Arrive AI Whitepaper

Autonomous Systems in Active Care Environments: Insights from Arrive AI's Live Hospital Deployment

arrive ai

Executive Summary

Hospitals are operating under sustained pressure from rising clinical demand and ongoing staffing shortages. As care shifts toward outpatient and ambulatory settings, workflows are becoming more complex, without the ability to scale human resources in parallel (Jaffe, 2024).

Health systems are increasingly deploying robotics for clinical and operational tasks, including internal transport (Birkhoff et al., 2024). In active care environments, success depends less on autonomous capability and more on reliable performance in live operations, where workflow timing, staff interaction, environmental variability, and trust shape outcomes (Cruz et al., 2024).

This paper presents five key insights from Arrive AI's live hospital deployment at Hancock Health. Rather than focusing only on technical performance, the findings highlight the real-world conditions required for automation to operate safely and predictably in patient care settings. The paper is intended for hospital operations leaders, clinical innovation teams, and stakeholders evaluating autonomous logistics solutions.

Why Hospitals Are Testing Automated Delivery Now

Hospitals face increasing operational pressure from rising clinical demand, staffing shortages, and growing internal logistics complexity (Kumar et al., 2023). Some have adopted digital and automation technologies to streamline internal transport and coordination. For instance, research from McKinsey suggests that redesigning care delivery through technology enablement and task delegation could free up 15—30% of nursing time per shift (Berlin et al. 2023). In practice though, performance depends not only on technology, but on how systems function within everyday clinical work - where workflow conditions and system design strongly influence reliability and safety (Carayon et al., 2006).

Observational time-motion studies show that less than half of nursing shift time is spent in direct patient care, with estimates often around 30—40% of total shift time (Hendrich et al., 2008; Westbrook et al., 2011; Michel et al., 2021, Berlin et al. 2023). The remaining time is distributed across coordination, medication-related tasks, documentation, and movement within the hospital.

New systems should fit into existing workflows without adding extra steps or confusion and, where appropriate, reduce skilled time spent on delegable tasks. This deployment focused on biospecimen transport, it was designed to integrate into established routines and minimize additional burden for clinical staff.

Hancock Health Initial Deployment: Operational Setting and Objectives

Hancock Health operates a fully serviced healthcare network in East Central Indiana, centered on Hancock Regional Hospital and more than 30 care sites. Arrive AI partnered with Hancock Regional Hospital to evaluate asynchronous, autonomous transport in a live clinical environment.

The initial deployment ran from September to December 2025 and focused on repeated biospecimen transport between the Sue Ann Wortman Cancer Center and the Laboratory (0.25 miles round trip). The workflow used Arrive Points™ (Figure 1) as smart, secure, climate-assist holding compartments that serve as fixed handoff locations for autonomous pickup and drop-off. Two Arrive Points™ were paired with an Ottobot (autonomous delivery robot), as illustrated in Figure 2, to reduce staff walking time and support time-sensitive workflows. Figure 3 presents lidar images of hospital hallways captured and mapped by the Ottobot during the initial deployment phase.

Figure 1. Arrive Point™ enabling secure, unattended handoff for autonomous biospecimen transport.

