: Self-supervised learning using LiDAR as ground truth. The LiDAR provides geometric measurements of surface height; the camera model learns to predict these categories from visual appearance. This avoids manual labeling of snow depth.

Ice detection: Visual detection of ice is challenging due to transparency and variable appearance. The system uses a combination of visual cues (specular reflection, texture) and contextual priors (temperature, recent precipitation, shaded areas). Confidence thresholds are set conservatively; uncertain areas are flagged for operator review or brine application.

7.2.3 Path Planning

Task: Select collision-free trajectories that keep the rover on the sidewalk, avoid obstacles, and maintain efficient coverage.

Architecture: Hybrid approach combining learned and classical methods:

1. **Traversability estimation (learned):** A segmentation model classifies terrain into traversable (cleared sidewalk), semi-traversable (snow-covered sidewalk), and non-traversable (grass, obstacles, road). This replaces hand-tuned cost maps with learned representations that generalize across environments.
2. **Local planning (classical):** Dynamic Window Approach (DWA) or Model Predictive Control (MPC) generates velocity commands that respect kinematic constraints while following the traversability map. Classical planners are predictable and verifiable; learned traversability provides the environmental understanding.
3. **Global planning (graph-based):** Pre-mapped routes stored as waypoint graphs. The rover follows the graph while the local planner handles obstacle avoidance. Route graphs are generated from GIS data and refined during initial teleoperated surveys.

Training data: Egocentric video from teleoperation sessions, automatically labeled by projecting the rover's actual trajectory onto the camera view. Paths the operator chose are labeled as traversable; areas avoided are labeled as obstacles or non-traversable.

7.2.4 Reinforcement Learning for Navigation

In addition to the hybrid classical/learned approach above, the system supports end-to-end reinforcement learning (RL) policies for goal-seeking navigation. This approach trains a policy network in simulation to map observations directly to velocity commands.

Architecture: A simple linear policy with tanh activation: $\boldsymbol{a} = \tanh(\boldsymbol{W} \cdot \boldsymbol{o} + \boldsymbol{b})$, where $\boldsymbol{o}$ is a 7-dimensional observation vector (normalized pose, velocity, and goal-relative position) and $\boldsymbol{a}$ is a 2-dimensional action (linear and angular velocity). The linear architecture enables fast inference (sub-millisecond on the Jetson) and interpretable behavior.

Training: Policies are trained using the REINFORCE algorithm in a physics simulation of the rover dynamics. The simulation models skid-steer kinematics, motor response curves, and basic terrain interaction. Training a navigation policy to 75%+ success rate requires approximately 10,000 episodes (roughly 30 minutes on a desktop GPU).

Policy format: Trained policies are exported as versioned JSON files containing weights, biases, architecture metadata, and training metrics (success rate, average reward, episode count). The versioned format enables A/B testing, rollback, and audit trails. Example:

```json
{
  "version": "1.0.0",
  "name": "nav",
  "observation_size": 7,
  "action_size": 2,
  "architecture": "linear",
  "weights": [[...], [...]],
  "biases": [0.0, 0.0],
  "metrics": { "success_rate": 0.85, "avg_reward":
95.2 }
}
```

Deployment: The `bvrd` daemon loads policies at startup and runs inference at the control loop rate (100 Hz). When in autonomous mode with a goal waypoint set, the policy generates velocity commands based on the current pose estimate. Goal-reached detection (within 0.5m) triggers mode transition.

Current status: Basic goal-seeking navigation policies are implemented and functional in simulation. Field deployment is pending integration with the pose estimation pipeline and operator controls for goal specification. This RL approach complements rather than replaces the perception-based path planning: RL handles high-level goal-seeking while perception handles obstacle avoidance and traversability.

7.2.5 Deployment Pipeline

Learned perception models (obstacle classification, surface assessment) follow a standardized deployment pipeline:

1. **Training:** PyTorch on workstation GPUs using collected data
2. **Validation:** Held-out test set plus adversarial examples (edge cases)
3. **Export:** Convert to ONNX format for portability
4. **Optimization:** TensorRT compilation with INT8 quantization for Orin NX

Figure 14: Slip-and-fall incidents on icy sidewalks represent significant municipal liability exposure

5. **Integration:** C++ inference runtime with Rust bindings for bvrd
6. **Monitoring:** Runtime confidence tracking; low-confidence triggers fallback to operator

RL navigation policies use a simpler path: training outputs versioned JSON files containing weights directly, which the `policy` crate loads and executes in pure Rust. This avoids the ONNX/TensorRT dependency for simple linear policies while maintaining the same versioning and audit capabilities.

Current status: RL-based navigation policies (goal-seeking) are implemented and functional in simulation. The learned perception systems (obstacle classification, surface assessment) are not yet implemented; development is blocked on LiDAR hardware integration (pending sensor arrival). The architecture and model choices described above represent the planned approach based on literature review and hardware constraints. Target timeline: obstacle classification Q2 2026, surface assessment Q3 2026, full perception-based path planning Q4 2026. Current autonomous operation uses RL policies for navigation with deterministic safety behaviors (obstacle stop, watchdog) as the safety layer.

7.3 Human-in-the-Loop Operations (Current)

These functions require human decision-making:

- **Route selection:** Operator assigns rover to route
- **Exception handling:** Operator resolves ambiguous situations
- **Quality verification:** Operator confirms clearing completion
- **Pedestrian interaction:** Operator manages complex encounters

Target state: Reduce operator intervention as autonomy improves, but never eliminate oversight entirely.

