

## The Physical AI Dossier

A selection of high-  
impact use cases across  
seven major industries

GLOBAL AI & EMERGING MARKETS





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## Cross Industry



## Consumer



## ER&I

1. Autonomous patrolling and threat detection
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7. Robotic quadrupeds for stadium operations and sports broadcasting



## LSHC



## TMT

# Foreword

Artificial intelligence is expanding from the screen into the physical world.



A new generation of AI systems can now perceive physical environments, reason about them, and take action within them. Physical AI is not a distant prospect; it is actively being deployed in factories, warehouses, utility networks, hospitals, farms, city streets, and homes. And the pace of adoption is accelerating.

This dossier features use cases across six major industries—Consumer; Energy, Resources & Industrials; Financial Services; Government & Public Services; Life Sciences & Health Care; and Technology, Media & Telecommunications—as well as a chapter of use cases that apply broadly across many industries.

For each industry, how Physical AI is being used, or may soon be used, to address operational challenges, improve safety and reliability, and create new sources of value is explored. The use cases span the range of Physical AI applications and form factors, including autonomous mobile robots (AMRs), drones, humanoid robots, autonomous vehicles, quadrupeds, and task-specific machines.

At the frontier of this evolution are dark factories—highly autonomous operating environments where Physical AI enables systems to run continuously with minimal human presence under governed oversight—demonstrating that Physical AI is not a distant prospect, but an emerging operational reality.

Deploying Physical AI at scale is not simply a technology challenge. It requires reimagining how work gets done, how humans and machines collaborate, and how accountability is defined when autonomous systems act on an organization's behalf. The following pages address where Physical AI stands today, where it's headed, and the governance principles that should guide its responsible deployment.

The goal is to help business and government leaders assess where Physical AI is most relevant to their organizations, understand what successful deployment actually requires, and build the strategic perspective to act with both ambition and discipline.



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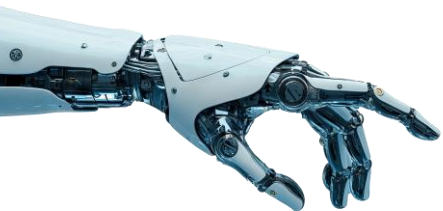


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# Introduction

## From intelligence to action: reimagining the physical enterprise



*Physical AI represents a fundamental shift in how organizations design, operate, and scale their businesses—not simply a new wave of automation. As AI moves beyond the digital realm into physical environments, it unlocks the ability to reimagine how work is performed, how assets are deployed, and how value is created across the enterprise. The real promise of Physical AI lies not in deploying individual robots or automating isolated tasks, but in redesigning end-to-end physical systems. By combining AI, robotics, simulation, digital twins, and human knowledge, organizations can fundamentally change their operating economics—to help enable new business models, step-change cost optimization, faster cycle times, and more resilient operations. Leaders who approach Physical AI as a transformation lever—not a collection of use cases—can move beyond incremental efficiency gains toward structurally different ways of operating. This shift opens the door to new sources of growth, scalable innovation, and sustained competitive advantage. This is the art of the possible with Physical AI—and it is closer than most organizations realize.*



# From intelligence to action: reimagining the physical enterprise

## Today

Physical AI systems (intelligent systems that perceive, reason about, and act upon the physical world) are in the early stages of deployment across most industries. Pockets of maturity exist: autonomous vehicles in controlled logistics environments; AI-assisted surgical platforms in leading medical centers; robotic inspection systems operating in places too hazardous or remote for human workers. However, broad, large-scale adoption remains the exception rather than the rule.

The reasons are straightforward. Physical AI is not a software upgrade. It is a capital-intensive convergence of hardware, mechanical systems, sensors, edge computing, connectivity, and AI software, which should work together reliably in dynamic real-world environments. This involves a combination of both software and machines, and the required investment reflects that complexity. Implementation costs are significant, integration timelines can be long, and the margin for error in physical systems is unforgiving.

## The next wave of AI

The next wave of AI is defined by action, not interaction. Advances in computer vision, reasoning models, sensors, and edge computing are rapidly expanding what Physical AI systems can do in unstructured, dynamic environments (well beyond the controlled factory floors where industrial automation first took hold). This coupled by falling hardware costs and improved energy efficiency has the power of moving from pilot programs to mainstream adoption. Simulation and digital twins play a central role, enabling organizations to design, test, and validate physical systems virtually before deploying them at scale. This shift unlocks new business models—such as Robotics2Service, AI-enabled Operate models, and outcome-based delivery.

## What this means for your organization

The organizations that may benefit most from Physical AI are those that treat it as a strategic and operational transformation, not just a technology procurement. Done well, Physical AI requires reimagining how work gets done: which tasks are automated; which require human judgment; and how people and machines collaborate. And it requires integration across each layer of the enterprise—physical infrastructure, mechanical equipment, edge hardware, software platforms, data pipelines, and AI models—together working in concert.

Success requires ambition paired with discipline: clear value hypotheses, thoughtful Capex–Opex trade-offs, simulation-driven validation, and responsible deployment frameworks. The use cases in this dossier illustrate what is deployable today, what is emerging for the future, and where the most significant opportunities lie across industries. Physical AI technology is advancing faster than most organizations' ability to absorb it. The strategic question is not whether the resulting innovations can reshape your business—it's whether you can lead the disruption or chase it.

# Cross Industry Physical AI Dossier



# Summary: Physical AI Use Cases For Simulation

Simulation is the control plane for Physical AI



Simulation and digital twins are foundational enablers of Physical AI. They provide a safe, scalable environment where intelligent machines can be designed, trained, validated, and governed before acting in the real world.<sup>1</sup>

Simulation creates high-fidelity virtual environments—combining physics-based modeling, synthetic data, and AI-driven scenarios—to test how robots, autonomous systems, and physical infrastructure behave under real operating conditions, including rare and hazardous edge cases. Digital twins extend this capability into live operations by continuously mirroring physical assets, environments, and workflows, to help enable closed-loop learning between virtual and physical systems.

Together, simulation and digital twins reduce deployment risk, accelerate development cycles, and lower the cost of experimentation—while improving safety, reliability, and regulatory confidence. This simulation-first approach applies across industries, from warehouses and factories to utilities, networks, healthcare facilities, and financial infrastructure.

As Physical AI scales, simulation is no longer a design-phase tool. It becomes shared, enterprise-wide infrastructure that turns experimental automation into production-ready systems—to help enable organizations move faster with confidence, not caution.





# Simulation-first development and digital twins (1/2)

## Validating physical systems virtually before real-world deployment

### DESCRIPTION

Simulation environments, synthetic data, and digital twins underpin the design, training, testing, validation, and certification support of Physical AI systems, including machines, robots, and vehicles, prior to real-world deployment. Simulation platforms help enable iterative, consequence-free learning that helps organizations identify risks, accelerate prototyping, significantly reduce development costs and timelines, and improve the operational readiness of robotic and autonomous systems before deployment.

### ISSUE/OPPORTUNITY

Physical AI systems operate in environments where failures cause physical harm, making real-world learning, testing, and iteration prohibitively risky without simulation-based validation.

Testing autonomous robots, vehicles, or industrial equipment in live environments exposes workers and equipment to risk, limits the range of scenarios that can be safely evaluated, and makes it difficult to reproduce rare or hazardous edge cases consistently. Inconsistent risk analysis methods across development teams further complicate regulatory approval, with safety assessments varying in depth and documentation quality.

The opportunity is to shift most development, training and validation work into simulation, where AI systems can be tested against thousands of scenarios—including edge cases that would be impractical or unsafe to recreate physically, before hardware is deployed.

### HOW PHYSICAL AI CAN HELP

#### Scenario generation at scale

AI creates high-variance test conditions covering normal operations, edge cases, equipment failures, and hazardous scenarios that would be difficult, costly, or dangerous to replicate in physical environments.

#### Evidence generation for compliance

Simulation outputs—scenario logs, performance metrics, failure mode analyses—provide structured documentation that supports regulatory submissions and certification processes across industries and jurisdictions.

#### Regression testing for updates

Repeatable simulation-based test suites verify that software updates or model changes do not degrade existing capabilities, to help enable continuous development without requiring full physical re-validation.

#### Standardized risk analysis workflows

AI tools structure hazard identification and risk assessment consistently across development teams, reducing variability in safety documentation and supporting more predictable regulatory review processes.

#### Design validation before build

Digital twins help enable testing of system designs and software changes against virtual representations of physical equipment and environments, identifying issues before physical trials and reducing the need for hardware modifications.

#### Reduced real-world trial burden

Fewer physical experiments are required when simulation has already validated system behavior across a broad scenario space, lowering development costs and reducing exposure to test-related incidents.

### POTENTIAL BENEFITS

#### Faster development cycles

Shorter iteration loops because design flaws and performance gaps are identified in simulation rather than through physical testing.

#### Reduced deployment risk

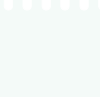
Systems reach physical deployment with broader validation coverage and fewer untested failure modes.

#### Smoother approvals

Better-structured documentation reduces back-and-forth with regulators and accelerates certification timelines.

#### Lower redesign costs

Earlier detection of issues reduces expensive hardware modifications and late-stage rework.



# Simulation-first development and digital twins (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Simulation environments used to validate Physical AI must be sufficiently faithful to real-world conditions to provide meaningful safety assurance. A digital twin that fails to represent environmental variability, sensor noise, or rare edge cases generates validation evidence that overstates readiness—potentially advancing systems to deployment with untested failure modes.



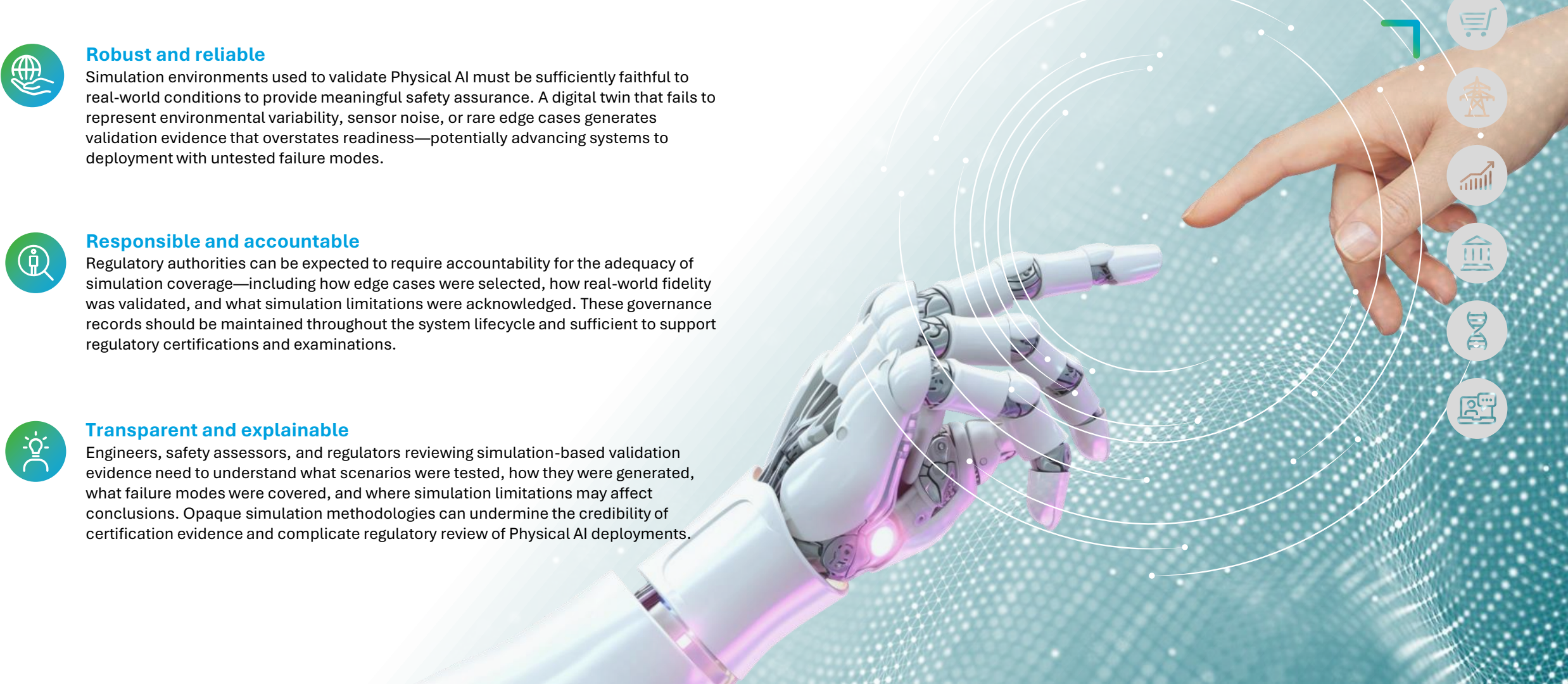
### Responsible and accountable

Regulatory authorities can be expected to require accountability for the adequacy of simulation coverage—including how edge cases were selected, how real-world fidelity was validated, and what simulation limitations were acknowledged. These governance records should be maintained throughout the system lifecycle and sufficient to support regulatory certifications and examinations.



### Transparent and explainable

Engineers, safety assessors, and regulators reviewing simulation-based validation evidence need to understand what scenarios were tested, how they were generated, what failure modes were covered, and where simulation limitations may affect conclusions. Opaque simulation methodologies can undermine the credibility of certification evidence and complicate regulatory review of Physical AI deployments.





# Simulation-trained, human-supervised closed-loop remediation (1/2)

## Safe, simulation-trained intervention for physical systems

### DESCRIPTION

Physical AI systems monitor and reason over live physical infrastructure—networks, grids, plants, and facilities—using simulation-trained models to recommend and execute corrective actions. Human-in-the-loop controls validate changes before physical interventions occur, enabling safe, adaptive remediation across safety conscious environments.

### ISSUE/OPPORTUNITY

Physical AI systems—robots, drones, autonomous vehicles, and intelligent infrastructure—must operate reliably in complex, safety-conscious environments. However, testing and training directly in live environments is costly, disruptive, and risky, while real-world edge cases are difficult to anticipate. Organizations across industries face growing pressure to scale Physical AI quickly without compromising safety, compliance, or operational continuity. The opportunity lies in using simulation and digital twins to shift experimentation, learning, and validation into virtual environments—allowing Physical AI systems to mature faster while keeping humans accountable for final decisions.

### HOW PHYSICAL AI CAN HELP

#### Simulation-trained intervention policies

AI models are trained in digital twins to learn safe remediation actions before being allowed to recommend changes in live physical systems.

#### Edge-based physical signal interpretation

Physical AI fuses telemetry from sensors, cameras, meters, and equipment controllers to detect anomalies that software-only monitoring would miss.

#### Closed-loop learning with digital twins

Performance data from live environments feeds back into digital twins, continuously improving models, policies, and predictions over time.

#### Approval-based execution

Humans approve changes before implementation, maintaining accountability and enabling operators to reject recommendations when local knowledge suggests alternative actions.

#### Action impact prediction before execution

Proposed remediation steps are stress-tested in simulation to predict downstream physical effects (safety, stability, service impact) before approval.

### POTENTIAL BENEFITS

#### Faster resolution

Routine fixes occur sooner as AI presents validated solutions immediately rather than requiring operators to research procedures and manually configure changes through multiple system interfaces.

#### Lower operator load

Manual effort declines as operators shift from diagnosis and solution development to review and approval, enabling smaller control room teams to manage larger grid footprints.

#### Stronger governance and trust

Human-in-the-loop validation supports regulatory compliance and builds organizational confidence in Physical AI systems.

#### Trust preservation

Risk remains controlled through mandatory human approval, addressing regulatory requirements and organizational concerns while still capturing efficiency benefits from AI assistance.

#### Transferable remediation patterns across industries

Once trained, remediation logic can be adapted across utilities, telecom, manufacturing, and infrastructure with minimal rework.



# Simulation-trained, human-supervised closed-loop remediation (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Simulation-trained remediation models must perform reliably when applied to live physical infrastructure; however, the real world inevitably presents conditions not fully captured in digital twins. A model that recommends incorrect remediation actions in live safety-critical environments because its training did not represent actual operating conditions creates the very failures it was designed to prevent.



### Responsible and accountable

Human approval is required for all changes before implementation, preserving accountability for safety-critical interventions. However, this governance design principle must be enforced in practice. Effective accountability requires clear and consistent documentation of what the AI recommended, what simulation stress-testing showed, who approved the action, and what outcome occurred.



### Transparent and explainable

Operators approving AI-recommended remediations need to understand what anomaly was detected, what action was proposed, and what downstream effects were predicted by simulation and stress-testing. True human oversight is only possible if AI's reasoning and outputs are transparent and explainable.





# Simulation-driven remote operations and training (1/2)

## Scaling expertise through digital twins and immersive simulation

### DESCRIPTION

AR/VR digital twins create high-fidelity virtual replicas of offshore platforms and production facilities, to help enable specialists to perform remote troubleshooting, technical oversight, and operator training from onshore locations without traveling to hazardous sites.

### ISSUE/OPPORTUNITY

Operating and maintaining complex, hazardous, or geographically remote physical assets traditionally requires expert personnel to be physically present on site. This dependence increases safety risk, travel cost, downtime, and delays—particularly when specialist availability, weather conditions, or access constraints limit rapid response. Training new operators is similarly constrained, as hands-on learning in live environments is costly, slow to scale, and exposes people and assets to operational risk. Traditional remote monitoring tools lack the fidelity and interactivity needed to support effective troubleshooting, skill transfer, and decision-making for complex physical systems. The opportunity is to shift oversight, training, and validation into high-fidelity simulation and digital twins—enabling safe, scalable knowledge, faster decision-making, and reduced physical exposure without compromising control or accountability.

### HOW PHYSICAL AI CAN HELP

#### Simulation-first skill transfer and validation

AI uses high-fidelity digital twins to model assets, procedures, and failure scenarios, enabling operators and specialists to train, rehearse, and validate actions in a risk-free virtual environment before interacting with live systems.

#### Knowledge capture and replay

Simulation environments encode expert decision paths, diagnostic logic, and safe operating envelopes, allowing scarce expertise to be reused consistently across locations and shifts without requiring physical presence.

#### Remote decision support with contextual awareness

AI continuously synchronizes simulation models with live asset data, enabling remote specialists to reason about current conditions, test interventions virtually, and provide guidance grounded in predicted physical outcomes.

#### Governed human-in-the-loop operations

AI supports recommendations and scenario evaluation, while humans retain approval authority for physical actions—preserving accountability, safety, and regulatory alignment.

#### Simulation-trained action policies

Physical AI systems learn safe operating envelopes in simulation before executing actions on real assets, reducing reliance on trial-and-error in hazardous environments.

### POTENTIAL BENEFITS

#### Transformational safety improvement

Keeping personnel out of hazardous offshore environments for routine technical service and troubleshooting represents the primary value driver, reducing exposure to the safety risks inherent in offshore operations.

#### Major cost efficiency gains

Eliminating the majority of specialist travel to remote sites for technical service and troubleshooting removes significant aviation and logistics costs that accumulate across large offshore portfolios.

#### Faster workforce development

Operator training and onboarding conducted in onshore back offices rather than on offshore platforms accelerates skills development, reduces training logistics costs, and helps enable more flexible scheduling of new hire cohorts.

#### Proven deployment

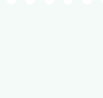
Digital twin remote operations technology has already been fully deployed and validated at scale in offshore operations, representing a mature capability with established return on investment rather than an emerging proof of concept.

#### Scalable knowledge transfer

Simulation-trained AI encapsulates expert knowledge, allowing consistent execution across assets without depending on scarce specialists.

#### Cross-industry applicability

Applicable wherever Physical AI systems operate in safety conscious, remote, or complex environments—including ER&I, logistics, and healthcare facilities, where simulation-first validation improves safety, reliability, and operational confidence.



# Simulation-driven remote operations and training (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Digital twins used for remote troubleshooting must faithfully represent current physical conditions. A simulation that diverges from the live system state due to synchronization failures can lead remote experts to recommend interventions based on inaccurate virtual representations. Reliable synchronization between the digital twin and live physical data is a prerequisite for safe remote operations.



### Responsible and accountable

In this use case, humans retain approval authority for all physical actions. AI supports recommendations but does not act autonomously. To maintain accountability, organizations need to document what the simulation predicted, what the remote expert recommended, and what action was approved and taken.



### Transparent and explainable

Remote experts and operators using digital twins for troubleshooting need to understand how the simulation represents current physical conditions, what assumptions underlie predicted outcomes, and where simulation limitations may affect recommendation reliability.



# Summary: Physical AI Use Cases Across Industries

Some of the most powerful Physical AI capabilities are horizontal—defined not by industry but by the operational problem they solve

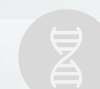


Physical AI is difficult to define within sector boundaries. Many of the most impactful capabilities in this dossier are defined not by the industry they serve but by the operational challenge they address, and those challenges recur across industries in forms similar enough that the same underlying approach can be deployed broadly.

The cross-industry use cases collected here share a common characteristic: the problem they solve is sufficiently universal, and the solution sufficiently transferable, that limiting them to a single industry chapter would understate their relevance. For example, quality assurance, logistics automation, human-machine interaction in physical environments, and operational simulation are challenges that companies in many different industries face in similar forms. A capability developed to solve such a problem in one industry frequently transfers to others with meaningful adaptation but without reinvention.

This horizontal applicability changes the economics of Physical AI investment. Organizations that recognize the phenomenon can leverage implementations across multiple business units, geographies, and functions—compounding the return on their investments and building institutional capabilities that extend well beyond single deployment. Horizontal applicability also suggests a different framing for how leaders should evaluate Physical AI opportunities: not just "what is my industry doing?" but "what operational problem am I trying to solve, and where has it already been solved in a way I can learn from and adapt?"

As Physical AI matures, the boundary between industry-specific and cross-industry capabilities may continue to blur. The use cases in this chapter represent the leading edge of that convergence.



# Autonomous self-calibrating quality and process control (1/2)

## From defect detection to self-maintaining, defect-preventing production systems

### DESCRIPTION

Physical AI systems combine advanced vision, sensing, and closed-loop process control to continuously monitor production quality and their own operational performance. These systems detect defects, process drift, sensor misalignment, and environmental changes in real time, and autonomously recalibrate sensors, retrain models, or adjust equipment parameters to prevent defect propagation—maintaining accuracy and stability without relying on periodic human intervention.

### ISSUE/OPPORTUNITY

Traditional quality systems detect defects after production, resulting in scrap, rework, batch losses, and delayed root-cause analysis. At the same time, Physical AI deployments themselves degrade over time as cameras shift, sensors drift, lighting changes, and thermal conditions evolve—requiring frequent manual recalibration and maintenance. These gaps create production inefficiencies, quality risk, and ongoing operational overhead. The opportunity is to move beyond reactive inspection and manual upkeep toward Physical AI systems that both prevent defects and self-maintain performance, sustaining quality and reliability continuously in dynamic production environments.

### HOW PHYSICAL AI CAN HELP

#### Real-time defect analysis and closed-loop control

Vision systems identify emerging quality issues and automatically adjust process parameters (e.g., temperature, pressure, speed, positioning) before defects spread.

#### Self-monitoring and drift detection

AI continuously evaluates its own accuracy, false-positive rates, and environmental inputs to detect performance degradation early.

#### Predictive quality modeling

Machine-learning models forecast defect risk based on process variables, enabling proactive intervention rather than reactive correction.

#### Integrated inspection across stages

Quality data is shared across process steps, enabling upstream adjustments based on downstream signals and optimizing the full production line.

#### Automated calibration and correction

Systems autonomously recalibrate cameras, sensors, and models when misalignment or drift is detected, without stopping production.

### POTENTIAL BENEFITS

#### Reduced scrap and rework

Preventing defects at the source lowers material waste, batch losses, and costly rework cycles.

#### Sustained accuracy and reliability

Self-calibrating systems maintain consistent performance over time, avoiding degradation between maintenance cycles.

#### Minimized downtime and production disruption

Automated correction prevents failures that would otherwise require systems to be taken offline.

#### Lower maintenance overhead

Reduced reliance on manual calibration and inspection frees specialized staff for higher-value work.

#### Continuous quality improvement

Closed-loop learning progressively tightens process control beyond human-achievable consistency.

#### Stronger auditability and validation

Quality and process data supports regulatory audits and customer certifications.



# Autonomous self-calibrating quality and process control (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Systems autonomously recalibrating sensors, retraining models, and adjusting process parameters must do so reliably. An incorrect self-calibration that degrades detection accuracy can allow defects to propagate undetected. The self-monitoring capability must itself be monitored and validated to ensure it correctly identifies genuine drift rather than triggering inappropriate recalibrations that disrupt production.



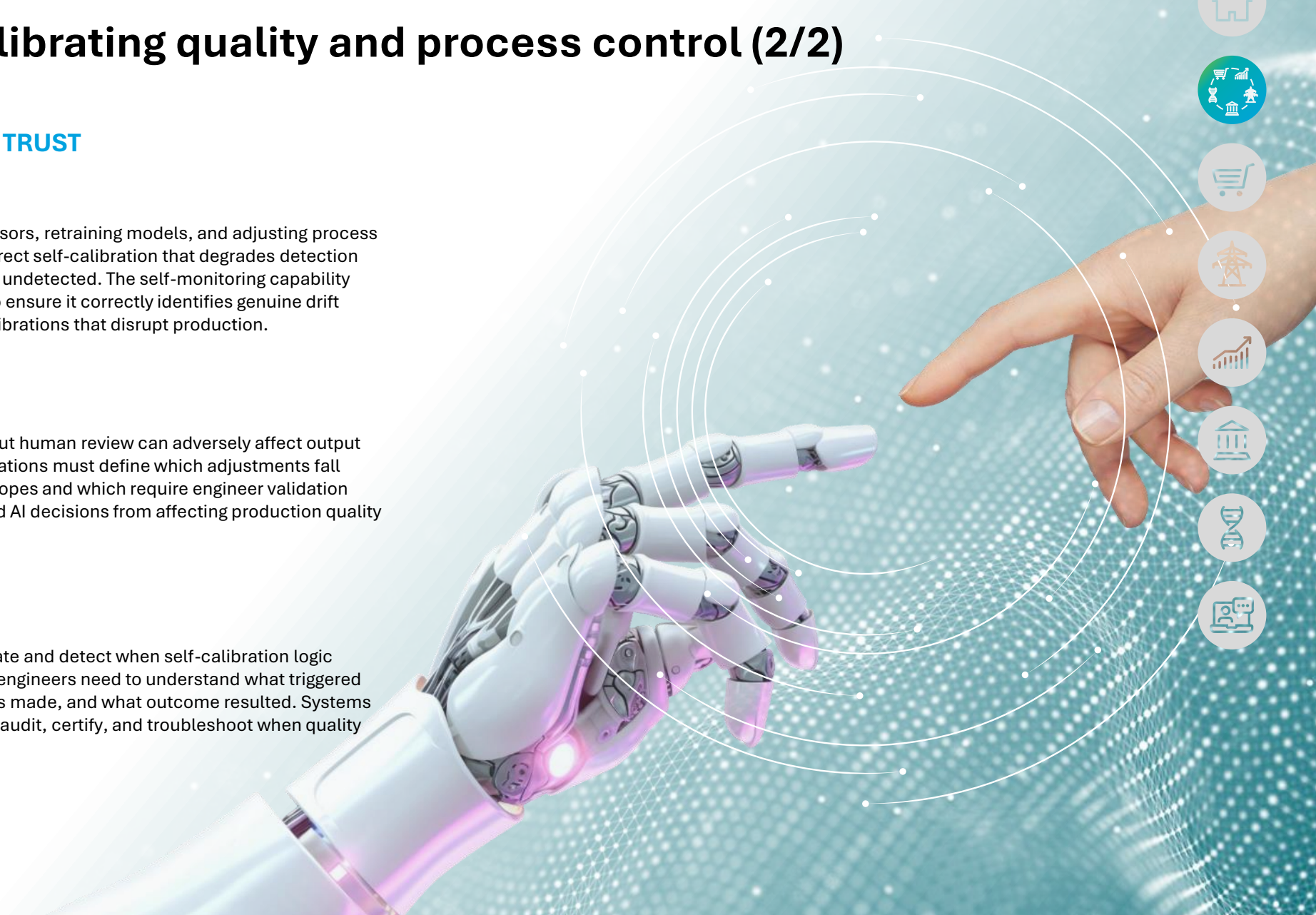
### Responsible and accountable

Autonomous process adjustments without human review can adversely affect output quality and equipment behavior. Organizations must define which adjustments fall within pre-validated safe operating envelopes and which require engineer validation before execution—preventing unreviewed AI decisions from affecting production quality or equipment integrity at scale.



### Transparent and explainable

To validate that corrections are appropriate and detect when self-calibration logic responded to a spurious signal, process engineers need to understand what triggered the self-calibration, what adjustment was made, and what outcome resulted. Systems that self-correct opaquely are difficult to audit, certify, and troubleshoot when quality issues arise in production.



# Semi-autonomous warehouse loading and unloading robotics (1/2)

## Human-supervised Physical AI for dynamic material handling

### DESCRIPTION

Mobile robots assist with unloading containers, rearranging goods, and optimizing pallet placement within warehouse environments under supervised operation, increasing throughput while maintaining human fallback capability.

### ISSUE/OPPORTUNITY

Warehouse loading and unloading are physically demanding, repetitive, and throughput-sensitive processes. Manual handling introduces variability and ergonomic risk while limiting scalability during peak demand. Workers manually unload shipping containers, lift heavy boxes onto pallets, and stack goods in warehouse locations, performing physically taxing work that causes injuries, fatigue, and high turnover.

During peak seasons or promotional periods, warehouses struggle to find sufficient labor to process increased container volumes, creating bottlenecks that delay inventory availability and frustrate customers expecting rapid delivery. Pallet stacking quality varies by worker skill and fatigue level, leading to inefficient space utilization when goods are stacked loosely or unstably.

Traditional fixed automation often requires costly infrastructure redesign. Fixed conveyor systems and automated storage require extensive facility modifications and work well only for standardized products, not the diverse container contents typical of modern distribution centers.

The opportunity is to deploy Physical AI systems that can perceive, reason, and act in the physical world, while keeping humans in the loop for judgment, safety, and accountability. This enables automation of physically demanding tasks without sacrificing operational resilience or control.

### HOW PHYSICAL AI CAN HELP

#### Perception of unstructured physical environments

Vision and sensor fusion help enable systems to identify objects, assess orientation, detect obstacles, and understand spatial constraints in real time.

#### Physical reasoning and adaptive manipulation

AI models infer stable grasp points, load balance, and movement paths, adjusting actions dynamically as conditions change.

#### Fallback continuity mechanisms

Manual override capability helps to ensure uninterrupted operations during technical interruptions, help enable workers to complete tasks manually if robots experience downtime.

#### Supervised autonomy controls

Robots execute predefined tasks while escalating exceptions to human supervisors when they encounter situations outside normal parameters or require judgment calls.

#### Environmental sensing integration

Robots detect obstacles and adjust paths in real time, navigating around workers, equipment, and temporary obstructions common in busy warehouse environments.

### POTENTIAL BENEFITS

#### Reduced unloading time

Robotic assistance increases processing speed as machines work continuously without fatigue, enabling faster container turnover during peak periods.

#### Improved space utilization

Optimized stacking enhances warehouse capacity by consistently applying space-efficient pallet configurations that maximize vertical storage and minimize wasted space.

#### Lower ergonomic strain

Automation reduces physically intensive tasks, decreasing worker injuries from heavy lifting and repetitive motions.

#### Operational resilience through fallback mechanisms

Human fallback maintains continuity during outages as workers can manually perform robot tasks if equipment fails, preventing complete operational stoppage.

#### Cross-industry applicability

Applicability across logistics, manufacturing, healthcare facilities, construction sites, and industrial plants—wherever physical materials should be handled safely in dynamic environments.



# Semi-autonomous warehouse loading and unloading robotics (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

Mobile robots in shared warehouse environments must safely detect and respond to human presence—particularly during high-pressure peak periods when workers are fatigued and moving unpredictably. Validation of safety boundaries must cover actual operating conditions that include the congested, fast-paced peak periods when robot assistance is most needed and human-robot proximity is greatest.