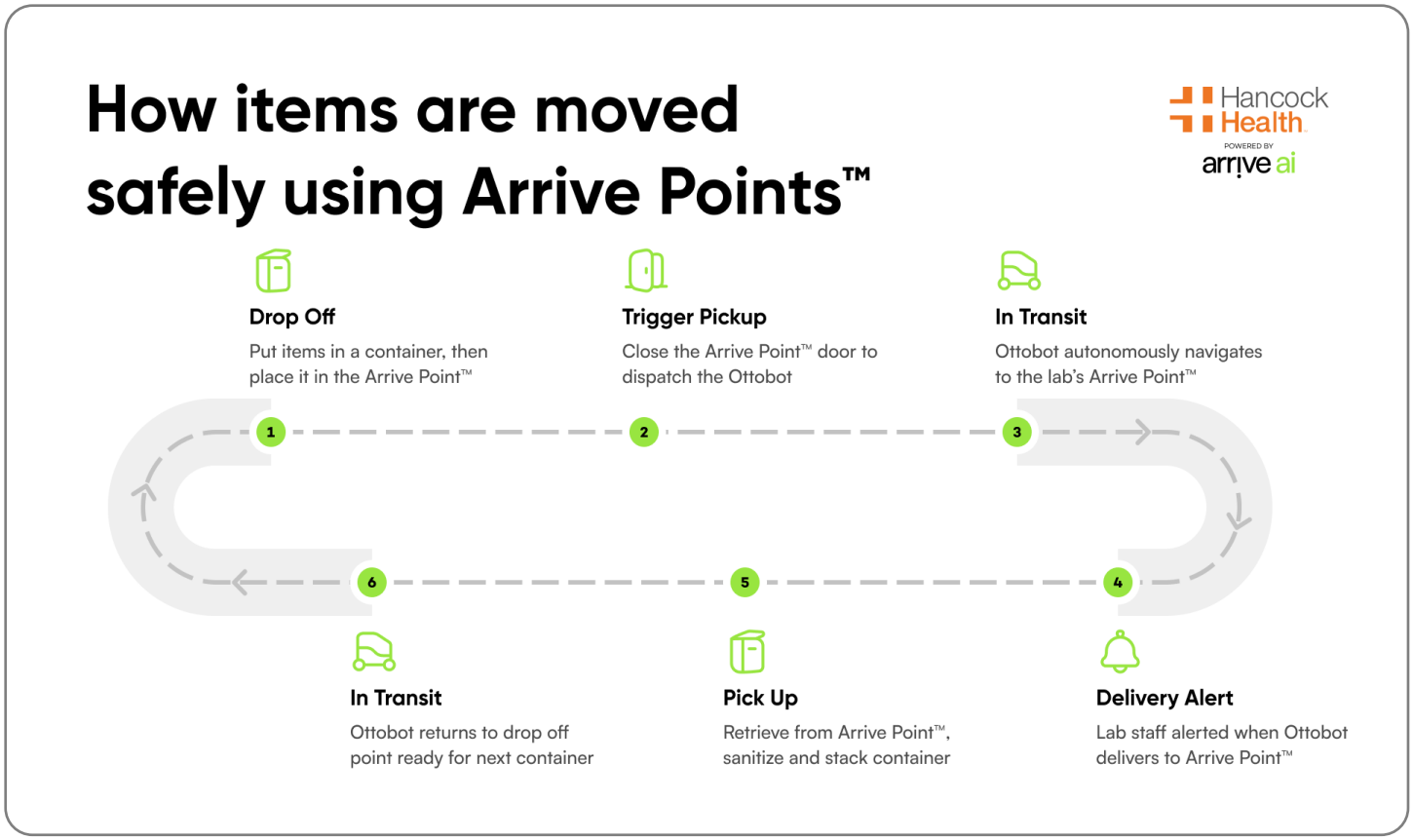

Figure 2. Biospecimen transport workflow using Arrive Points™ and an Ottobot.

