

# INTELLIGENCE AS INFRASTRUCTURE

The Economic and Operational Case for  
AI-First Organ Procurement

*A Strategic Brief for OPO Leadership*

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## Executive Summary

The organ procurement industry is entering a period of simultaneous pressure and opportunity unlike any in its history. The CMS final rule (CMS-3409-P) establishes outcome-based performance metrics with decertification consequences for underperforming OPOs. Labor costs consume 55–65% of total revenue across the industry, with coordinator burnout and turnover at crisis levels. And for the first time, artificial intelligence has crossed the competence threshold necessary to perform the cognitive work that constitutes the majority of OPO operational activity.

This document makes the case that these three forces—regulatory pressure, labor economics, and AI capability—are not independent challenges to be managed separately. They are a single convergence that demands a strategic response: the systematic deployment of AI onto the mission-critical operational backbone of organ procurement.

The argument proceeds in eight sections. We identify the convergence of forces creating both urgency and opportunity. We introduce the core wire versus scaffolding distinction—the single most important strategic concept for AI investment in OPOs. We walk through the operational transformation stage by stage, grounding every claim in technology available today. We present the economics: the labor cost structure of a representative OPO, the categories of work that AI can and cannot perform, and the return-on-investment math. We explain why headless AI agents operating via API represent a qualitatively different capability than AI assistants operating through human interfaces. We address the trust and safety architecture required for regulated healthcare. We analyze the competitive dynamics under CMS-3409-P that make early adoption a structural advantage rather than a discretionary investment. And we provide a concrete getting-started framework with three tiers of entry.

The core thesis: **AI is not a productivity tool for OPOs. It is infrastructure.** The organizations that treat it as such—deploying it on their mission-critical processes rather than their administrative scaffolding—will define the performance standard that all others are measured against. Under CMS-3409-P, that distinction is the difference between Tier 1 and decertification.

*Every organ saved is a life continued. Every minute reduced from the core wire potentially adds minutes to organ viability. Every coordinator freed from documentation is a coordinator available for the work that only humans can do. This is not about replacing people. It is about aiming intelligence at the right place.*

# 1. The Convergence

Three forces are hitting organ procurement organizations simultaneously. Each alone would demand strategic attention. Together, they create both an urgent threat and a transformative opportunity.

## 1.1 Regulatory Pressure: CMS-3409-P

The CMS final rule published January 30, 2026 establishes a three-tier outcome-based performance evaluation system for OPOs. Tier placement is comparative—based on performance relative to peers, not absolute thresholds. OPOs in the lowest tier face decertification proceedings within approximately 18 months. The metrics center on donation rates, organ transplantation rates, and organ yield per donor.

This is not a reporting requirement. It is an existential accountability framework. For the first time, OPOs face the real possibility of losing their right to operate based on measurable performance outcomes. The organizations that improve fastest—that find ways to increase donor conversion, reduce organ discard, accelerate placement, and improve documentation quality—will pull ahead. Those that maintain current workflows face a widening performance gap as peers adopt new capabilities.

## 1.2 Unsustainable Labor Economics

Labor costs constitute 55–65% of total revenue across the OPO industry. For a mid-size OPO with \$50–100M in annual revenue, this represents \$27–65M in annual workforce expense. This proportion has been increasing steadily as the complexity of regulatory compliance grows, documentation requirements expand, and the scope of OPO responsibilities broadens.

Simultaneously, the transplant coordination workforce faces a retention crisis. Coordinator burnout is driven by 24/7 on-call schedules, emotional intensity, and the cognitive load of managing complex cases with fragmented tools. The cost of replacing a trained coordinator—recruiting, onboarding, and reaching proficiency—is estimated at 1.5–2x annual salary. Every departure represents both a financial loss and a loss of institutional knowledge that cannot be easily recovered.

The labor model is structurally unsustainable. OPOs cannot hire their way out of performance pressure. The supply of experienced coordinators is finite, training pipelines are slow, and compensation is competing with less demanding healthcare roles. A fundamentally different approach to how cognitive work gets done is required.