7.4 What Is Explicitly Not Automated

The system does not attempt to automate public interaction beyond yielding (no verbal communication or negotiation with pedestrians), property access (will not enter private property or cross driveways autonomously), snow disposal (clears snow to side but does not transport or dump), ice treatment decisions (operator decides when to apply brine), or emergency response (cannot respond to accidents or medical emergencies). These boundaries are intentional. Attempting to automate these functions would increase liability, reduce reliability, and delay deployment.

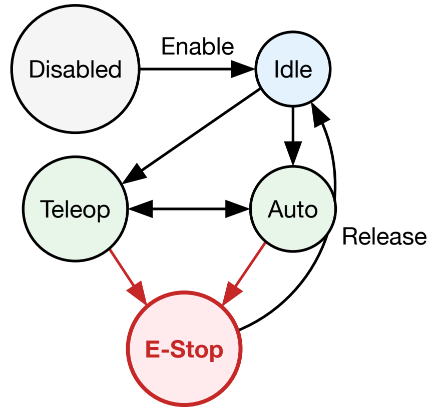


Figure 15: Rover state machine: E-stop is reachable from any operational state

Condition	Detection	Response	Recovery
Obstacle detected	LiDAR, camera	Stop, assess, route around	Automatic or escalate
Communication loss	Heartbeat timeout	Coast to stop, hold	Auto-resume on reconnect
Operator loss	Heartbeat timeout	Zero velocity	Resume when operator returns
Low battery	Voltage monitor	Reduce speed, return	Charge cycle
Critical battery	Voltage monitor	Safe stop, disable	Manual recovery
Hardware fault	Self-diagnostics	Safe stop, alert	Manual inspection
E-stop activated	Operator command	Immediate stop	Explicit release required

Table 7: Failure modes and system responses

8 Safety and Liability

This section addresses safety engineering and liability allocation. It is written for risk officers and city attorneys, not engineers.

8.1 Safety Design Philosophy

The system is designed to fail safe, not fail smart. When uncertainty exceeds thresholds, the rover stops. The priority order is:

1. Do not harm people
2. Do not damage property
3. Do not damage the rover
4. Complete the task

This ordering is enforced in firmware. Task completion is always the lowest priority.

Figure 15 shows the rover state machine. The system can only transition to operational states (Teleop, Autonomous) from Idle, and any fault or E-stop immediately halts operations.

8.2 Failure Modes and Responses

Table 7 shows the system response to various failure conditions.

8.3 Pedestrian Interaction

The system operates on shared pedestrian infrastructure. Maximum speed is 1.2 m/s in normal operation, reduced to 0.5 m/s when pedestrians are detected within 3 meters. The rover always yields to pedestrians and does not attempt to pass or navigate around people in motion. Stopping distance is less than 500mm at maximum speed on dry pavement and less than 1 meter on snow or ice. Visibility is provided by amber marker lights at all corners and retroreflective markings on all sides, with an optional low-volume alert tone before movement. The system does not rely on pedestrians to behave predictably. If a pedestrian stops in front of the rover, the rover waits indefinitely.

8.4 Incident Logging and Replay

All operational data is logged. Telemetry (position, velocity, motor currents, battery state) is recorded at 1 Hz and retained for 90 days. All operator commands are logged with timestamps and retained for 90 days. Video is recorded continuously during operation and retained for 30 days. Events (obstacles detected, stops triggered, faults occurred) are retained indefinitely. Logs are stored locally on the rover and synced to the base station. In the event of an incident, complete session replay is available within hours.

Component	Quantity	Notes
Rovers	2-3	Allows comparison, provides redundancy
Attachments	1 per rover	Match to season
Operator workstation	1	Can supervise all pilot units
Charging infrastructure	1 bay per rover	Co-located with storage

Table 8: Recommended pilot configuration

8.5 Insurance and Liability

Coverage model: Robotic sidewalk equipment is classified as mobile equipment under standard commercial general liability (CGL) policies. Most municipal insurers (CIRMA, PennPRIME, OMAG, similar pools) cover robotic operations under existing fleet or equipment endorsements without separate riders.

Typical coverage structure:

- General liability: $1–2M per occurrence (existing municipal policy)
- Equipment floater: Replacement value per unit ($15–25k)
- Cyber liability: Recommended for fleet management systems
- Umbrella/excess: Per municipal risk tolerance

Premium impact: Early deployments report premium increases of $200–600 per rover annually, comparable to ride-on mowers or utility vehicles. Insurers familiar with autonomous equipment (from warehouse and agricultural robotics) typically require operational documentation and incident response procedures rather than specialized policies.

Vendor liability: The vendor warrants that the system performs as specified. The vendor does not assume operational liability for incidents arising from operator error, environmental conditions outside specified limits, or unauthorized modifications.

Incident investigation: In the event of an incident involving injury or significant property damage, the vendor will provide full access to telemetry and logs, technical support for investigation, and cooperation with legal and regulatory processes.

8.6 Regulatory Status

Sidewalk robots are not federally regulated in the United States. Regulation, where it exists, is at the state or municipal level. As of December 2025, 14 states have enacted personal delivery device (PDD) legislation [27] with weight limits typically ranging from 80–550 lbs and speed limits of 6–12 mph. Most require yielding to pedestrians, operator oversight, and liability insurance. The system described in this paper is designed to comply with the most restrictive common requirements.