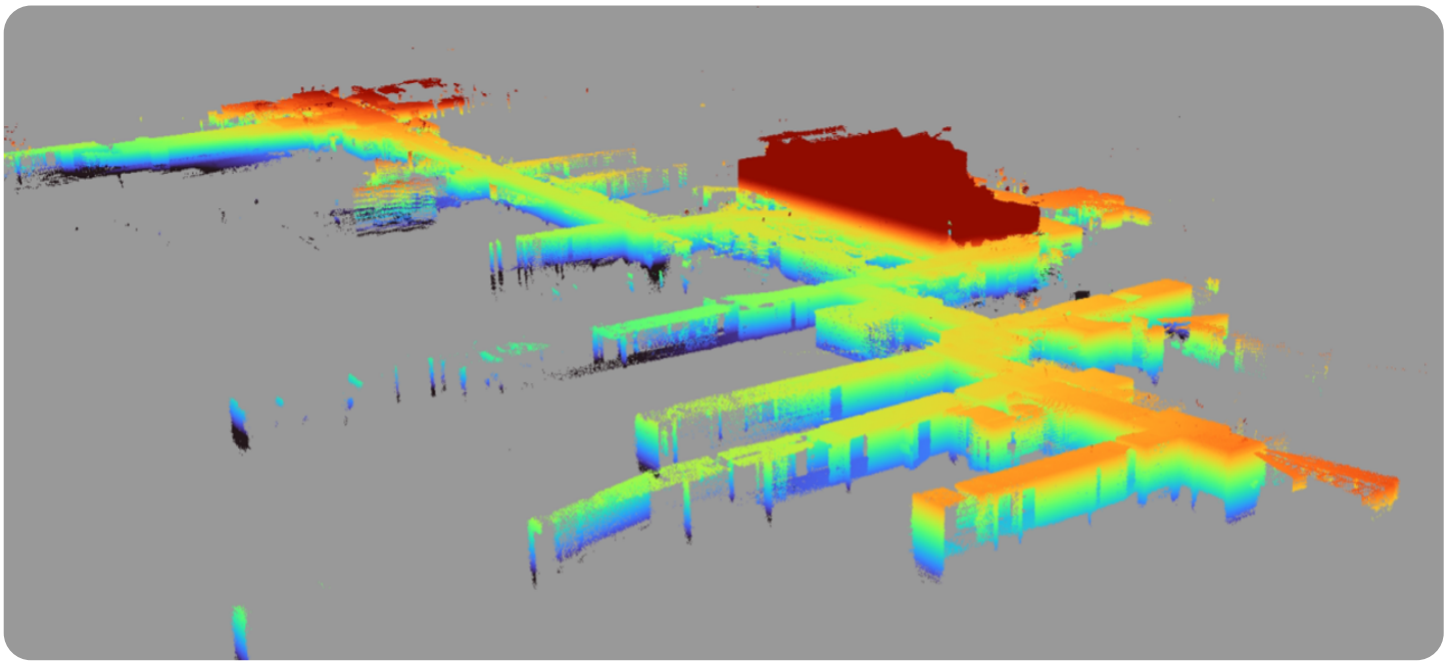

Figure 3. Lidar image of the hallways of Hancock Regional Health Hospital that the Ottobot mapped.

The initial deployment phase examined how autonomous logistics function during routine clinical work. The system operated on a demand-based model, supporting up to 10 deliveries between 8 a.m. and 5 p.m. While the observed workflow focused on transport between the Cancer Center and the Laboratory, the insights reflect broader patterns in how hospital staff interact with autonomous systems across care environments.

Across routes, times of day, and environmental conditions, performance was shaped by workflow timing, human behavior, and the availability of clear, timely system feedback. For example, Cancer Center staff described pausing to confirm a successful handoff before leaving a specimen, while Lab technicians noted that arrival alerts sometimes conflicted with time-sensitive clinical tasks. The five insights that follow are presented collectively, not in order of priority, as each represents a critical condition for dependable clinical integration.

Five Critical Insights

Insight 1: Sensor Reliability affects Workflow Timing

Why this matters:

During the initial deployment phase, a short delay in the Arrive Point™ LED changing from green (Arrive Point™ is in empty and ready state) to blue (Arrive Point™ has a sample in it) (Figure 4) led staff to wait an extra moment to confirm that it had the sample inside it. Even brief uncertainty causes staff to pause or verify system state, disrupting their workflow momentum. Staff only need a notification if something requires their attention and without clear handoff confirmation, staff remain mentally accountable even when the system is functioning correctly. Observations indicated that:

- Staff mentally track item status; inconsistency forces them to double-check
- Lighting, item placement, and handoff speed influenced detection reliability, leading to uncertainty.

Figure 4. Blue LED light indicating that the Arrive Point™ has an item inside it which the Ottobot will pick up.

Key Insight:

The system must consistently recognize item presence at handoff under normal operating conditions.

Design Implication:

Arrive AI ensured that the sensor systems prioritized clarity, consistency, and simplicity over unnecessary sophistication. The system must always know, without ambiguity, when an item is being delivered, the status and location of the item enroute, and a notification when the item has been successfully delivered.

Insight 2: Clear Signals at the Point of Interaction Matter

Why this matters:

Hospital staff do not have time to track system operations. They need clear, immediate confirmation at the point of interaction, everything else should happen automatically. As shown in Figure 5, Arrive Points™ reduce staff effort by shifting engagement to the clearly signaled handoff moments, rather than requiring ongoing attention and monitoring for the coordination and in the manual transport of the blood samples.