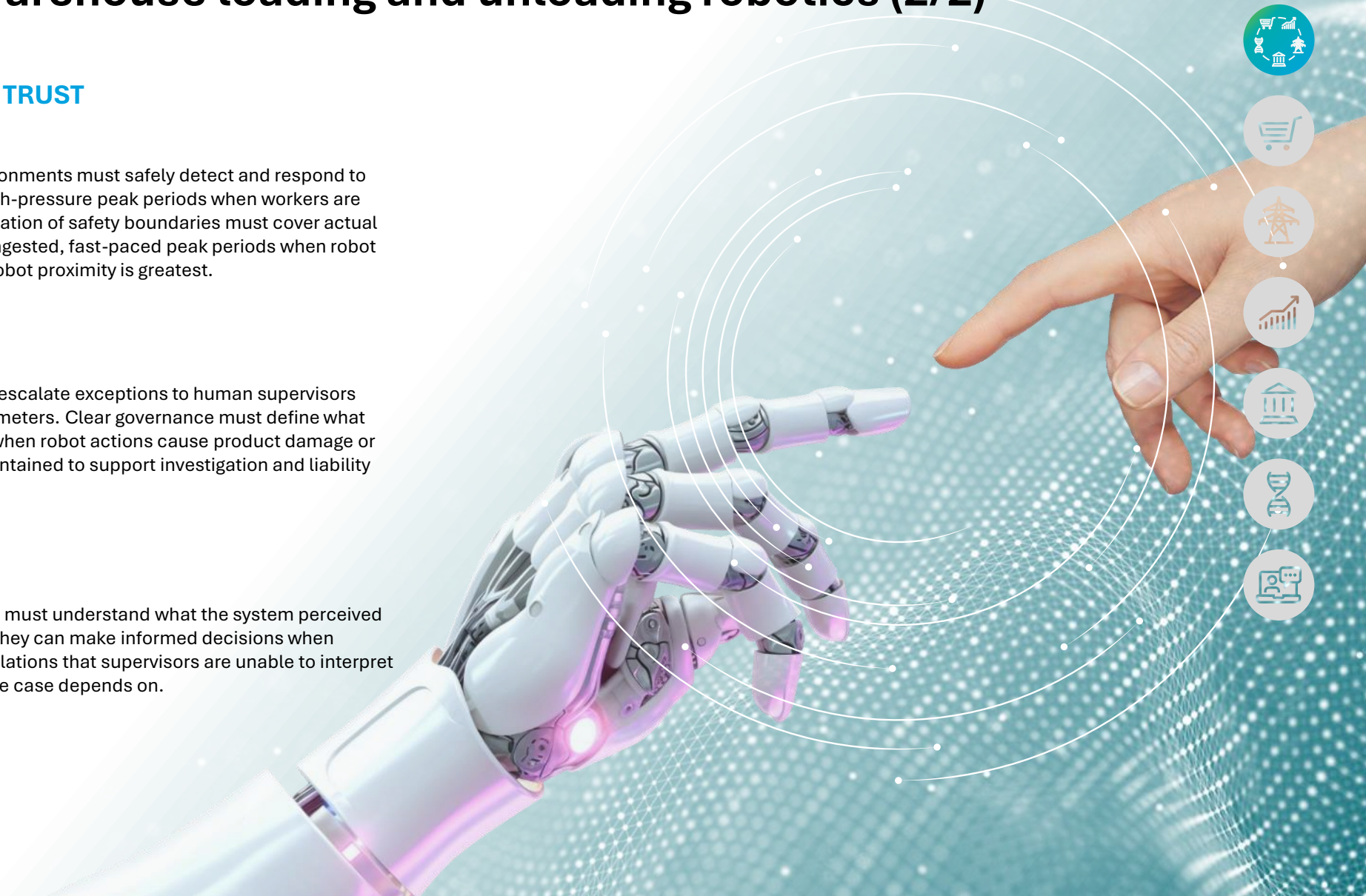
### Responsible and accountable

Supervised autonomy requires robots to escalate exceptions to human supervisors when situations fall outside normal parameters. Clear governance must define what triggers escalation, who is accountable when robot actions cause product damage or worker injury, and what logs must be maintained to support investigation and liability determination when incidents occur.



### Transparent and explainable

Human supervisors handling escalations must understand what the system perceived and why it is requesting an exception so they can make informed decisions when authorizing requests. Opaque robot escalations that supervisors are unable to interpret undermine the governance model this use case depends on.



# Voice-controlled Physical AI assistants for industrial operations (1/2)

## Hands-free human-machine collaboration in safety-critical environments

### DESCRIPTION

Voice-controlled Physical AI systems designed specifically for industrial environments help enable workers to interact naturally with physical machines and robotic systems, request information, trigger actions, and receive alerts through voice commands, even in high-noise factory and field settings. These systems combine voice recognition optimized for industrial acoustics with multi-modal interfaces (voice, touch, visual) to support human-AI collaboration in hands-occupied or hazardous work environments.

### ISSUE/OPPORTUNITY

Industrial workers operating machinery, conducting inspections, or performing maintenance often need to interact with AI systems and access digital information while their hands and visual attention are occupied with physical tasks. Traditional interfaces requiring screens and keyboards or touchscreens force workers to stop physical work to interact with systems, interrupting workflow, reducing efficiency, and creating safety risks when workers must divert attention from potentially hazardous operations.

Consumer voice assistants fail in industrial environments due to noise, task complexity, and lack of operational context. The opportunity is to enable safe, hands-free interaction tailored to industrial realities.

### HOW PHYSICAL AI CAN HELP

#### Noise-robust voice recognition

Advanced speech recognition models trained specifically for industrial environments filter machine noise, mechanical sounds, and background conversations to accurately recognize worker commands in realistic production settings.

#### Contextual AI understanding

Natural language processing helps enable workers to ask questions and give commands conversationally rather than memorizing specific phrases, with AI understanding context from current tasks and equipment states to interpret intent correctly.

#### Hands-free, safety-aware interaction

Workers access information, trigger actions, and receive alerts without stopping work or shifting attention away from safety-conscious tasks.

#### Multi-modal interaction design

Systems combine voice input with touch, gesture, and visual confirmations, allowing workers to choose the most appropriate interaction method based on immediate conditions and task requirements rather than forcing single-mode interaction.

#### Human-in-the-loop operation

Assistants support decision-making and execution without autonomous control, preserving human judgment and accountability.

### POTENTIAL BENEFITS

#### Hands-free operation in critical environments

Workers can access information and control systems—and receive AI insights—without interrupting physical tasks or diverting visual attention from safety-critical work, improving both efficiency and safety in hands-occupied operations.

#### Reduced training and adoption barriers

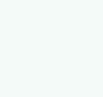
Natural voice interaction lowers the learning curve for AI system adoption, enabling workers to leverage AI capabilities without extensive technical training on complex interfaces or memorizing command sequences.

#### Faster response to AI alerts and recommendations

Voice-based notifications and alerts reach workers immediately without requiring them to check screens, enabling faster response to quality issues, safety warnings, or process anomalies detected by AI monitoring systems.

#### Cross-industry applicability

Applicable wherever workers interact with physical systems under safety, time, or mobility constraints—including manufacturing, energy, logistics, healthcare facilities, construction sites, and field service operations.



# Voice-controlled Physical AI assistants for industrial operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Voice recognition must perform reliably in real industrial environments, not just controlled testing conditions. Background noise, acoustic variability, and worker speech patterns all affect accuracy. A system that misinterprets commands during safety-critical or time-sensitive operations creates the workflow interruptions and safety risks it is deployed to prevent.



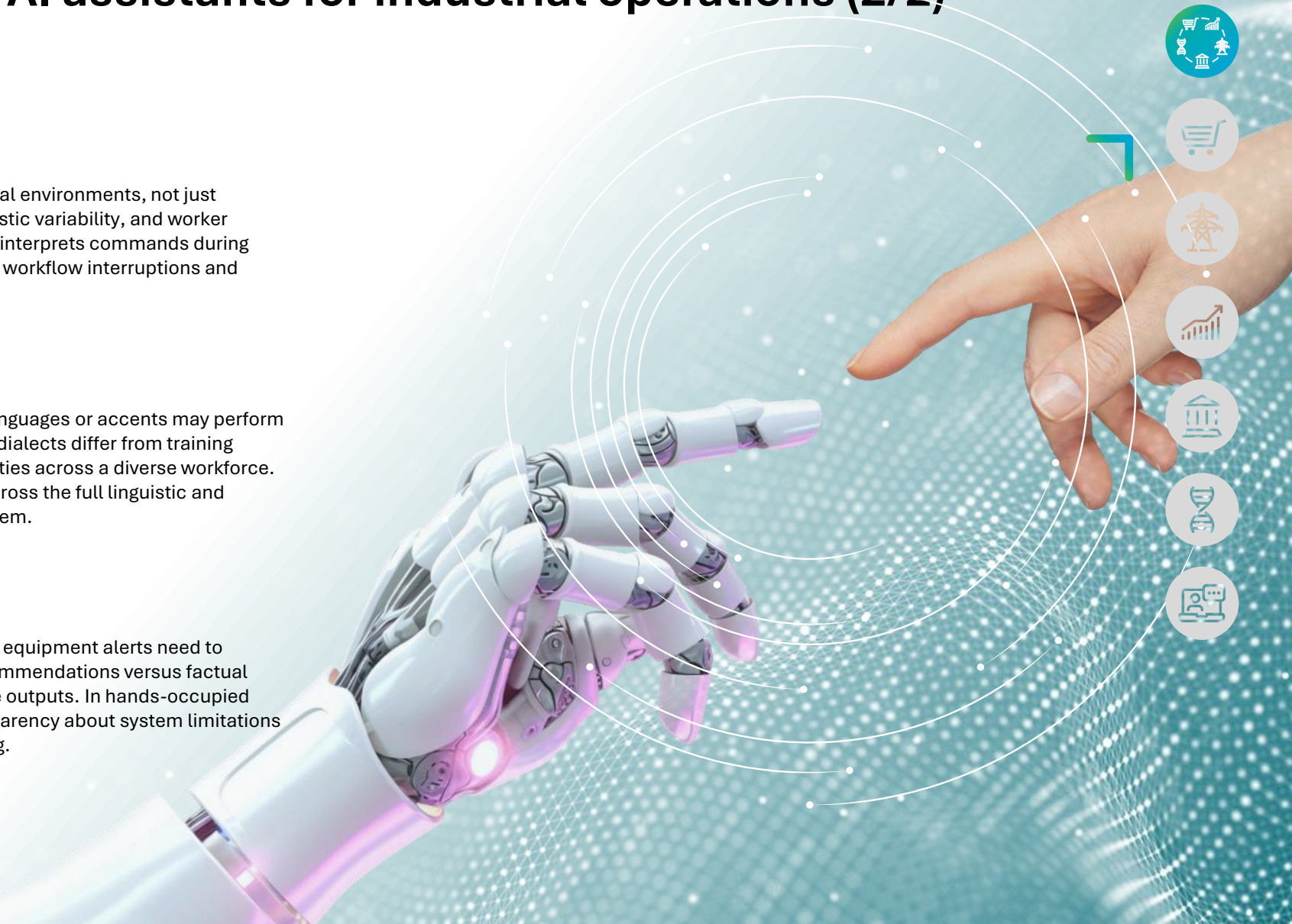
### Fair and impartial

Voice recognition trained predominantly on specific languages or accents may perform less accurately for workers whose speech patterns or dialects differ from training data—creating unequal access to AI-assisted capabilities across a diverse workforce. Organizations should validate recognition accuracy across the full linguistic and demographic diversity of workers who will use the system.



### Transparent and explainable

Workers using voice AI for safety-critical guidance and equipment alerts need to understand when they are receiving AI-generated recommendations versus factual data, how confident the system is, and how to override outputs. In hands-occupied environments where cross-checking is difficult, transparency about system limitations is directly relevant to safe operational decision-making.



# The Consumer Physical AI Dossier



# Summary: The Consumer Physical AI Dossier

Physical AI is reshaping how goods move, how stores operate, and how consumers experience the world around them

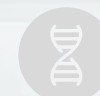


Consumer companies operate across one of the broadest and most varied physical footprints of each industry—supply chains spanning continents, distribution networks measured in thousands of locations, retail environments that should be staffed and maintained at scale, and an end point that is the most unpredictable physical environment of all: the home. This breadth has historically meant high labor dependency, significant operational variability, and limited ability to maintain consistency across touchpoints.

Physical AI addresses each of these structural characteristics directly. Where consumer operations are labor-intensive and repetitive, autonomous systems can take on physical tasks more reliably and at greater scale. Where quality and compliance depend on human observation across hundreds of locations, AI-powered vision can provide continuous and consistent oversight that manual auditing cannot. Where consumers expect faster, more responsive service, AI-coordinated physical systems can help companies meet those expectations without proportional increases in cost.

The consumer sector also presents some of Physical AI's most demanding deployment conditions. Consumer environments are dynamic and unpredictable: stores rearrange, delivery routes change constantly, and homes are entirely unique. Unlike industrial settings where Physical AI can be deployed in controlled, structured conditions, consumer applications must function reliably in human-scale environments. This raises the bar significantly on robustness and adaptability.

Consumer trust adds another layer. As Physical AI becomes more visible to end consumers (in stores, in delivery interactions, and increasingly in the home) the standards for transparency and privacy are set not just by regulators but by consumers themselves. Companies that earn that trust may find Physical AI to be a source of lasting competitive advantage.



# Autonomous transport for urban mobility services (1/2)

## AI-driven mobility in unpredictable urban environments

### DESCRIPTION

Autonomous vehicles provide ride-hailing, mobility services, and delivery of goods without human drivers, bringing Physical AI directly into daily consumer transportation.

### ISSUE/OPPORTUNITY

Urban mobility systems may face driver shortages, rising costs, and inconsistent service availability. Traditional transport models struggle to scale efficiently. Cities can experience mobility gaps in underserved neighborhoods where ride-share driver availability is limited and in off-peak hours when driver supply drops sharply despite continued passenger need.

The opportunity is to deploy autonomous passenger services that improve accessibility while reducing reliance on human drivers, enabling consistent service across hours and locations within regulatory frameworks that help enable safety and public acceptance.

### HOW PHYSICAL AI CAN HELP

#### Perception and navigation

AI interprets complex urban environments including traffic patterns, pedestrian behavior, construction zones, and road conditions to navigate safely through city streets.

#### Safety-constrained autonomy

Operations remain supervised and comply with strict safety requirements through speed limits, restricted operating zones, and conservative decision-making that prioritizes passenger and public safety.

#### Regulatory-compliant design

Systems align with approval requirements including data reporting, safety certifications, and operational restrictions mandated by local transportation authorities.

#### Passenger interaction systems

Vehicles communicate with users directly through voice interfaces, in-vehicle displays, and mobile apps to coordinate pickups, provide route information, and address passenger requests.

#### Fleet-level optimization

Vehicles with fleet telemetry are deployed based on demand patterns, positioning cars near areas with expected pickup requests to minimize wait times and improve service coverage.

#### Human fallback mechanisms

Escalation paths exist for edge cases where remote operators can provide guidance or take control when the autonomous system encounters situations outside its operational design domain.

### POTENTIAL BENEFITS

#### Broader access

Mobility access improves for a broader population as service can be provided in areas and at times when driver availability dips, expanding to new locations and times.

#### Lower costs

Operating costs decrease as driver dependence is reduced, potentially enabling lower fares and expanded geographic coverage.

#### Improved scalability

Service scalability increases as fleets can be sized to match demand without recruiting and retaining drivers.

#### Better service

Passenger experience becomes more consistent and predictable as vehicle behavior, routing, and service quality follow standardized protocols, subject to regulatory approval and public acceptance.



# Autonomous transport for urban mobility services (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

Autonomous vehicles are high-risk AI systems, making cybersecurity a fundamental design requirement. Systems must be hardened against sensor spoofing, adversarial attacks, and unauthorized access, with clear incident-response protocols and regular third-party security assessments occurring before and throughout commercial operation.



### Responsible and accountable

When an autonomous vehicle is involved in a public incident, accountability cannot be ambiguous. Responsibility frameworks must be established before deployment begins. Detailed operational logs and safety event records should be maintained to support incident investigation, regulatory reporting, and iterative safety improvement.



### Fair and impartial

The promise of autonomous mobility—expanding access to underserved neighborhoods and off-peak hours—can only be realized if fleet deployment algorithms are actively designed for equity, not just efficiency. Routing, availability, and pricing models should be regularly audited to ensure they do not systematically disadvantage riders based on location, income, or inability to access digital payment methods.



# Multipurpose household service robots (1/2)

## Reasoning-enabled service robots for home environments

### DESCRIPTION

Physical AI-enabled service robots that use reasoning models to perform household support tasks (e.g., cleaning assistance, item retrieval, setup, basic monitoring) in dynamic home environments, within defined safety and autonomy boundaries.

### ISSUE/OPPORTUNITY

Current household robots require detailed task programming for each specific action, limiting their usefulness to narrow, pre-defined activities. Users should explicitly instruct robots on each step of a task—where to go, what to pick up, how to handle objects, and when to stop—making deployment time-consuming and limiting robots to repetitive, identical tasks. Household environments change constantly with objects moved, furniture rearranged, and new items introduced, causing pre-programmed instructions to quickly become outdated and require manual updates.

The barrier to adoption is the programming burden rather than hardware capability—households need robots that can reason about their environment and infer appropriate actions based on context, goals, and safety constraints rather than following rigid scripts.

The opportunity is to shift from scripted automation to reasoning-based Physical AI that can interpret context, infer appropriate actions, and operate reliably in unstructured home environments—dramatically reducing setup effort while expanding practical value.

### HOW PHYSICAL AI CAN HELP

#### Contextual reasoning

AI infers appropriate actions by understanding the current situation, user goals, and environmental context rather than requiring explicit step-by-step instructions for each task variation.

#### Human interaction

Systems respond naturally to conversational requests and environmental cues, allowing users to communicate intent at a high level rather than specifying detailed procedures.

#### Reduced task programming

Explicit instructions are minimized as systems learn to generalize across similar tasks and adapt to environmental changes without requiring manual reprogramming.

#### Safety-constrained autonomy

Actions remain bounded within defined safety envelopes that prevent damage to property, help enable human safety, and mitigate behaviors outside approved operational limits.

### POTENTIAL BENEFITS

#### Ease of use

Less instruction required as users can communicate goals at a high level and help enable systems to determine implementation details based on environmental reasoning.

#### Broader task coverage

More activities automated as systems can handle variations and novel situations without explicit programming for each specific scenario encountered.

#### Improved interaction

Systems feel more intuitive as they respond to natural language and contextual cues rather than requiring users to learn specialized programming interfaces or command structures.

#### Long-term scalability

Automation expands gradually as reasoning capabilities improve and systems learn to handle increasingly complex household tasks through experience and model updates.



# Multipurpose household service robots (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

A robot that physically manipulates objects inside a home—around children, elderly occupants, and pets—presents harm potential that is immediate and concrete. Safety boundaries must be rigorously defined and tested well beyond lab conditions, and network-connected systems must be secured against unauthorized access that could allow external parties to remotely observe or control devices operating inside private residences.



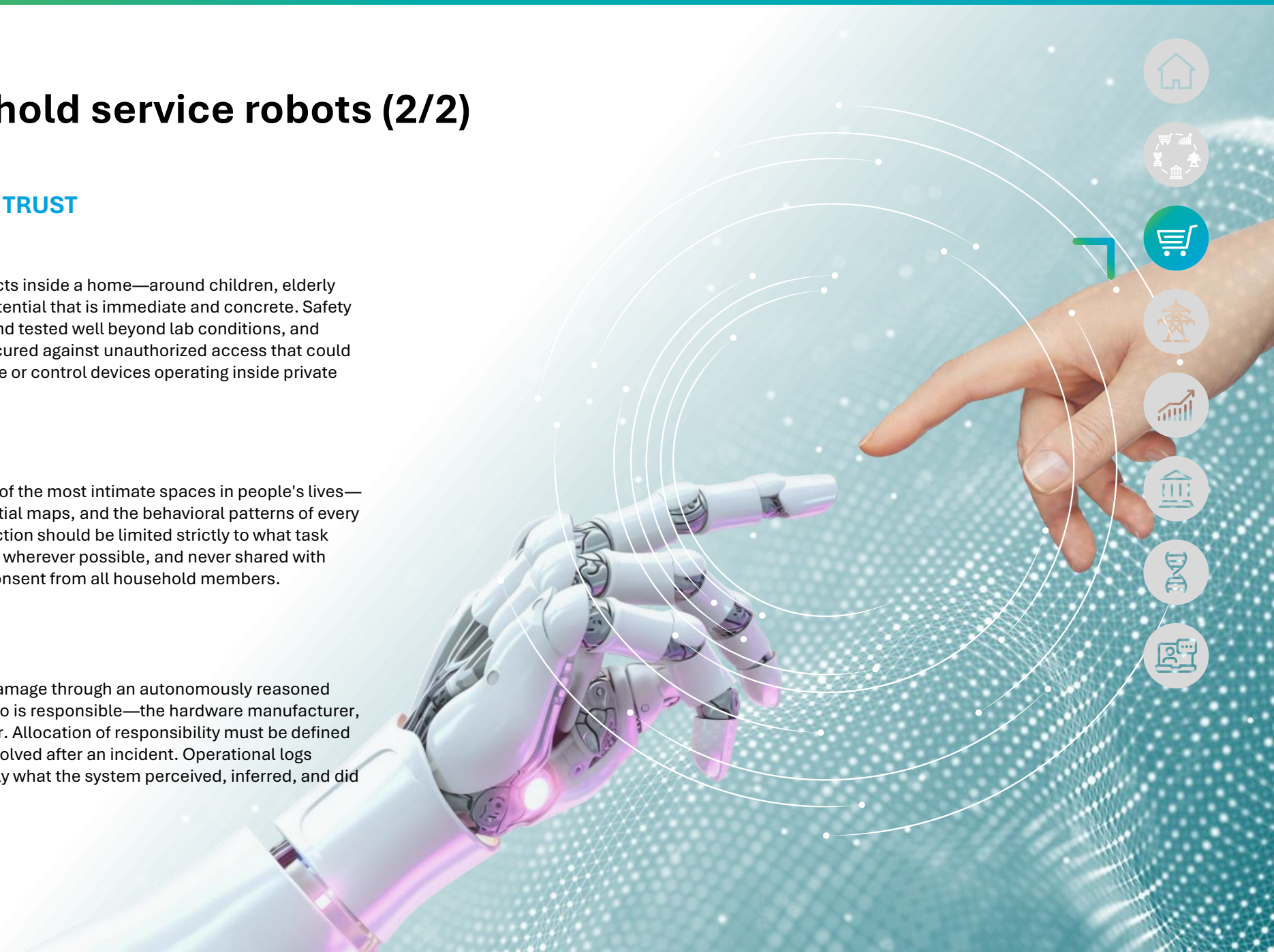
### Private

Household service robots observe some of the most intimate spaces in people's lives—continuously capturing audio, video, spatial maps, and the behavioral patterns of every occupant, including children. Data collection should be limited strictly to what task execution requires, processed on-device wherever possible, and never shared with third parties without explicit, informed consent from all household members.



### Responsible and accountable

When a robot causes harm or property damage through an autonomously reasoned action, it can be difficult to determine who is responsible—the hardware manufacturer, the AI developer, or the platform operator. Allocation of responsibility must be defined contractually before deployment, not resolved after an incident. Operational logs should be sufficient to reconstruct exactly what the system perceived, inferred, and did at the time.



# Vision-enabled store operations (1/2)

## Real-time retail execution through vision

### DESCRIPTION

Vision-enabled store operations leverage in-store computer vision and edge analytics to track shelf execution and planogram adherence, enabling timely adjustments to product placement based on real-time conditions.

### ISSUE/OPPORTUNITY

Retail execution and shelf compliance are traditionally validated through manual audits, which are time-consuming, inconsistent, and reactive. Field representatives visually inspect product placement, stock levels, and promotional displays across distributed retail environments, traveling from store to store to compare physical shelf arrangements against planogram specifications. Each inspection requires the representative to mentally compare what they see against ideal layouts, estimate spacing and facings, and document deviations for later follow-up.

Manual validation limits coverage and slows corrective action, as representatives can visit a fraction of locations each week, and by the time audit reports reach stores, shelf conditions may have changed. Inconsistent shelf execution can reduce sales performance and brand visibility, as products placed in wrong locations receive less customer attention, out-of-stock situations go undetected, and promotional displays fail to meet brand standards.

The opportunity lies in automating visual validation through computer vision, enabling faster identification of misplacement, out-of-stock risk, or suboptimal layout. However, accuracy should remain high across varying lighting conditions, store formats, and device types to help enable trust and usability at scale.

### HOW PHYSICAL AI CAN HELP

#### Edge vision in the aisle

Computer vision models analyze shelf images to detect product placement and spacing, identifying individual SKUs, counting facings, and recognizing when items are incorrectly positioned.

#### Real-time feedback loops

Field users receive immediate guidance on corrective actions, with visual overlays showing which products need adjustment.

#### Human-in-the-loop execution

Field staff remain in control; AI provides recommendations and visual overlays, to help enable fast, informed corrections without autonomous physical action.

#### Context-aware planogram reasoning

AI compares observed layout, with ERP-integrated reconciliation, against expected configuration templates, highlighting deviations and prioritizing corrections.

#### Scalable validation coverage

Automated analysis increases inspection frequency without increasing labor, enabling daily checks rather than weekly or monthly manual audits.

### POTENTIAL BENEFITS

#### Faster compliance validation

Immediate detection reduces correction lag, enabling same-visit fixes rather than waiting for audit reports to be processed and communicated.

#### Improved merchandising effectiveness

Optimized placement increases sales performance, as products consistently appear in planned positions that maximize visibility and align with promotional campaigns.

#### Reduced manual auditing effort

Automation lowers time spent on inspections, freeing representatives to focus on relationship building and strategic merchandising improvements.

#### Higher execution consistency

Standardized validation improves brand reliability across locations, ensuring consistent shelf presentation across store formats and markets.



# Vision-enabled store operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Accuracy across the full range of real-world retail conditions is a prerequisite for this use case at scale—and those conditions are demanding, such as, variable store lighting, shelf clutter, inconsistent device camera quality, and thousands of SKU variations across product ranges and regional markets. Models validated on a narrow set of stores can struggle in new environments, so performance monitoring must be conducted continuously across the live deployment footprint, not as a one-time pre-launch exercise.



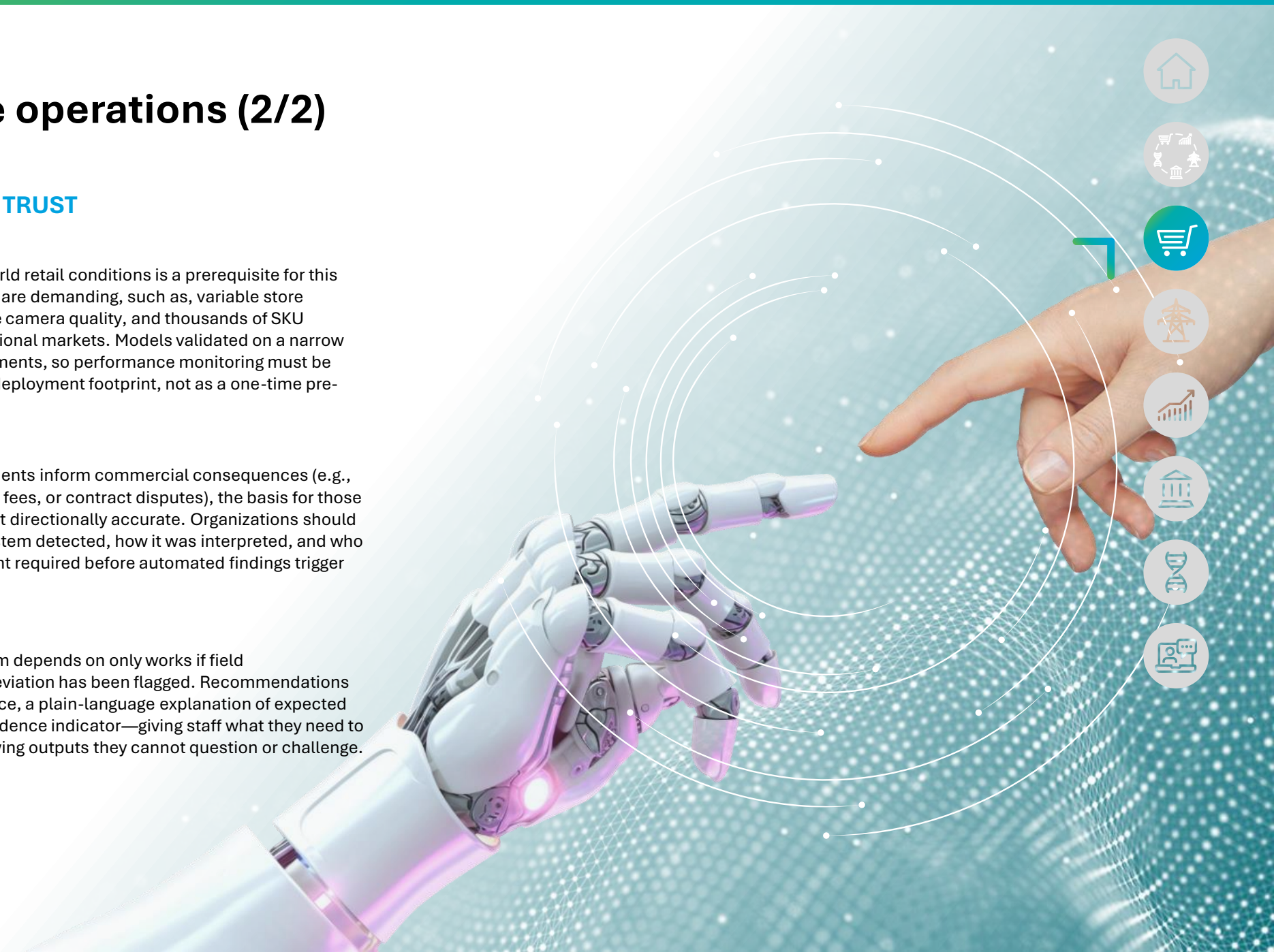
### Responsible and accountable

When AI-generated compliance assessments inform commercial consequences (e.g., supplier penalties, disputed promotional fees, or contract disputes), the basis for those assessments must be defensible, not just directionally accurate. Organizations should maintain clear audit trails of what the system detected, how it was interpreted, and who acted on the output, with human oversight required before automated findings trigger any consequential commercial action.



### Transparent and explainable

The human-in-the-loop design this system depends on only works if field representatives can understand *why* a deviation has been flagged. Recommendations should be accompanied by visual evidence, a plain-language explanation of expected versus observed shelf layout, and a confidence indicator—giving staff what they need to exercise true judgment rather than following outputs they cannot question or challenge.



# Fleet telemetry and route optimization (1/2)

## Adaptive logistics driven by edge intelligence

### DESCRIPTION

Physical AI systems embed intelligence directly into delivery vehicles, using onboard sensors, edge computing, and real-time connectivity to continuously perceive operating conditions and adapt routing, driving behavior, and delivery execution while vehicles are in motion.

### ISSUE/OPPORTUNITY

Delivery networks operate across diverse traffic conditions, distribution constraints, and customer delivery windows. Static route planning fails to adapt dynamically to real-time conditions, leading to delays and inefficiencies. Multiple tracking vendors and inconsistent telemetry standards create integration challenges that slow scaling. Logistics inefficiencies increase fuel consumption, delay deliveries, and reduce retailer service levels.

The opportunity is to deploy Physical AI-enabled fleets where vehicles themselves become intelligent actors—continuously sensing conditions, adjusting execution in real time, and coordinating with fleet systems to maintain service reliability at scale. However, interoperability, data standardization, and secure integration with manufacturing and warehouse systems are prerequisites for system-wide orchestration.

### HOW PHYSICAL AI CAN HELP

#### Real-time route optimization

AI models analyze location, traffic, and delivery progress to dynamically adjust routing in response to changing conditions, accidents, or unexpected delays.

#### Driver behavior analytics

Telemetry supports identification of inefficient or unsafe driving patterns including harsh braking, excessive idling, or suboptimal speed management that increases fuel consumption and risk.

#### Load sequencing optimization

Algorithms optimize delivery sequencing and product mixing to reduce turnaround times, ensuring products are loaded in the order they'll be delivered and minimizing time spent searching for items at each stop.

#### Predictive delay modeling

Edge-deployed AI anticipates disruptions and recommends proactive rerouting before delays impact delivery schedules, accounting for historical traffic patterns, weather forecasts, and known construction zones.

#### Cross-system data integration

Fleet data aligns with production schedules and warehouse dispatch systems for coordinated outbound logistics, ensuring vehicles depart when orders are ready and arrive when receiving docks are available.

### POTENTIAL BENEFITS

#### Reduced time-to-retailer

Dynamic routing improves service-level performance by avoiding delays, minimizing wait times at delivery locations, and ensuring on-time arrivals within promised delivery windows.

#### Lower transportation cost

Fuel efficiency and idle-time reduction decrease expenses through optimized routes, reduced unnecessary mileage, and improved driver behavior that eliminates wasteful practices.

#### Improved safety monitoring

Behavior analytics reduce operational risk by identifying drivers who need additional training, detecting patterns that predict accidents, and enabling proactive interventions before incidents occur.

#### Higher delivery reliability

Real-time adjustments mitigate disruption impact, to help enable logistics managers to communicate accurate arrival times to retailers and maintain service commitments despite unexpected obstacles.



# Fleet telemetry and route optimization (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

Continuous fleet monitoring generates substantial personal data about drivers: precise location history, behavioral patterns, working hours, and biometric data (when driver-facing cameras are used). To address emerging legal requirements on biometric data collection, AI-enabled fleet solutions will need explicit driver consent, clear retention limits, and regular vendor security audits before and after deployment.