9 Deployment and Integration

This section describes how the system is deployed in practice. It is written for operations managers and IT staff.

9.1 Pilot Sizing

Recommended pilot configuration is shown in Table 8.

Pilot duration: Minimum one full season (3–4 months for snow) to observe performance across weather conditions.

Pilot scope: 5–15 miles of sidewalk, selected for mix of conditions, accessible staging location, and representative of broader network.

9.2 Integration Touchpoints

The system integrates with existing municipal infrastructure at several points. GIS and mapping integration imports the sidewalk network as routes using standard formats with low complexity. Work order integration exports clearing logs and can optionally receive dispatch commands at medium complexity. Weather service integration receives forecasts for pre-positioning at low complexity. Citizen complaint systems can cross-reference complaints with clearing logs at medium complexity. Fleet management provides a dashboard for status, telemetry, and alerts. Full integration is not required for pilot; minimum viable integration is GIS import for route planning.

9.3 Training

Training is provided on-site during commissioning. Refresher training recommended annually.

9.4 Storage and Maintenance Facility

Requirements: 100 sq ft per rover, 20A 120V circuit per 2 rovers, above-freezing climate preferred, locked facility with GPS tracking and remote disable, internet access for telemetry sync.

Role	Training Time	Content
Operator	4-8 hours	Teleoperation, monitoring, exception handling, safety
Supervisor	2-4 hours	Fleet dashboard, reporting, escalation
Maintenance	8-16 hours	Inspection, consumables, repairs, diagnostics

Table 9: Training requirements by role

Parameter	Value	Source
Loaded labor rate	$35-45/hour	BLS [13]
Productivity (shovel)	0.08-0.12 mi/hr	SaMS Toolkit [28]
Productivity (blower)	0.15-0.25 mi/hr	SaMS Toolkit [28]
Snow events/season	15-25	NOAA [7]
Clearing requirement	4-12 hrs post-snowfall	Municipal ordinance

Table 10: Manual labor cost parameters

Category	Cost
Chassis and drivetrain	$950
Electronics (compute, CAN, LTE)	$890
Perception (LiDAR, camera)	$1820
Power system	$400
Snow clearing attachment	$365
Assembly, wiring, integration	$400
Total hardware cost	**$4825**

Table 11: Per-unit hardware cost (current prototype, $5,000)

Most municipalities can accommodate pilots in existing public works facilities.

10 Economics

This section presents the economic case for robotic sidewalk maintenance. All figures are based on current hardware costs, observed productivity rates, and published municipal labor data.

10.1 Baseline: Current Municipal Costs

Note: Productivity rates from the SaMS Toolkit assume 2–3 inches of snow on a 4-foot-wide sidewalk. Hand shoveling clears 1,500–3,000 sq ft/hr; 24-inch snow blowers clear approximately 5,000 sq ft/hr [28]. These rates align with field observations from timed clearing of 100m sidewalk segments across four snow events in Northeast Ohio during the 2024–2025 season.

The cost per mile cleared is derived from labor rate and productivity:

$$C_{\text{mile}} = \frac{L}{P}$$

where L is the loaded labor rate ($/hour) and P is productivity (miles/hour). At $L = 40$ and $P = 0.12$ (blended shovel and blower work):

$$C_{\text{mile}} = \frac{40}{0.12} \approx 333 \quad \text{dollars/mile}$$

For a city with $M = 50$ miles of priority sidewalk network and $E = 20$ events per season:

$$C_{\text{season}} = C_{\text{mile}} \times M \times E = 333 \times 50 \times 20 = 333,000$$

Per-event contractor rates range from $150–400 per mile. Seasonal contracts for 50 miles of sidewalk typically range from $150,000–400,000, with $200/mile being a common benchmark.

10.2 System Capital Costs

Target production cost at scale (100+ units): **$3,400**. Sale price (target): $12,000 base, $15,000 with snow clearing, $18,000 with full sensor suite.

Asset lifetime: 5-year service life with annual maintenance. Mid-life refurbishment at year 3 ($800–1,200). Chassis can be refurbished for a second 5-year cycle at approximately 40% of new unit cost.

Parameter	Value
Clearing rate	0.5 mi/hr
Battery endurance	4 hours continuous
Miles per rover per charge	2 miles
Clearing time window	8-12 hours post-snowfall
Effective miles per rover per event	4 miles (with one recharge)

Table 12: Rover productivity assumptions

Cost Category	1:1 Teleop	1:10 Supervised	Notes
Operator labor	$4000	$400	160 hrs/season × $25/hr ÷ ratio
LTE connectivity	$360	$360	Fixed
Maintenance	$500	$500	Fixed
Battery (amortized)	$200	$200	Fixed
Charging energy	$125	$125	Fixed
Software subscription	$1200	$1200	Fixed
Insurance	$400	$400	Fixed
Total per rover	**$6785**	**$3185**	

Table 13: Annual operating cost per rover by supervision mode

Mode	Ratio	Op. Cost/hr	Cost/Rover-Hr
Direct teleop	1:1	$25	$25.00
Assisted teleop	1:2	$25	$12.50
Supervised autonomy	1:10	$25	$2.50
Full autonomy	1:50+	$25	$0.50

Table 14: Operator economics by autonomy level

10.3 Fleet Sizing

The number of rovers required depends on network size, clearing time window, and redundancy requirements.