## 1.3 AI Crosses the Competence Threshold

Between 2023 and 2025, large language models crossed a critical capability boundary for healthcare knowledge work. Current frontier models (as of early 2026) can reliably perform multi-step reasoning across complex regulatory documents, maintain coherence over hundreds of pages of context, generate clinically appropriate documentation, and follow detailed behavioral specifications without fine-tuning. They can be deployed via API for programmatic integration with existing systems, operate 24/7 without fatigue, and process information at speeds that human cognition cannot match.

This is not the chatbot era. Modern AI systems can ingest a complete regulatory corpus, reason about multi-authority intersections, generate confidence-calibrated responses, and maintain behavioral boundaries under adversarial pressure. When augmented with retrieval systems that ground responses

in specific policy text, they achieve accuracy levels that are clinically useful—not perfect, but sufficient to dramatically reduce the cognitive burden on human practitioners.

The economics of this capability compound the urgency. An NVIDIA H200 GPU (the infrastructure running these models) rents for approximately \$2 per hour. The per-query cost of a sophisticated regulatory Q&A interaction—including retrieval of relevant policy sections, multi-step reasoning, and confidence-calibrated response generation—is \$0.05–0.50 depending on model tier. The cost of having a human coordinator spend 20 minutes researching the same question is \$15–25 in loaded labor cost.

*When the cost of high-quality cognitive work drops by 50–500x, the question is not whether organizations will adopt AI, but which organizations will adopt it first—and how large the performance gap will be before the rest catch up.*

## 2. Core Wire vs. Scaffolding: Where AI Investment Matters

Every organization has a core wire—the irreducible chain of processes that defines its purpose and sustains its existence. For an OPO, this is: **Referral → Evaluation → Authorization → Donor Management → Allocation → Recovery → Transport → Reporting**. This is where minutes matter, where CMS metrics live, and where failure means organs lost and lives not saved.

Everything else—HR, finance, email, learning management systems, IT service desks, meeting coordination—is scaffolding. Scaffolding is necessary. It keeps the organization functioning. But it is not where the mission lives.

The defining strategic error in healthcare AI adoption is deploying intelligence on scaffolding while the core wire remains manually operated. When an OPO licenses Microsoft Copilot to summarize meetings and draft emails, it achieves marginal convenience gains on tasks that do not move CMS metrics, do not reduce organ discard rates, and do not improve coordinator capacity during active donor cases. The return on that investment is real but small.

When the same OPO deploys AI on the core wire—automating referral documentation, providing real-time regulatory decision support during allocation, optimizing organ offer sequencing, generating compliance reports automatically—the return is transformative. It directly impacts the metrics that CMS measures, the workload that drives coordinator burnout, and the speed that determines organ viability.

*The strategic question is not “Should we adopt AI?” It is: “Are we aiming our AI investment at the core wire or the scaffolding?” Organizations that get this distinction right will outperform those that spend the same dollars on the wrong target.*

This distinction drives every recommendation in this document. When we discuss operational transformation, economics, or competitive dynamics, we are discussing AI applied to the core wire. The scaffolding will benefit incidentally. The core wire is where the mission lives.

### 3. The Operational Transformation: AI on the Core Wire

This section walks through each stage of the OPO core wire and identifies what AI can do today, what remains human, and what the near-term trajectory looks like. Every capability described below is grounded in technology that exists and is commercially available as of early 2026.

#### 3.1 Donor Identification and Referral

**Today:** Hospitals refer potential donors to the OPO via phone. Coordinators take calls 24/7, manually capture clinical details, check donor registries, and document information in case management systems. This process is labor-intensive, prone to transcription errors, and dependent on individual coordinator availability and attentiveness.

**With AI:** Automatic speech recognition transcribes referral calls in real time, populating case management fields directly. Natural language processing extracts structured clinical data (age, diagnosis, lab values, ventilator status) from unstructured phone conversations. AI monitors electronic health record feeds from partner hospitals to proactively identify potential donors before hospital staff initiate referral—flagging patients meeting clinical triggers such as severe brain injury on mechanical ventilation. Donor registry checks are automated. The coordinator receives a pre-populated case file rather than a blank screen and a ringing phone.