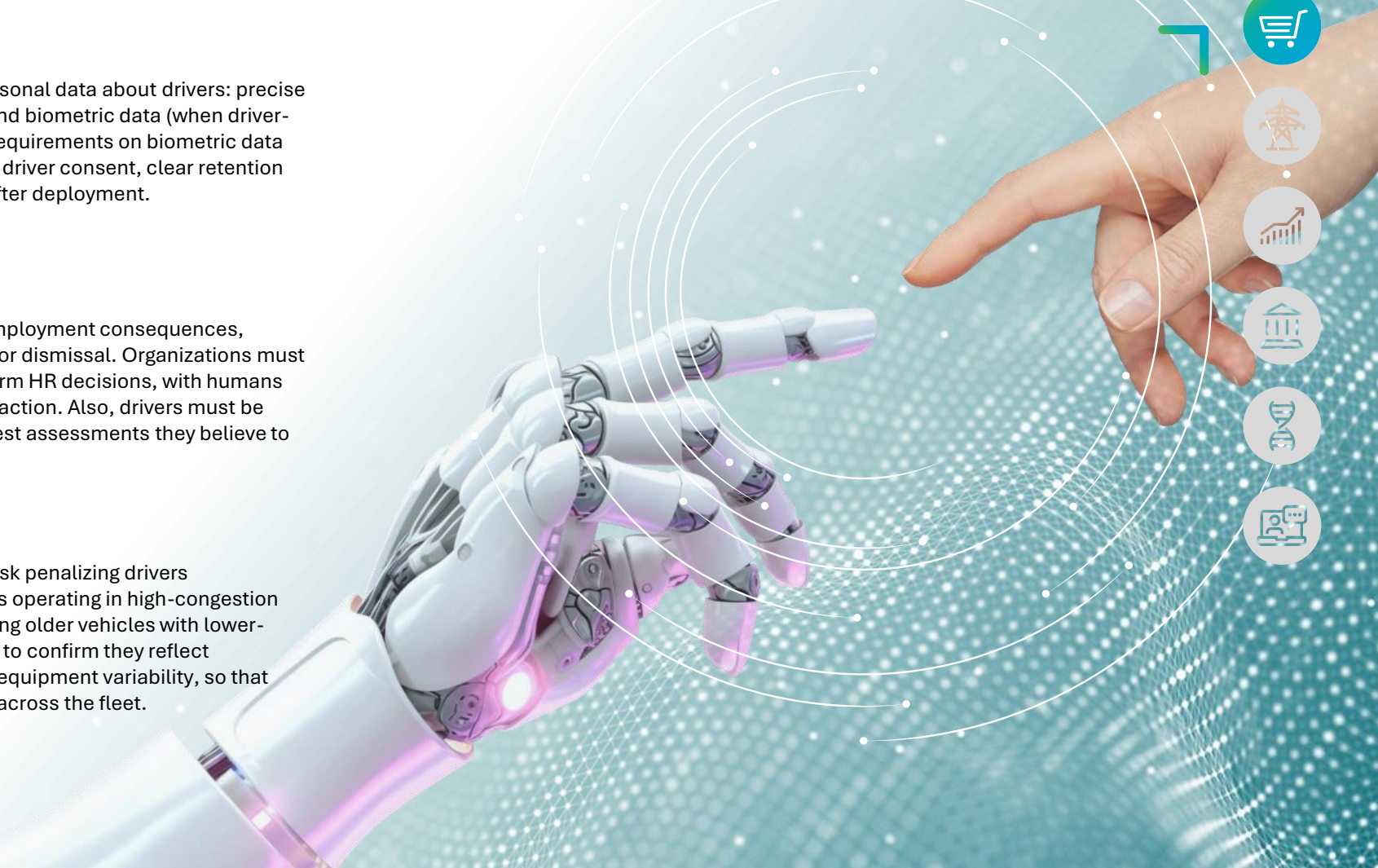
### Responsible and accountable

AI-generated driver behavior scores can have direct employment consequences, including disciplinary action, retraining requirements, or dismissal. Organizations must establish clear governance over how these scores inform HR decisions, with humans retaining authority for any consequential employment action. Also, drivers must be allowed to access their own data and to formally contest assessments they believe to be inaccurate.



### Fair and impartial

Driver scoring models trained on historical fleet data risk penalizing drivers systematically for factors outside their control, such as operating in high-congestion urban areas, covering more demanding routes, or driving older vehicles with lower-quality sensors. AI models should be regularly audited to confirm they reflect genuine driving behavior rather than route difficulty or equipment variability, so that performance assessments are genuinely comparable across the fleet.



# Edge–cloud architecture for consumer mobility (1/2)

## Distributed intelligence enabling real-time physical action in vehicles

### DESCRIPTION

An edge–cloud Physical AI architecture distributes intelligence between vehicles and centralized platforms to help enable real-time perception and control at the edge, while supporting fleet-wide learning, data management, and continuous improvement in the cloud. This approach balances ultra-low-latency safety requirements with scalable model training and deployment across geographically distributed mobility fleets.

### ISSUE/OPPORTUNITY

Mobility vehicles generate volumes of sensor data from cameras, LiDAR, radar, and other onboard systems while operating in dynamic, safety-critical environments. Many driving decisions should be made within milliseconds, making it impractical and unsafe to rely solely on cloud-based processing due to network latency, bandwidth constraints, and connectivity variability. At the same time, fully localized intelligence limits the ability to learn from fleet-wide experiences, slowing improvement of perception and control models and preventing vehicles from benefiting from rare or geographically distributed edge cases.

Managing, transferring, labeling, and reusing raw sensor data at scale is costly and creates development bottlenecks. Infrastructure limits on onboard compute, storage, and network capacity further constrain how much data can be processed or transmitted. The opportunity is a unified edge–cloud architecture that enables real-time local execution while coordinating centralized learning, data management, and deployment to accelerate autonomous driving development without violating real-world system constraints.

### HOW PHYSICAL AI CAN HELP

#### Real-time physical intelligence at the edge

Vehicles locally process camera, LiDAR, radar, and telemetry data to perceive surroundings and execute physical actions immediately. Edge AI ensures millisecond-level response for safety-critical maneuvers even during connectivity loss.

#### Fleet-level learning in the cloud

Edge–cloud data platforms curate, prioritize, and replay real-world driving scenarios (including rare edge cases) to continuously improve perception and control models. Simulation and synthetic data augment real-world data to accelerate learning without increasing on-road risk.

#### Continuous closed-loop improvement

Edge systems infer component health from real-world behavior, reducing sensor dependence, while fleet data and simulation refine models in the cloud. Validated updates are pushed back over-the-air, steadily improving safety, performance, and reliability across vehicles without hardware changes.

### POTENTIAL BENEFITS

#### Operational resilience

Vehicles remain functional during network disruptions due to edge autonomy. Easier rollout across regions.

#### Lower system cost

Selective data transmission and local inference reduce bandwidth and cloud compute costs.

#### Broader scenario coverage and model robustness

Fleet-wide data aggregation combined with synthetic data generation improves performance across diverse weather, traffic, and road conditions.

#### Faster innovation cycles

Fleet-wide learning accelerates improvement without manual recalibration.

#### Consistent experience at scale

Ride quality, braking behavior, and navigation improve uniformly across fleets.

#### Safer consumer mobility

Real-time, on-vehicle decision-making reduces accident risk in dynamic environments.



# Edge–cloud architecture for consumer mobility (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

This architecture requires that edge AI be consistently capable of making safety-critical decisions—emergency braking, hazard avoidance, collision detection—within milliseconds. A model that performs well in testing but degrades unpredictably under real-world conditions of sensor noise, adverse weather, or hardware variation across vehicle generations creates direct safety risk. Continuous validation across the live fleet is not optional; it is the foundation on which everything else depends.



### Responsible and accountable

Continuous cloud-based model updates create an accountability challenge that is structurally unique to this architecture. When an AI-driven safety event occurs, determining which model version was running on which vehicle at that moment is not straightforward when models are being updated fleet-wide on an ongoing basis. Operators must maintain version-controlled deployment records that are precise enough to reconstruct the exact system state at the time of any safety-related event, and governance processes must ensure independent validation before any update reaches production vehicles.



### Safe and secure

The over-the-air update pipeline, which pushes new AI models simultaneously to an entire deployed fleet, is both this architecture's greatest strength and its most acute vulnerability. A compromised or insufficiently validated update could affect thousands of vehicles at once. Securing the full update lifecycle, from model training through cryptographic signing and staged deployment, should be treated as a critical fleet-wide safety requirement, not an IT governance checkbox.



# Robotic stowing and picking system (1/2)

## Shelf based picking and stowing in warehouses

### DESCRIPTION

Robotic systems automate stowing and picking at warehouse shelf interfaces and delivery stations, using computer vision to identify items in cluttered slots, spatial modeling to track shelf occupancy, and force-sensitive manipulation to handle products in tight clearances.

### ISSUE/OPPORTUNITY

Shelf-based warehouse operations require workers to repeatedly reach into densely packed slots, bend to low shelves, lift items overhead, and manipulate products with varying fragility and weight in minimal clearance spaces. These repetitive motions create ergonomic risks—back injuries, shoulder strain, repetitive stress injuries—that drive workers' compensation costs and turnover.

Traditional rigid automation cannot handle obstructed items in cluttered slots, navigate tight clearances without damaging adjacent inventory, or grasp items of varying shapes without crushing or dropping them.

AI-enabled robotic systems can perform shelf-based picking and stowing for a substantial portion of SKUs (Stock Keeping Unit), reducing ergonomic risk while expanding automation scope.

### HOW PHYSICAL AI CAN HELP

#### Accurate perception in dense shelf slots

Vision models can identify items despite partial occlusion, varied shelf lighting, and tight spacing that creates ambiguity about item boundaries and grasp points.

#### Item-level automation decisions

AI evaluates each SKU's physical characteristics to determine which items can be reliably handled robotically versus which should route to human workers, optimizing labor division based on actual system capabilities.

#### Footprint-aware system design

AI supports layout optimization for limited space.

#### Fine manipulation with force feedback

Force sensors provide real-time feedback during grasping, adjusting grip pressure based on item rigidity and detecting contact with shelf edges to abort unsafe motions before damage occurs.

#### World modeling of shelf geometry

AI tracks which slots are occupied, how items are positioned, and available clearances, enabling motion planning that avoids collisions with shelves and neighboring inventory.

### POTENTIAL BENEFITS

#### Ergonomic risk reduction

Reduced repetitive reaching, bending, and lifting for human workers by offloading physically demanding shelf interactions, particularly for heavy items and awkward positions.

#### Expanded automation coverage

Current systems can handle approximately 75% of SKUs based on physical characteristics, compared to much lower coverage with traditional fixed automation.<sup>2</sup>

#### Operational consistency

Reduced performance variability across shifts, sites, and seasonal workforce fluctuations, with robotic systems maintaining consistent throughput.

#### Labor cost savings

Lower manual handling effort allows facilities to maintain throughput with fewer workers (or redeploy workers to tasks requiring human judgment).

#### Improved order accuracy

Standardized and consistent picking logic minimizes human error, ensuring the right items are picked each time and significantly reducing mis-picks, rework, and customer returns.



# Robotic stowing and picking system (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

Robotic arms operating near human workers pose immediate physical safety risks if force control or object detection fails. Safety boundaries must be validated across the full range of real operating conditions—not just controlled testing scenarios—with reliable fallback behaviors when the system encounters situations, objects, or worker proximity outside its defined operational envelope.



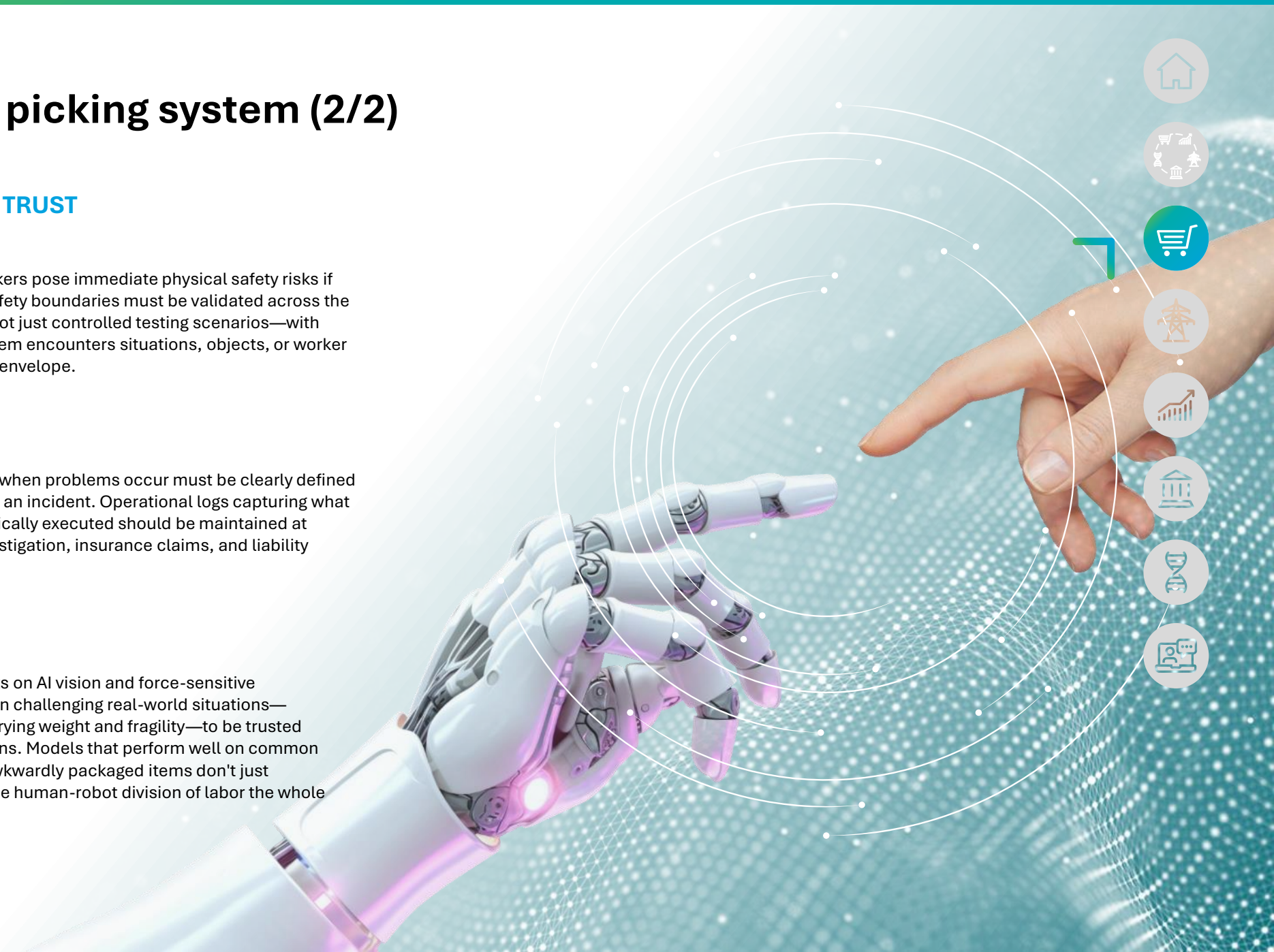
### Responsible and accountable

A framework for allocating responsibility when problems occur must be clearly defined before deployment—not negotiated after an incident. Operational logs capturing what the system perceived, inferred, and physically executed should be maintained at sufficient fidelity to support incident investigation, insurance claims, and liability determination.



### Robust and reliable

The commercial case for this system rests on AI vision and force-sensitive manipulation being dependable enough in challenging real-world situations—irregular packaging, partial occlusion, varying weight and fragility—to be trusted with a substantial share of shelf operations. Models that perform well on common products but degrade on unfamiliar or awkwardly packaged items don't just reduce efficiency; they actively disrupt the human-robot division of labor the whole system depends on.



# Vision-enabled robotic induction for high-variability consumer logistics (1/2)

## Handling SKU variability at industrial throughput

### DESCRIPTION

Vision-enabled robotic systems use advanced computer vision, perception, and machine-learning models to identify, orient, grasp, and transfer a wide variety of items across inbound logistics flows. These systems operate across conveyor-based induction as well as floor-loaded and palletized trailer unloading, handling high SKU diversity, reflective or damaged packaging, inconsistent presentation, and unstructured environments at industrial throughput.

### ISSUE/OPPORTUNITY

Conveyor induction in distribution centers involves extreme product variability—including SKUs with different geometries, weights, packaging materials, and labeling—making manual induction a physically demanding, error-prone bottleneck. Traditional rule-based automation often fails when handling reflective surfaces, damaged packaging, inconsistent item presentation, or unlabeled products because these systems depend on rigid templates and known item geometries.

The opportunity is to deploy Physical AI systems that can reason about physical objects in motion and adapt manipulation behavior in real time—without reconfiguration—while operating at industrial throughput.

### HOW PHYSICAL AI CAN HELP

#### Tolerance of variability

AI models can identify and classify items despite significant differences in geometry, surface reflectivity, label placement, and packaging condition, eliminating the need for pre-configured templates for each SKU.

#### Real-time classification and routing

Vision models process items continuously as they arrive, supporting immediate routing decisions in high-speed conveyor environments where delays create bottlenecks.

#### Edge-based execution

AI Inference runs on local computing hardware positioned near the robot to meet the low-latency requirements needed for continuous industrial throughput.

#### Closed-loop learning from physical outcomes

Execution results (drops, misfeeds, successful placements) feed back into model behavior, improving robustness across new SKUs and packaging variations.

#### Adaptive manipulation in the physical loop

AI adjusts robotic grasp points, placement force, and release timing dynamically based on observed item characteristics, reducing jams, misfeeds, and dropped items.

#### Non-safety-critical deployment context

Systems operate in zones isolated from human workers, reducing the safety certification and liability burden compared to collaborative robot applications.

### POTENTIAL BENEFITS

#### Higher throughput

Increased items inducted per hour by removing manual handling bottlenecks at inbound stations.

#### Labor productivity

Reduced reliance on repetitive manual induction tasks, allowing workers to focus on exception handling and quality verification.

#### Operational consistency

Stable performance across SKU changes, seasonal product variations, and peak demand periods without system recalibration.

#### Lower error rates

Reduced misrouting, mislabeling, and downstream exception handling through more consistent item identification and placement.

#### Reduced ergonomic strain and injury risk

Automation removes repetitive lifting and manual handling from high-risk inbound tasks.



# Vision-enabled robotic induction for high-variability consumer logistics (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

High throughput industrial environments leave little room for error. A vision model that misclassifies reflective packaging, damaged labels, or unfamiliar SKUs doesn't just slow the line; it creates misrouting, exceptions, and bottlenecks that ripple across the entire distribution center. Performance must be validated continuously across the full range of real-world items that the system will encounter in production, not just the SKUs present at the time of design and testing.



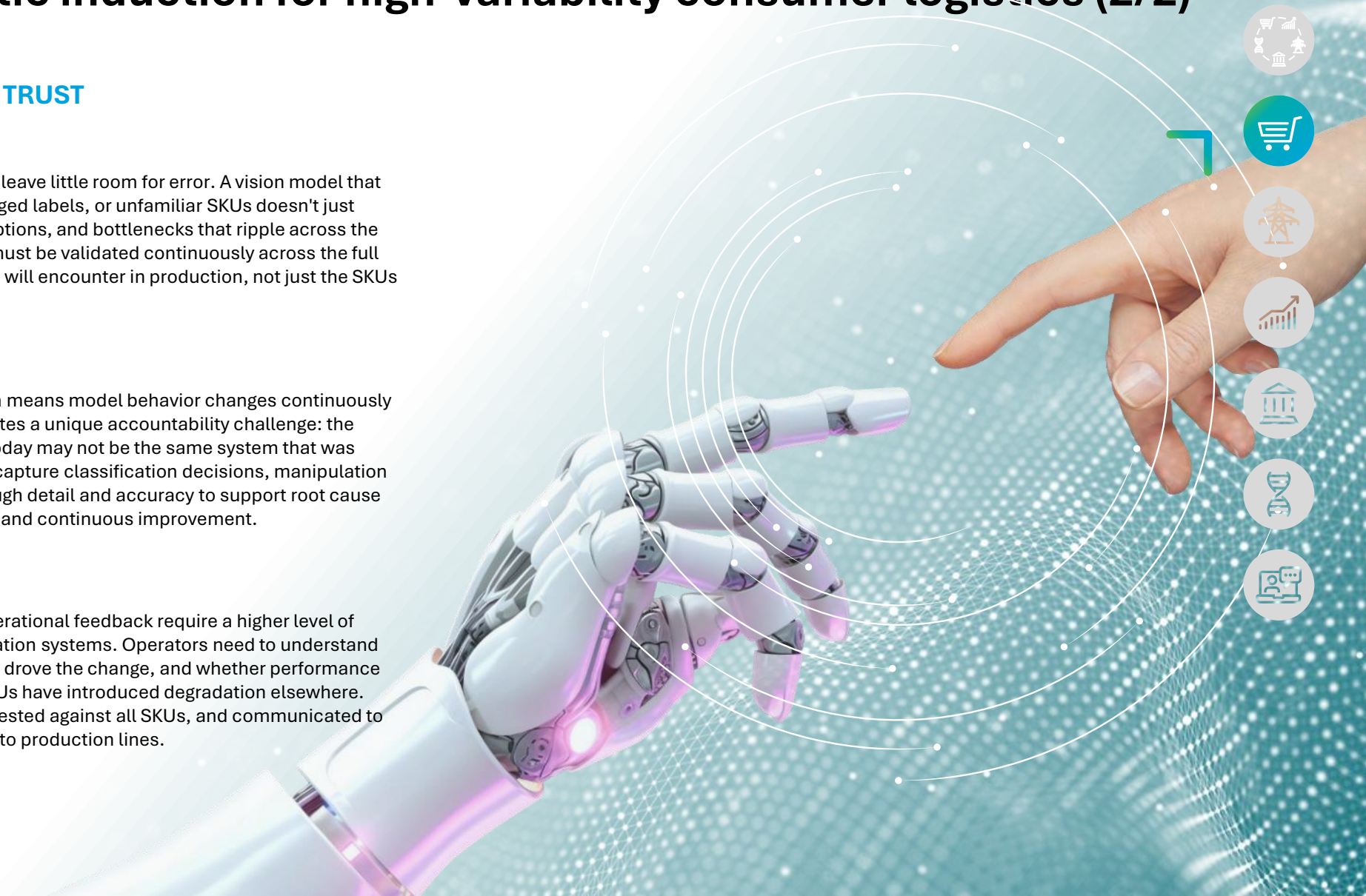
### Responsible and accountable

The system's closed-loop learning design means model behavior changes continuously based on real-world outcomes. This creates a unique accountability challenge: the system that caused a misrouting event today may not be the same system that was used last month. Operational logs must capture classification decisions, manipulation outcomes, and model versions with enough detail and accuracy to support root cause analysis, contractual dispute resolution, and continuous improvement.



### Transparent and explainable

Continuous model updates based on operational feedback require a higher level of governance discipline than static automation systems. Operators need to understand when model behavior has changed, what drove the change, and whether performance improvements on newly encountered SKUs have introduced degradation elsewhere. Model updates should be documented, tested against all SKUs, and communicated to operations teams before being deployed to production lines.



# Autonomous material movement in consumer fulfillment environments (1/2)

## Physical AI-driven logistics in dynamic, human-shared facilities

### DESCRIPTION

Autonomous mobile robots safely transport materials across warehouses and factory floors shared with human workers. Using AI-based perception and edge autonomy, robots detect people, equipment, and obstacles in real time, dynamically adjusting routes and speed. Fleet-level orchestration coordinates multiple robots to reduce congestion, improve throughput, and maintain safe, flexible operations without fixed infrastructure.

### ISSUE/OPPORTUNITY

Internal material transport in warehouses and manufacturing facilities relies heavily on manual labor using forklifts, pallet jacks, and hand carts. Traditional automated guided vehicles (AGVs) require fixed guide tracks, magnetic tape paths, or segregated operational zones that isolate them from human workers. As facility layouts and workflow patterns change frequently to accommodate seasonal demand, new product lines, or process improvements, fixed-path automation becomes a constraint that limits operational flexibility.

Mobile automation that can safely operate in dynamic environments alongside human workers without requiring permanent infrastructure modifications enables facilities to efficiently reconfigure layouts and processes while maintaining automated material flow.

As robotic fleets grow, local autonomy alone creates systemic bottlenecks: traffic jams at high-use corridors, task queuing at popular workstations, and cascading delays when disruptions occur. The opportunity is to deploy Physical AI systems that can safely reason and act in motion, enabling flexible material transport that adapts continuously to real-world conditions while operating alongside people.

### HOW PHYSICAL AI CAN HELP

#### Human-object discrimination

Perception models using computer vision and machine learning differentiate humans from static objects like pallets, storage racks, carts, and structural obstacles, enabling the robot to apply different behavioral rules depending on what it detects in its path.

#### Adaptive speed control

Robots automatically reduce speed or stop when humans are detected within defined proximity zones, with behavior adjusted based on approach angle, human movement patterns, and local safety requirements.

#### Human-aware safety envelopes

Robots enforce dynamic speed limits, stopping distances, and approach behaviors tuned to local safety standards, facility zones, and regulatory requirements.

#### Dynamic navigation

AI continuously recomputes optimal paths based on real-time observations of congestion patterns, temporary obstacles, floor conditions, and human activity, avoiding the need for pre-programmed routes that become obsolete when layouts change.

#### Edge-based decision execution

Edge-based autonomy helps enable immediate responses to sudden obstacles or human movements without requiring communication with centralized traffic control systems, reducing latency and maintaining safe operation even during network disruptions.

#### Fleet-level orchestration

AI-based fleet orchestration optimizes task allocation, path planning, and workload balancing in real time, enabling coordinated multi-robot operations while reducing bottlenecks and idle time.

### POTENTIAL BENEFITS

#### Reduced transport labor

Lower dependence on manual material movement for repetitive routes, helps enable workers to focus on tasks requiring judgment and dexterity.

#### Operational flexibility

Facility layouts, storage locations, and workflow patterns can be modified without reengineering robot paths or installing new guidance infrastructure.

#### Scalable deployment

Reduced infrastructure requirements enable faster rollout across multiple sites without extensive facility modifications or downtime.

#### Improved safety

Reduced collision risk in shared human-robot spaces through consistent detection and predictable, conservative robot behavior around people.

#### Higher asset utilization

Reduced robot idle time through better task sequencing and routing, allowing facilities to handle higher workloads with existing fleets rather than purchasing additional robots.



# Autonomous material movement in consumer fulfillment environments (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

The success of this system hinges on robots safely sharing space with workers. Human-object discrimination must perform reliably across all live operating conditions: poor lighting, crowded peak-period aisles, workers in non-standard positions, and edge cases not well-represented in training data. Failures here are not just performance shortfalls; they could lead to human injury or death.



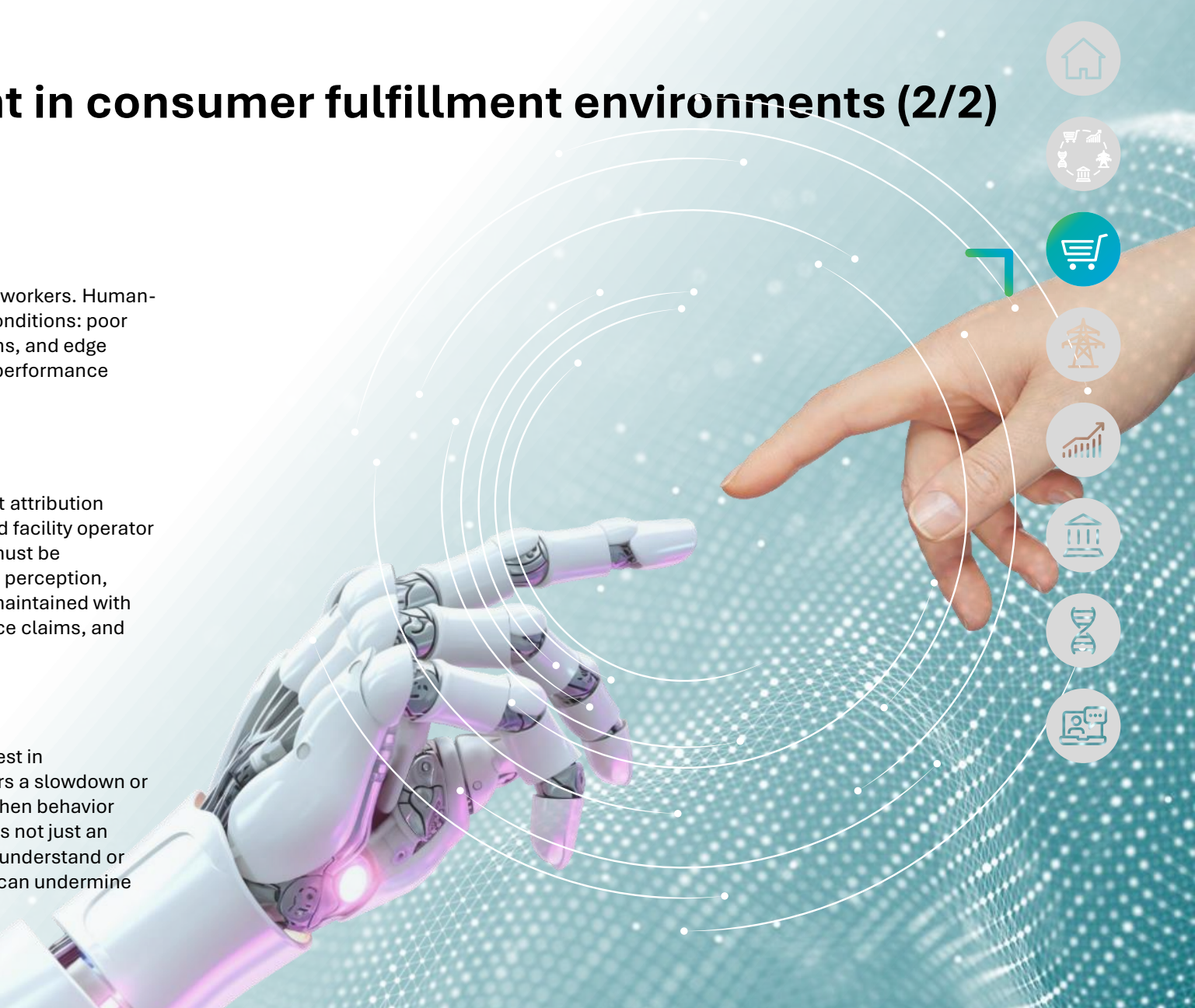
### Responsible and accountable

When an AMR is involved in a collision or near-miss with a worker, fault attribution between the AI developer, robot manufacturer, systems integrator, and facility operator can be a serious and complex challenge. Accountability frameworks must be established before deployment. Also, operational logs capturing robot perception, decision-making, and motion at the time of any safety event must be maintained with sufficient accuracy and detail to support regulatory reporting, insurance claims, and liability determination.



### Transparent and explainable

Workers sharing a facility with autonomous robots have a vested interest in understanding how those robots will behave around them: what triggers a slowdown or stop, how they should act when a robot approaches, and what to do when behavior seems unexpected. Clear communication about robot behavior rules is not just an ethical obligation; it's an operational requirement. Workers who don't understand or trust robot behavior create unsafe interactions and workarounds that can undermine the human-robot collaboration the system depends on.



# Programmable and general-purpose robots for consumer operations (1/2)

## Adaptive Physical AI systems operating across dynamic consumer environments

### Description

General-purpose Physical AI robots, including humanoid and mobile platforms, are designed to perform multiple tasks across dynamic consumer environments. Powered by unified vision-language-action models, these systems can adapt to inspection, material handling, basic maintenance, and support tasks through software updates, enabling flexible deployment, human-supervised autonomy, and reuse of the same hardware as operational needs evolve.

### ISSUE/OPPORTUNITY

Most industrial robots are designed for narrowly defined physical tasks, limiting flexibility when products, layouts, or processes change. A welding robot cannot easily be repurposed for material handling, and a picking robot cannot perform quality inspection without significant hardware modification or replacement.

This specialization creates substantial retooling costs and long deployment timelines whenever operational needs evolve, forcing organizations to maintain large fleets of single-purpose machines that sit idle when their specific task is not needed. Traditional automation fails in these environments because it depends on fixed layouts, rigid programming, and narrow task definitions. Reconfiguring automation when workflows change is slow and capital-intensive. The opportunity is Physical AI systems that can perceive, reason, and act in real time, enabling the same robotic platform to adapt to new tasks, environments, and workflows without physical retooling—while operating safely alongside human workers.

### HOW PHYSICAL AI CAN HELP

#### Real-time environmental perception

Robots continuously perceive shelves, products, people, tools, and obstacles using vision and sensor fusion, maintaining an up-to-date world model rather than relying on static maps.

#### Shared learning across tasks

Experience and training from one application transfers to others, as skills learned for inspection (e.g., object recognition) support maintenance tasks (e.g., part identification).

#### Safety-constrained behavior

AI limits actions to defined safety envelopes, ensuring robots operate within speed, force, and proximity constraints appropriate for shared human-robot workspaces.

#### Software-driven capability expansion

New tasks are added through software updates and model training without hardware changes, allowing the same robot platform to take on additional tasks over time.

#### Human-supervised autonomy

Robots operate under controlled conditions with human oversight, performing routine tasks autonomously while escalating complex or ambiguous situations to human operators.

#### Multi-task adaptability

Robots dynamically transition between picking, material transport, inspection, and support tasks, allowing a single platform to serve multiple operational roles.