For a 50-mile network with 8-hour clearing window:

$$N_{\text{rovers}} = \frac{M}{P_{\text{event}}} = \frac{50}{4} = 12.5 \rightarrow 13 \quad \text{rovers}$$

With N+2 redundancy for 90%+ fleet availability: **15 rovers**.

Capital investment: $15 \times 18,000 = 270,000$

10.4 Operating Costs

Annual per-rover operating costs vary significantly by operator ratio:

The operator-to-rover ratio is the dominant variable. At 1:10 supervision, operating costs drop by 53% compared to 1:1 teleoperation.

10.5 Operator Economics

The viability of robotic sidewalk maintenance depends on the operator-to-rover ratio R. The effective labor cost per rover-hour is:

$$C_{\text{rover-hr}} = \frac{L_{\text{op}}}{R}$$

where L_{op} is the operator hourly rate. At $L_{\text{op}} = 25$ and $R = 10$:

$$C_{\text{rover-hr}} = \frac{25}{10} = 2.50 \quad \text{dollars/rover-hour}$$

This represents a 10× reduction in labor cost per unit of work compared to 1:1 teleoperation.

Figure 16 illustrates the operator scaling difference. At 1:1 (current), each rover requires a dedicated operator. At 1:10 (target), one operator monitors ten rovers with autonomous waypoint following.

Current capability: Direct teleoperation (1:1). Operator labor savings come from reduced physical labor and reduced injury risk, not from ratio improvement.

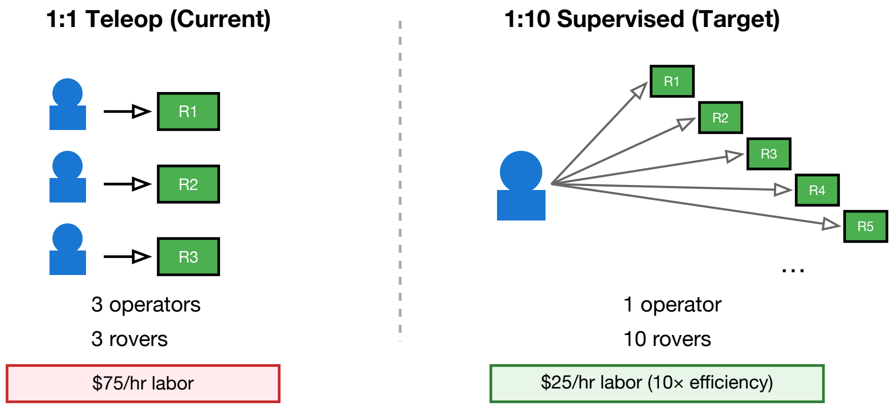


Figure 16: Operator scaling: 1:1 teleop vs 1:10 supervised autonomy

Approach	Year 1	Years 2-5	5-Year TCO
Manual labor (municipal)	$333000	$333,000/yr	$1665000
Contractor ($200/mi)	$200000	$200,000/yr	$1000000
Robotic (1:1 teleop)	$372000	$102,000/yr	$780000
Robotic (1:10 supervised)	$318000	$48,000/yr	$510000

Table 15: Total cost of ownership comparison (50 miles, 15 rovers)

Target capability: Supervised autonomy (1:10). This requires autonomous waypoint following, static obstacle detection, dynamic obstacle avoidance, and exception handling. Basic goal-seeking navigation via RL policies is implemented; static obstacle detection and dynamic obstacle avoidance are pending LiDAR integration.

Labor considerations: Robotic systems change the nature of sidewalk maintenance labor; they do not eliminate it. Operators are typically drawn from existing staff and reassigned from physical clearing to supervisory roles.

10.6 Operator Workload and Ergonomics

At 1:10 supervision ratios, operator fatigue becomes a design constraint. Monitoring ten simultaneous video feeds for 4–8 hours induces cognitive load that differs qualitatively from physical labor fatigue.

Shift structure: Recommended maximum shift length is 4 hours of active supervision with 15-minute breaks every 90 minutes. Snow events requiring 8+ hours of clearing should use rotating operator pairs.

Workstation design: Operators work from climate-controlled stations with ergonomic seating, multiple monitors (one primary view, one fleet overview), and low-latency audio alerts for exceptions. Physical stress is minimal; cognitive stress requires active management.

Attention allocation: At 1:10, operators do not watch all feeds continuously. The system surfaces exceptions (obstacle stops, low battery, connectivity loss, pedestrian encounters) and the operator responds to alerts. Between exceptions, operators cycle through rover views on a 30-second rotation. Autonomous waypoint following handles nominal operation.

Fatigue indicators: Response time to alerts, intervention frequency, and override accuracy are logged per operator session. Degradation beyond baseline triggers mandatory breaks or shift handoff.

This operational model mirrors air traffic control and industrial SCADA supervision rather than vehicle operation. Staffing plans should account for the distinct fatigue profile.

10.7 Total Cost of Ownership Comparison

Scenario: 50 miles of priority sidewalk, 20 snow events per season, 5-year analysis period, 15-rover fleet.

Robotic Year 1 includes capital ($270,000) plus first-year operating costs. Years 2–5 are operating costs only.

Figure 17 visualizes the 5-year TCO comparison. At supervised autonomy (1:10), robotic systems reduce total cost by **69% vs manual labor** and **49% vs contractors**.