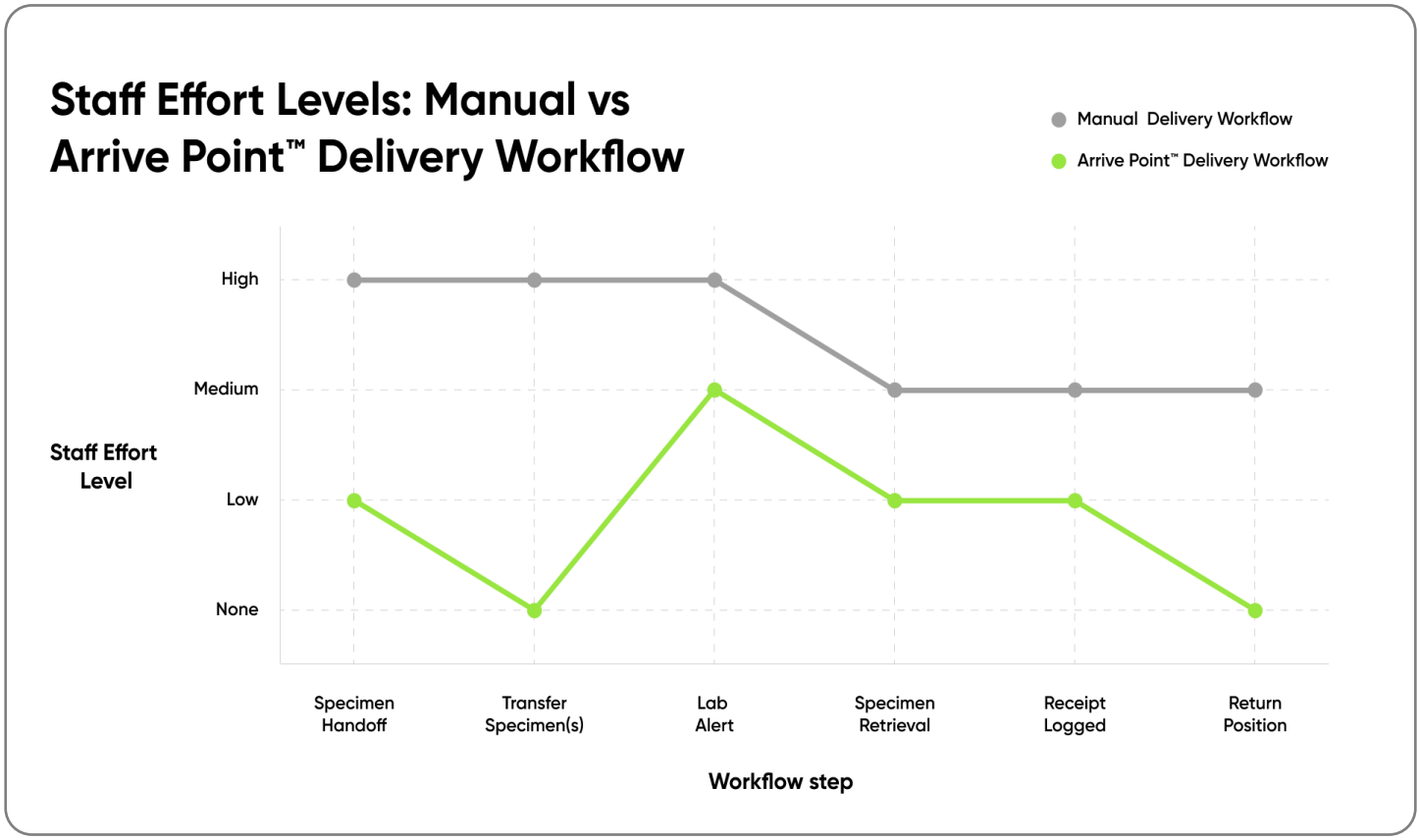

Figure 5. Illustrative example of staff effort levels reduced with the Arrive Point™ system versus the manual workflow.

Staff simply need to know:

- Did it detect the item I placed?
- Has the handoff been completed?

During the initial deployment phase, lab staff retrieved deliveries from an Arrive Point™ located just outside the laboratory. To signal that a delivery was ready for pickup, Arrive AI implemented a beacon inside the lab to provide both visual and audible alerts. In clinical environments, excessive or unclear notifications contribute to alert fatigue. Alerts must be timely, relevant, and actionable to avoid disrupting care delivery (Michels et al. 2025). Because the lab already relied on multiple alerting systems, Arrive AI worked with lab staff to select a distinct light color and sound that could be immediately recognized as an Arrive Point™ notification requiring collection.

Key Insight:

The handoff moment is about responsibility, not about system status, and requires clear confirmation.

Design Implication:

Arrive AI must communicate only what hospital staff need to know at the Arrive Point™: simple, timely confirmations and clear alerts when intervention is required. All other system behavior should be handled autonomously in the background. If the system could not complete a handoff, the failure state is designed to be explicit and require minimal staff action, preventing silent delays or unclear responsibility.

Asynchronous handoff also means staff and automated systems do not have to be available at the same time. As more locations, routes, or robots are added, coordinating exact timing becomes harder and places more burden on staff. Separating handoff from transport makes workflows easier to scale across departments and facilities. As networks grow, this becomes a core design requirement, not just an efficiency improvement.

Insight 3: Connectivity Is the Hidden Limiting Factor

Why this matters:

Connectivity, the WiFi or cellular signal the system depends on to navigate and communicate, governs moment-to-moment behavior and is the invisible force behind reliable automation. The initial deployment phase revealed:

- Hallway-to-hallway variance in signal strength
- Floor transitions that temporarily altered telemetry
- Momentary drops creating hesitation or routing inconsistencies
- "Digital shadows" near certain clinical equipment areas

Key Insight:

Reliability is not determined by route length but by environmental stability. Automation must be engineered around infrastructure variability and not assume stability.