### POTENTIAL BENEFITS

#### Improved flexibility

Single platforms support multiple tasks, enabling organizations to redeploy robots as operational priorities shift without purchasing specialized equipment for each new application.

#### Extended hardware lifespan

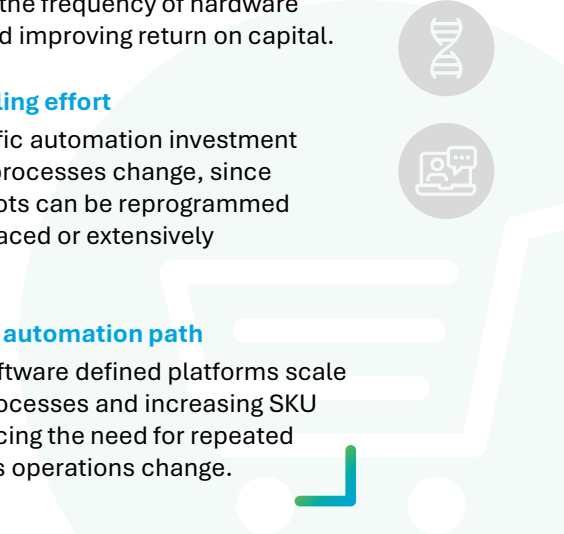
Software updates extend platform usefulness by adding capabilities and adapting to new tasks, reducing the frequency of hardware replacement and improving return on capital.

#### Reduced retooling effort

Less task-specific automation investment required when processes change, since generalized robots can be reprogrammed rather than replaced or extensively reengineered.

#### Future proofed automation path

Generalized, software defined platforms scale with evolving processes and increasing SKU variability, reducing the need for repeated reengineering as operations change.



# Programmable and general-purpose robots for consumer operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

General-purpose robots that acquire new capabilities through software updates without hardware changes create a safety certification challenge that single-purpose automation doesn't face. Specifically, safety validation completed at commissioning may be invalidated by a subsequent update. As such, each meaningful software-driven capability expansion should trigger a fresh risk assessment—not be treated as a routine update covered by existing certification.



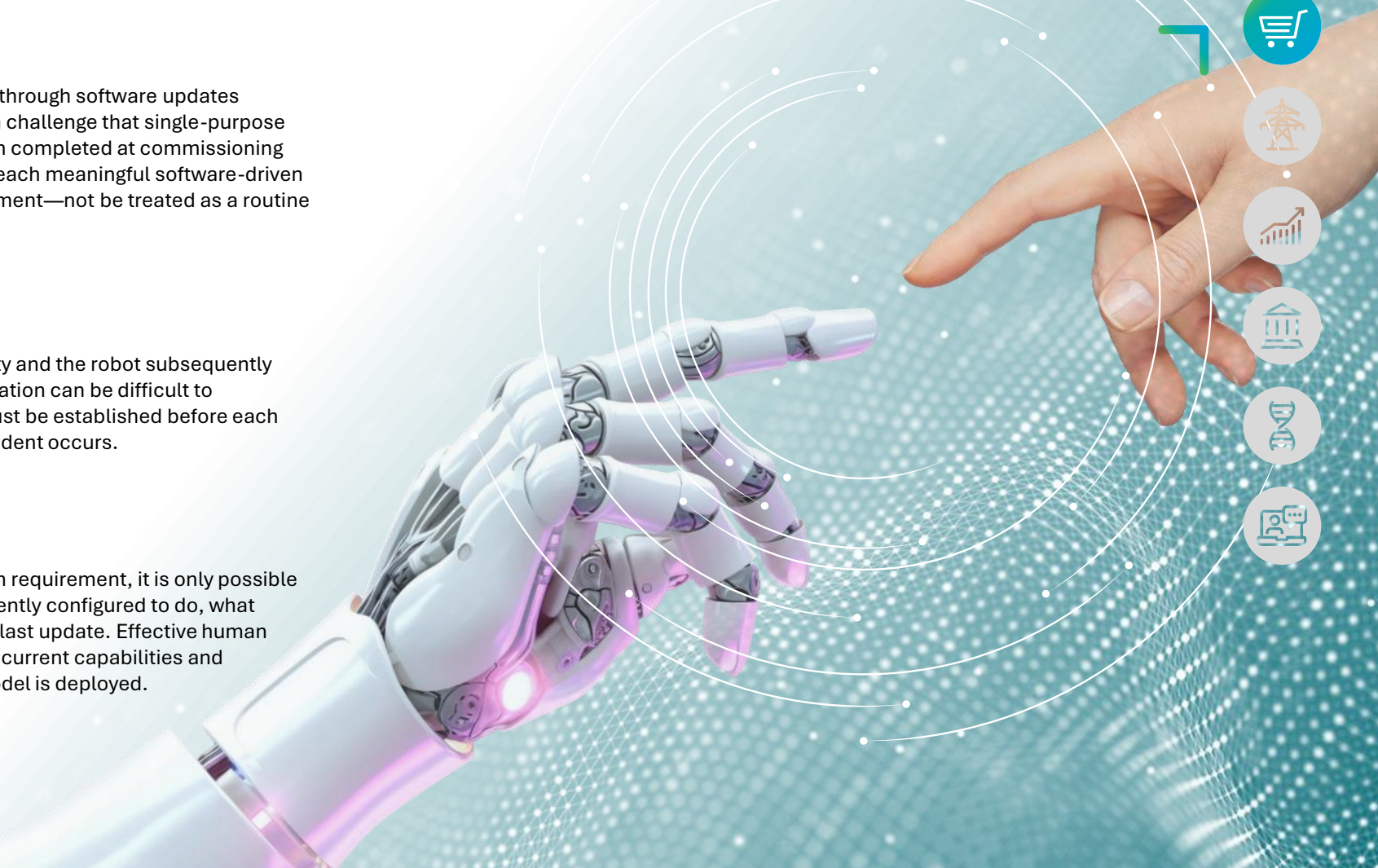
### Responsible and accountable

When a software update adds a new physical capability and the robot subsequently causes harm or damage during that task, liability allocation can be difficult to determine. Contractual accountability frameworks must be established before each new capability is deployed, not negotiated after an incident occurs.



### Transparent and explainable

Although human-supervised autonomy is a core design requirement, it is only possible if workers and supervisors know what the robot is currently configured to do, what constraints govern it, and what has changed since the last update. Effective human oversight requires clear, accessible documentation of current capabilities and limitations that is updated every time a new task or model is deployed.



# The Energy, Resources & Industrials Physical AI Dossier



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# Summary: The Energy, Resources & Industrials Physical AI Dossier

In sectors defined by asset intensity, geographic scale, and unforgiving safety standards, AI that can sense, act, and adapt in the physical world is a transformative capability



Few industries are better positioned to benefit from Physical AI than energy, resources, and industrials. Yet, few face a steeper path to realizing that benefit. These are sectors defined by massive, geographically distributed physical assets; environments that range from remote and harsh to acutely hazardous; workforces under sustained pressure; and operational consequences when things go wrong that are measured not just in financial terms but in human safety and environmental impact.

The fundamental challenge these industries share is one of scale and access. Assets are too numerous, too dispersed, and in some cases too dangerous for human inspection and oversight at the frequency optimal operations demand. Failures that could be prevented with early detection instead become costly or catastrophic events. Maintenance that could be planned becomes emergency intervention. Decisions that could be made with comprehensive data are instead made with incomplete information gathered intermittently.

Physical AI shifts this equation. Systems that can operate continuously in hazardous environments, cover geographic distances that defy human inspection, and synthesize sensor data from thousands of assets simultaneously offer a fundamentally different level of operational visibility and control. In an era when these industries also face mounting pressure to decarbonize, build resilience, and operate with leaner workforces, Physical AI is not a productivity enhancement. It's a strategic necessity.

The deployment challenges are proportional to the opportunity. Safety validation for AI systems operating near workers or in important infrastructure is demanding and non-negotiable. Integration with legacy operational technology is complex. And the regulatory environments governing industrial operations vary widely across geographies, affecting both what Physical AI can do and how quickly it can be deployed.



# Predictive monitoring for environment health & safety (1/2)

## Vision based safety enforcement at industrial scale

### DESCRIPTION

Physical AI systems embedded in vision-enabled drones, robots, and fixed infrastructure continuously perceive safety conditions across ER&I environments, reason about evolving risk in context, and perform predictive monitoring (e.g., early detection of equipment anomalies or evolving hazards), triggering governed physical interventions or escalations to prevent incidents before harm occurs.

### ISSUE/OPPORTUNITY

Environment Health & Safety (EHS) monitoring is often inconsistent and reactive when it relies on manual observation and reporting. Unsafe behaviors may go unnoticed until incidents occur, and enforcement can vary across shifts and sites. Supervisors cannot continuously observe work areas, and workers may cut corners when oversight is absent, creating gaps in safety compliance that accumulate until an accident reveals the problem.

Manual incident reporting depends on workers recognizing and documenting near-misses or violations, but reporting rates are low when workers fear repercussions or when the urgency of production deadlines overshadows safety protocols. Enforcement varies across shifts as different supervisors apply safety rules with different levels of rigor, and compliance tends to be highest when leadership is present and lowest during off-shifts when oversight is minimal.

Continuous, automated monitoring improves compliance while minimizing operational disruption, enabling consistent enforcement regardless of shift, location, or supervisor availability.

### HOW PHYSICAL AI CAN HELP

#### Continuous video analysis

AI reviews camera/drone feeds in near real time to detect safety-relevant behaviors and conditions across monitored areas simultaneously, providing coverage that manual observation cannot sustain.

#### Contextual filtering

AI can reduce noise by distinguishing true violations from benign activity in complex environments where authorized workers may temporarily enter restricted zones for legitimate maintenance or where PPE requirements vary by task.

#### Scalable multi-site deployment

A consistent detection framework can be rolled out across facilities, ensuring uniform safety standards and comparable metrics regardless of location, facility size, or local supervision practices.

#### Rule-based safety interpretation

Models apply predefined rules (zones, PPE requirements) combined with sensor-driven context from robotic/drones to consistently detect violations without variation across shifts or individual judgment differences.

#### Event-driven alerting

Detected risks trigger alerts and follow-up workflows for supervisors or EHS teams, enabling immediate intervention when unsafe conditions are identified rather than waiting for scheduled safety audits.

#### Non-intrusive integration

Systems leverage existing camera infrastructure and operate alongside current procedures, avoiding the cost and disruption of installing new sensor networks or redesigning facility layouts.

### POTENTIAL BENEFITS

#### Improved compliance

More consistent enforcement of safety rules and restricted zones as automated monitoring maintains the same vigilance regardless of shift, production pressure, or supervisor presence.

#### Lower monitoring burden

Less manual observation and reporting overhead allows EHS personnel and supervisors to focus on investigating root causes, implementing corrective actions, and improving safety training rather than routine surveillance.

#### Standardized practices

Comparable monitoring and metrics across sites for governance helps enable enterprise-wide safety benchmarking, identification of high-risk locations, and evidence-based allocation of safety resources.

#### Reduced incident risk

Earlier detection of unsafe behavior through real-time physical environment (including drone imagery) monitoring lowers intervention before violations escalate into injuries, equipment damage, or environmental releases.



# Predictive monitoring for environment health & safety (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

Continuous video monitoring of workers across an entire facility—capturing behaviors, locations, and movements throughout every shift—is one of the most expansive forms of workplace surveillance an employer can deploy. Organizations should apply data minimization principles, retain footage only as long as operationally necessary, anonymize where feasible, and be explicit with workers about what is monitored, how long data is retained, and who can access it and under what circumstances.



### Responsible and accountable

AI-assisted safety monitoring creates accountability exposure in both directions: the system can be implicated for acting on a false positive that disrupts operations or triggers an unwarranted disciplinary action, and for failing to detect a genuine hazard that preceded a workplace injury. Governance must clearly establish that AI outputs are merely inputs to human judgment and that accountability for safety outcomes remains with qualified EHS personnel.



### Fair and impartial

Biased detection in a safety enforcement context carries direct legal consequences, not just ethical ones. Models trained on historical violation data that over-represents certain demographic groups might disproportionately flag those workers for enforcement action, creating discrimination exposure under employment law.



# Autonomous haulage systems for safe and intelligent mining operations (1/2)

## Autonomous trucks optimizing safety, uptime, and haulage efficiency

### DESCRIPTION

Autonomous mining trucks and AMRs use LiDAR, radar, and AI-managed vision to handle hauling, inspections, and maintenance with safe sensor-based hand-offs. This same technology surveys electric grids and transformers, autonomously detecting infrastructure defects and safety hazards.

### ISSUE/OPPORTUNITY

Mining operations involve large, expensive vehicles operating in hazardous conditions. Human error and limited visibility increase accident risk and equipment damage. Manual operations also constrain productivity.

Haul truck operators work long shifts in dusty, noisy environments with limited sightlines, navigating massive vehicles weighing hundreds of tons along narrow roads carved into pit walls. Fatigue, distraction, or misjudgment can result in catastrophic accidents including collisions with other equipment, running off roadways, or striking workers on foot.

Driver recruitment and retention are challenging given the remote locations, harsh working conditions, and monotonous nature of repetitive hauling cycles. Equipment damage from operator error—such as overloading, improper dumping, or collisions—creates costly downtime and repair expenses that significantly impact mining economics.

The opportunity is to deploy Physical AI systems that enable autonomous operation while maintaining extremely high safety standards through redundancy and continuous monitoring, removing workers from hazardous roles while improving operational consistency.

### HOW PHYSICAL AI CAN HELP

#### Sensor fusion for perception

AI combines truck LiDAR, radar, and cameras with complementary drone RGB/thermal imaging and AMR/quad 3D mapping to build an accurate, multi-altitude site model.

#### Safety-zone enforcement

AI maintains dynamic safety buffers around vehicles that adjust based on speed, load weight, road conditions, and proximity to other equipment or personnel.

#### Continuous telemetry monitoring

Vehicle health and operation are tracked centrally, enabling fleet managers to monitor performance, predict maintenance needs, and intervene remotely if needed.

#### Redundant safety validation

Multiple sensors cross-check detections to mitigate false alarms, ensuring that critical safety determinations are confirmed by independent sensor systems before actions are taken.

#### Fail-safe autonomy design

Uncertainty triggers immediate stops, prioritizing safety over productivity when sensor disagreement, unexpected obstacles, or system anomalies are detected.

#### Controlled-environment deployment

Autonomy is restricted to defined mining zones with known characteristics, avoiding the complexity of public roads and unpredictable environments outside the controlled mining area.

### POTENTIAL BENEFITS

#### Less accident risk

Accident risk can be significantly reduced in hazardous environments as autonomous systems may reduce operator fatigue, distraction, and judgment errors while maintaining consistent adherence to safety protocols.

#### Reduced equipment losses

Expensive equipment losses are avoided through precise vehicle control that prevents damage from operator error such as collisions, overloading, or driving off roadways, extending the life of multi-million-dollar haul trucks.

#### Greater efficiency

Operational efficiency may improve through continuous, predictable vehicle operation that maintains consistent cycle times without breaks or shift changes, maximizing equipment utilization around the clock.

#### Improved worker safety

Uncertainty triggers immediate stops, prioritizing Workforce exposure to danger declines as human operators are removed from hazardous roles involving heavy equipment navigation in confined spaces and extreme conditions, allowing workers to be redeployed to safer supervisory and maintenance positions.

#### Higher overall productivity

Mining productivity increases without compromising safety as autonomous fleets can be scaled more easily than human workforces.



# Autonomous haulage systems for safe and intelligent mining operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

The safety case for autonomous haulage relies on the system outperforming human drivers; however, autonomous trucks can introduce their own failure modes in the conditions that define mining environments: wet roads that degrade traction sensing, dust that compromises vision, GPS-limited areas that undermine positioning, and sudden obstacle detection that causes emergency stops and lane breaches. Validation must account for these conditions explicitly, not treat them as edge cases.



### Safe and secure

GPS spoofing, signal jamming, and unauthorized command injection are potential attack vectors against autonomous haulage systems—and on an active mine site where massive vehicles operate at speed, a successful attack could redirect vehicles, suppress safety alerts, or lock entire fleets with potentially fatal consequences. Cybersecurity must be governed with the same rigor as physical safety, with layered defenses and regular adversarial testing as standard operational requirements.



### Responsible and accountable

Regulators may impose enforceable incident reporting and investigation obligations that create formal governance requirements for autonomous systems. Operational logs capturing vehicle perception, decision-making, and control states must be maintained with sufficient detail and accuracy to satisfy regulators and support liability determination.



# Autonomous inspection in safety-critical physical environments (1/2)

## Drone-first inspection with robotic intervention

### DESCRIPTION

Physical AI robots operate in hazardous environments such as oil wells, energy facilities, and industrial plants. Small hybrid fleet such as drones for aerial inspection and a robotic-hand equipped ground unit for simple actuation are used to keep people out of risk zones.

### ISSUE/OPPORTUNITY

Human inspection in hazardous environments exposes workers to significant risk and limits inspection frequency. Inspectors should enter confined spaces with toxic gases, high temperatures, or radiation exposure to check equipment conditions and identify developing problems. The need for extensive safety protocols, personal protective equipment, and standby rescue teams makes each inspection expensive and time-consuming.

Inspection frequency is constrained by the hazards involved—facilities may inspect important equipment quarterly or annually when continuous monitoring would be preferable. However, if failures are detected late—or occur between inspections—the consequences can be very unfortunate, including explosions, fires, toxic releases, or environmental contamination.

The opportunity is to deploy Physical AI robots that continuously inspect and intervene where safe, enabling constant vigilance in areas too dangerous for human presence.

### HOW PHYSICAL AI CAN HELP

#### Selective physical intervention

Robots perform simple corrective actions such as closing valves, tightening fittings, or applying temporary sealants to contain minor issues before they require major repairs.

#### Early fault identification

Issues are detected before escalation as continuous robotic patrols identify subtle changes in equipment condition that would be missed during infrequent manual inspections.

#### Remote human supervision

Operators oversee robot behavior from control rooms, reviewing sensor data, directing inspection priorities, and authorizing interventions without entering hazardous areas.

#### Autonomous navigation in hazards

Drones handle overhead access and unstable surfaces remotely while robotic-hand platforms are ruggedized to approach and work in short-range hazardous pockets where wheeled AMRs cannot.

#### Multisensor anomaly detection

AI interprets gas, temperature, and visual signals to identify developing problems such as gas concentration changes indicating leaks, thermal anomalies suggesting equipment stress, or visual evidence of corrosion and structural degradation.

### POTENTIAL BENEFITS

#### Safety improvement

Human exposure is reduced, keeping workers out of toxic, explosive, or structurally compromised environments while maintaining thorough inspection coverage.

#### Failure avoidance

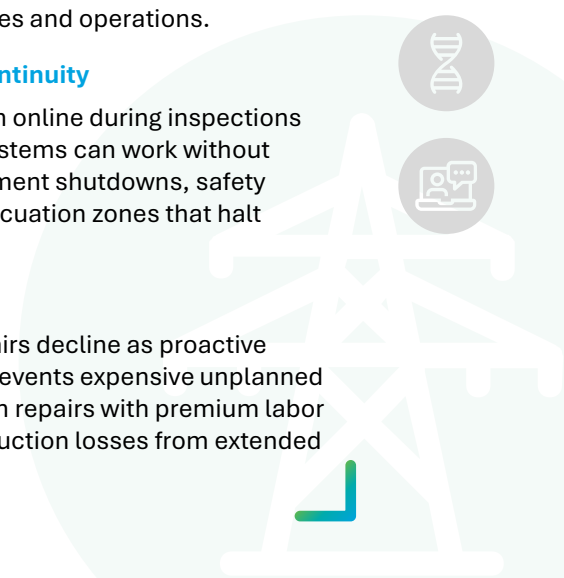
Early detection prevents incidents by identifying minor equipment degradation before it escalates into catastrophic failures that threaten lives and operations.

#### Operational continuity

Facilities remain online during inspections since robotic systems can work without requiring equipment shutdowns, safety lockouts, or evacuation zones that halt production.

#### Cost reduction

Emergency repairs decline as proactive identification prevents expensive unplanned shutdowns, rush repairs with premium labor costs, and production losses from extended outages.



# Autonomous inspection in safety-critical physical environments (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

These systems are deployed specifically because human inspection is too dangerous or infrequent, which means a missed gas leak, thermal anomaly, or structural defect does not just represent underperformance—it produces false assurance that can be more dangerous than no monitoring at all. AI detection models must be validated continuously against the specific degradation modes that define these environments (e.g., dust, heat, humidity, and gas interference), not just against controlled laboratory benchmarks.



### Safe and secure

Autonomous systems with physical intervention capabilities operating inside critical energy infrastructure are some of the most tempting targets for cyberattack in the Physical AI landscape. Intervention workflows must require human confirmation that cannot be bypassed by automated processes or externally injected commands under any circumstances.



### Transparent and explainable

Remote operators supervising autonomous inspection systems from control rooms must be able to understand why the AI has flagged a particular anomaly, how confident the detection is, and what intervention is being recommended. Alert and recommendation outputs should include the sensor evidence, detection logic, and confidence level that drove them, giving operators the information they need to make fully informed authorization decisions.



# Precision-critical high-value manufacturing (1/2)

## AI-guided perception and actuation in safety-critical assembly environments

### DESCRIPTION

Physical AI systems combine sensing, reasoning, and robotic actuation to execute precision-critical assembly tasks in environments where tolerance, safety, and reliability are non-negotiable. These systems continuously perceive alignment, force, and surface conditions; reason about acceptable operating envelopes; and execute physical actions under human supervision—enabling consistent outcomes at a scale and precision difficult to achieve manually.

### ISSUE/OPPORTUNITY

Heavy industrial manufacturing of complex assets such as aircraft, ships, and spacecraft involves precision-critical assembly operations that must meet extremely tight tolerances and rigorous safety standards. Workers perform repetitive tasks like drilling holes, installing fasteners, applying sealants, and conducting dimensional inspections across massive structures where even minor deviations can compromise structural integrity or safety certification. Manual execution introduces variability as worker fatigue, attention levels, and individual technique affect quality consistency. For example, an aircraft fuselage may require tens of thousands of fasteners installed at precise torque specifications, while spacecraft components demand micron-level precision that challenges human capability.

Quality defects discovered late in production trigger expensive rework that can delay delivery schedules, while undetected errors create catastrophic safety risks. The opportunity is to deploy robotic systems for repetitive precision tasks while maintaining human oversight for critical decision points, combining automation consistency with experienced technician judgment.

### HOW PHYSICAL AI CAN HELP

#### Precision perception

AI detects fine tolerances through advanced sensing that measures dimensions, alignment, and surface conditions at levels exceeding human visual capability, ensuring that components meet exacting specifications.

#### Human-supervised operation

Critical steps are overseen by experienced technicians who monitor robot performance, verify quality checkpoints, and intervene when situations require judgment or fall outside normal parameters.

#### Repeatable execution

Robots perform consistent actions with identical technique, torque application, and positioning across thousands of repetitions, eliminating the variability introduced by human fatigue or attention lapses.

#### Integration with tooling

Robots align with existing processes and production workflows, working alongside human teams without requiring complete facility redesigns or replacement of proven manufacturing methods.

### POTENTIAL BENEFITS

#### Throughput gains

Predictable throughput under safety and quality constraints. Production accelerates as robots work continuously without breaks, maintain consistent cycle times, and minimize delays.

#### Quality consistency

Errors decline through repeatable execution that eliminates common defect sources—such as improper torque, misalignment, or inconsistent material application—that occur with manual operations.

#### Labor efficiency

Manual repetition is reduced, allowing human knowledge focused on judgment-intensive tasks, quality verification, and problem-solving that requires human knowledge rather than physically demanding repetitive operations.

#### Cost control

Rework is minimized as consistent robot execution reduces defects that would otherwise require expensive repairs, schedule delays, and in severe cases, scrapping of high-value components or assemblies.



# Precision-critical high-value manufacturing (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

The entire value proposition of this system—that AI-guided robotic execution is more consistent and precise than human performance—must be demonstrable to regulators and certification bodies before it can be deployed in industries such as aerospace and defense. Validation must cover the full range of production conditions, not just the configurations present during initial commissioning.



### Responsible and accountable

Full traceability is a regulatory requirement in aerospace and defense manufacturing. Every AI-guided measurement, execution step, and human verification sign-off must be logged with enough detail and accuracy to reconstruct exactly what happened and who was responsible.



### Transparent and explainable

Although human-supervised operation is a core design requirement, such oversight only works if technicians can find out what the AI measured, what tolerance deviation was detected, and why a specific action was recommended. Technicians who cannot meaningfully challenge or verify AI outputs cannot provide genuine oversight.





# Autonomous agriculture and precision farming (1/2)

## AI-driven agricultural field operations

### DESCRIPTION

Physical AI systems orchestrate drones and autonomous ground robots to continuously sense field conditions, reason over crop and environmental signals, and execute targeted physical interventions under human supervision.

### ISSUE/OPPORTUNITY

Agricultural operations face mounting challenges from labor shortages, rising input costs, and the need to increase productivity on limited arable land. Farmers struggle to find seasonal workers for labor-intensive tasks like weeding, thinning, and harvesting, while blanket application of seeds, fertilizers, pesticides, and water across entire fields wastes resources.

Manual field monitoring is time-consuming and imprecise, as farmers walk fields to visually assess crop health, often missing early signs of problems until they've spread. Traditional precision agriculture relies on periodic data collection and manual decision-making, which limits responsiveness to rapidly changing field conditions. The opportunity is to deploy Physical AI systems that continuously interpret environmental signals and coordinate physical actions in real time—scaling expert judgment across vast agricultural operations without requiring constant human presence.

### HOW PHYSICAL AI CAN HELP

#### Environmental sensing

Drones run scheduled multispectral/thermal passes to map crop stress and pest hotspots while AMRs carry close-range sensors to validate and collect plant-level sample.

#### Selective intervention

Actions target specific areas or individual plants based on actual need rather than blanket treatment, applying herbicides where weeds are detected or adjusting seeding density based on soil quality.

#### Simulation-and model-driven intervention policies

Intervention strategies are validated against historical field data and seasonal simulations before deployment, reducing risk and improving predictability in large-scale agricultural operations.

#### Closed-loop physical task execution

AMRs and drones navigate fields independently, performing seeding, weeding, spraying, or harvesting - while continuously validating outcomes against expected results.

#### Governed human-in-the-loop control

Operators approve intervention policies, review exceptions, and retain authority over high-impact decisions, ensuring safety, compliance, and environmental accountability.

### POTENTIAL BENEFITS

#### Yield optimization

Crop outcomes improve through precise intervention that addresses plant needs at the right time and location, reducing stress from over or under-treatment and maximizing productive plant growth.

#### Labor reduction

Manual work declines as autonomous systems handle repetitive field tasks, reducing dependence on seasonal labor that is increasingly difficult to recruit and retain.

#### Input efficiency

Resources are used more precisely as targeted application reduces waste from blanket treatment, lowering costs for seeds, fertilizers, pesticides, and water while minimizing environmental runoff.

#### Scalability

Large areas are managed efficiently as autonomous systems can cover extensive acreage with consistent quality, enabling farmers to increase operational scale without proportional increases in labor overhead.



# Autonomous agriculture and precision farming (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

AI models trained on data from specific geographies, crop varieties, or seasons might struggle to handle different situations. Before autonomous systems can be trusted to operate at scale, they must be validated against the full range of climates, soil types, and crop conditions present in the targeted deployment environment.



### Private

Farm data generated by continuous drone and sensor monitoring is commercially sensitive information that could reveal the economic position of individual farm operators. In an industry where large agricultural technology vendors actively seek to aggregate and monetize field data, governance policies must clearly define what is collected, who owns it, and whether vendors can use farm data to train shared models without explicit consent.



### Fair and impartial

AI systems developed and validated primarily on large commercial operations may systematically underserve smaller, more diverse, or mixed-crop farms—potentially recommending strategies optimized for commodity monocultures that are poorly suited to other contexts.





# Workforce scheduling and dispatch (1/2)

## Predictive coordination of physical repair crews

### DESCRIPTION

Physical AI models forecast likely network faults using historical failures, environmental signals, and asset data, continuously updating field-force scheduling to dispatch the right engineer by skill, proximity, and urgency. Next-gen inspection wearables with lightweight industrial glasses gives technicians hands-free, real-time guidance, equipment data, and AI diagnostics via heads-up overlays, replacing tablets and manuals and enabling fully hands-free maintenance.

### ISSUE/OPPORTUNITY

Field service operations can be costly and hard to optimize because failures are unpredictable, assets are geographically dispersed, and skill needs vary, so static schedules and manual dispatch drive inefficiencies, longer repairs, and avoidable travel. This is especially acute in energy, industrial, and resource operations spread across vast areas, where dispatchers juggle specialized crews, competing emergencies, and long distances that can consume much of a technician's day, making rapid response critical to mitigate safety incidents and production losses.

In the field, technicians still depend on tablets, phones, or paper manuals for procedures and diagnostics, forcing constant context-switching that slows work and increases safety risk; earlier AR (Augmented Reality) alternatives were too bulky and unreliable for industrial use.

The opportunity is to use Physical AI to anticipate where physical interventions will be needed and dynamically coordinate field resources to respond faster and at lower cost.

### HOW PHYSICAL AI CAN HELP

#### Fault likelihood prediction

AI models forecast where physical equipment issues are most likely to occur based on asset age, operating conditions, maintenance history, and environmental stressors such as weather or load patterns.

#### Skill-based assignment

Engineers are matched to jobs based on capability, ensuring specialized equipment such as high-voltage transformers or pressure vessels receives attention from appropriately certified technicians.

#### Manager oversight

Supervisors retain control over final decisions, reviewing AI recommendations and adjusting assignments based on factors the system cannot assess such as customer relationships or operational priorities.

#### Remote expert collaboration

Technicians can share their AR field of view with remote experts who can provide guidance, annotate the technician's view, and collaborate on complex repairs without traveling to site.

#### Schedule optimization

Predictions feed directly into workforce scheduling systems, enabling proactive assignment of technicians to areas where failures are anticipated rather than waiting for emergency calls.

#### Continuous schedule updates

Assignments are refreshed frequently as conditions change, rerouting technicians when higher-priority emergencies arise or when predicted failures materialize sooner than expected.

#### Real-time visual guidance overlay

AR glasses display step-by-step repair instructions, measurements, and equipment specifications directly overlaid on the physical equipment technicians are working on, eliminating the need to reference separate screens.

### POTENTIAL BENEFITS

#### Productivity gains

Engineer utilization may improve as optimized routing reduces idle travel time and helps to ensure technicians are dispatched to locations where their specific skills are needed most.

#### Faster physical repairs

Response times may decrease through predictive positioning of crews near anticipated failure locations and intelligent routing that accounts for real-time traffic and site access constraints.

#### Cost reduction

Travel inefficiencies may decline as AI minimizes unnecessary mileage, consolidates nearby service calls into single trips, and reduces emergency overtime by enabling proactive maintenance.

#### Service reliability

Issues may be resolved sooner through better resource allocation, preventing minor problems from escalating into major outages that affect production, safety, or customer service.

#### Increased technician productivity

Hands-free access to information and guidance helps enable technicians to work faster and more efficiently, eliminating time spent searching manuals, measuring equipment, or switching between tools and tablets.



# Workforce scheduling and dispatch (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

AI predictions that consistently misdirect field crews—deploying technicians to the wrong locations or failing to anticipate failures that subsequently cause outages—undermine the operational case for the system and erode dispatcher trust. Model accuracy must be validated continuously against actual failure outcomes across the entire asset portfolio, accounting for seasonal variation and aging infrastructure that changes risk profiles over time.