**What stays human:** Clinical verification of AI-generated assessments. Complex cases requiring judgment about donor suitability. Relationship management with hospital partners. The human role shifts from data capture to quality assurance and exception handling.

#### 3.2 Donor Evaluation and Medical Suitability

**Today:** Coordinators manually gather lab results, imaging reports, and medical history. They synthesize this information to assess which organs may be viable. This involves cross-referencing multiple data sources, interpreting trends, and making preliminary suitability determinations—a process that can take hours per case.

**With AI:** Document understanding models ingest electronic health records, lab reports, and imaging results automatically. Optical character recognition processes faxed documents and handwritten notes. Medical language models summarize donor history and flag contraindications. Predictive models trained on national transplant outcomes data estimate organ viability and graft survival probability for each organ. The AI generates a comprehensive donor summary report with risk assessments in minutes rather than hours.

**What stays human:** Final medical director sign-off on organ suitability. Complex clinical judgment where AI models lack sufficient training data. Decisions involving unusual donor circumstances or ethical considerations. The medical director's role shifts from assembling information to reviewing AI-generated assessments.

#### 3.3 Family Approach and Authorization

**Today:** Trained requestors engage with grieving families in compassionate conversations about the opportunity of organ donation. This is the most emotionally demanding and irreducibly human aspect of OPO work.

**With AI:** AI supports the human interaction without replacing it. Real-time decision support provides requestors with suggested responses to common family questions. AI manages documentation logistics — auto-filling consent forms, recording digital signatures, guiding families through donor history questionnaires via tablet interface. Natural language processing summarizes the authorization conversation for the case record. AI handles all administrative tasks surrounding the interaction so the human counselor can focus entirely on the family.

**What stays human:** Everything about the conversation itself. Empathy, emotional intelligence, trust-building, and compassionate presence cannot be replicated by AI and should not be attempted. This is the Human Line—a boundary that is architectural, not advisory. The human stands unencumbered in the room because AI has handled every other burden.

### 3.4 Donor Management and Organ Preservation

**Today:** OPO coordinators (often trained critical care nurses) work with hospital ICU teams to manage donor physiology—maintaining blood pressure, oxygenation, fluid balance, and organ perfusion. This requires continuous monitoring and frequent intervention, often for 12–24 hours per donor.

**With AI:** Clinical decision support models analyze vital sign trends, lab results, and ventilator data in real time. AI predicts hemodynamic instability before it manifests, recommending preemptive interventions. Predictive models forecast which organs may be declining and suggest management adjustments to preserve viability. In the near term, closed-loop systems can automate routine parameter adjustments (vasopressor titration, ventilator optimization) with human oversight, similar to systems emerging in ICU automation research.

**What stays human:** Clinical oversight of AI recommendations. Hands-on procedures. Response to unexpected clinical events. Complex medical judgment. The human clinical role shifts from minute-by-minute monitoring to supervisory oversight of multiple cases, intervening only when AI flags exceptions or when manual procedures are required.

### 3.5 Organ Allocation and Matching

**Today:** Coordinators manually communicate donor information to transplant centers in match run order, primarily via phone calls. They wait for responses, answer surgeon questions, manage provisional acceptances and declines, and document every interaction. For a multi-organ donor, this can involve dozens of phone calls over many hours—often through the night.

**With AI:** This is the highest-impact automation opportunity on the core wire. AI can package donor information into structured electronic offers sent simultaneously to multiple transplant centers via secure API. Predictive models trained on historical acceptance patterns identify which centers are most likely to accept, enabling intelligent offer sequencing that reduces cold ischemic time. AI agents can handle routine surgeon questions by referencing the donor's complete clinical dataset. Responses are logged automatically for compliance. The entire offer/acceptance workflow can be compressed from hours to minutes.

**What stays human:** Complex negotiations involving organ-specific clinical nuance. Policy exception requests. Situations where a transplant surgeon has questions that exceed the AI's clinical knowledge base. Oversight of the AI's compliance with OPTN allocation policy. The coordinator's role shifts from making phone calls to monitoring an AI-managed allocation process and handling exceptions.