Design Implication:

Arrive AI designs for these conditions using redundancy, dynamic fallback logic, and route awareness, and fine-tunes behaviors to each environment. This means customizing rules for specific areas (e.g., slowing in a narrow hallway, widening turns near doorways, or ignoring brief signal drops until connection is reestablished downstream) so the system performs consistently within the realities of the hospital.

Insight 4: Multidirectional Movement Is the Real Workflow

Why this matters:

Clinical logistics are rarely linear. Items move in multiple directions, specimens outbound, containers back, documentation across units, supplies redistributed, and workflows depend on all of these movements happening reliably. Although the initial deployment phase focused on outbound movement, staff routines revealed a more complex reality:

- Lab teams rely on predictable movement of requisitions, transport bags, and supplies
- Containers/totes, paperwork, and supplies needing to travel back to the originating unit
- Nurses frequently fold multiple-direction handoffs into a single workflow
- Staff intuitively expect the system to support full-cycle and cross-unit movement, not just one direction

Key Insight:

The initial deployment phase helped clarify that supporting all directions of material movement is essential to maintaining the natural rhythm of clinical workflows.

Design Implication:

Although the initial phase focused on outbound activity, observations surfaced opportunity to support multidirectional movement, outbound, inbound, and between units, by reflecting how items naturally circulate through departments and where handoffs already occur, ensuring the logistics fits existing workflows without adding steps.

Insight 5: Automation Should Fit Workflows and Surface Adjustments

Why this matters:

Clinical work depends on steady routines and timing. Even small interruptions can add friction. During the initial phase, lab staff noted that the Arrive AI system enabled earlier processing of individual samples rather than waiting for batched deliveries. At the same time, this shift occasionally meant receiving a pickup alert while actively processing a time-sensitive sample. This highlighted an important learning: even minor added steps, alerts, or timing mismatches can impact established workflows and influence how staff engage with the system:

- Staff manage attention as well as tasks
- Timing of alerts matters as much as system accuracy
- Automation shifts when work happens, not just how much
- Predictable behavior supports planning and focus

Key Insight:

Effective automation fits current workflows while clearly signaling when small adjustments may be needed.

Design Implication:

Arrive AI prioritizes predictable behavior, minimal interaction, and clear signals so systems can be used reliably within existing workflows.

Safety and Oversight

The initial deployment phase followed hospital protocols. To ensure continuous safety, Arrive AI provided 24/7 monitoring and immediate support, and enabled hospital staff and volunteers to defer to clinical judgment and on-call technical experts whenever issues arose. Arrive AI retained operational responsibility for system performance, monitoring, and escalation.

How These Insights are Shaping Arrive AI's Product Roadmap

While this initial deployment phase evaluated a single transport path with two Arrive Points™ and one Ottobot, results and observations validated and sharpened Arrive AI's design priorities:

1. Design for environmental reality, not idealized routes
2. Engineer clinical-grade detection
3. Prioritize clear, timely communication
4. Build trust from the first interaction
5. Remove friction relentlessly - simplicity above all

Together, these priorities strengthen our workflow-first approach and our commitment to protect clinical continuity; the foundation of reliable hospital automation.

Conclusion + Contact

While this initial deployment phase focused on a single transport path, the insights generalize to broader autonomous logistics deployments across departments and facilities. During the phase, small gaps in sensing or notifications sometimes left staff unsure whether responsibility had fully transferred. Although these moments did not affect safety and were immediately managed by the Arrive AI team, they showed how uncertainty could quickly reduce trust and limit adoption. Asynchronous hospital automation must be predictable; in a care environment, there is no room for ambiguity.

The Hancock Health initial deployment phase showed that real success depends on the realities of hospital environments: environmental variability, human behavior, timing pressure, and trust dynamics. By grounding our systems in workflow-first design and protecting clinical continuity, Arrive AI builds solutions that align with and optimize how care is delivered. This initial phase focused on ground-based transport; the same design can support multiple delivery methods without disrupting hospital workflows. As hospital campuses grow and transport spans multiple buildings, fixed handoff points allow new systems, including ground robots or drones, to be added without burdening staff and their workflows. When autonomous workflow logistics preserve the rhythm of care, it stops feeling like technology and starts feeling like a part of the hospital. To learn more or explore opportunities with Arrive AI: contact@arrive.ai

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