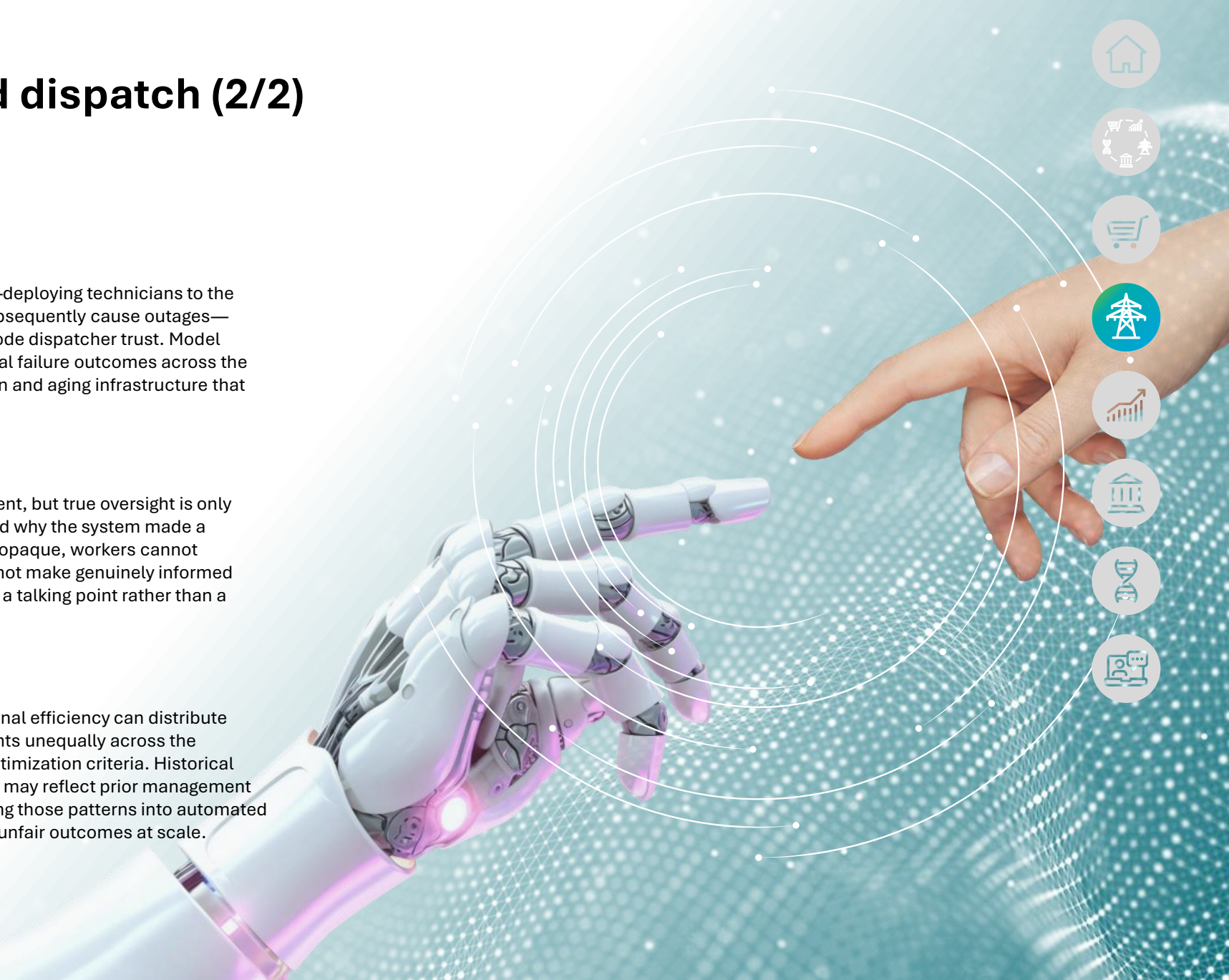
### Transparent and explainable

Human supervisor oversight is a core design requirement, but true oversight is only possible if dispatchers and technicians can understand why the system made a particular recommendation. When scheduling logic is opaque, workers cannot meaningfully challenge assignments, supervisors cannot make genuinely informed adjustments, and human-in-the-loop design becomes a talking point rather than a genuine safeguard.



### Fair and impartial

Scheduling algorithms optimized primarily for operational efficiency can distribute workloads, travel burdens, and undesirable assignments unequally across the workforce if equitable treatment is not built into the optimization criteria. Historical dispatch patterns used to train or calibrate the system may reflect prior management decisions that were themselves inequitable, embedding those patterns into automated recommendations that appear objective but replicate unfair outcomes at scale.



# Inspection of network and utility infrastructure (1/2)

## Vision-based inspection of physical assets

### DESCRIPTION

Vision-driven Physical AI systems use satellite imagery, LiDAR, drones, and environmental data. These systems monitor poles, towers, substations, cables, and surrounding environments to detect physical degradation, vegetation encroachment, and environmental risks earlier and more consistently than manual inspections.

### ISSUE/OPPORTUNITY

Manual inspection of distributed infrastructure is slow, costly, and infrequent, especially in remote areas. Failures often originate from gradual physical degradation. Utility companies maintain thousands of miles of transmission lines, distribution poles, and towers spread across diverse terrain including forests, mountains, and farmland where access requires specialized vehicles and significant travel time. Inspectors visually examine poles for rot, cracks, or corrosion, check cables for fraying, assess vegetation encroachment, and identify structural issues with towers.

Manual inspection cycles may occur every few years due to cost, allowing problems to develop undetected between visits.

Critical infrastructure in hard-to-reach locations receives even less frequent attention, increasing the risk of unexpected failures. Weather events, wildlife damage, and natural aging cause continuous degradation that accumulates between inspection cycles.

### HOW PHYSICAL AI CAN HELP

#### Vision-based inspection at scale

Drones and mobile inspection platforms capture high-resolution visual, thermal, and LiDAR data across vast and hard-to-reach infrastructure, enabling frequent inspection without physical site access.

#### Large-area coverage

Assets across wide geographies are inspected systematically through aerial surveys that can cover hundreds of miles of infrastructure in days rather than months required for ground-based inspection.

#### Human validation

Inspectors review results before authorizing repairs, verifying AI findings and applying knowledge to distinguish urgent problems from conditions that can be monitored.

#### AI-driven defect and risk detection

Computer vision models identify early signs of asset degradation—such as corrosion, structural fatigue, conductor wear, or vegetation proximity—before issues escalate into outages or safety incidents.

#### Risk-based prioritization of interventions

AI ranks detected issues based on severity, asset criticality, environmental conditions, and potential customer impact, enabling field teams to focus resources on the highest-risk assets first.

### POTENTIAL BENEFITS

#### Lower inspection cost

Fewer manual visits required as aerial inspection covers large areas quickly, reducing vehicle expenses, labor hours, and specialized equipment needed for accessing remote terrain.

#### Earlier risk detection

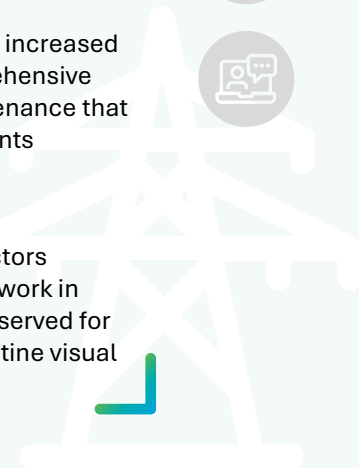
Earlier detection of vegetation encroachment, conductor wear, and structural fatigue—reducing outage risk, wildfire exposure, and unplanned shutdown.

#### Improved asset reliability

Infrastructure health improves as increased inspection frequency and comprehensive coverage enable proactive maintenance that extends equipment life and prevents cascading failures.

#### Safety gains

Reduced field exposure as inspectors mitigate hazardous climbing and work in difficult terrain, with field visits reserved for actual repair work rather than routine visual checks.



# Inspection of network and utility infrastructure (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

The system's value relies on AI inspection being more consistent and comprehensive than infrequent manual visits—which means a model that underperforms doesn't just reduce efficiency; it produces false assurance in the locations where the inspection gap is most dangerous. Validation must explicitly cover the full range of environmental and asset conditions across the deployment territory, not just those well-represented in training data.



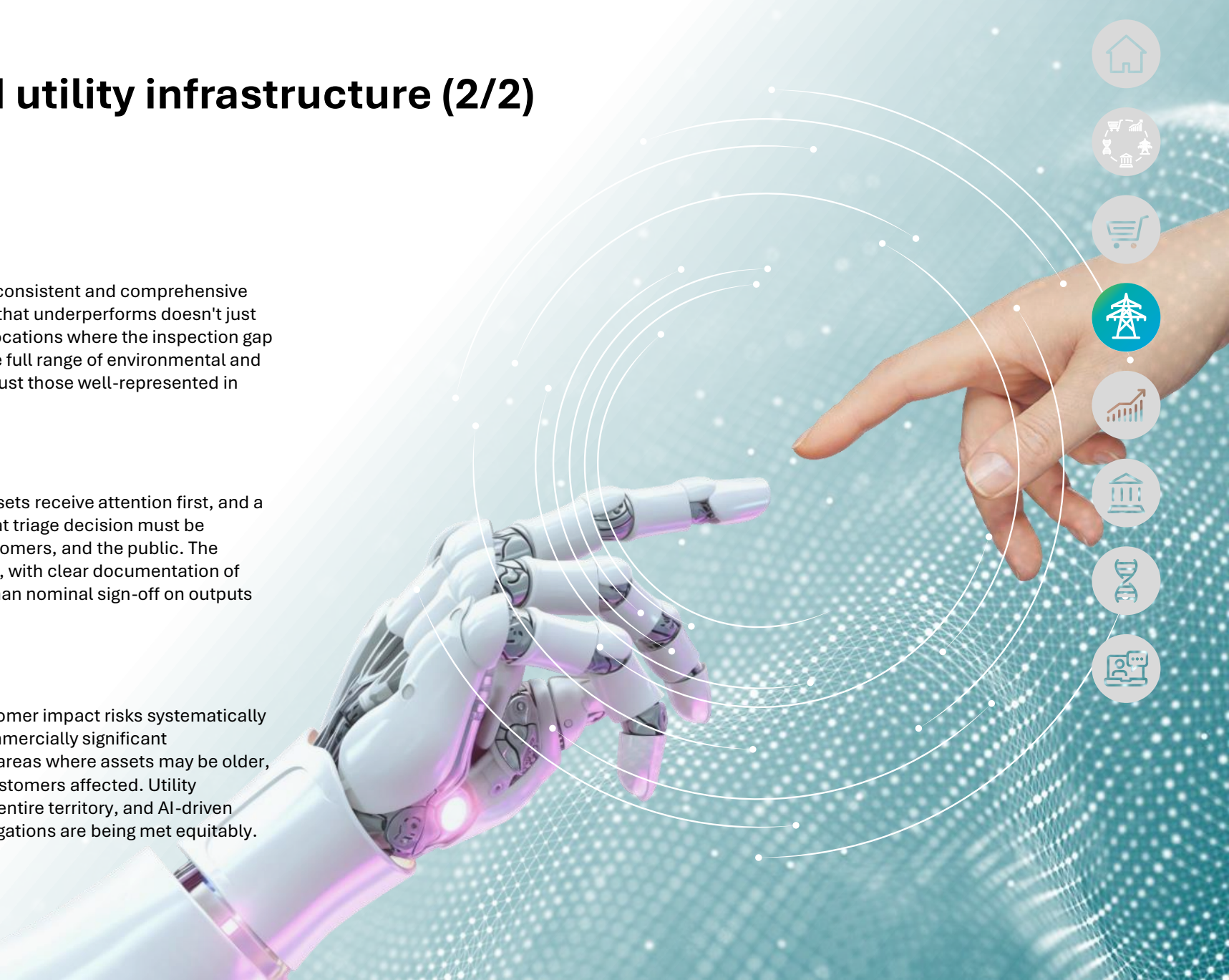
### Responsible and accountable

When AI-driven risk prioritization determines which assets receive attention first, and a deprioritized asset subsequently fails, the basis for that triage decision must be auditable and defensible—to regulators, affected customers, and the public. The human validation step must constitute genuine review, with clear documentation of what inspectors assessed and on what basis, rather than nominal sign-off on outputs they cannot meaningfully interrogate.



### Fair and impartial

AI prioritization optimized for asset criticality and customer impact risks systematically directing maintenance resources toward urban or commercially significant infrastructure at the expense of rural or lower-density areas where assets may be older, more vulnerable, and failures more isolating for the customers affected. Utility operators have public service obligations across their entire territory, and AI-driven triage should be regularly audited to ensure those obligations are being met equitably.



# Defect detection for industrial machinery (1/2)

## Vision-supported inspection with human validation

### DESCRIPTION

AI enabled vision systems support the end-to-end repair lifecycle of large industrial components (e.g., turbine parts and blades) by automating intake identification, augmenting defect detection during inspection, and enabling robotic inspection and selective repair, while keeping human experts in the decision loop for safety critical judgments. The solution combines computer vision, operational context, and robotics to improve consistency, coverage, safety, and cycle time across repair and maintenance operations.

### ISSUE/OPPORTUNITY

Manual inspection of complex industrial components is time-consuming, requires specialized knowledge, and is subject to variability across inspectors, shifts, and facilities. Defects may be missed during initial inspection or identified late in the repair cycle, increasing rework costs and extending equipment downtime. Yet, fully automated inspection systems are not reliable enough for safety-critical applications due to false positives from lighting variations, surface contamination, and reflection artifacts, as well as false negatives that miss subtle defects in challenging viewing conditions.

Augmenting human inspectors with AI-based vision systems can improve coverage and consistency while retaining human decision authority for final accept/reject determinations—combining the pattern recognition capabilities of computer vision with the judgment and accountability that expert inspectors provide.

### HOW PHYSICAL AI CAN HELP

#### Defect pattern recognition

Vision models analyze component imagery to highlight cracks, wear patterns, erosion, and anomalous surface conditions that warrant closer inspector review, improving detection of subtle defects that might otherwise be missed.

#### Human-in-the-loop confirmation

AI outputs are treated as recommendations requiring expert validation, preserving inspector judgment and accountability for final component disposition.

#### Inspection prioritization

AI directs inspector attention to high-risk regions based on component type, operational history, and observed patterns, improving the efficiency of limited inspection resources by focusing expert review where it matters most.

#### Defect pattern recognition across inspection stages

Computer vision models analyze imagery from manual, robotic, or in situ inspections to highlight cracks, erosion, wear, delamination, and anomalous surface conditions—directing inspector attention to high-risk regions that warrant expert review.

#### Correlation with operational history

AI connects observed defects to field operating conditions, sensor data, and maintenance history to provide contextual clues for root cause analysis, helping inspectors understand whether damage patterns align with expected wear or indicate abnormal operating conditions.

#### Robustness to inspection artifacts

Models trained on diverse imagery learn to reduce sensitivity to lighting variations, glare, surface contamination, and reflection artifacts that create false positives, improving the signal-to-noise ratio for human reviewers.

#### Bounded decision support

AI is constrained to assistance and highlighting roles rather than automated accept/reject authority, maintaining human responsibility for safety-critical determinations.

### POTENTIAL BENEFITS

#### Earlier defect identification

Potential issues are surfaced sooner in the repair cycle, to help enable proactive repair planning and reducing the risk that defects progress undetected through multiple inspection stages.

#### Engineering efficiency

Reduced time spent on low-risk scanning and documentation helps enable inspectors to focus their knowledge on important assessments, root cause analysis, and judgment-intensive decisions.

#### Quality consistency

Lower variance in detection rates across inspectors, shifts, and facilities improves repeatability of inspection outcomes and supports more predictable repair planning and component lifecycle management.

#### Higher inspection coverage

AI-assisted systems can reduce the variability introduced by inspector workload, fatigue, and experience differences, leading to more consistent and thorough reviews across components, sites, and time periods.

#### Reduced cycle time and downtime

Automated intake and prioritized inspection accelerate engineering triage and repair planning, shortening asset turnaround and turbine shutdown durations.

#### Extended asset life and lower cost

Earlier detection and targeted repairs can prevent damage progression, reducing premature component replacement and overall maintenance cost.



# Defect detection for industrial machinery (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

False positives waste inspector time and erode trust; false negatives allow genuine defects to pass undetected through safety-critical components. Both have serious consequences in critical contexts such as turbine and industrial component repair. Robustness must be validated across the full range of lighting conditions, surface states, and component types that the system will encounter, not just favorable training conditions.



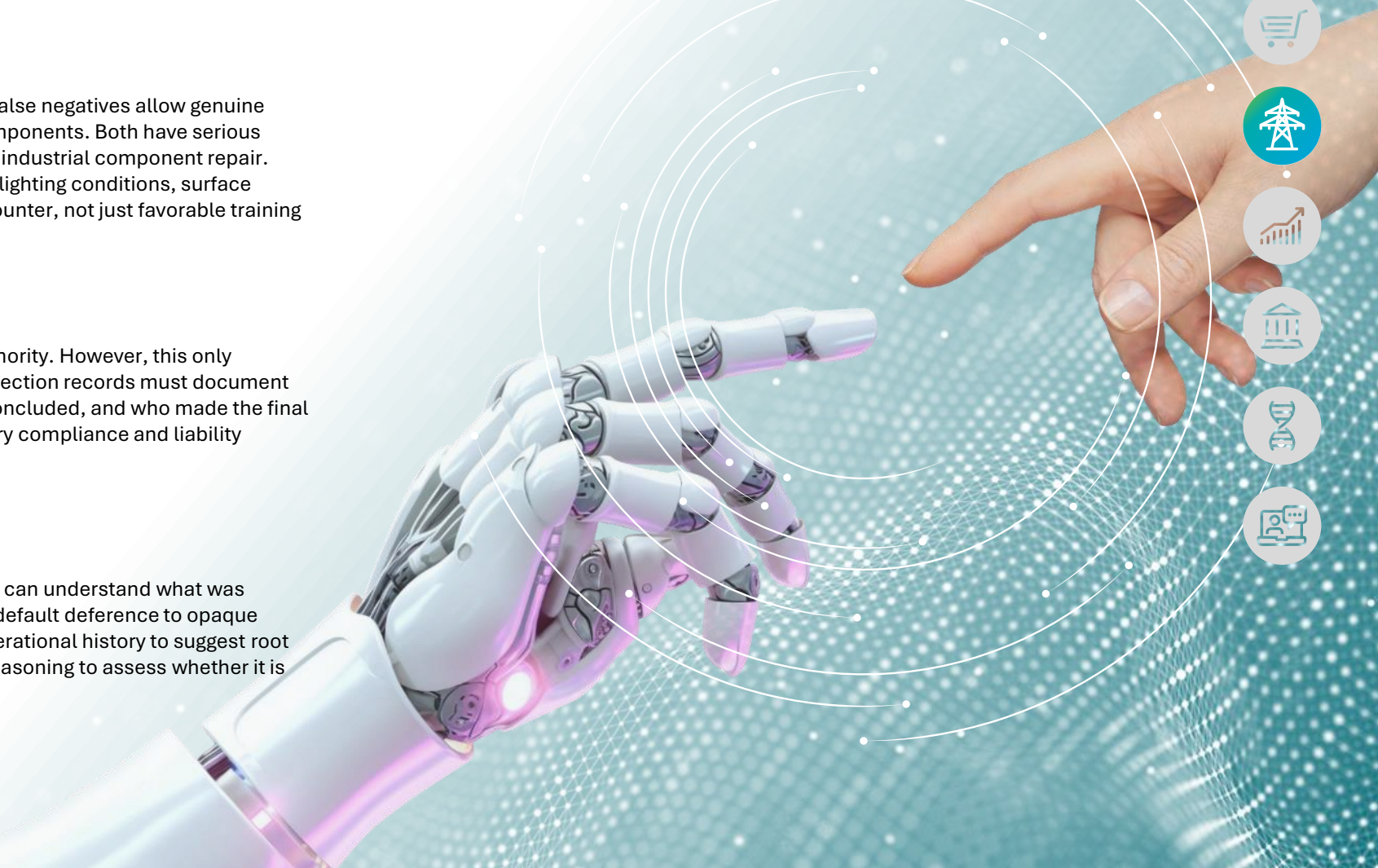
### Responsible and accountable

In this use case, humans retain final accept/reject authority. However, this only provides genuine protection if applied in practice. Inspection records must document which defects were AI-flagged, what human experts concluded, and who made the final decision—creating an audit trail sufficient for regulatory compliance and liability determination.



### Transparent and explainable

The human-in-the-loop design only works if inspectors can understand what was flagged and why—enabling true judgment rather than default deference to opaque outputs. When AI correlates observed defects with operational history to suggest root causes, inspectors need sufficient visibility into that reasoning to assess whether it is contextually sound before acting on it.



# Chemical manufacturing workflow automation (1/2)

## Autonomous handoff control for chemical lines

### DESCRIPTION

Embedded AI (including physical-AI systems on robots and equipment) manage process handoffs across the manufacturing lifecycle, autonomously coordinating materials, sequencing tasks, allocating resources, and resolving routine exceptions to minimize bottlenecks and accelerate throughput. AMRs handle materials and inter-stage movement while robotic hands perform valve turns, sampling, and minor adjustments at equipment handoffs without human entry.

### ISSUE/OPPORTUNITY

Chemical manufacturing involves hundreds of process handoffs where information, materials, or decisions transfer between steps or personnel. When one production stage completes, operators should notify the next team, confirm material availability, verify equipment readiness, and coordinate timing—creating coordination bottlenecks that slow overall throughput. Each handoff creates opportunities for delays, errors, and inefficiencies as workers wait for approvals, materials sit idle between stages, or miscommunication causes incorrect sequencing.

Manual coordination of these workflows consumes significant labor hours and limits production speed as supervisors spend time orchestrating activities rather than addressing exceptions or improving processes. Traditional automation addresses repetitive individual tasks such as valve control or temperature regulation, not the complex decision-making and coordination required across end-to-end processes that involve judgment about priorities, resource allocation, and exception handling.

Fragmented, machine-specific automation solutions further increase complexity. Different OEM equipment often uses isolated control logic, making integration across lines and sites difficult, slowing replication of improvements, and increasing engineering effort to scale operations. Deploying a physical-AI-first workflow automation and AI platform—embedded on robots, AMRs, quadrupeds, autonomous vehicles, and process equipment—creates an opportunity to unlock latent capacity, materially increase productivity, and scale output without proportional labor growth.

### HOW PHYSICAL AI CAN HELP

#### Physical task sequencing

Physical AI coordinates AMR movement to help ensure materials, samples, and intermediate products move seamlessly without manual scheduling or waiting periods.

#### Human-agent hybrid processes

Safety-critical actions and non-standard conditions require human approval. Physical AI can operate within defined safety envelopes, preserving accountability and regulatory compliance.

#### Real-time process-aware sequencing

AI models re-sequence physical tasks based on throughput, safety constraints, and equipment status—reducing idle time between process steps and preventing downstream bottlenecks.<sup>3</sup>

#### Unified physical control across heterogeneous equipment

Physical AI coordinates across OEM machines, robots, and material-handling systems, to help enable system-level optimization rather than isolated, machine-by-machine automation.

#### Unified AI control layer across equipment

A standardized AI control architecture spans multiple machine types and OEMs, replacing isolated point solutions and enabling system-level optimization rather than machine-by-machine tuning.

#### Scalable, repeatable operations

Standardized Physical AI control logic helps enable consistent execution across lines and sites, supporting scale-up without re-engineering workflows or adding coordination layers.

### POTENTIAL BENEFITS

#### Productivity improvement

Help eliminate handoff delays and coordination overhead, dramatically accelerating production cycles by removing waiting periods between process stages.

#### Error reduction

Remove human errors at process transitions through consistent, automated handoffs and decision execution that apply the same logic each time.

#### System-level optimization across equipment

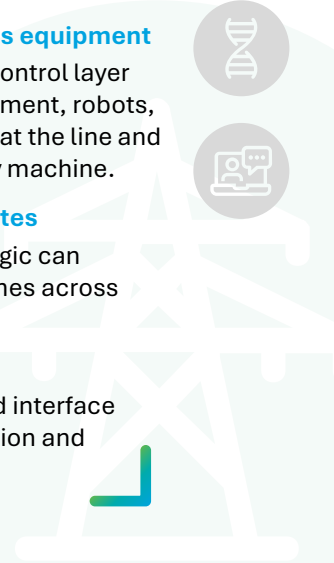
Physical AI can provide a unified control layer across heterogeneous OEM equipment, robots, and AMRs—optimizing workflows at the line and plant level rather than machine by machine.

#### Improved repeatability across sites

Standardized agent and control logic can deliver consistent process outcomes across production lines and facilities.

#### Lower integration effort

Reduced bespoke engineering and interface work through unified AI orchestration and control layers.



# Chemical manufacturing workflow automation (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Autonomous coordination of process handoffs in chemical manufacturing is not a context where degraded performance is merely inconvenient. Incorrect sequencing of hazardous materials between process stages can create conditions that are difficult to reverse quickly. Validation must cover heterogeneous equipment combinations, edge cases, and the full range of exception scenarios the system will likely encounter in production.



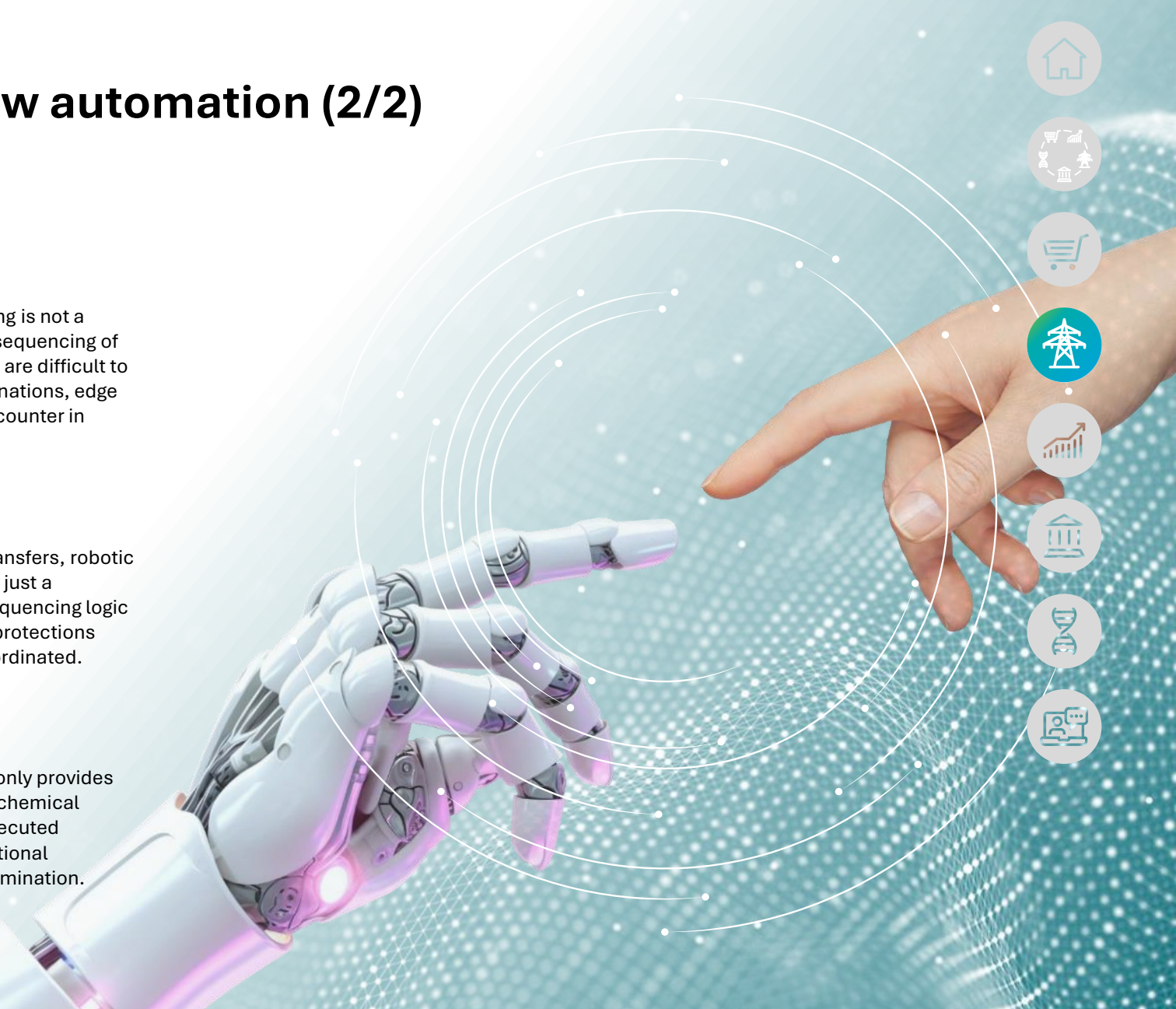
### Safe and secure

The physical actions this system controls—valve operations, material transfers, robotic movements—make the integrity of the AI control layer a safety issue, not just a cybersecurity issue. Unauthorized access or manipulation of process sequencing logic in a chemical facility could trigger dangerous physical actions. Security protections must be commensurate with the hazard level of the processes being coordinated.



### Responsible and accountable

Human approval of safety-critical actions and non-standard conditions only provides true protection if the audit trail is accurate and complete. In a regulated chemical manufacturing environment, documentation of which decisions were executed autonomously, which were escalated, and who approved them is not optional governance; it is a regulatory requirement and the basis for liability determination.



# Industrial facilities and space optimization (1/2)

## AI and sensor-driven building efficiency

### DESCRIPTION

Physical AI sensors and edge devices across buildings stream occupancy and environmental signals to edge AI controllers that optimize lighting and Heating, Ventilation, and Air Conditioning (HVAC) systems, as well as space utilization, in near real time.

### ISSUE/OPPORTUNITY

Office buildings are often inefficient due to static operating rules and limited visibility into real usage patterns. Lighting, heating, and cooling systems typically run on fixed schedules that ignore actual occupancy, wasting energy in empty spaces while failing to adjust for peak usage periods when demand exceeds capacity. Manual processes lead to wasted energy and underutilized space as facilities teams lack real-time visibility into how buildings are actually being used versus how scheduling systems suggest they should be used, preventing optimization based on observed patterns.

The opportunity is to operate buildings more responsively using real occupancy data while preserving safety and manual override capabilities that help enable facilities managers to intervene when AI-driven adjustments conflict with operational needs or emergency situations.

### HOW PHYSICAL AI CAN HELP

#### Occupancy pattern analysis

AI combines sensor, access, and booking data to learn true space utilization and identify underused areas.

#### Meeting-room utilization optimization

AI aligns booking systems with actual presence to reduce friction between scheduled and actual usage.

#### Localized execution

Decisions are executed close to building systems for responsiveness without requiring centralized coordination.

#### Dynamic environment adjustment

Lighting and energy systems are adjusted based on real usage rather than schedules, reducing waste in unoccupied areas.

#### Energy demand forecasting

Models can predict consumption and identify opportunities to reduce waste through pattern analysis.

#### Override and safety controls

Facility teams retain manual override to pause AI adjustments when operational or safety needs require intervention.

### POTENTIAL BENEFITS

#### Energy savings

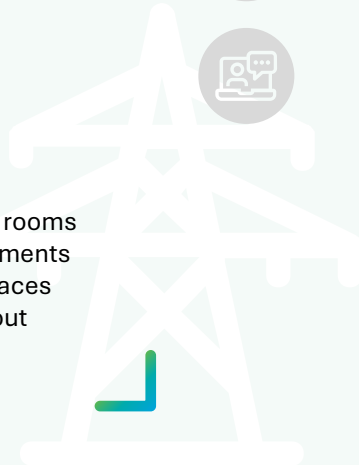
Lower operating costs through optimized heating, cooling, and lighting that respond to actual occupancy rather than fixed schedules or conservative assumptions.

#### Space efficiency

Better utilization of offices as AI identifies underused areas and helps optimize space allocation based on real usage patterns rather than theoretical capacity.

#### Employee experience

Reduced daily friction as meeting rooms reflect actual availability, environments adjust to occupancy, and workspaces respond to employee needs without requiring manual requests.



# Industrial facilities and space optimization (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

Continuous occupancy monitoring generates detailed records of how individuals move through building spaces throughout the working day—more than most occupants would expect from a facilities optimization tool. Data should be used exclusively for building management purposes, with clear retention limits and explicit communication to occupants about what is monitored and how their data is used.



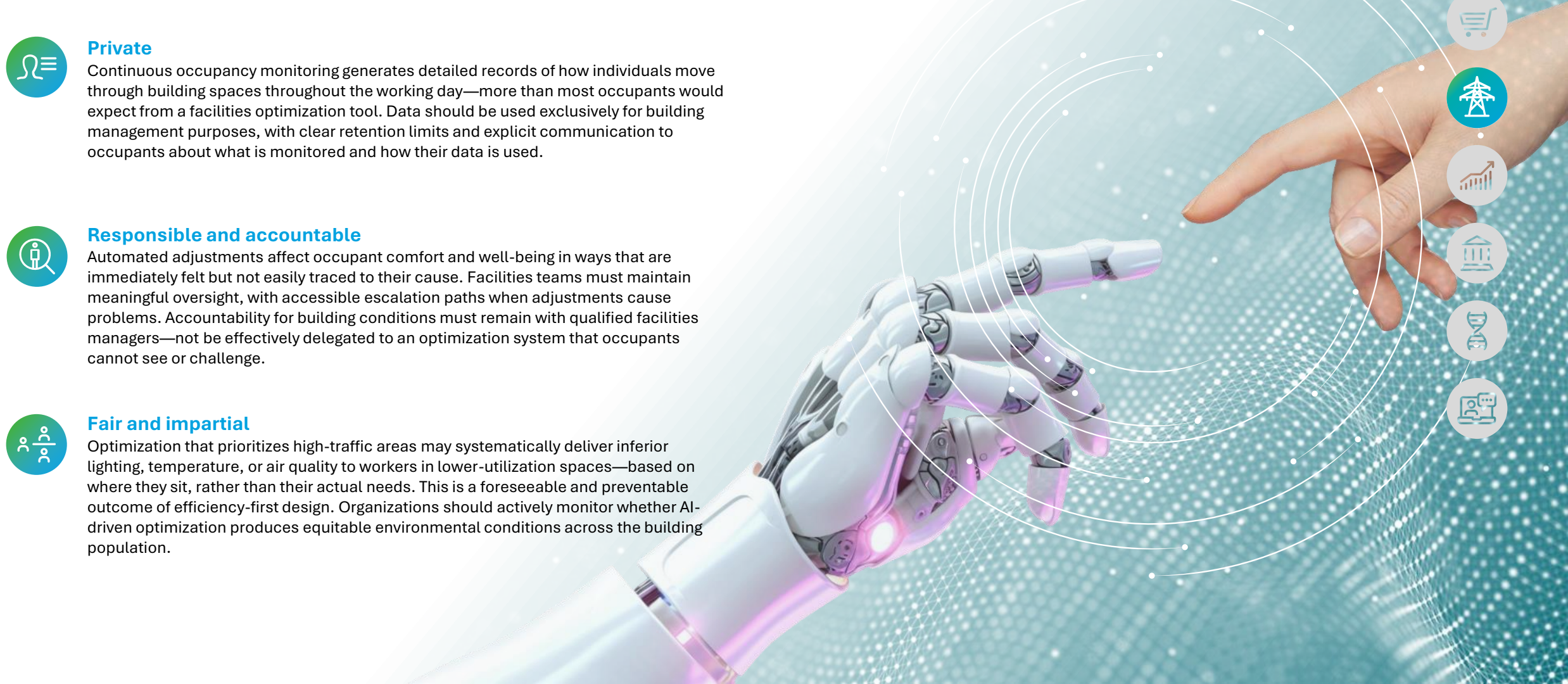
### Responsible and accountable

Automated adjustments affect occupant comfort and well-being in ways that are immediately felt but not easily traced to their cause. Facilities teams must maintain meaningful oversight, with accessible escalation paths when adjustments cause problems. Accountability for building conditions must remain with qualified facilities managers—not be effectively delegated to an optimization system that occupants cannot see or challenge.