### 3.6 Surgical Recovery Coordination

**Today:** The OPO coordinates multiple surgical teams arriving at the donor hospital, books operating rooms, arranges travel, manages surgical sequencing, and handles real-time schedule changes. This is a complex logistics challenge currently managed through phone calls and manual coordination.

**With AI:** Constraint satisfaction algorithms optimize surgical scheduling by analyzing team travel times, OR availability, and organ-specific time limits. Automated systems book operating rooms, arrange flights or ground transport, and issue itineraries to all parties. Real-time monitoring adjusts plans when variables change—rerouting teams, adjusting surgical order, or activating backup plans if a flight is delayed. Surgical checklists and compliance documentation are generated automatically.

**What stays human:** The surgery itself. Surgeons performing organ recovery. On-site clinical presence. Decision-making when organs are found to be unsuitable upon direct inspection. The coordination work—currently a major labor burden—is what AI eliminates.

### 3.7 Organ Preservation and Transportation

**Today:** Coordinators arrange organ transport via commercial flights, charter aircraft, or ground couriers. They track organs in transit, communicate estimated arrival times to transplant centers, and manage contingencies when delays occur.

**With AI:** Logistics AI compares transit options in real time (factoring weather, traffic, flight schedules) and selects the fastest reliable method. IoT sensors on organ containers provide continuous temperature and location data. Transplant centers receive automated real-time tracking updates. Predictive models flag potential delays and trigger rerouting before they become critical. The system operates as an autonomous logistics dispatcher.

**What stays human:** Physical handling of organ containers. Extraordinary contingency response. Oversight of the logistics system. In the near term, drone delivery for local/regional organ transport is moving from experimental to operational, further reducing human logistics requirements.

### 3.8 Post-Transplant Reporting and Follow-up

**Today:** Staff spend significant hours entering data into OPTN/UNOS and CMS reporting systems, compiling case documentation, conducting quality reviews, and managing donor family correspondence. This administrative tail can consume more staff hours than the donor case itself.

**With AI:** If AI has been managing data flow throughout the case, final reports are generated automatically by compiling the data already collected. OPTN donor forms, CMS compliance documentation, and internal quality reports can be populated and submitted programmatically via API—eliminating entire layers of data entry. AI generates draft family correspondence using natural language generation, calibrated for sensitivity and personalized with case-specific details. Quality review becomes automated anomaly detection rather than manual chart audit.

**What stays human:** Sign-off on regulatory submissions. Personal outreach to donor families where human connection is important. Strategic quality improvement decisions based on AI-generated analytics. Most administrative functions become oversight of automated processes rather than execution of manual tasks.

## 4. The Economics: Labor Arbitrage and Return on Investment

The economic case for AI on the core wire is driven by a simple structural fact: the majority of OPO labor cost is spent on cognitive work that AI can now perform at a fraction of the cost. Understanding where that labor goes—and which categories are automatable—reveals the scale of the opportunity.

### 4.1 The Three Categories of OPO Labor

OPO labor divides into three categories based on what the work fundamentally requires:

Category	% of Labor	Description	AI Impact
A: Physical-World Work	25–30%	Hospital presence, OR participation, bedside donor management, family meetings, organ transport	Cannot automate
B: Cognitive Work via Software	50–60%	Documentation, compliance reporting, data entry, allocation phone calls, scheduling, email correspondence, policy research, training materials	High automation potential
C: Judgment & Relationship Work	15–20%	Strategic decisions, regulatory negotiation, clinical judgment, community relationships, staff mentoring, donor family aftercare	AI augments, does not replace

**Category B is the target.** It represents the majority of labor hours and consists entirely of work mediated by computer interfaces—a human looking at a screen, processing information, and producing outputs. This is precisely the work that AI agents can perform via API, often 100x faster and at a fraction of the cost.

### 4.2 The Math for a Representative OPO

Consider a mid-size OPO with \$75M annual revenue and \$45M in labor costs (60%). Approximately 400 FTEs across coordinators, administrative staff, clinical personnel, and leadership.