Payback period: The payback period T_{payback} in months is:

$$T_{\text{payback}} = \frac{C_{\text{capital}}}{C_{\text{manual}} - C_{\text{robotic}}} \times 12$$

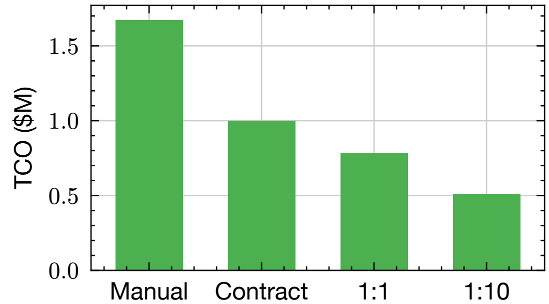


Figure 17: 5-year total cost of ownership comparison (50 miles, 20 events/season)

Variable	Base Case	Break-Even vs Contractor
Operator ratio	1,:10	1:3
Snow events/season	20	10
Clearing rate	0.5 m,i/h,r	0.25 ,mi/,hr
Hardware cost	$18000	$40000
Rover lifespan	5 y $\times 10^{ars}$	2.5 y $\times 10^{ars}$
Fleet uptime	90%	70%

Table 16: Sensitivity analysis: break-even points vs contractor baseline

Metric	vs Manual	vs Contractor
5-year TCO reduction (1:10)	69%	49%
5-year TCO reduction (1:1)	53%	22%
Payback period (1:10)	11 months	16 months
Payback period (1:1)	14 months	21 months

Table 17: Economic summary (50 miles, 20 events/season)

At 1:10 supervision:

$$T_{\text{payback}} = \frac{270000}{333000 - 48000} \times 12 \approx 11.4 \quad \text{months}$$

At 1:1 teleoperation, payback extends to approximately 14 months. Both scenarios achieve payback within the first full season of operation.

10.8 Liability and Injury Avoidance

Beyond direct operating costs, robotic systems reduce two categories of indirect cost:

Slip-and-fall liability: As noted earlier, 58% of municipalities have been sued for pedestrian accidents on improperly maintained sidewalks [15], with average claims of $19,776 [16]. Consistent robotic clearing reduces both incident frequency and legal exposure. If a municipality currently experiences 2–5 claims per year ($40,000–100,000), even a 50% reduction represents $20,000–50,000 in annual savings, not including legal defense costs.

Worker injury reduction: Snow removal ranks among the highest-risk municipal activities for musculoskeletal injuries. A single worker's compensation claim averages $30,000–50,000. Shifting from physical shoveling to supervisory roles eliminates this exposure for assigned staff. For a crew of 10 seasonal workers, preventing 1–2 claims per season represents $30,000–100,000 in avoided costs.

These indirect savings are difficult to guarantee but can exceed direct labor savings in high-claim environments. They should be considered qualitatively when evaluating total value.

10.9 Sensitivity Analysis

The economic model is most sensitive to operator ratio and snow event frequency:

The system remains cost-competitive even under pessimistic assumptions. At 1:1 teleoperation (current capability), robotic systems still beat contractors by 22% due to eliminated markup and consistent productivity.

10.10 Summary

Robotic sidewalk maintenance is economically viable at **both** current (1:1) and target (1:10) autonomy levels. The difference is

Data Type	Owner	Retention
Telemetry	Customer	90 days standard
Video recordings	Customer	30 days standard
Route and map data	Customer	Indefinite
Fleet analytics	Vendor (anonymized)	Indefinite
Firmware/software	Vendor (licensed)	Escrow available

Table 18: Data ownership and retention

magnitude: supervised autonomy doubles the savings. Additional value from liability reduction and injury avoidance is not included in these figures but can be substantial.

11 Governance, Data, and Vendor Risk

This section addresses questions that arise in procurement: Who owns what? What happens if the vendor fails? How do we exit?

11.1 Data Ownership

Customers can export all operational data at any time in standard formats (CSV, JSON, GeoJSON).

11.2 Auditability

The system is designed for public accountability: open logs (clearing routes, times, and coverage are exportable), incident reports (full documentation for any flagged event), performance metrics (uptime, coverage completion, response times), and third-party audit availability on request.

11.3 Vendor Continuity Risk

Hardware: Rovers are owned by the customer. Hardware is based on commodity components. Third-party maintenance is feasible.

Software: Firmware source code is held in escrow. In the event of vendor dissolution, escrow is released to customers with active support contracts.

Transition period: Vendor commits to 12 months notice before discontinuing support for any product generation.

11.4 Exit Strategy

Customers can exit the system at any time. Hardware can be resold, repurposed, or disposed. All data is exportable in standard formats. Annual software subscriptions can be cancelled with 30 days notice.

12 Roadmap

This section describes what capabilities are expected to improve over time, without specifying timelines that cannot be guaranteed.

12.1 What Improves with Software

Autonomy level is the primary software-gated capability. Current systems require 1:1 teleoperation. As perception and planning algorithms mature, the operator-to-rover ratio will increase to 1:2, then 1:5, then 1:10. Each transition requires demonstrated reliability over a full season before deployment. Route optimization, fleet coordination, and predictive maintenance also improve with software updates and accumulated operational data.

12.2 What Requires Hardware Revision

Clearing width, battery capacity, and sensor range are hardware-constrained. The current platform clears a 24-inch path. Wider clearing requires a new chassis generation. Battery capacity improvements depend on cell technology advances and are expected at 5–10% per year. Sensor upgrades (higher-resolution LiDAR, thermal cameras) require hardware swaps but are designed to be field-installable.