### Fair and impartial

Optimization that prioritizes high-traffic areas may systematically deliver inferior lighting, temperature, or air quality to workers in lower-utilization spaces—based on where they sit, rather than their actual needs. This is a foreseeable and preventable outcome of efficiency-first design. Organizations should actively monitor whether AI-driven optimization produces equitable environmental conditions across the building population.



# Autonomous and semi-autonomous robotics in construction (1/2)

## Physical AI-enabled execution across dynamic construction sites

### DESCRIPTION

Autonomous and semi-autonomous machines are taking on essential construction duties—earthmoving, grading, rebar tying, bricklaying, and on-site additive manufacturing. The rising “print-to-build” approach is tightening the link between physical systems and digital twins, streamlining design-to-field transfers for MEP (mechanical, electrical, plumbing) deliverables and cutting both handoff time and execution errors when AI-driven equipment performs on-site tasks.

### ISSUE/OPPORTUNITY

Robotics in construction represents a pressing issue and a strategic opportunity: persistent labor shortages, rising project complexity, and the demand for greater efficiency threaten schedules, budgets, and safety if traditional methods continue. At the same time, integrating robotics with data capture and AI offers a clear path to fill workforce gaps, boost on-site productivity and accuracy, reduce safety risks, and help enable predictive, data-driven planning and management—shifting projects from manual, fragmented workflows to integrated, scalable delivery models.

### HOW PHYSICAL AI CAN HELP

#### Automated bricklaying systems

Robotic bricklayers can place up to roughly 3000 bricks per day<sup>4</sup>— well beyond typical manual output—taking on repetitive masonry so experienced masons can concentrate on complex or detail work.

#### 3D printing and additive manufacturing

Large-format robotic 3D printers can build entire structures in days, dramatically shortening construction timelines. Demonstration projects show this approach can make housing delivery faster and more resource-efficient.

#### Model-to-field execution

Digital twins and Building Information Modeling (BIM) models are directly translated into physical actions, reducing interpretation errors and rework.

#### Demolition and renovation robots

Radio- or remote-controlled demolition robots handle hazardous, confined-space work with precision, lowering worker exposure to danger and improving control over selective demolition and refurbishment tasks.

#### Surveying and monitoring with drones

AI-enabled drones fitted with advanced optical sensors generate detailed 3D site maps within hours, accelerating site surveys, progress tracking, and safety inspections so teams can spot and address risks earlier.

### POTENTIAL BENEFITS

#### Increased efficiency:

Automation can refine workflows, lower staffing expenses, and shorten project schedules by handling repetitive tasks quickly and consistently.

#### Enhanced safety:

Robots can take on dangerous activities and confined-space work, cutting worker exposure and reducing the incidence of injuries.

#### Improved quality:

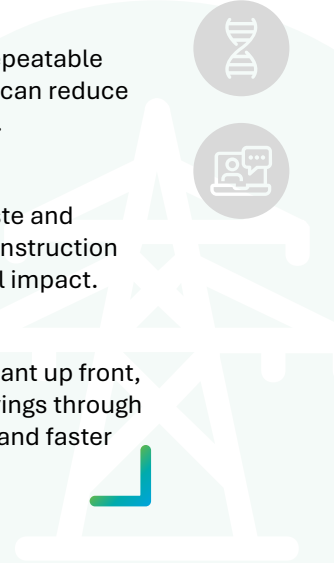
Automated systems can deliver repeatable precision and consistency, which can reduce errors, defects, and costly rework.

#### Higher sustainability:

Robotics can reduce material waste and energy use, supporting greener construction methods and lower environmental impact.

#### Long-term cost savings:

While capital costs can be significant up front, robotics often deliver lifecycle savings through reduced labor needs, less waste, and faster completion times.



# Autonomous and semi-autonomous robotics in construction (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Safe and secure

Construction sites are among the most hazardous working environments, and autonomous systems that fail to reliably detect human proximity or enforce operational boundaries create exactly the injury risk the technology is meant to reduce. Safety boundaries must be validated under actual site conditions—not just controlled testing—with robust mechanisms for responding to unexpected human entry into autonomous zones.



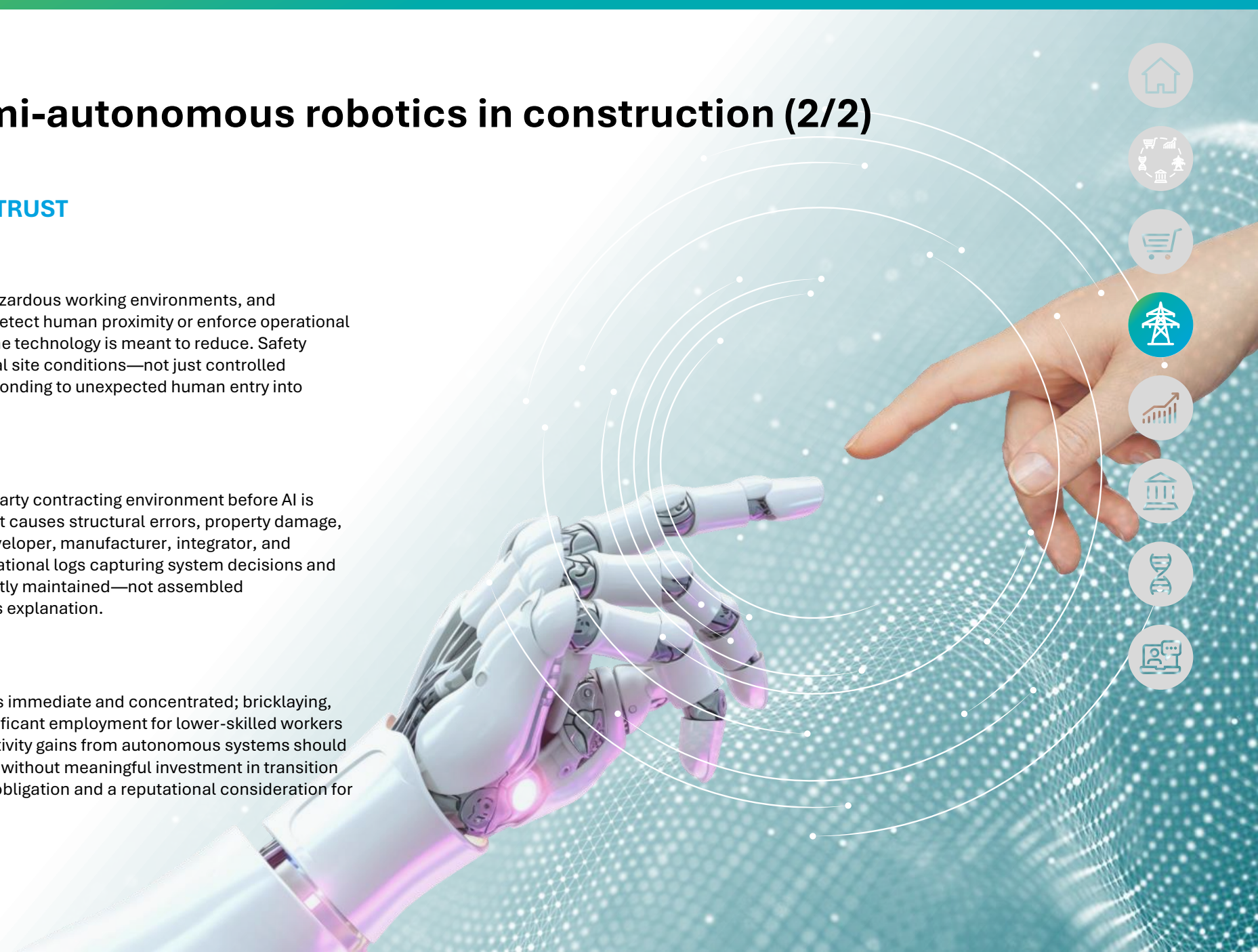
### Responsible and accountable

Construction is already a complex multi-party contracting environment before AI is introduced. When autonomous equipment causes structural errors, property damage, or worker injury, accountability across developer, manufacturer, integrator, and contractor is even harder to resolve. Operational logs capturing system decisions and human oversight actions must be constantly maintained—not assembled retrospectively when an incident demands explanation.



### Fair and impartial

Workforce displacement in construction is immediate and concentrated; bricklaying, rebar tying, and demolition represent significant employment for lower-skilled workers with limited alternative pathways. Productivity gains from autonomous systems should not come at the expense of this workforce without meaningful investment in transition support and reskilling, both as an ethical obligation and a reputational consideration for deploying organizations.



# The Financial Services Physical AI Dossier



# Summary: The Financial Services Physical AI Dossier

For an industry where reliability is foundational and regulatory scrutiny is constant, Physical AI offers powerful capabilities—but requires equally rigorous governance



Financial services may not appear, at first glance, to be a heavily physical industry. But beneath the digital surface, financial institutions operate extensive and consequential physical infrastructure (ATM networks, data centers, server farms, trading terminals, and branch technology) on which customers, markets, and regulatory obligations directly depend. Unlike most physical assets in other sectors, this infrastructure does not degrade gradually and visibly; it can fail suddenly, with immediate and highly visible consequences for customers and counterparties alike.

This characteristic makes financial services infrastructure a particularly compelling environment for Physical AI's predictive capabilities. The value of anticipating a failure before it occurs—rather than responding after the fact—is asymmetric: prevention is dramatically cheaper than remediation, and the reputational and regulatory cost of an outage far exceeds the cost of the maintenance that would have prevented it.

At the same time, financial services is an industry where the governance dimensions of any AI deployment are unusually consequential. These institutions operate under some of the most rigorous regulatory oversight of each sector, with strict requirements around system reliability, auditability, data residency, and accountability<sup>5</sup>. A Physical AI system that cannot explain its predictions, trace its reasoning, or demonstrate consistent performance to a regulatory standard is not deployable in this environment—regardless of its technical capability.

This creates a discipline that, while demanding, ultimately serves the industry well. Financial institutions that build Physical AI deployments to the governance standards their regulators require should have built systems that are also more trustworthy, more auditable, and more resilient than those deployed under less demanding conditions.



# Predictive maintenance for IT and ATM infrastructure (1/2)

## Predictive monitoring enabled by edge integration of physical machines

### DESCRIPTION

AI models continuously sense, interpret, and act on real-world signals from distributed physical assets (ATMs, servers, cooling systems), enabling autonomous, edge-based detection and intervention to prevent failures, maintain uptime, and help enable operational continuity even in low-connectivity environments.

### ISSUE/OPPORTUNITY

Failures of physical Information Technology (IT) and Operational Technology (OT) infrastructure and ATMs affect customer access, trading operations, and regulatory obligations. When ATMs fail, customers lose access to cash services—potentially at critical moments—damaging trust and satisfaction, cash-handling component wear and sensor faults are common physical failure modes. Server, network, power, and cooling failures can disrupt market access and channels, creating missed opportunities and potential reporting gaps. Traditional reactive maintenance leads to outages, emergency interventions, and elevated operational risk.

The core gap is lack of edge integration across heterogeneous machines—without it, you can't collect high-frequency signals reliably, act locally during connectivity loss, or enforce consistent device identity/security—so models remain “blind” or delayed.

The opportunity is to anticipate physical asset degradation earlier and reduce incidents through AI-powered predictive maintenance, while cautiously progressing to limited, controlled action under strict governance and human oversight that satisfies regulatory requirements for accountability.

### HOW PHYSICAL AI CAN HELP

#### Telemetry-driven failure prediction

AI models analyze historical and real-time telemetry sourced through edge gateways/agents to identify degradation patterns that typically precede failure events, to help enable earlier intervention than rule-based monitoring.

#### Preparation of remediation actions

For low-risk scenarios, AI systems prepare potential remediation steps—such as restart, patching, or component replacement—without executing them autonomously.

#### Human-in-the-loop control

All actions remain subject to human approval, to help ensure accountability, auditability, and regulatory compliance.

#### Asset-specific health modeling

Different classes of physical assets are modeled separately, accounting for hardware type, age, usage intensity, and operating conditions rather than applying generic thresholds.

#### Risk-weighted assessment

Predicted failures are evaluated in terms of customer impact, operational criticality, and regulatory sensitivity, helping teams prioritize responses.

#### Edge-compatible inference

Inference can be executed close to physical assets to meet latency, reliability, and data-residency requirements.

### POTENTIAL BENEFITS

#### Reduced downtime

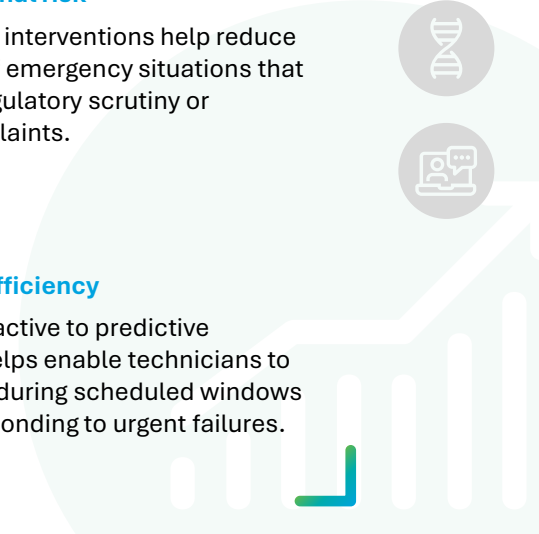
Fewer customer-facing outages as predictive maintenance prevents ATM and infrastructure before service impact and edge-local detection reduces time-to-detect and time-to-triage.

#### Lower operational risk

Earlier, planned interventions help reduce the likelihood of emergency situations that could trigger regulatory scrutiny or customer complaints.

#### Maintenance efficiency

Shifting from reactive to predictive maintenance helps enable technicians to address issues during scheduled windows rather than responding to urgent failures.



# Predictive maintenance for IT and ATM infrastructure (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

The main gap being addressed is unreliable edge integration that leaves models blind to degradation signals. A predictive system that misses failures in older or non-standard assets creates exactly the reactive maintenance cycle it is designed to prevent—with direct consequences for customer access, operational continuity, and the business case for deployment.



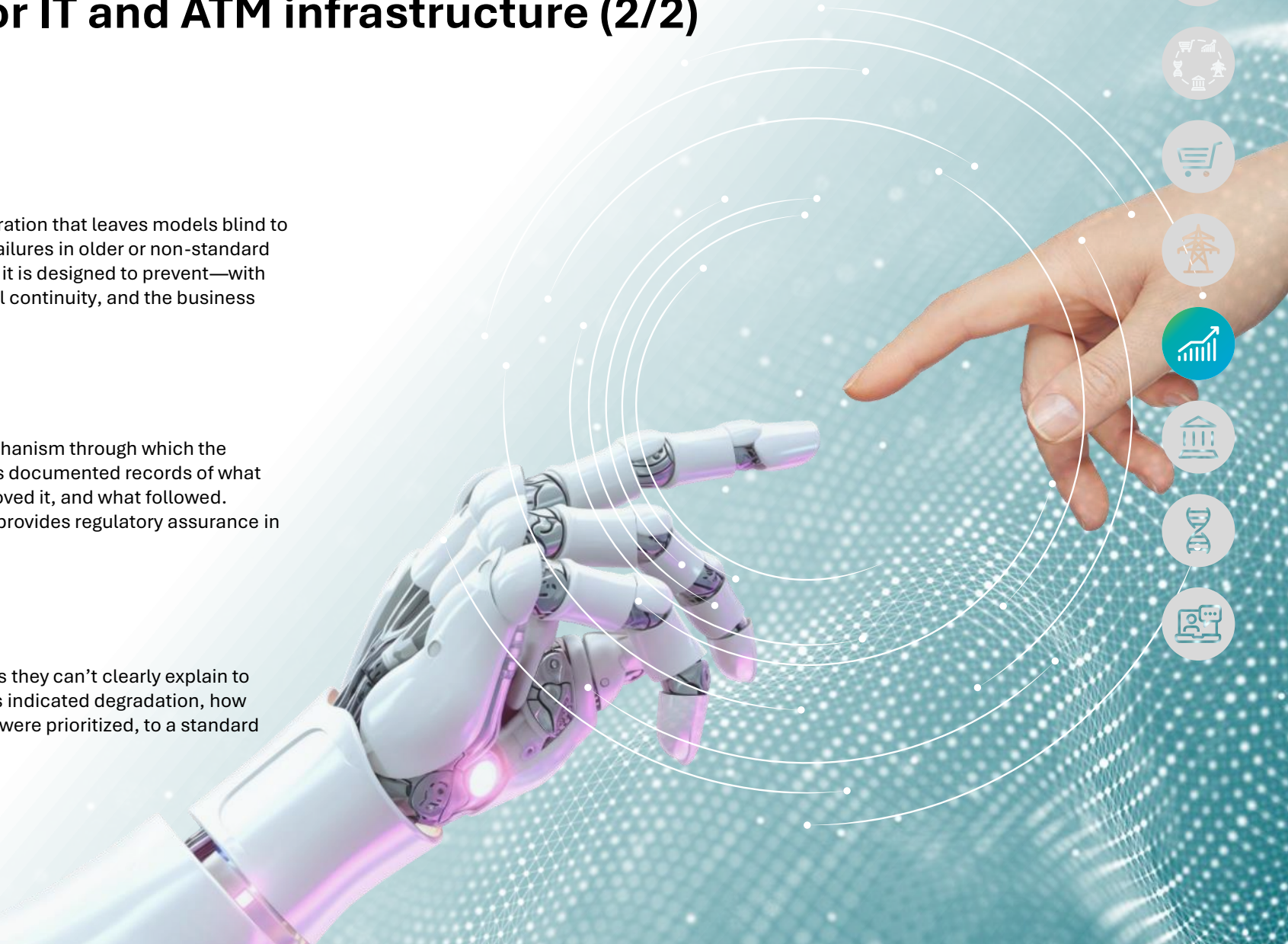
### Responsible and accountable

Human approval for all remediation actions is the mechanism through which the system maintains regulatory compliance. This requires documented records of what the AI predicted, what action was prepared, who approved it, and what followed. Without this audit trail, the human-in-the-loop design provides regulatory assurance in principle but not in practice.



### Transparent and explainable

Financial institutions cannot deploy predictive systems they can't clearly explain to regulators. Models must be able to show which signals indicated degradation, how failure probability was scored, and why certain assets were prioritized, to a standard that satisfies regulatory examination.



# Humanoid robots for branch operations (1/2)

## Automating front-of-house experiences with governance

### DESCRIPTION

Humanoid robots act as a “digital receptionist” in bank branches, sensing customer presence, movement, and queue dynamics to autonomously manage check-in, triage, and routing. By combining embodied interaction, on-device perception, and governed human oversight, they optimize front-of-branch operations in regulated financial environments.

### ISSUE/OPPORTUNITY

Branch lobbies still rely heavily on human reception and ad-hoc queue handling, which can create inconsistent experiences, longer waits, and avoidable staff load, especially during peak traffic. Customers often need quick routing (who to see, where to go, what to bring) rather than a full teller interaction, but traditional processes don’t scale efficiently. Banks also need ways to reduce friction at the front desk while maintaining service continuity and reinforcing in-branch experience standards. The opportunity is to deploy humanoid robots to digitalize branch reception, reducing delays and improving access to information via automated check-in/out, appointment booking, and real-time wait-time updates, while preserving human staff for higher-value interactions.

### HOW PHYSICAL AI CAN HELP

#### Spatial perception & crowd sensing

Robots detect queue length, congestion, and customer flow using vision and proximity sensors—adjusting triage behavior dynamically without manual supervision.

#### Edge-based execution for resilience

Core sensing and routing logic runs locally, to help ensure continued branch operation during network latency or partial outages.

#### Embodied escalation control

Physical presence helps enable controlled handoff—robot can physically guide customers to service points or staff, reducing misrouting and confusion.

#### Conversational triage

Answers common questions and routes to the right staff/team. Captures intent fast (e.g., “replace card,” “open account”) to help enable the right first handoff.

#### Branch-aware behavior

Robots adapt interaction patterns based on branch layout, time of day, and live staffing levels—something screen-based systems cannot do.

### POTENTIAL BENEFITS

#### Reduced wait times

Faster intake and better queue flow. Fewer re-queues and faster routing can improve throughput during peak periods.

#### Lower exception load on human staff

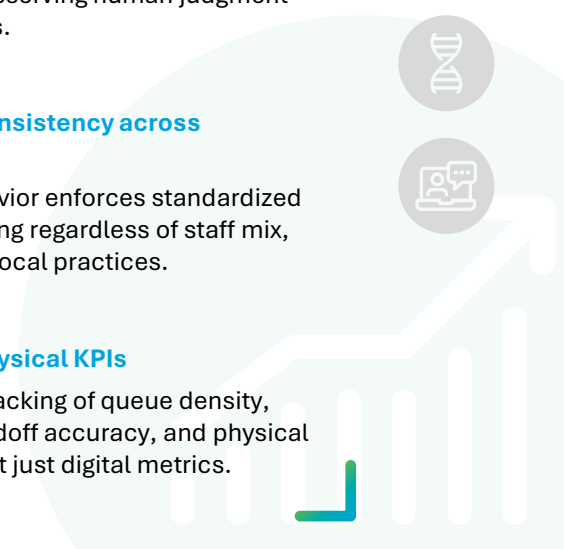
Staff engage when Physical AI flags ambiguity, VIP handling, or regulatory exceptions—preserving human judgment where it matters.

#### Operational consistency across branches

Embodied behavior enforces standardized intake and routing regardless of staff mix, branch size, or local practices.

#### Measurable physical KPIs

Helps enable tracking of queue density, dwell time, handoff accuracy, and physical congestion—not just digital metrics.



# Humanoid robots for branch operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

A humanoid robot continuously sensing customer presence, movement, and behavior in a bank branch collects biometric and behavioral data about identifiable individuals who have not necessarily consented to automated observation. Organizations must be transparent about what is captured, apply strict retention limits, and ensure that data is not repurposed beyond the immediate branch interaction it was collected to support.



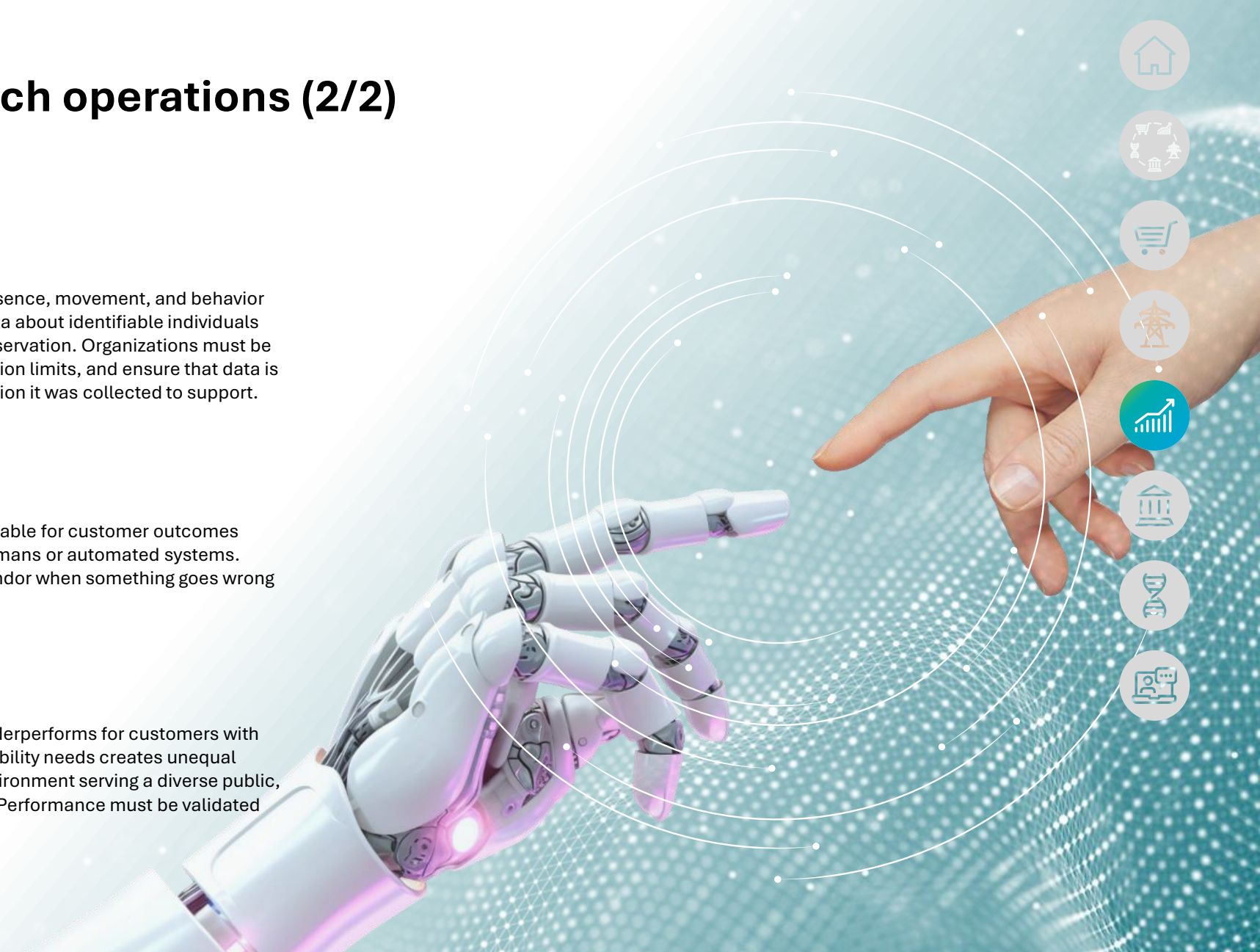
### Responsible and accountable

Financial services regulators hold institutions accountable for customer outcomes regardless of whether interactions are delivered by humans or automated systems. Accountability cannot be passed to the technology vendor when something goes wrong in a regulated customer-facing environment.



### Fair and impartial

A triage system that works well for the majority but underperforms for customers with different languages, communication styles, or accessibility needs creates unequal access to branch services. In a regulated financial environment serving a diverse public, this is both a reputational and a compliance concern. Performance must be validated across the full customer population.



# ATM cash forecasting, replenishment and autonomous cash logistics (1/2)

## Predictive cash availability through edge intelligence

### DESCRIPTION

AI models running on edge-equipped ATMs predict cash depletion using physical machine signals and contextual factors (day-of-week, seasonality, local events). Cash forecasting and intelligent replenishment are being deployed with the goal of autonomous coordination of cash logistics.

### ISSUE/OPPORTUNITY

Out-of-cash ATMs erode customer trust and drive-up emergency servicing costs. When customers hit empty ATMs, frustration and inconvenience reduce satisfaction and loyalty and can push them to competitors with more reliable cash access. Static replenishment thresholds break under variable demand because fixed rules don't adapt to changing withdrawal patterns from holidays, local events, weather disruptions, or neighborhood shifts.

Manual planning also struggles to incorporate irregular but predictable spikes (concerts, sporting events, payday cycles). Without edge integration, real-time visibility into machine health, cash levels, and local demand signals remains limited, delaying detection and response.

The opportunity is to equip ATMs with edge intelligence that continuously interprets physical machine signals and contextual demand drivers, enabling accurate cash forecasting, risk-based prioritization, and optimized replenishment planning—reducing outages and logistics costs while keeping execution under strict human and security controls.

### HOW PHYSICAL AI CAN HELP

#### Edge-enabled cash demand forecasting

AI models run on edge-connected ATMs, combining cash-level telemetry and device signals with usage patterns to predict depletion timelines more accurately than fixed thresholds.

#### Dynamic replenishment recommendations

AI adjusts replenishment timing and quantities based on predicted demand rather than relying on static refill schedules.

#### Logistics planning support

In the future, AI could assist in coordinating routes and schedules for cash handling teams to optimize operational efficiency.

#### Contextual signal integration

Models incorporate temporal effects, seasonal patterns, and local events influencing withdrawal behavior to anticipate demand changes before they occur.

#### Risk-based prioritization

ATMs with the highest likelihood of customer impact are prioritized for intervention based on location importance and depletion probability.

#### Human-controlled execution

Replenishment and logistics decisions remain under human oversight, to help ensure accountability for security-sensitive operations.

### POTENTIAL BENEFITS

#### Fewer out-of-cash events

Higher ATM availability as predictive forecasting prevents cash depletion before customers are affected.

#### Lower logistics costs

Fewer emergency replenishment trips and better route density driven by real-time edge visibility into depletion risk and machine status.

#### Improved customer experience

More reliable access to cash strengthens customer trust and satisfaction by ensuring ATMs are available when needed.



# ATM cash forecasting, replenishment and autonomous cash logistics (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Inaccurate forecasting directly produces the out-of-cash events and unnecessary logistics costs the system exists to eliminate. Models must be validated across the full range of demand conditions they will encounter in production, including irregular spikes from local events and neighborhood shifts that fixed thresholds and historical averages cannot anticipate.



### Safe and secure

AI forecasting outputs that reveal replenishment timing and ATM cash status are operationally sensitive intelligence that, if compromised, could directly enable criminal exploitation of logistics operations. This is not a generic cybersecurity concern; it is specific to this use case. Forecasting outputs and machine-level cash data must be secured with protections commensurate with the physical security risks of cash handling.



### Fair and impartial

Risk-based prioritization that favors high-traffic or commercially significant ATMs may systematically result in lower cash availability in lower-income or lower-density areas where customers have the fewest alternatives. Cash availability is a basic financial access need, and for institutions with public service obligations, AI-driven prioritization that disadvantages underserved communities is both a regulatory and a reputational concern.



# The Government & Public Services Physical AI Dossier



# Summary: The Government & Public Services Physical AI Dossier

Physical AI offers governments powerful tools to protect people, deliver services, and manage public infrastructure—but its deployment demands the highest standards of accountability and public trust

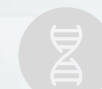


Governments at every level face pressure to deliver more with fewer resources<sup>6</sup>. Specifically, the obligation: to protect all citizens; deliver essential services equitably regardless of ability to pay; manage the physical infrastructure on which communities depend; and to do so with a level of transparency and accountability that private sector organizations are not held to. Physical AI intersects with each of these obligations, and that intersection creates both significant opportunity and unique complexity.

The opportunity is real. Government and public sector organizations manage enormous physical domains (e.g., roads, utilities, public buildings, transit systems, public safety infrastructure) that are chronically under-resourced given the maintenance and oversight they require. They deliver services that are inherently physical: emergency response, public health, education, social support. And in many jurisdictions, they face workforce pressures that make scaling those services through human labor alone increasingly difficult.

Physical AI can extend the reach and effectiveness of government operations in ways that are genuinely valuable to the citizens they serve. But the deployment context is fundamentally different from the private sector. For example, AI systems that operate in public spaces, inform law enforcement decisions, or manage infrastructure that communities depend on carry obligations of fairness, transparency, and human oversight that are higher than almost any commercial application. Errors or biases in these systems do not simply create operational problems; they can cause tangible harm to real people and erode the institutional trust on which democratic governance depends.

Regulatory complexity adds further constraints. Governments operate within strict legal frameworks, procurement requirements, and inter-agency coordination structures that slow deployment in ways that private sector organizations do not face. Privacy law, civil liberties protections, and public accountability requirements shape what Physical AI can do in government contexts—and how.



# Autonomous patrolling and threat detection (1/2)

## Robotic patrolling for government facilities

### DESCRIPTION

Autonomous mobile robots (AMRs) patrol buildings and facilities, continuously monitoring environments, detecting potential threats, and escalating incidents based on severity. Systems interpret scenes locally and alert security personnel when intervention is required.

### ISSUE/OPPORTUNITY

Continuous physical security coverage is costly and difficult to staff with humans alone. Fixed cameras lack mobility and context. Security guards patrol facilities on fixed routes or remain stationed at checkpoints, creating predictable gaps in coverage that leave areas unmonitored for extended periods.

Fatigue and attention degradation affect human guards during overnight shifts or long patrol routes, reducing vigilance when monitoring repetitive environments where incidents are infrequent. Guards cannot be in multiple locations simultaneously, forcing facilities to choose between comprehensive coverage requiring large security teams or accepting blind spots during routine patrols. Fixed cameras provide static views but cannot investigate suspicious activity, follow subjects through facilities, or provide contextual assessment of situations that require mobile perspective.