	Current Annual Cost	With 50% Category B Automation
Category A (Physical)	\$11.3–\$13.5M	\$11.3–\$13.5M (unchanged)
Category B (Cognitive/Software)	\$22.5–\$27.0M	\$11.3–\$13.5M (50% automated)
Category C (Judgment/Relationship)	\$6.8–\$9.0M	\$6.8–\$9.0M (unchanged)
AI Infrastructure Cost	—	\$0.5–\$1.5M
<b>Net Annual Savings</b>	—	<b>\$9.8–\$12.0M</b>

The AI infrastructure cost includes API fees (at 10,000+ queries/day across all agents at \$0.05–0.50 per query), compute infrastructure for local model deployment, vector databases for retrieval, and a small AI operations team. Even at conservative estimates, the return ratio is 8:1 to 12:1 on the automation investment.

Critically, these savings do not require layoffs as the primary mechanism. Coordinator turnover rates of 15–25% annually mean that natural attrition, combined with redeployment of existing staff from Category B tasks into higher-value Category A and C work, can absorb the transition over a 2–3 year period. The organization gets leaner through attrition while redirecting human capacity toward mission-critical work that only humans can perform.

#### **4.3 The Revenue Side: Performance Under CMS-3409-P**

The economics are not limited to cost reduction. Under CMS-3409-P, performance improvement translates directly into organizational survival and potential expansion. An OPO that places organs faster (reduced cold ischemic time), converts more referrals to donors (improved referral triage), and utilizes more organs per donor (better predictive models for marginal organs) will score higher on the metrics that determine tier placement. Higher-tier OPOs are positioned for territorial expansion as lower-tier OPOs face decertification—potentially increasing service area and revenue.

Moreover, reduced organ discard means more transplants. More transplants mean more lives saved. The economic case and the mission case are perfectly aligned: the same investments that reduce cost also improve the metrics that CMS measures and, most importantly, save more lives.

## 5. The Headless Insight: Why API-Native AI Is Different

Most organizations conceptualize AI as a smarter version of existing software—a chatbot, an assistant, a “Copilot” that helps humans use the same tools faster. This mental model dramatically underestimates what is actually possible.

The key insight: **the user interface was built for human cognition. AI does not need it.**

Every screen, every dropdown menu, every form field, every dashboard in an OPO’s software stack exists because the human brain cannot directly interface with a database. The graphical user interface is a translation layer—an adapter between human perception and digital information systems. It is a necessary cost of using biological hardware to process digital information.

AI agents operating via API bypass this translation layer entirely. When an AI agent needs to check a donor’s lab results, it does not open an application, navigate to a patient record, and read a screen. It queries the database directly and receives structured data in milliseconds. When it needs to submit an organ offer, it does not fill out a form. It posts structured data to an API endpoint. When it needs to book an OR, it does not call a scheduling desk. It writes directly to the scheduling system.

The speed differential is not 2x or 5x. For individual transactions, it is 100x to 1,000x, because the entire I/O bottleneck of human perception, comprehension, and motor control is eliminated. A task that takes a coordinator 20 minutes—pulling up records, reading through notes, synthesizing information, typing a summary—takes an API-native AI agent 2–3 seconds.

But the more profound implication is what happens when AI agents communicate with each other. In a human-operated OPO, information moves between people via email, phone calls, meetings, and shift handoffs. Each communication event introduces latency (waiting for a response), information loss (details forgotten or not communicated), and coordination overhead (scheduling time to talk). These communication costs are invisible in most organizational analyses, but they constitute a significant fraction of total operational time.

When AI agents on the core wire communicate via API—the referral triage agent passing structured data to the allocation agent, the allocation agent passing acceptance data to the logistics agent, the logistics agent passing transport details to the reporting agent—the communication latency drops to near zero. Information loss drops to zero (every data element is structured and logged). Coordination overhead drops to zero (no meetings, no emails, no phone tag).