12.3 What Is Constrained by Physics

Snow clearing rate is fundamentally limited by auger capacity and forward speed. The current platform clears approximately 0.5 miles per hour in 4-inch snow. Doubling this rate would require either a wider auger (which exceeds sidewalk width constraints) or faster forward speed (which reduces clearing quality and increases pedestrian risk). Battery energy density limits range. Current lithium-ion technology provides approximately 4 hours of continuous operation in cold weather. Step-change improvements require new battery chemistry.

12.4 What Depends on Regulation

Autonomous operation in public rights-of-way is subject to state and local regulation. As of December 2025, 14 states have personal delivery device legislation. Expansion to other jurisdictions requires either legislative action or municipal pilot agreements. The system is designed to comply with the most restrictive current requirements, ensuring broad deployability as regulations evolve.

13 The Path to Full Autonomy

This section addresses a question that sophisticated readers will ask: where does this end? The answer is full autonomy, rovers that clear sidewalks without human oversight. This section explains why we believe this is achievable, what technical and regulatory gates must be passed, and why we are building toward it even though we are not there today.

13.1 Why Full Autonomy Matters

The economics of robotic sidewalk maintenance scale with the operator-to-rover ratio. At 1:1 (current), the system provides coverage consistency and reduced injury risk but does not reduce labor cost. At 1:10 (near-term target), labor cost drops by 90%. At 1:50 or higher (full autonomy), marginal labor cost approaches zero.

At full autonomy, the cost structure inverts. Sidewalk clearing becomes a capital and energy problem rather than a labor problem. A municipality could clear 200 miles of sidewalk with a fleet of 40 rovers, zero operators during clearing, and one maintenance technician. Seasonal labor shortages become irrelevant. Response time becomes a function of fleet size and charging infrastructure, not staff availability.

This is not a marginal improvement. It is a category change in how sidewalk maintenance can be delivered.

13.2 Technical Requirements

Full autonomy requires capabilities beyond current state-of-the-art:

Perception in degraded conditions. Snow, fog, darkness, and glare all reduce sensor effectiveness. Current LiDAR and camera systems work well in moderate conditions but degrade in heavy precipitation. Full autonomy requires sensor fusion and learned perception that maintain safe operation across the full environmental envelope.

Edge case handling. Supervised autonomy allows operators to intervene for unusual situations: a car parked on the sidewalk, construction barriers, a fallen tree. Full autonomy requires the rover to recognize these situations, plan around them, or safely abort and retry. The long tail of edge cases is the primary technical challenge.

Night and low-visibility operation. Snow events often occur at night. Clearing before morning commute requires operation in darkness. This is achievable with current sensors but requires additional validation.

Multi-rover coordination. At scale, rovers must avoid interfering with each other, hand off routes efficiently, and coordinate around shared obstacles. This is a solved problem in warehouse robotics but less tested in outdoor environments.

Graceful degradation. When the system cannot proceed safely, it must fail in a way that does not create new hazards. A rover stopped in the middle of a sidewalk is a problem. Full autonomy requires planning for failure states as carefully as success states.

13.3 The Liability Shift

Under supervised autonomy, operator error is a plausible cause for any incident. The operator saw (or should have seen) the pedestrian. Under full autonomy, this defense disappears. Every incident becomes a potential product liability claim.

This is not a reason to avoid full autonomy. It is a reason to reach it only through demonstrated safety. The path is:

1. Accumulate millions of operational hours under supervision
2. Document incident rates, near-misses, and intervention frequency
3. Demonstrate that autonomous operation is **safer** than supervised operation (fewer interventions, faster stops, more consistent behavior)
4. Obtain regulatory approval based on this evidence

The precedent is aviation autopilot: full autonomy was achieved not by claiming safety in advance, but by demonstrating it over decades of incremental deployment.

13.4 Regulatory Path

No jurisdiction currently permits unsupervised robotic operation on public sidewalks. Personal delivery device (PDD) legislation