Physical AI robots can provide persistent, mobile monitoring while reserving human attention for verified incidents requiring judgment, de-escalation, or physical intervention.

### HOW PHYSICAL AI CAN HELP

#### Autonomous navigation

Robots move through buildings independently, following patrol routes, navigating around obstacles, using elevators, and adapting paths when areas are blocked or access is restricted.

#### Visual scene interpretation

AI identifies abnormal situations such as unauthorized personnel in restricted areas, doors left open after hours, unattended packages, or environmental hazards like water leaks or smoke.

#### Threat escalation logic

Events are classified by severity, with minor anomalies logged for review while urgent threats trigger immediate alerts with live video feeds to security personnel.

#### Human alerting

Security teams are notified when needed, receiving situational context, robot location, and video evidence to inform their response without requiring constant monitoring of robot feeds.

#### Continuous operation

Robots patrol without fatigue, maintaining consistent coverage during overnight hours, weekends, and holidays when staffing human security teams is most expensive and challenging.

### POTENTIAL BENEFITS

#### Improved coverage

Facilities are monitored continuously as robots provide round-the-clock patrols without breaks, shift changes, or attention lapses that create security gaps.

#### Lower labor dependence

Fewer routine guard tasks as robots handle repetitive patrols, enabling security personnel to focus on response, investigation, and situations requiring human judgment.

#### Faster detection

Threats may be identified earlier through constant mobile monitoring that catches developing situations before they escalate, rather than discovering incidents during periodic guard rounds.

#### Security consistency

Coverage should not degrade over time as robots maintain identical patrol patterns and alertness levels regardless of hour, day, or duration of deployment.

#### Audit-ready physical decision trails

Sensor data, movement paths, and escalation decisions can be logged for post-incident review, public accountability, and legal scrutiny.



# Autonomous patrolling and threat detection (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Robots that misclassify routine activity as threats create alert fatigue that causes security teams to discount warnings; those that miss genuine incidents defeat the purpose of deployment. Both failure modes are serious. Reliability across varying lighting, occupancy levels, and facility configurations is essential for the system to deliver sustained operational value.



### Private

Autonomous robots continuously recording video as they patrol occupied facilities capture detailed data about individuals' movements and behaviors throughout the working day. Organizations must define clear limits on what is recorded, how long footage is retained, who can access it, and what prevents patrol data from being used for employee monitoring beyond legitimate security purposes.



### Fair and impartial

Threat classification models trained on specific facility types or populations may generate disproportionate false positives for individuals whose appearance or behavior differs from training data norms. In government facilities serving the public, biased threat detection creates civil rights exposure and undermines the institutional trust on which legitimate security operations depend.



# Smart city operations and urban infrastructure modernization (1/2)

## City-scale intelligence for monitoring, service delivery, and resilient operations

### DESCRIPTION

Physical AI combines urban sensors, drones, and autonomous robots to monitor and manage city infrastructure in real time. Edge intelligence detects events, sending data to cloud platforms for analysis and decision-making, while robots perform tasks like inspection and maintenance, linking sensing and action across the city.

### ISSUE/OPPORTUNITY

Smart city initiatives aim to deliver dense, sustainable urban environments with high service quality and operational efficiency. In practice, however, both city infrastructure and large public complexes still rely heavily on fragmented data, manual inspections, and labor-intensive operations. Urban systems—transportation, utilities, public safety, and environment—operate in silos with limited real-time, street-level visibility, making it difficult to detect issues early, coordinate responses, or prioritize maintenance. At the same time, large residential and commercial developments depend on sizable human workforces for cleaning, maintenance, and deliveries, resulting in high operating costs, uneven service quality, and limited scalability as demand grows. The opportunity is to deploy Physical AI as foundational urban infrastructure. Edge-integrated sensors, drones, and autonomous mobile robots enable continuous, real-time monitoring and verification across cities and facilities. By detecting hazards at the edge, streaming curated events to the cloud, and unifying insights across systems, Physical AI helps enable coordinated dispatch, proactive intervention, and demand-driven resource allocation—delivering more consistent services, improved resident experience, and more resilient urban operations without relying on static schedules or manual oversight.

### HOW PHYSICAL AI CAN HELP

#### City-scale sensor and edge integration

AI aggregates data from transportation, utilities, and environmental sensors with edge compute to detect anomalies locally (e.g., hazards, leaks, congestion) and publish event alerts with minimal latency.

#### Robotic service execution

AMRs handle cleaning, waste handling, internal logistics, and routine maintenance across public buildings, transit hubs, campuses, and residential complexes. Service schedules adapt dynamically based on actual usage patterns.

#### Decision support for operators

AI informs planners without exerting autonomous control, providing recommendations that human operators review and approve before implementation.

#### Infrastructure health monitoring

Detects stress and failure in urban systems by analyzing diverse data such as bridge vibration patterns, water flow irregularities, or grid fluctuations, identifying maintenance needs before failures disrupt service.

#### Mobility and crowd analysis

Improves traffic and pedestrian flow by identifying congestion patterns, predicting rush-hour bottlenecks, monitoring crowd density at public events, or detecting unusual movement patterns.

#### Human governance and oversight

Public authorities retain control over policy decisions and operational changes, with AI systems providing analysis and recommendations.

### POTENTIAL BENEFITS

#### Reduced operating costs

Can replace large human teams performing repetitive tasks with autonomous systems, significantly lowering facility management expenses while enabling smart city developments to achieve financial sustainability.

#### Consistent service quality

Eliminates variability in service delivery based on staffing availability, to help ensure residents receive uniform maintenance and support as envisioned in smart city livability standards.

#### 24/7 facility operations

Helps enable round-the-clock service delivery—cleaning, deliveries, maintenance—without shift-based labor costs or coordination complexity, supporting the always-on nature of smart city infrastructure.

#### Greater urban resilience

Cities respond more effectively to stress and incidents, as cross-system visibility helps enable faster detection of cascading failures, coordinated response across departments, and proactive mitigation of predictable disruptions.

#### Better-informed planning

Decision-makers gain clearer visibility into city operations, to help enable evidence-based infrastructure investments, more accurate service demand forecasts, and better understanding of how proposed changes might affect interconnected systems.



# Smart city operations and urban infrastructure modernization (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

City-scale sensors, drones, and robots operating continuously across public spaces and residential areas create a mass surveillance capability covering entire urban populations that have no practical ability to opt out. Governments must define strict, publicly documented limits on what is collected, how long it is retained, and what prevents repurposing beyond the infrastructure management purposes that justified deployment.



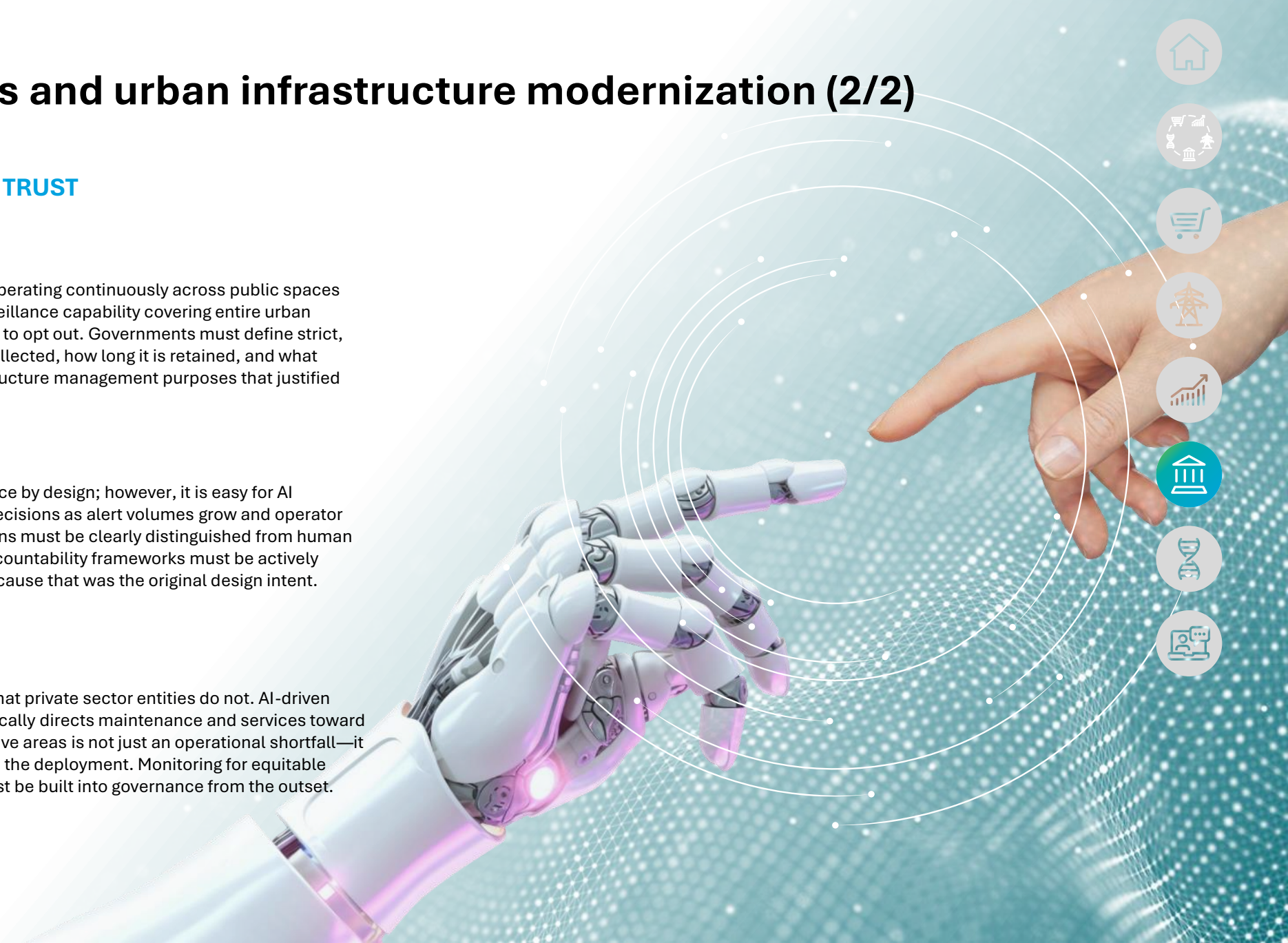
### Responsible and accountable

The use case preserves human governance by design; however, it is easy for AI recommendations to become de facto decisions as alert volumes grow and operator capacity is stretched. AI recommendations must be clearly distinguished from human decisions in operational records, and accountability frameworks must be actively maintained, not assumed to hold just because that was the original design intent.



### Fair and impartial

Governments have fairness obligations that private sector entities do not. AI-driven urban resource allocation that systematically directs maintenance and services toward higher-density or more commercially active areas is not just an operational shortfall—it is a failure of the public duty that justifies the deployment. Monitoring for equitable outcomes across the full jurisdiction must be built into governance from the outset.



# The Life Sciences & Health Care Physical AI Dossier



# Summary: The Life Sciences & Health Care Physical AI Dossier

In sectors where precision, reliability, and human welfare are inseparable, Physical AI is enabling capabilities that were, until recently, beyond reach



Life sciences and health care share a defining characteristic that shapes everything about how technology should be deployed within them: the consequences of failure directly affect human beings. A surgical error can cause harm. A drug that reaches patients after unnecessary delay causes harm. A hospital that cannot deliver a medication on time can cause harm. This reality does not make these sectors unsuitable for innovation; it makes them demand a higher standard of it.<sup>7</sup>

Physical AI in life sciences and health care therefore operates under requirements that are highly stringent. Validation standards for AI systems that touch clinical or manufacturing processes are rigorous by design. Regulatory pathways for AI-assisted medical devices and procedures introduce additional time and cost into deployment. And the human oversight requirements in clinical environments are non-negotiable: Physical AI in health care augments clinicians; it does not replace their judgment.

Within those constraints, however, the opportunity is substantial. Health care is structurally labor-intensive, with skilled professionals spending significant time on tasks that do not require their clinical knowledge. Life sciences research is constrained by the physical limits of how many experiments humans can design, execute, and analyze. Pharmaceutical manufacturing demands levels of precision and consistency that human processes struggle to maintain reliably at scale. Each of these characteristics represents a point where Physical AI can meaningfully contribute.

The sectors also face a shared workforce dynamic: a global shortage of clinical and scientific talent that cannot be resolved through recruitment alone. Physical AI that can extend the effective capacity of existing professionals, rather than simply substituting for them, is therefore not just operationally useful but strategically essential for sustaining the quality of care and pace of discovery that patients and health systems need.



# Transforming pharmaceutical research and development (1/2)

## Physical AI smart labs for drug discovery

### DESCRIPTION

Physical AI-powered “smart labs” autonomously execute the entire design-make-test-analyze (DMTA) cycle in drug discovery. These systems design molecules using AI-driven computational models (“in silico”), generate synthesis plans, and directly execute them through integrated robotic lab platforms. These systems orchestrate execution, physically synthesize molecules, transfer samples via automated handling systems, and run assays using connected lab instruments, analyze results, and initiate the next iteration—with minimal human intervention beyond oversight and exception handling.

### ISSUE/OPPORTUNITY

Pharmaceutical discovery is constrained by slow, manual DMTA cycles that take 8-12 weeks per iteration, limiting the number of molecules that can be tested and delaying time-to-market for new therapies. Traditional discovery requires manual setup of experiments, physical sample movement, and fragmented instrument workflows—creating bottlenecks and increasing error risk in repetitive tasks. Capital-constrained biotech companies face existential time pressure but lack the workforce to scale discovery operations. Physical AI and robotics offer an opportunity to automate up to 70-80% of standardized processes<sup>2</sup>, accelerating cycle times and enabling faster kill decisions on failing candidates while progressing winners. Autonomous systems can work continuously, handle greater experimental loads, and improve portfolio NPV (net present value) by compressing discovery timelines.

### HOW PHYSICAL AI CAN HELP

#### AI-driven molecule design & synthesis

AI algorithms design novel molecules in silico, predict synthetic routes, and generate execution plans, including reagent plating, liquid handling sequences, and robotic orchestration.

#### AI-optimized experimental design

Machine learning models predict which experiments may yield the most information, reducing unnecessary data generation by up to 50% and maximizing throughput from existing lab capacity.<sup>2</sup>

#### Real-time data analysis & adaptive iteration

AI monitors experimental outcomes in real time, evaluates performance against objectives, identifies failures early, and autonomously designs the next DMTA cycle—compressing iteration time from weeks to days.

#### Autonomous sample transport

AMRs transport samples between synthesis, purification, and testing stations. Automated assay platforms run efficacy and safety screens, upload results directly to AI systems, and close the loop for next-cycle decision-making.

#### Robotic synthesis & purification

Robotic arms and automated synthesis platforms execute AI-generated protocols autonomously, performing liquid handling, reaction setup, purification, and quality control (QC) without human intervention, operating 24/7 when facilities permit.

### POTENTIAL BENEFITS

#### Radical cycle time compression

Autonomous smart labs may reduce DMTA cycle times from 8–12 weeks to under 2 weeks, enabling faster progression of viable drug candidates, earlier termination of failures, and significant improvement in portfolio Net Present Value (NPV).

#### Capital efficiency for biotech

Small biotech companies can deploy smart labs to replace large discovery teams, reducing headcount requirements while achieving higher throughput—critical for one-product companies racing against cash burn.

#### Scalable innovation infrastructure

Pharma companies can scale discovery operations by adding parallel robotic workstations, creating a path to continuous, factory-style drug discovery without workforce constraints.

#### Increased discovery capacity

By automating 80% of standardized workflows, labs can handle larger portfolios with the same physical infrastructure and workforce, focusing human effort on the 20% of artisanal, non-standardizable tasks.

#### Enhanced reliability & reproducibility

Robotic systems can minimize human error in repetitive tasks, help enable consistent execution of protocols, and capture tacit operator knowledge that would otherwise be lost, improving data quality and experimental reproducibility.



# Transforming pharmaceutical research and development (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Silent error propagation is the most distinctive reliability risk here. Errors in robotic synthesis, sample handling, or AI iteration decisions can compound across multiple cycles before detection, advancing flawed candidates and discarding viable ones. This corrupts the scientific foundation on which regulatory submissions rest. Reliability must be validated across the full automated workflow, not just individual steps.



### Responsible and accountable

Regulatory authorities expect documented human accountability for scientific decisions. A system operating with minimal human intervention must have an exceptionally robust audit trail to satisfy that expectation. Organizations must clearly document the boundary between AI-generated recommendations and human-validated judgments at every stage, making full traceability of experimental decisions a deployment prerequisite, not a backward-looking governance addition.



### Transparent and explainable

Regulatory accountability requires that qualified scientists can assess and stand behind the AI's scientific reasoning—not just validate its outputs. When AI makes decisions to drop candidates or advances molecules based on predicted properties, the reasoning must be traceable to a standard that satisfies both internal scientific review and external regulatory examination.



# Automated drug dispensing systems (1/2)

## AI-powered robotic systems for accurate and scalable medication management

### DESCRIPTION

AI-powered robotic pharmacy systems automate medication dispensing using Physical AI and robotics. Prescription dispensing robots handle counting, packaging, and labeling, while prescription filling robots accurately fill vials or blister packs. Automated storage and retrieval systems organize inventory and enable rapid access. Combined with AI algorithms and computer vision, these systems help enable accurate verification, dosage calculation, and low-error, continuous pharmacy operations with minimal manual intervention.

### ISSUE/OPPORTUNITY

Manual pharmacy workflows rely on repetitive tasks such as counting, filling, and inventory handling, which increase errors and slow down operations. These processes are difficult to scale while maintaining accuracy and consistency, leading to delays and higher workload for pharmacists. Physical AI-driven robotic systems offer an opportunity to automate dispensing, filling, and storage, reducing errors, improving efficiency, and enabling scalable, high-throughput pharmacy operations.

### HOW PHYSICAL AI CAN HELP

#### AI-driven prescription processing

AI validates prescriptions, helps ensure accurate data verification, and reduces manual review effort to speed up processing.

#### Computer vision verification

Helps enable correct medication identification and labeling while detecting discrepancies to prevent dispensing errors.

#### Automated storage & retrieval

Manage inventory and help enable fast medication access while optimizing stock organization and reducing retrieval time.

#### Robotic dispensing systems

Automate counting, packaging, and labeling of medications while supporting precision and consistency in repetitive tasks.

#### Robotic filling systems

Fill vials and blister packs with high precision, reducing variability and improving dosage accuracy.

#### Real-time safety checks

Detect drug interactions and patient risks while supporting informed decision-making for safer dispensing.

### POTENTIAL BENEFITS

#### Reduced errors & improved safety

Minimize manual errors in dispensing and filling while enhancing patient safety and reducing adverse events.

#### Faster processing time

Accelerate prescription handling and delivery while reducing patient wait times and improving service levels.

#### Higher workforce efficiency

Reduce repetitive workload for pharmacy staff with a greater focus on patient care activities.

#### Consistent & accurate operations

Help enable standardized and reliable processes while improving quality control and reproducibility.

#### Scalable 24/7 operations

Support continuous, high-volume dispensing while enabling pharmacies to handle increased demand efficiently.

#### Optimized inventory management

Improve stock organization and retrieval speed while reducing shortages and enhancing inventory visibility.



# Automated drug dispensing systems (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Medication dispensing errors cause direct patient harm—and a system that introduces its own error modes in place of human ones does not improve patient safety; it substitutes one risk for another. Reliability must be validated continuously across the full range of medications and dosage forms handled, not just the products well-represented during design and testing.



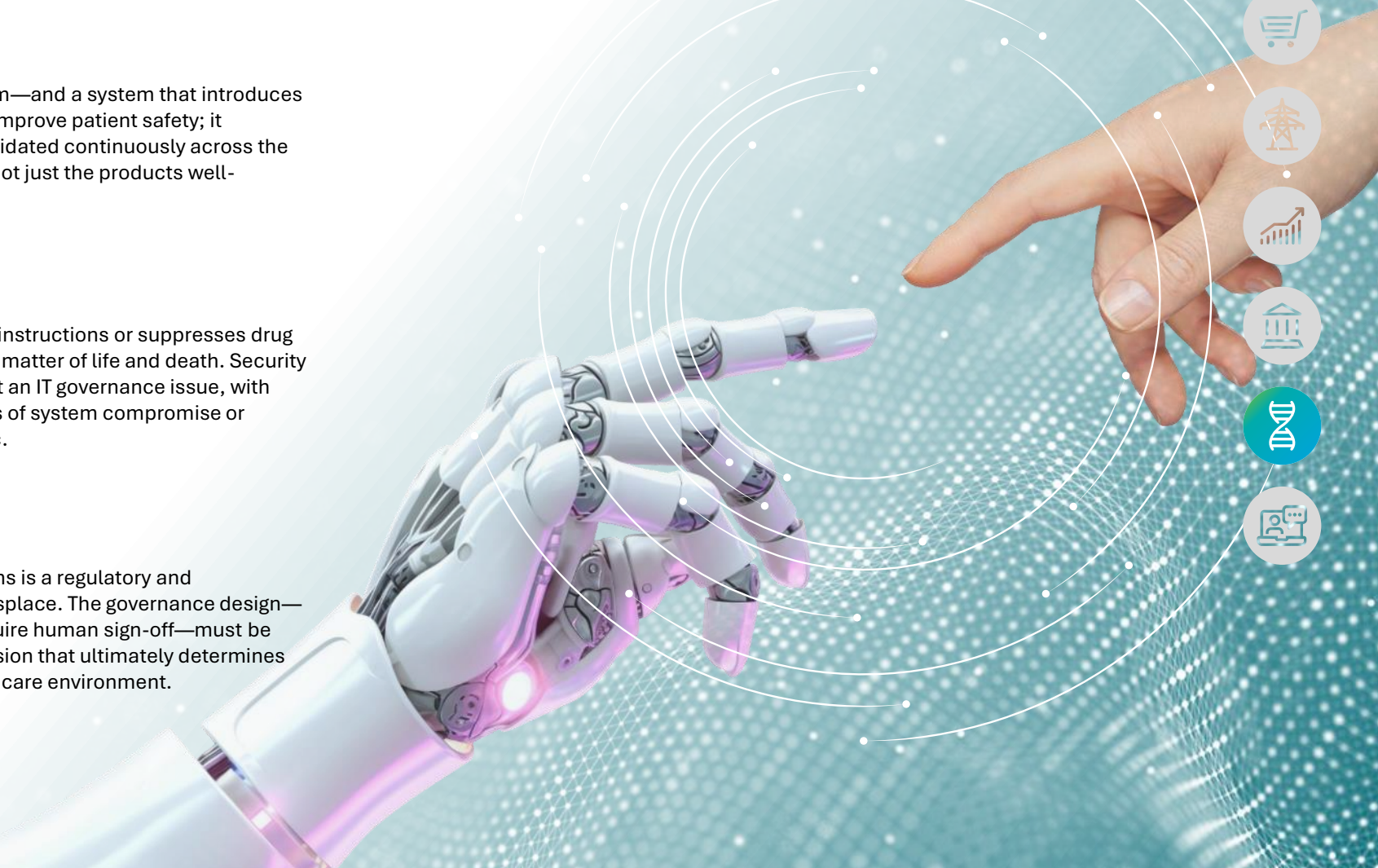
### Safe and secure

A compromised dispensing system that alters dosage instructions or suppresses drug interaction checks is not an IT problem—it is literally a matter of life and death. Security must therefore be treated as a patient safety issue, not an IT governance issue, with protections reflecting the direct clinical consequences of system compromise or manipulation of prescription data and dispensing logic.



### Responsible and accountable

Pharmacist accountability for final dispensing decisions is a regulatory and professional requirement that AI assistance cannot displace. The governance design—including which checks are AI-assisted and which require human sign-off—must be explicit, enforced, and documented. This is the dimension that ultimately determines whether the system is deployable in a regulated healthcare environment.



# Surgical robotics for microsurgery (1/2)

## AI-assisted precision surgery

### DESCRIPTION

High-precision surgical robots/robotic hands support microsurgical procedures under direct human supervision. These systems feature extremely low latency, high accuracy, and tight integration between AI perception and physical actuation during live operations.

### ISSUE/OPPORTUNITY

Microsurgery demands precision beyond normal human motor capability, while safety requirements leave no tolerance for error. Manual procedures limit consistency and accessibility. Delicate operations such as nerve repair, vascular reconstruction, or ophthalmic surgery require movements measured in fractions of millimeters, performed while the surgeon's hands naturally experience tremor and fatigue. Surgical outcomes vary based on individual surgeon dexterity, experience level, and physical condition, creating inconsistency in patient results for identical procedures. Complex microsurgical techniques remain accessible to specialists at major medical centers, limiting patient access based on geography and surgeon availability. The opportunity is to use Physical AI to enhance surgical precision while keeping clinicians fully in control. Leveraging robotic hands helps enable direct translation of surgeon intent into controlled end-effector motions at the point of contact, reducing tremor at the source and enabling precise force control.

### HOW PHYSICAL AI CAN HELP

#### High-resolution perception

AI interprets visual and sensor data during surgery, enhancing the surgeon's view with magnification, filtering, and highlighting of critical anatomical structures that guide precise intervention.

#### Latency-constrained execution

Decisions and actions occur in real time with minimal delay between surgeon input and robotic response, maintaining the natural feel of direct tissue interaction critical for surgical judgment.

#### Safety-critical integration

AI operates within strict procedural constraints including movement boundaries, force limits, and anatomical safety zones that prevent inadvertent damage to surrounding structures.

#### Precision motion control

Robotic hand executes movements at sub-millimeter accuracy, filtering out hand tremor and scaling surgeon hand movements to finer instrument movements for delicate tissue manipulation.

#### Human-controlled operation

Surgeons retain authority over actions, with robotic systems translating their commands into precise physical movements rather than making autonomous surgical decisions.

### POTENTIAL BENEFITS

#### Improved surgical outcomes

The robotic hand helps enable finer tissue handling and more accurate suture placement, reducing trauma and complication rates and improving healing times for microsurgical cases.

#### Expanded treatment capability

More procedures become feasible as robotic precision helps enable operations that exceed manual capabilities, bringing advanced microsurgical techniques to cases previously considered too complex.

#### Consistency

End-effector level actuation and sensing from the robotic hand deliver uniform precision regardless of surgeon fatigue or tremor, reducing variability in outcomes.

#### Patient benefit

Recovery outcomes improve through less tissue trauma, reduced scarring, shorter hospital stays, and lower complication rates that translate into better long-term function.



# Surgical robotics for microsurgery (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

A latency spike or motion control failure during nerve repair or vascular reconstruction is not a recoverable error—it's a matter of life and death. Validation must reflect actual surgical conditions, not laboratory benchmarks, and must demonstrate performance across the full range of procedures, tissue types, and edge cases the system might encounter in live use.



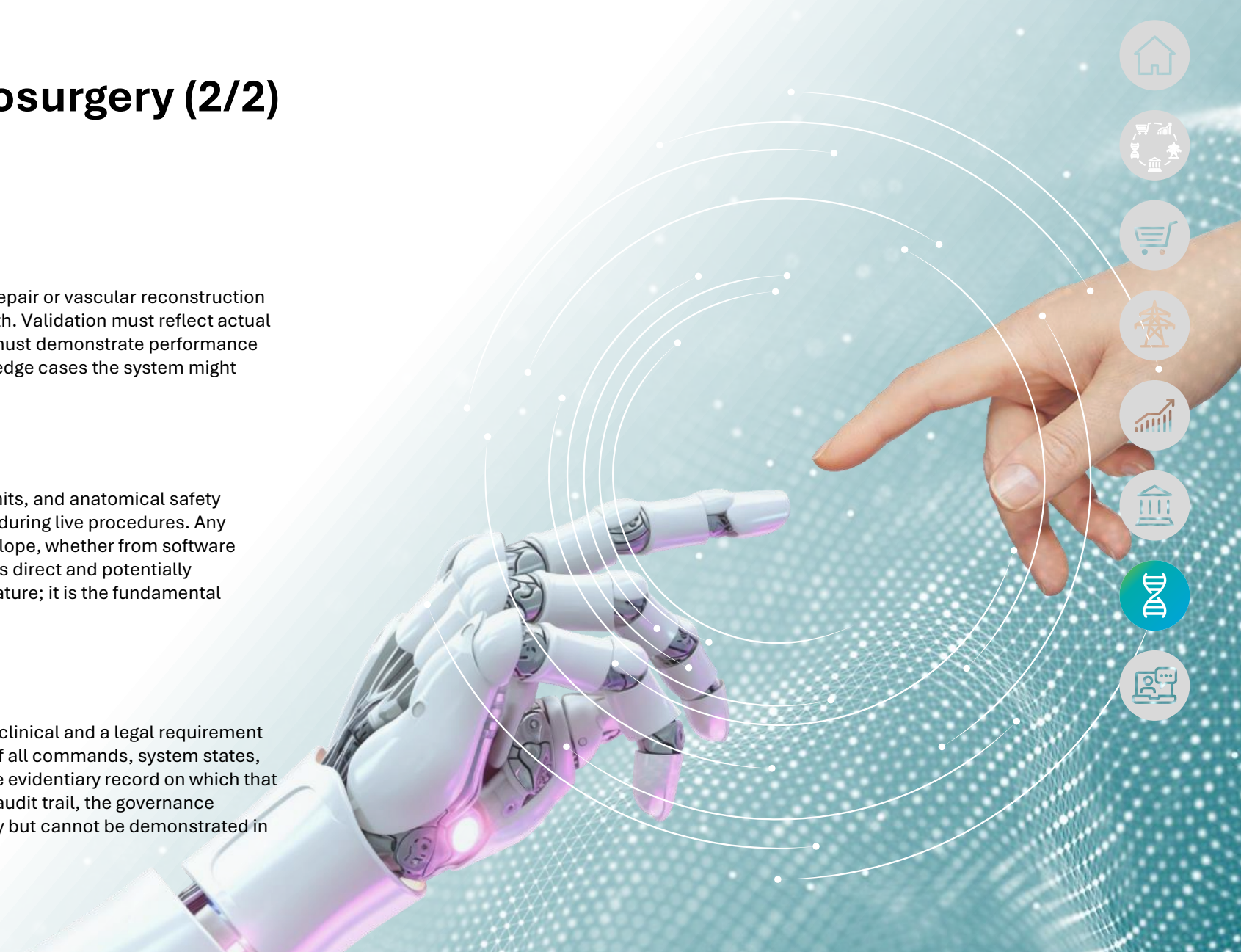
### Safe and secure

The safety envelope—movement boundaries, force limits, and anatomical safety zones—is the primary mechanism protecting patients during live procedures. Any failure that causes the system to act outside that envelope, whether from software error, sensor malfunction, or external compromise, has direct and potentially irreversible consequences. Fail-safe design is not a feature; it is the fundamental condition for clinical deployment.



### Responsible and accountable

Surgeon accountability for patient outcomes is both a clinical and a legal requirement that the system's design must actively support. Logs of all commands, system states, and force feedback throughout each procedure are the evidentiary record on which that accountability rests. Without a complete and reliable audit trail, the governance principle (“surgeon retains authority”) applies in theory but cannot be demonstrated in practice.



# Service robots for hospital operations (1/2)

## Autonomous execution of routine logistics

### DESCRIPTION

Robots perform repetitive service tasks in hospitals, such as transporting medications, meals, linens, and supplies. These systems navigate human environments and interact with staff and patients. Robots physically move items through corridors, elevators, and clinical areas while making real-time route and task decisions.

### ISSUE/OPPORTUNITY

Hospitals face labor shortages and high turnover in repetitive service roles. Manual task execution consumes skilled staff time, nurses and porters spend significant portions of shifts transporting medications, lab samples, linens, and supplies between nursing stations, pharmacies, laboratories, and patient rooms.

The opportunity is to deploy AMRs to automate routine point-to-point logistics, freeing clinical staff for direct patient care. On-robot Physical AI enables resilient local decision-making (obstacle avoidance, dynamic re-routing, queued handoffs) that preserves service continuity during peak demand or partial network outages.

### HOW PHYSICAL AI CAN HELP

#### Indoor navigation

Robots move safely in human spaces, navigating hallways, elevators, and doorways while mitigating obstacles like patients, visitors, equipment, and staff moving through dynamic hospital environments.

#### Human interaction handling

Robots operate around people, yielding right-of-way, communicating arrival through alerts or displays, and responding appropriately when staff or patients need to access items or clear pathways.

#### Operational reliability

Tasks are executed consistently with predictable delivery times, proper handling of temperature-sensitive medications or fragile items, and automated documentation of completed deliveries.

#### Task execution

Deliveries are completed autonomously as robots transport items between designated locations, confirm delivery through digital handoffs, and return for the next assignment without human intervention.

#### Fleet coordination

Multiple robots operate together, sharing elevator access, coordinating routes to avoid congestion, and balancing workload distribution to maintain service levels during peak demand periods.

### POTENTIAL BENEFITS

#### Labor relief

Staff focus on higher-value work; for example, nurses can spend more time on patient assessment and care rather than transport and other routine service tasks.

#### Operational efficiency

Routine tasks are automated, eliminating delays from staff unavailability, reducing delivery errors from miscommunication, and maintaining consistent service during peak periods.