*The organization does not just do the same work faster. It does work that was previously impossible because the coordination cost was too high. An AI-orchestrated OPO can run dozens of parallel allocation scenarios, optimize across multiple simultaneous donor cases, and maintain perfect information continuity across shift changes—capabilities that are structurally impossible in a human-operated system regardless of staffing levels.*

This is not a future capability. API-native AI agents operating on structured data via programmatic interfaces are commercially available today. The infrastructure required—API endpoints on existing OPO systems, retrieval-augmented generation for policy compliance, and orchestration frameworks for multi-agent coordination—can be built with current technology on existing cloud platforms.

## 6. The Trust Architecture: Safety in Regulated Healthcare

Every OPO leader's first question about AI on the core wire is: "How do we do this safely?" The question is legitimate and the answer must be concrete. AI systems operating in organ procurement must be bounded by an explicit trust architecture that ensures safety, compliance, and accountability.

### 6.1 The Human Line

Certain decisions must remain with human practitioners regardless of AI capability. This boundary—the Human Line—is not a temporary limitation awaiting better technology. It is a permanent architectural principle:

**AI will never approach a family for authorization.** The donation conversation is sacred human territory. AI handles every administrative burden surrounding it so the human counselor can focus entirely on the family.

**AI will never make clinical determinations about organ viability.** AI provides data, predictions, and recommendations. The medical director makes the determination. The system is designed so that AI cannot bypass this checkpoint.

**AI will never override allocation policy.** AI optimizes within policy constraints. It may recommend offer sequencing strategies that are more efficient, but it cannot violate OPTN allocation rules. Policy compliance is enforced programmatically, not through behavioral instructions.

**Irreversible actions require human attestation.** For any action that cannot be undone—submitting an organ offer, finalizing an allocation, filing a regulatory report—a human must explicitly review and approve. The AI recommends; the human authorizes. This attestation is logged with identity and timestamp for full accountability.

### 6.2 Confidence Calibration

A well-designed AI system does not just give answers. It tells you how certain it is. Every AI-generated response should carry an explicit confidence signal: HIGH when grounded in retrieved policy text with clear applicability, MODERATE when reasoning from domain knowledge with some interpretive uncertainty, and LOW when operating at the edge of its knowledge. Coordinators always know how much to trust the answer. This is not a feature—it is a safety requirement.

### 6.3 Forensic Auditability

Every AI reasoning step must be logged and traceable. When an AI agent recommends a course of action, the system records: what data it consulted, what policy sections it referenced, what reasoning chain it followed, what confidence level it assigned, and what the human reviewer decided. This creates a complete forensic trail that satisfies regulatory audit requirements and enables continuous quality improvement.

Under CMS-3409-P's documentation requirements, this auditability is not just a safety feature—it is a compliance advantage. An AI system that automatically logs every decision rationale produces audit-ready documentation that manual processes struggle to match.

### 6.4 HIPAA Compliance and Data Architecture

Production AI systems handling protected health information (PHI) must operate within HIPAA-compliant infrastructure. This means either deploying models on-premises (local models like Qwen, LLaMA, or Mistral running on OPO-owned hardware where no PHI leaves the building) or using cloud APIs covered by Business Associate Agreements (BAAs) with appropriate encryption, access controls, and audit logging.

For proof-of-concept and non-PHI use cases (such as regulatory compliance Q&A using public policy documents), cloud deployment via standard API is appropriate. For production systems touching real donor data, the architecture must ensure that PHI either stays on-premises or moves only within BAA-protected channels. Both paths are technically mature and commercially available today.

## **6.5 Anti-Sycophancy and Adversarial Resilience**

In organ procurement, telling someone what they want to hear can cost a life. AI systems on the core wire must be specifically designed to maintain analytical integrity under pressure—from frustrated surgeons, stressed coordinators, or ambiguous situations where the easy answer is not the right one. This means behavioral specifications that explicitly instruct the AI to disagree when the evidence warrants it, to flag uncertainty rather than confabulate confidence, and to hold firm on safety boundaries even when a user pushes back. These behavioral properties can be tested and measured—an evaluation framework (AORTA-Bench) for exactly this purpose is available as open-source infrastructure.

## 7. The Competitive Dynamics: Why Early Adoption Is a Structural Advantage

Under CMS-3409-P, OPO performance is comparative. Tier placement is determined by how an OPO performs relative to all other OPOs on the same metrics. This creates a dynamic where absolute performance improvement is necessary but insufficient—what matters is performance relative to peers.