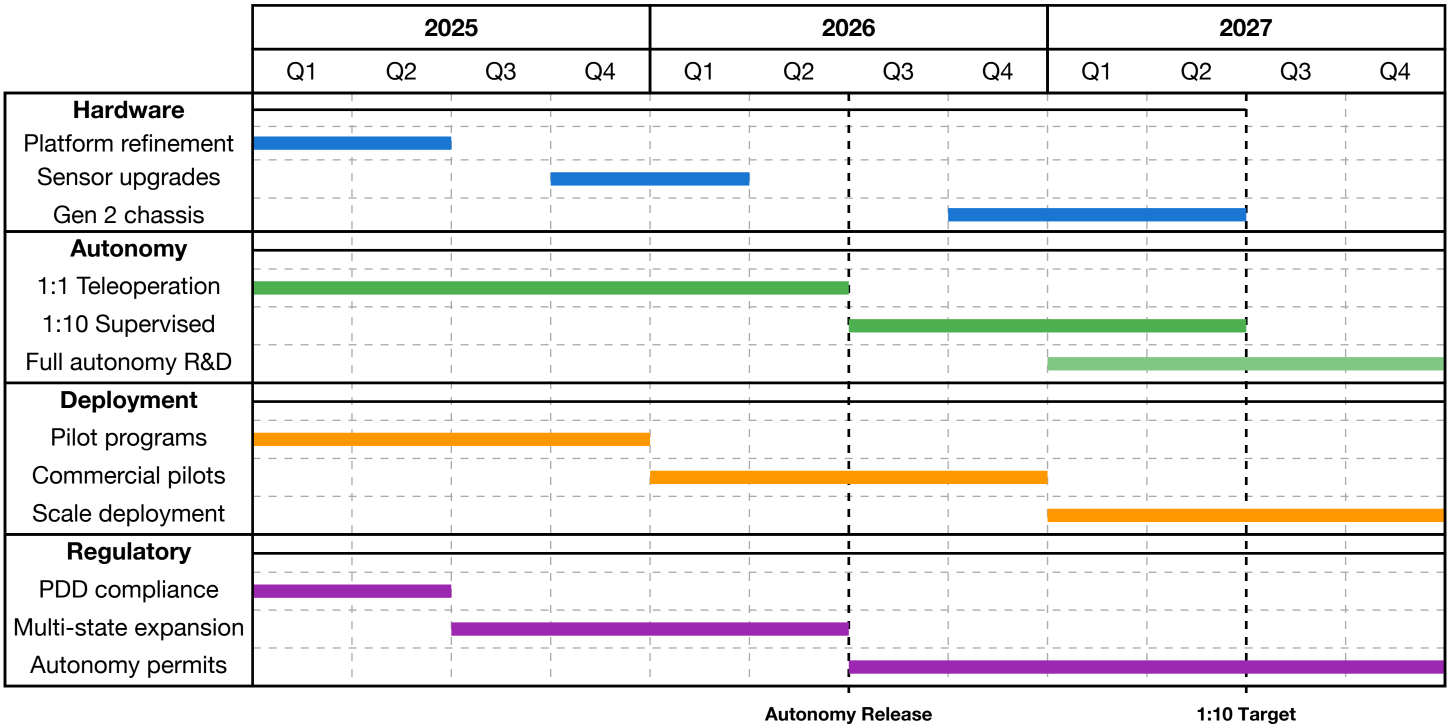


Figure 18: Development roadmap: autonomy progression and deployment phases

typically requires a human operator capable of monitoring and taking control. This is appropriate given current technology.

The regulatory path forward has two components:

Demonstrated safety record. Regulators respond to evidence. Years of supervised operation with low incident rates create the foundation for expanded permissions.

Pilot-to-permanent frameworks. Several states have enacted pilot programs that allow expanded autonomy under controlled conditions. These provide a testing ground for full autonomy without requiring legislative change.

We expect full autonomy to be permitted in some jurisdictions within 5–7 years, following the pattern of autonomous vehicle regulation: early pilots in permissive jurisdictions, gradual expansion based on safety data, eventual standardization.

13.5 Why We Build for It Now

The system described in this paper is designed for full autonomy even though it operates today under human supervision. This is intentional.

Sensor and compute overhead. The rover carries more perception capability than 1:1 teleoperation requires. This overhead enables autonomy development without hardware revision.

Data collection. Every supervised operation generates training data for autonomous systems. Routes, obstacles, interventions, and edge cases are logged and available for model development.

Fail-safe architecture. The safety systems (watchdog, E-stop, obstacle detection) are designed assuming no human is watching. This is the correct assumption for full autonomy and a conservative assumption for supervised operation.

Fleet coordination layer. The base station already manages multi-rover dispatch, route assignment, and status monitoring. These systems scale to full autonomy without architectural change.

The result is a system that can transition from supervised to autonomous operation through software updates, not hardware redesign. This is the strategic foundation for long-term cost advantage.

13.6 Timeline Honesty

We do not provide a timeline for full autonomy. Too many variables are outside our control: regulatory frameworks, sensor technology, insurance markets, and public acceptance.

What we can say:

- 1:10 supervised autonomy is targeted for Q3 2026
- Full autonomy (1:50+) is a multi-year effort dependent on regulatory progress

We are building a company, not a demo. The path to full autonomy is measured in years and validated in operational hours, not press releases.

14 Conclusion

Municipal sidewalk maintenance is a constrained optimization problem. Labor is scarce, seasonal, and expensive. Equipment designed for roadways cannot operate on sidewalks. The result is a persistent service gap.

Robotic systems can close this gap when the system operates reliably in the target environment (verified through pilot), supervised autonomy is achieved (one operator monitoring multiple units), total cost of ownership is lower than alternatives, and safety and liability frameworks are acceptable to the deploying organization. The system described in this paper is designed to meet these conditions. It is operational today in pilot configuration. Specifications in this document reflect current capabilities, not roadmap projections.

Municipal robotics is viable only if treated as infrastructure: reliable, maintainable, accountable, and boring. This system is designed accordingly.

Pilot Program Inquiries

Muni is accepting pilot partners for the 2026–2027 winter season.
Municipalities with 50+ miles of sidewalk and interest in operational evaluation are invited to inquire.

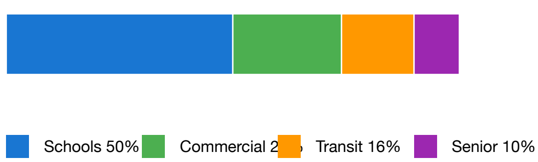
info@muni.works · muni.works

Parameter	Value	Source
Population	49,517	Census (2024)
Area	5.5 sq mi	Census
Population density	~9,000/sq mi	Highest in Ohio
Sidewalk network	180+ miles	City of Lakewood
Street network	90 miles	City of Lakewood
Snow events (1″+)	24/season	NOAA

Table 19: Lakewood, Ohio city profile

Route Category	Miles	Rationale
School walking routes	25	Student safety
Commercial districts	12	Economic activity
Transit corridors	8	Accessibility
Senior/disabled housing	5	Equity, ADA
Total	**50**	

Table 20: Priority network for Lakewood



Schools	25 mi
Commercial	12 mi
Transit	8 mi
Senior	5 mi
Total	**50 mi**

Table 21: Priority network allocation: school routes comprise half the priority miles

15 Appendix: Case Study, Lakewood, Ohio

This appendix applies the economic model to a specific municipality using publicly available data.