This comparative structure has a critical implication for AI adoption: **the first OPOs to deploy AI on the core wire will improve their metrics in ways that non-adopting OPOs cannot match by hiring more humans. The cost curves are fundamentally different.**

An AI-augmented OPO that automates allocation communication reduces average time from match run to organ acceptance by 30–60%. That time reduction directly translates to reduced cold ischemic time, which improves transplant outcomes, which improves the CMS metrics that determine tier placement. A non-adopting OPO cannot achieve the same time reduction by adding coordinators—human processing speed has a ceiling that AI does not share.

Similarly, an AI-augmented OPO that uses predictive models for organ viability will accept and transplant organs that non-adopting OPOs discard due to uncertainty. Higher organ utilization per donor directly improves the yield metric. The AI does not get fatigued at 3 AM, does not have variable judgment between shifts, and applies the same analytical rigor to every case.

The competitive dynamic accelerates over time. AI systems improve with use—learning from outcomes, refining predictions, accumulating institutional knowledge that does not walk out the door when a coordinator changes jobs. Human workforces improve incrementally through training and experience, but face turnover that resets institutional knowledge. Over a 3–5 year horizon, the performance gap between AI-augmented and non-augmented OPOs will widen, not narrow.

*The window for action is now. OPOs that begin AI deployment in 2026 will have 2–3 years of operational learning, model refinement, and performance improvement before CMS-3409-P's evaluation metrics fully take effect. Those that wait until the metrics bite will be trying to catch up from behind—against peers whose AI systems have been learning and improving for years.*

One additional competitive dimension: the GOLLA merger model. As OPOs merge (STA and TOSA into Gift of Life Alliance, and similar consolidations nationally), the organizations that possess AI infrastructure have a unifying integration advantage. Rather than the painful, years-long process of merging legacy IT systems, an AI-first architecture can serve as the shared operational nervous system that both heritage organizations plug into—leapfrogging traditional integration pain and creating a common operational picture immediately.

## 8. Getting Started: Three Tiers of Entry

AI adoption does not require a multi-year, multi-million-dollar initiative to begin. The path from current state to AI-augmented operations can start this quarter with minimal investment and scale as value is demonstrated. Three tiers of entry are available:

### Tier 1: Evaluate and Demonstrate (Weeks, Minimal Cost)

Deploy the AORTA framework as a proof-of-concept. AORTA (AI-Augmented Organ Recovery & Transplant Assistance) is an open-source framework that includes a behavioral specification (the “Soul Document”), a RAG-optimized regulatory policy corpus covering OPTN and CMS documents, and an evaluation benchmark (AORTA-Bench) for measuring AI performance on OPO-specific tasks. Using a frontier LLM via API (no fine-tuning required), an OPO can stand up a working regulatory compliance assistant in days—one that answers coordinator questions about OPTN policy, CMS requirements, and allocation rules with confidence calibration and source citations.

This is not a toy demo. It is a functional tool that demonstrates the behavioral surface of AI-augmented compliance support: how the AI handles hard questions, how it maintains boundaries, how it responds to ambiguity, and how it performs under adversarial pressure. Walk leadership and medical directors through realistic scenarios. Show them what calibrated, safety-constrained AI support actually looks like. Cost: API fees only, approximately \$100–500 for a thorough evaluation period.

### Tier 2: Build the First Core Wire Application (Months, Moderate Investment)

Deploy a branded, internally-hosted AI regulatory assistant with retrieval-augmented generation. This involves standing up a lightweight web application (hosted on existing Azure or cloud infrastructure), connecting it to the AORTA policy corpus via vector search, and routing queries through an LLM API with the behavioral specification as the system prompt. The result is an always-available, HIPAA-aware compliance tool that coordinators can query during active cases.

Simultaneously, begin automating documentation workflows: AI transcription of referral calls, automated population of case management forms, and AI-generated compliance reports. These are the quick wins—Category B tasks that consume significant coordinator time and translate directly into measurable hours saved per case.

Investment: \$50–150K for infrastructure, integration, and a small technical team (or contracted development). Expected payback period: 3–6 months based on documentation labor savings alone.

### Tier 3: Transform the Core Wire (12–36 Months, Strategic Investment)

Begin the phased transformation described in Section 3. Deploy AI agents on each stage of the core wire, starting with the highest-impact automation opportunities (allocation communication, logistics optimization, compliance reporting) and progressing to more complex capabilities (predictive donor management, intelligent referral triage). Invest in the integration layer—API connections between AI agents and existing OPO systems (electronic donor record, OPTN/UNOS interfaces, hospital EHR feeds).

This tier requires organizational commitment: executive sponsorship, dedicated technical resources (internal or contracted), change management for affected staff, and governance structures for AI oversight. But the return justifies the investment. An OPO that completes this transformation will operate

with fundamentally different capabilities—faster, more consistent, better documented, and more scalable than any human-only workflow can achieve.

Investment: \$500K–\$2M over 2–3 years for a mid-size OPO (including infrastructure, development, and staffing). Expected annual savings at steady state: \$5–15M depending on organization size and scope of automation. ROI: 3:1 to 10:1 over the investment period. More importantly: measurable improvement on every CMS-3409-P metric.

## 9. Open-Source Resources for the OPO Community

The resources necessary to begin this transformation are available today, released under open license for the benefit of the entire OPO community:

**AORTA Framework** — The complete open-source framework for AI-augmented organ procurement coordination. Includes the behavioral specification (“Soul Document”), the RAG-optimized regulatory policy corpus, and the evaluation benchmark. Available at [opnaorta.ai](https://opnaorta.ai) and on GitHub under MIT License.

**Every Organ Saved: A Practitioner’s Guide to AI-Augmented Organ Procurement** — A comprehensive 15-chapter guide covering the Soul Document specification, reasoning trace methodology, evaluation framework, and implementation roadmap for AI in organ procurement. Available as free PDF.

**Reasoning Trace Injection (RTI) Framework** — A methodology for pre-computing high-quality regulatory reasoning demonstrations and deploying them as in-context scaffolding for any LLM. Enables domain reasoning alignment without fine-tuning, portable across models and organizations. Specification published as companion research paper.

**AORTA-Bench** — An evaluation benchmark specifically designed to measure AI system performance on OPO-relevant tasks: regulatory compliance accuracy, confidence calibration, Human Line boundary respect, adversarial resilience, and multi-authority reasoning. Enables any OPO to objectively assess AI readiness before deployment.

These resources exist because the organ procurement community’s challenges are shared. Every OPO faces the same regulatory pressure, the same labor economics, and the same AI opportunity. The organizations that move fastest will benefit most—but the underlying infrastructure should be a public good, not a proprietary advantage. The mission is shared. The tools should be too.

## Closing: The Case for Urgency

We are accustomed, in healthcare, to moving slowly. The stakes are high, the regulations are complex, and the consequences of error are measured in human lives. Caution is appropriate and necessary.

But caution is not the same as inaction. And in the current environment, inaction carries its own risks — risks that are quantifiable and growing.

Every month that an OPO operates without AI-augmented allocation communication is a month of preventable delays in organ placement. Every case where a coordinator spends two hours on documentation is two hours not spent on clinical oversight or family support. Every organ discarded because a predictive model was not available to quantify its viability is a transplant that did not happen.

The technology exists. The economics are favorable by an order of magnitude. The regulatory environment is creating both the pressure and the accountability to act. The open-source tools are available. The only remaining variable is organizational will.

This document has made the case that AI is not a productivity tool for OPOs. It is infrastructure—as fundamental to 21st-century organ procurement as electronic donor records were to the previous generation. The organizations that recognize this and act on it will define the performance standard for the next decade. Those that treat AI as a convenience feature on the scaffolding while the core wire remains manually operated will find themselves on the wrong side of a widening gap.

The path forward is clear. Start with Tier 1. Demonstrate the capability. Build organizational confidence. Then scale. The core wire is waiting.

*Every organ saved is a life continued. The best time to start was yesterday. The second best time is now.*