15.1 City Profile

Lakewood is a first-ring suburb of Cleveland, located on Lake Erie. It is the most densely populated city in Ohio and has been recognized as the state's most walkable city. The city does not provide school busing; students walk to school, making sidewalk accessibility a public safety issue.

15.2 Current Approach

Legal framework: Lakewood Codified Ordinance 521.06 requires property owners to clear sidewalks within 24 hours after snowfall ends.

Enforcement: Division of Housing and Building handles complaints.

Assistance: LakewoodAlive operates a volunteer snow removal program for seniors and residents with disabilities.

Municipal clearing: None. The city clears streets but not sidewalks.

15.3 Priority Network Analysis

Rather than attempting to clear all 180 miles, a robotic system would focus on a priority network:

This represents 28% of the total network but covers the highest-liability and highest-visibility segments.

15.4 Cost Comparison

Lakewood's 24-event season (vs 20 in the base model) increases both manual costs and robotic operating hours proportionally. Fleet sizing: 15 rovers (50 mi ÷ 4 mi/rover + N+2 redundancy).

At supervised autonomy (1:10), robotic systems reduce 5-year TCO by **74% vs manual labor** and **57% vs contractors**. Even at 1:1 teleoperation, the system beats contractors by 30%. The higher savings compared to the base model reflect Lakewood's above-average snow frequency.

Approach	Year 1	Years 2-5	5-Year TCO
Manual (hypothetical)	$400000	$400,000/yr	$2000000
Contractor ($200/mi)	$240000	$240,000/yr	$1200000
Robotic (1:1 teleop)	$385000	$115,000/yr	$845000
Robotic (1:10 supervised)	$319000	$49,000/yr	$515000

Table 22: Lakewood 5-year TCO comparison (50-mile priority network, 24 events/season)

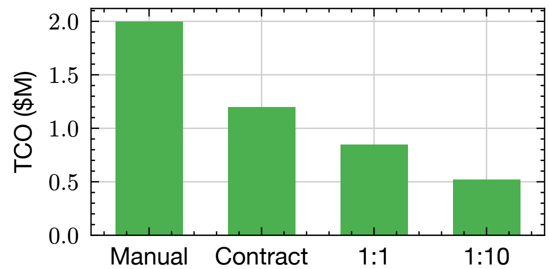


Figure 19: Lakewood 5-year TCO: supervised autonomy is 57% cheaper than contractors

15.5 Recommended Pilot

Scope: 8 miles of school walking routes (2 rovers × 4 mi/event)

Duration: One full winter season (December–March)

Fleet: 3 rovers (2 active, 1 spare)

Capital cost: 3 × $18,000 = $54,000

Operating cost (1:1 teleop): 3 × $6,785 = $20,355 for the season

Total pilot investment: $75,000

Evaluation criteria: Coverage completion rate (target: 95%+), clearing time per event (target: 8 hours), uptime during events (target: 85%+), incident rate (target: zero), resident feedback.

Decision point: If pilot succeeds, expand to full priority network (50 miles, 15 rovers) in Year 2 with demonstrated path to 1:10 supervision.

Parameter	Specification	Notes
Operating temperature	−20°F to 40°F (−29°C to 4°C)	Battery capacity reduced ~30% at low end
Storage temperature	−40°F to 120°F	Requires climate-controlled charging
Precipitation	IP65 rated	Continuous operation in snow, rain, sleet
Snow depth (clearing)	Up to 6 inches per pass	Deeper accumulations require multiple passes
Snow depth (navigation)	Up to 12 inches	Beyond this, navigation sensors obscured
Grade/slope	Up to 8% (1:12)	ADA-compliant ramps; steeper requires speed reduction
Surface types	Concrete, asphalt, pavers	Gravel and grass not supported
Sidewalk width	Minimum 36 inches	ADA minimum; narrower requires manual clearing

Table 23: Environmental operating envelope

Parameter	Specification	Notes
Continuous operation	4 hours at 20°F	Reduced to 2.5 hours at −20°F
Charge time	2 hours (0–80%)	Full charge 3 hours
Clearing rate	0.5 mi/hr (4″ snow)	0.3 mi/hr in 6″ snow
Maximum speed	1.2 m/s (2.7 mph)	Reduced near pedestrians
Obstacle detection range	10 m (LiDAR)	Reduced in heavy precipitation
Communication range (WiFi)	500 m line-of-sight	Extended with mesh repeaters
Communication range (LTE)	Carrier-dependent	Requires cellular coverage
Data logging	90 days telemetry	30 days video; events indefinite

Table 24: Operational specifications

Component	Expected Lifetime
Chassis/frame	10+ years
Drivetrain (motors, gearboxes)	5 years / 2,000 hours
Battery pack	3 years / 1,000 cycles
Electronics (compute, CAN)	5 years
Sensors (LiDAR, cameras)	5 years
Auger attachment	3 seasons / 500 hours
Tires	2 seasons

Table 25: Component lifetime estimates

16 Appendix: Environmental and Operational Specifications

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