#### Service consistency

Tasks are completed reliably with uniform timing and quality regardless of shift staffing levels, employee experience, or competing demands on human workers' attention.

#### Scalability

Operations expand without staffing increases as additional robots handle growing delivery volumes during facility expansions and workload peaks without proportional labor costs.



# Service robots for hospital operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Hospital service robots transporting medications, lab samples, and temperature-sensitive supplies must perform reliably across a live clinical environment that includes crowded corridors, elevator queues, and potential network outages. Delivery failures or unexpected stops can disrupt care workflows, delay medication administration, and create congestion in spaces where patient safety depends on clear access.



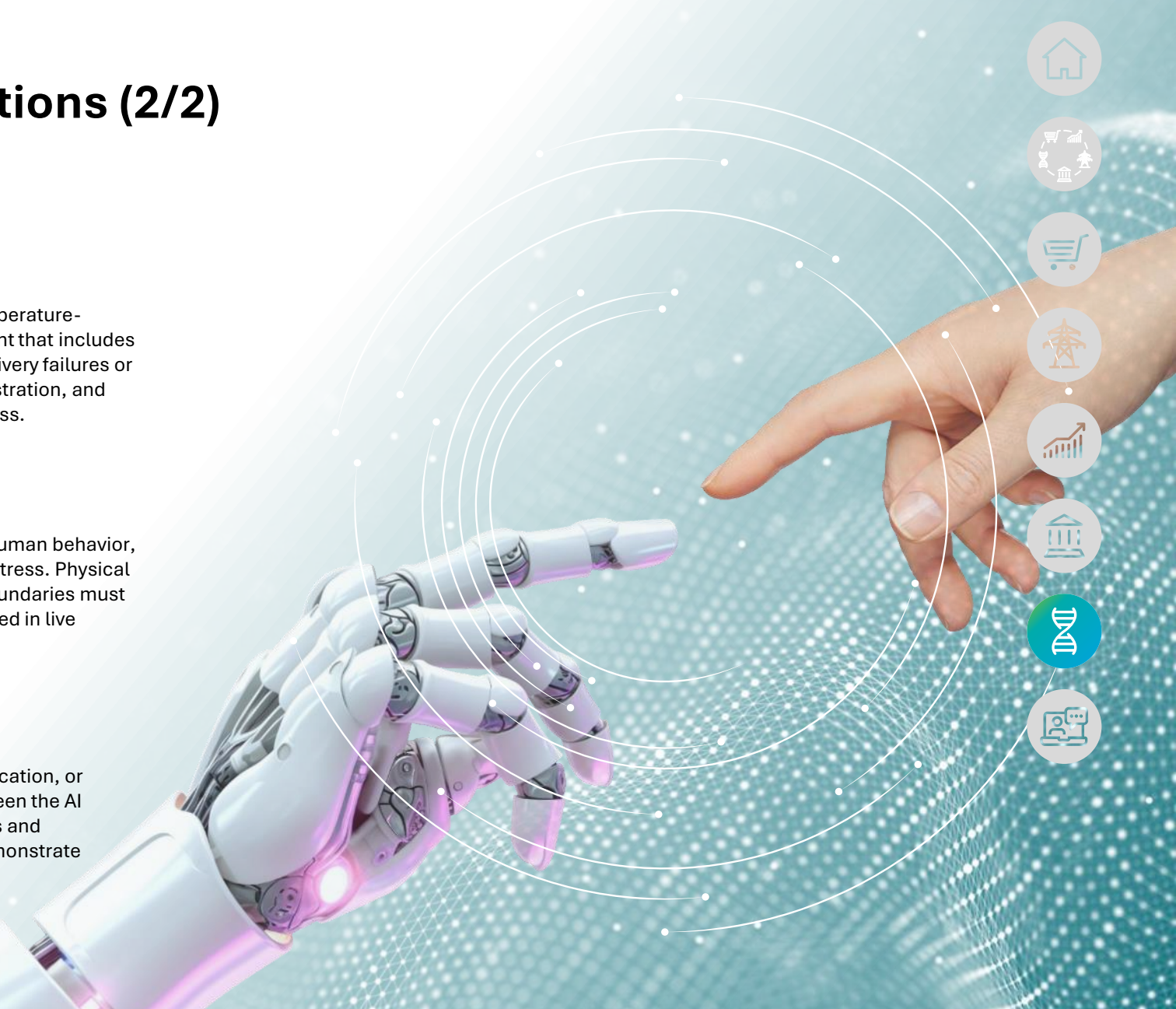
### Safe and secure

Autonomous robots in hospitals must respond safely to unpredictable human behavior, including patients with impaired mobility, children, and individuals in distress. Physical collisions in clinical spaces could cause injury or disrupt care. Safety boundaries must be validated across the full diversity of people and conditions encountered in live hospital environments, not just controlled testing environments.



### Responsible and accountable

When a robot fails to deliver medication on time, delivers to the wrong location, or causes a care disruption, accountability must be clearly allocated between the AI developer, manufacturer, integrator, and hospital operator. Delivery logs and operational records must be sufficient to support investigations and demonstrate compliance with hospital governance and patient care requirements.



# Eldercare and memory care support systems (1/2)

## Addressing critical care gaps through embodied AI

### DESCRIPTION

Humanoid robots deployed in memory care and eldercare settings provide companionship, medication management, and emotional support for individuals with Alzheimer's, dementia, and age-related care needs.

### ISSUE/OPPORTUNITY

Aging populations are pushing care needs beyond available caregiving capacity, leaving facilities and families struggling with staffing shortages, medication adherence, and meaningful engagement for patients with cognitive decline. Overburdened caregivers both professional and familial cannot provide continuous supervision or companionship, while isolation and medication errors accelerate health risks.

Humanoid AI assistants offer a path forward, they provide consistent, support for routine monitoring, medication reminders, and engagement—while keeping caregivers firmly in control of clinical and judgment-intensive decisions. By extending care continuity without replacing human empathy or accountability, Physical AI helps stabilize care quality, reduce caregiver burden, and improve patient well-being at scale.

### HOW PHYSICAL AI CAN HELP

#### Emotional connection & companionship

Humanoid form factor helps enable elderly individuals to personify and connect with the AI assistant, leveraging the innate human tendency to bond with physical objects. The robot engages in conversations on topics the patient raises, providing stimulation and reducing isolation.

#### Governed intervention

Escalation to caregivers when thresholds are crossed. No autonomous clinical decision-making.

#### Medication compliance & health monitoring

AI monitors medication schedules and reminds patients to take prescribed medications at appropriate times. System tracks compliance and can alert caregivers to missed doses or concerning patterns.

#### Consistent, reliable presence

Unlike human caregivers managing multiple patients or working shifts, the AI assistant provides continuous availability. Patients benefit from predictable, patient interaction without fatigue or irritability.

### POTENTIAL BENEFITS

#### Addresses eldercare labor shortages

Augments overstretched caregiving workforce by handling routine monitoring, companionship, and medication management tasks. Enables human caregivers to focus on tasks requiring judgment and empathy.

#### Improves patient outcomes

Consistent monitoring and medication compliance support reduce adverse health events. Emotional engagement and mental stimulation may slow cognitive decline for dementia patients.

#### Reduces caregiver burden

Family members and professional caregivers gain peace of mind from continuous patient monitoring. System handles routine reminders and engagement, reducing stress on human caregivers.

#### Improved medication adherence

Timely reminders and compliance tracking reduce missed doses and escalation risk, with alerts routed to caregivers when needed.



# Eldercare and memory care support systems (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

Robots monitoring elderly patients with cognitive decline collect highly sensitive data—medication adherence, behavioral patterns, and indicators of deterioration—about individuals who may lack capacity to consent. Strict governance is essential, with meaningful consent processes involving family members or legal guardians and clear limits on data access, retention, and secondary use.



### Safe and secure

Humanoid robots in close proximity to elderly patients with cognitive decline and impaired mobility must behave predictably under all conditions—including when patients become confused, agitated, or interact physically in unexpected ways. Safety boundaries must be validated specifically for memory care populations, whose responses cannot be assumed to mirror those of other user groups.



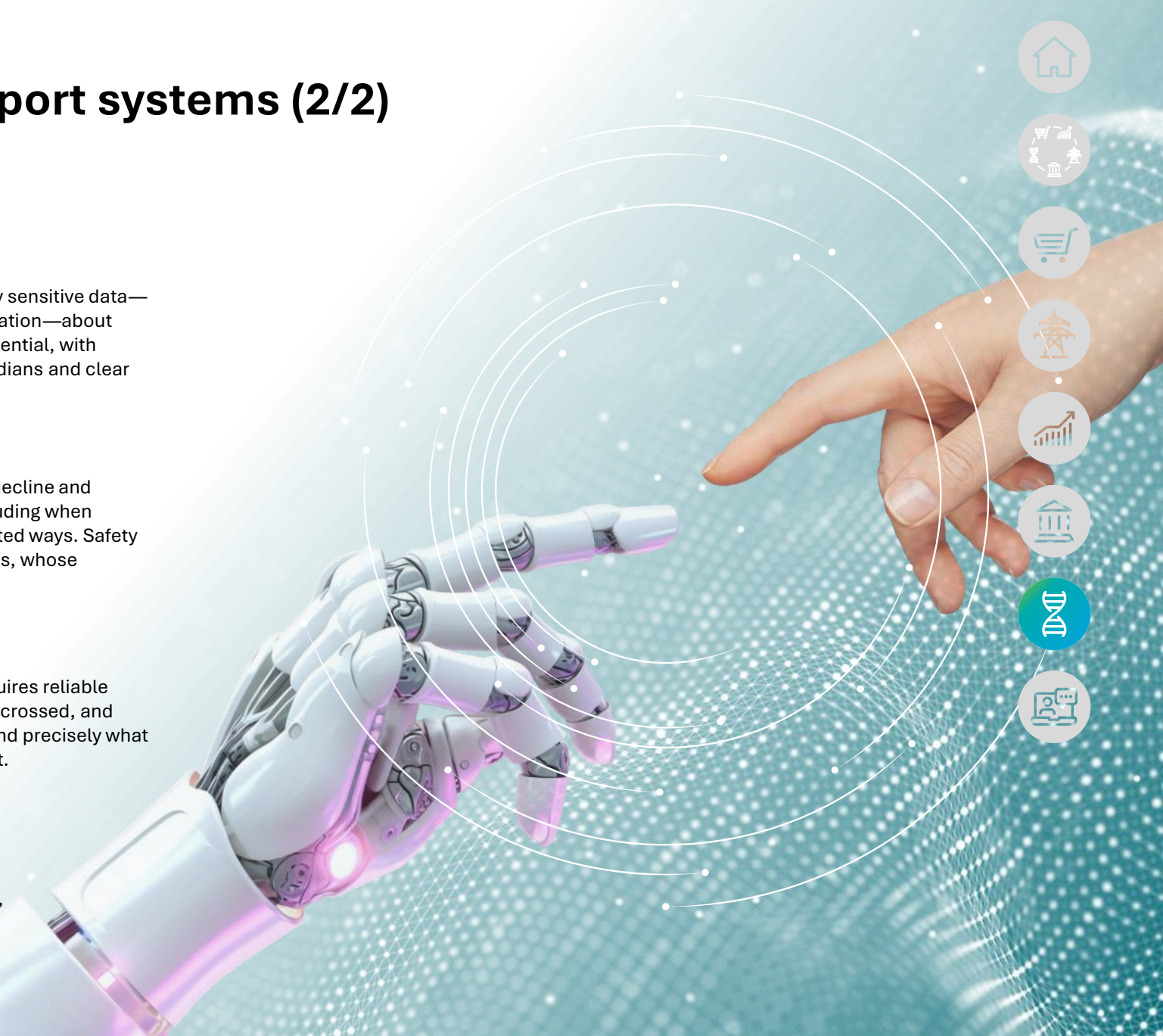
### Responsible and accountable

Caregivers must retain full clinical accountability. In practice, this requires reliable escalation protocols that alert human caregivers when thresholds are crossed, and governance frameworks ensuring families and care facilities understand precisely what the robot does autonomously versus what triggers human involvement.



### Transparent and explainable

Families and care facilities deploying robots with cognitively impaired patients must understand what the system does, what data it collects, and how it escalates concerns—since patients themselves may lack capacity to assess these things. Transparency obligations fall on deploying organizations, not just on individual users, given the vulnerability of the population being served.



# Cleanroom manufacturing automation (1/2)

## Precision operations in sterile environments

### DESCRIPTION

Robotic systems perform material handling, assembly, inspection, and localized environmental monitoring in pharmaceutical and biologics cleanroom spaces, reducing human presence in sterile zones while maintaining strict contamination control and validated quality standards.

### ISSUE/OPPORTUNITY

Pharmaceutical and biologics manufacturing requires sterile production environments where contamination control is critical, and quality failures carry massive costs. Cleanroom operations are labor-intensive, requiring workers to don extensive protective equipment, follow rigorous gowning procedures, and work in uncomfortable controlled environments with restricted airflow and temperature regulation. Human presence introduces contamination risk despite protective protocols, as people generate particulates through movement, breathing, and skin shedding even when fully covered.

Quality failures in sterile manufacturing trigger costly batch rejections that can reach millions of dollars, regulatory investigations that threaten facility operating licenses, and potential patient safety issues that create liability exposure.

Current Physical AI systems lack cleanroom certifications and ISO collaborative robotics standards for sterile environments, with updated standards expected in Q3 2028.

These automated cleanroom applications—especially post-certification can deliver substantial value in high-margin sterile production settings where quality and consistency are paramount and were reducing human presence directly reduces contamination risk while maintaining production capacity.

### HOW PHYSICAL AI CAN HELP

#### Certified cleanroom robotics

Purpose-designed systems that meet cleanroom classification standards perform material handling, assembly, and inspection tasks in sterile zones without introducing particulate or biological contamination, using specialized materials and designs validated for controlled environments.

#### Collaborative sterile operations

Physical AI in cleanroom manufacturing is optimized for minimal human presence to reduce contamination risk. Over time, evolving safety and cleanroom standards may enable limited, governed human-robot collaboration for exception handling and complex tasks—but this remains secondary to automation-first sterile operations.

#### AI-driven quality monitoring

Advanced vision systems with closed-loop process control detect anomalies in real-time and automatically adjust parameters to maintain sterile processing conditions and product quality, identifying deviations before they cause batch failures.

### POTENTIAL BENEFITS

#### Contamination risk reduction

Minimizing human presence in sterile zones reduces particulate generation and biological contamination while maintaining consistent environmental controls and product quality.

#### Enhanced product consistency

Robotic systems reduce human variability in repetitive tasks, delivering more consistent results in high-value sterile production where quality failures trigger costly batch rejections and regulatory scrutiny.

#### Regulatory compliance support

Automated documentation, process traceability, and consistent adherence to validated procedures strengthen an operation's regulatory compliance posture in heavily scrutinized pharmaceutical manufacturing.



# Cleanroom manufacturing automation (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Robotic systems in pharmaceutical cleanrooms must perform reliably within validated sterile environments where any deviation—a dropped component, a missed quality check, or an uncontrolled movement—can contaminate a batch and trigger regulatory investigation. Reliability standards must meet pharmaceutical validation requirements, not just general industrial robotics benchmarks.



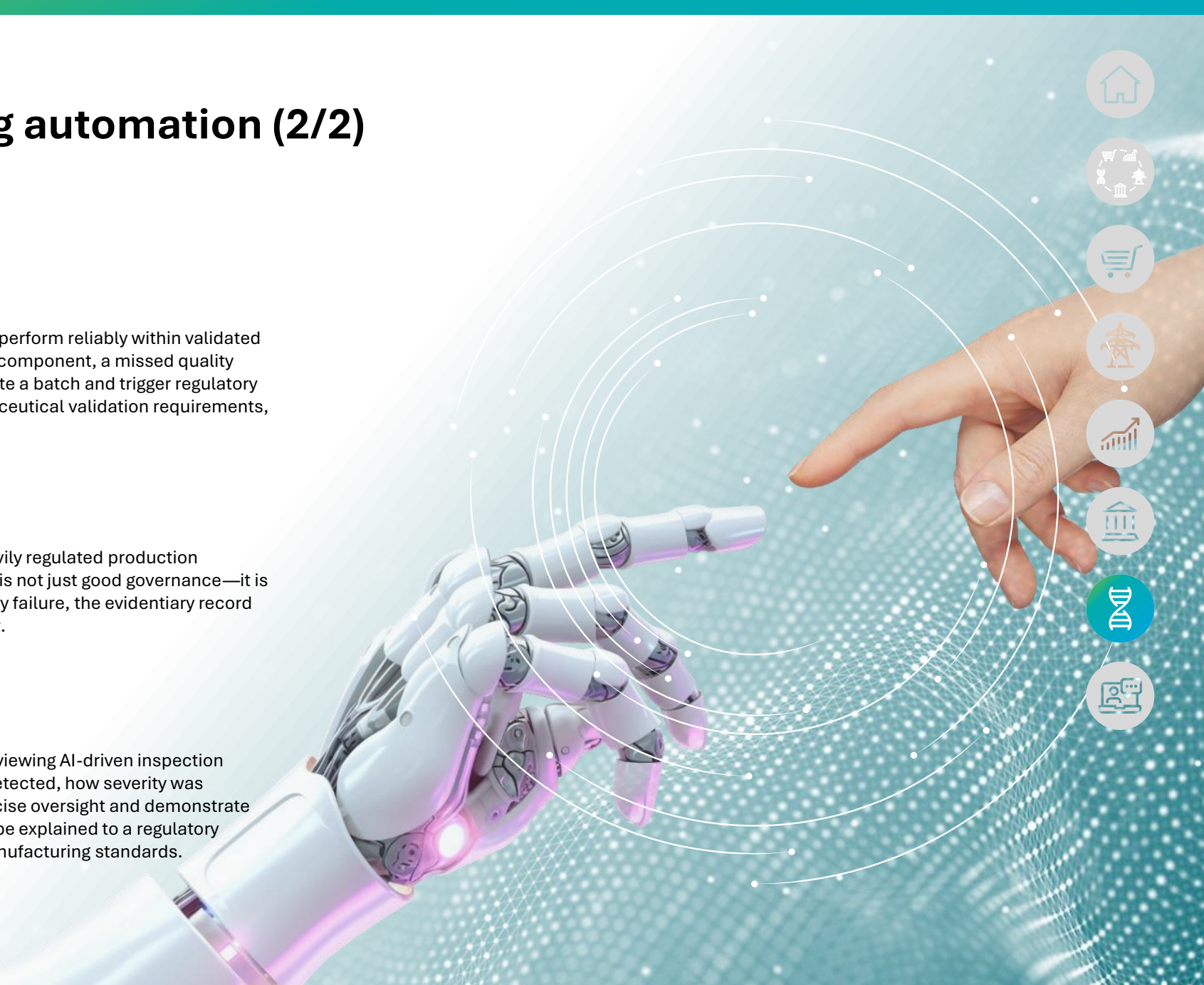
### Responsible and accountable

Pharmaceutical manufacturing is one of the most heavily regulated production environments in the world. The audit trail requirement is not just good governance—it is a regulatory obligation. When AI contributes to a quality failure, the evidentiary record must be sufficient to satisfy FDA or equivalent scrutiny.



### Transparent and explainable

Quality assurance teams and regulatory inspectors reviewing AI-driven inspection decisions need to understand what anomalies were detected, how severity was assessed, and what actions were taken—both to exercise oversight and demonstrate compliance. Opaque AI quality decisions that cannot be explained to a regulatory inspector are not compatible with pharmaceutical manufacturing standards.



# The Technology, Media & Telecommunications Physical AI Dossier



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# Summary: The Technology, Media & Telecommunications Physical AI Dossier

For the industries that build and operate the digital infrastructure of the modern economy, Physical AI is both a product and an operational imperative



Technology, media, and telecommunications companies occupy a distinctive position in the Physical AI landscape: they are both its architects and its operators. TMT companies design and manufacture the chips, sensors, edge hardware, and network infrastructure on which Physical AI systems run. They also operate some of the most complex and consequential physical infrastructure in the modern economy (e.g., data centers, telecommunications networks, semiconductor fabrication facilities) that Physical AI can help manage more effectively. This dual role gives the sector an unusually comprehensive stake in the Physical AI transition.

On the infrastructure operations side, scale and complexity are the defining characteristics. A hyperscale data center manages thermal, power, and hardware conditions in real time across thousands of interdependent systems. A semiconductor fabrication facility maintains environmental tolerances measured in nanometers across hundreds of process steps. The common thread is that human labor and oversight alone cannot operate, monitor, and manage these environments at the speed and granularity that optimal performance requires.

TMT is also the sector most directly exposed to the energy implications of the AI era<sup>10</sup>. Data centers and network infrastructure already account for a significant and growing share of global electricity consumption, and that share may increase as AI workloads expand. Physical AI that can optimize energy use across these systems is not just operationally valuable; it is a material business and sustainability imperative.

The governance stakes in this sector are amplified by interdependency. TMT infrastructure is the foundation on which other sectors' digital operations run. Security vulnerabilities in AI-controlled physical systems, or reliability failures in AI-managed networks, do not stay contained within the TMT sector; they propagate outward. This makes the trustworthy AI dimensions of transparency, security, and reliability especially consequential for TMT companies, whose failures have a blast radius that extends far beyond their own operations.



# Network sensing, assurance and autonomous recovery (1/2)

## AI-supported reliability for national networks

### DESCRIPTION

Machine learning and agentic AI systems analyze telemetry from network assets such as switches, routers, radio units, antennas, and fiber to detect faults, localize root causes, and assess severity. This is complemented by drone-based inspections that capture visual and sensor data from hard-to-reach infrastructure, with AI correlating physical observations and network signals to improve diagnosis. Human operators validate insights and execute remediation actions, ensuring control and compliance.

### ISSUE/OPPORTUNITY

Telecommunications networks are large, complex physical systems where localized faults can quickly cascade into widespread service disruption. Manual monitoring struggles to keep pace with the scale and velocity of telemetry data, resulting in delayed detection and prolonged outages, conditions made less tolerable by strict regulatory requirements and high customer expectations for uptime. Network operations centers receive thousands of alerts daily from distributed infrastructure spanning cell towers, fiber nodes, data centers, and customer premises equipment. Operators should distinguish genuine failures from routine fluctuations and trace root causes amid cascading alarms, where a single physical issue such as damaged fiber or a failing router can trigger hundreds of downstream alerts. Drone-based inspections are used to survey towers, antennas, and fiber routes, capturing visual and sensor data from hard-to-reach assets. Physical AI correlates this drone inspection data with network telemetry to identify incidents earlier, pinpoint root causes more clearly, and support faster resolution while keeping humans in control and ensuring regulatory compliance.

### HOW PHYSICAL AI CAN HELP

#### Telemetry-based fault detection

AI systems continuously monitor telemetry from physical network equipment to detect abnormal behavior indicating faults before they cause widespread service impact.

#### Cross-network correlation

Signals from multiple network components are analyzed together to identify where issues originate, filtering out cascading alarms that merely reflect downstream effects.

#### Severity and impact assessment

AI helps classify incidents based on scale and potential customer impact, enabling operators to prioritize responses to the most critical failures first.

#### Root-cause identification support

Likely causes are suggested based on observed network behavior and correlated with drone-based visual inspections of physical assets, accelerating diagnosis by highlighting probable failure points for targeted operator investigation.

#### Remediation recommendation

AI proposes corrective actions for operator review such as rerouting traffic, restarting equipment, or dispatching field technicians to specific locations.

#### Human-in-the-loop execution

Actions are validated and executed by operations teams, maintaining accountability and compliance with regulatory requirements for network changes.

### POTENTIAL BENEFITS

#### Reduced outage duration

Earlier detection and diagnosis shorten incidents by enabling faster operator response and reducing time spent on manual root cause analysis.

#### SLA protection

Improved compliance can lower penalty risk by preventing service level agreement violations through proactive incident management and faster restoration.

#### Operational focus

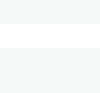
Teams spend less time triaging alerts and correlating symptoms, as AI combines network telemetry with drone-based inspection data from physical assets, to help enable network engineers to focus on resolution rather than diagnosis.

#### Faster fault isolation

Operators can identify and localize issues more quickly, reducing mean time to repair and minimizing the duration of service outages when failures do occur.

#### Lower field maintenance costs

Proactive maintenance can reduce emergency repair visits by preventing urgent failures, reducing overtime labor and expedited parts shipments.



# Network sensing, assurance and autonomous recovery (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

AI fault detection systems must distinguish genuine failures from routine fluctuations reliably. False positives waste operator attention, while false negatives allow faults to cascade into widespread outages. Reliable operation across a diverse set of network equipment, traffic patterns, and failure modes is essential.



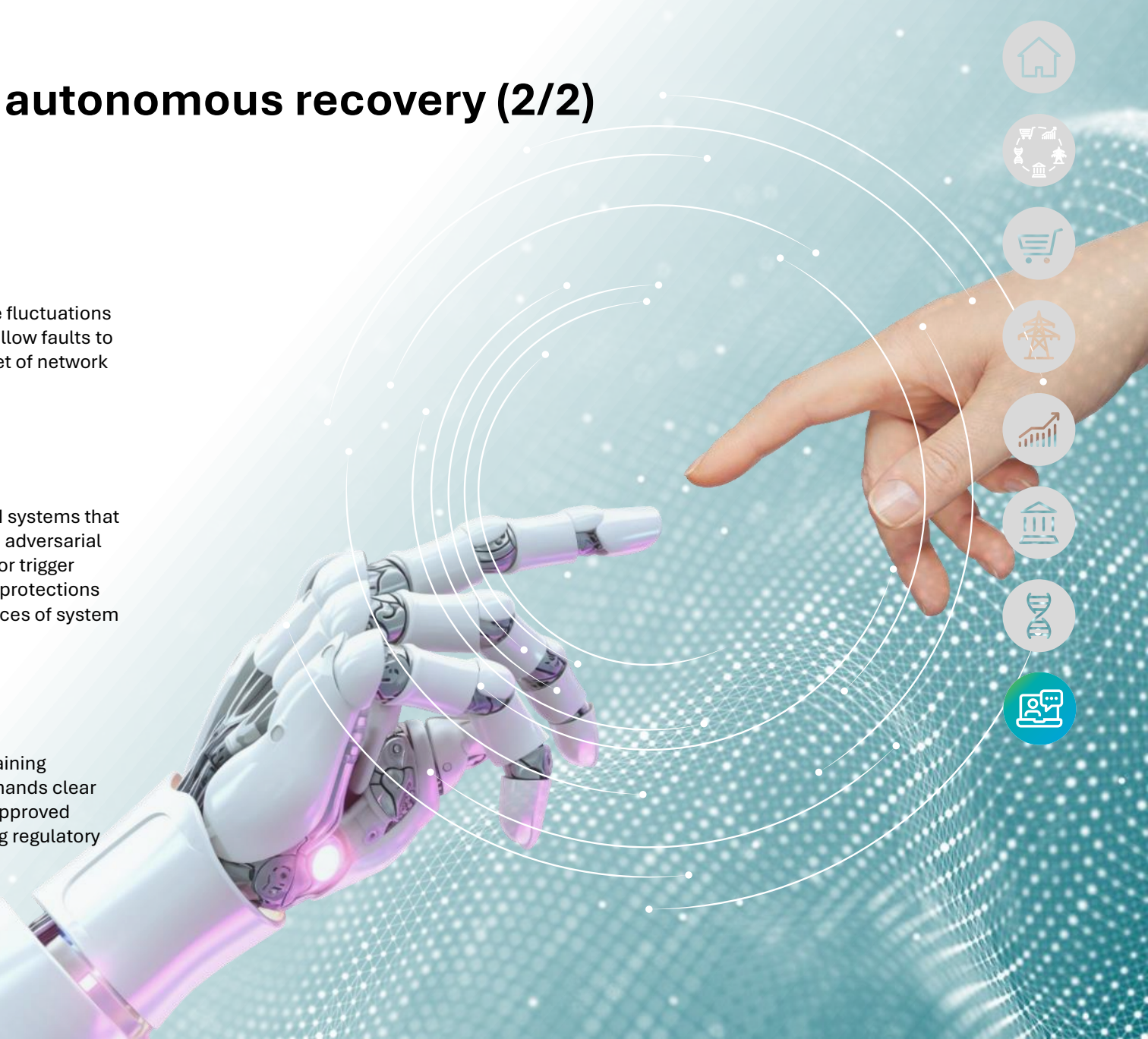
### Safe and secure

Telecommunications networks are critical national infrastructure, and AI systems that recommend traffic rerouting or equipment interventions are a high-value adversarial target. A compromised detection system could suppress genuine alerts or trigger unnecessary interventions, causing service disruption at scale. Security protections must reflect the critical infrastructure context and the public consequences of system compromise.



### Responsible and accountable

All remediation actions require human validation and execution—maintaining accountability and regulatory compliance for network changes. This demands clear documentation of what the AI detected, what was recommended, who approved execution, and what outcome occurred, creating an audit trail supporting regulatory reporting, SLA dispute resolution, and post-incident investigation.



# AMR-enabled Physical AI for predictive quality control (1/2)

## Predictive maintenance insights for operators

### DESCRIPTION

Physical AI systems analyze trends across the end-to-end infrastructure value chain from component quality and deployment conditions to network and equipment performance manufacturing facilities, and to predict and prevent service-impacting issues before they occur. Autonomous Mobile Robots act as mobile inspection and sensing platforms within data centers, network operations environments, capturing high-frequency visual, environmental, and asset-health data, reason over in-process signals in real time, and trigger corrective actions before defects propagate downstream.

### ISSUE/OPPORTUNITY

Quality control today is largely reactive, identifying defects after materials, machine time, and labor have already been consumed—driving scrap, rework, delays, and margin erosion. The core limitation is the lack of real-time visibility into upstream indicators such as material variation, equipment drift, and environmental change. Physical AI addresses this by continuously analyzing patterns across materials, processes, equipment, and environment, with Autonomous Mobile Robots serving as mobile, in-line sensing and inspection platforms across the factory floor. Equipped with vision systems, sensors, and edge AI, AMRs capture high-frequency, in-process quality and equipment data that is fused with production and material telemetry, enabling closed-loop AI systems to predict quality risks early and stabilize production before defects occur.

### HOW PHYSICAL AI CAN HELP

#### Predictive analytics across supply chain

AI systems continuously monitor material quality at intake, tracking variations and correlating them with downstream production outcomes to predict potential defects before materials enter production.

#### Real-time process optimization

Machine learning models analyze equipment performance data, environmental conditions, and production parameters to detect early signs of process drift and automatically trigger corrective adjustments.

#### Automated robot reprogramming

Based on predictive insights, AI systems autonomously adjust robot parameters, tooling settings, or process flows to compensate for predicted variations, eliminating manual intervention cycles.

### POTENTIAL BENEFITS

#### Defect prevention and scrap reduction

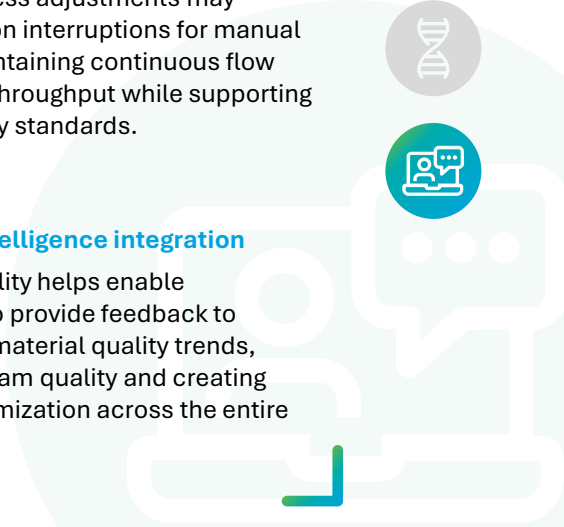
Predictive AI, supported by AMR-based in-line inspection, detects quality issues early in TMT manufacturing lines, to help prevent defects from spreading and reducing scrap, rework, and wasted materials.

#### Optimized production efficiency

Automated process adjustments may reduce production interruptions for manual corrections, maintaining continuous flow and maximizing throughput while supporting consistent quality standards.

#### Supply chain intelligence integration

End-to-end visibility helps enable manufacturers to provide feedback to suppliers about material quality trends, improving upstream quality and creating closed-loop optimization across the entire supply chain.



# AMR-enabled Physical AI for predictive quality control (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Predictive quality systems must perform reliably across continuous production variability. A system that misses early drift indicators allows defects to propagate through downstream processes, while a system that generates excessive false alerts disrupts production unnecessarily. Both failure modes erode the operational trust on which closed-loop automation depends.



### Responsible and accountable

If AI can autonomously adjust robot parameters and process flows, organizations must define clear governance boundaries specifying which adjustments can be made autonomously and which require human validation before execution. This helps prevent unreviewed AI decisions from affecting product quality at scale.



### Transparent and explainable

To validate the model's reasoning and detect drift, process engineers need to understand what upstream signals drove a quality risk prediction and what corrective adjustment was applied. Closed-loop systems that adjust processes without explainable reasoning make it difficult to identify systematic errors before they affect product quality or propagate downstream.



# Sustainable network operations (1/2)

## Energy-aware control of physical networks

### DESCRIPTION

Physical AI systems sense real-time conditions across distributed physical assets—radios, power units, cooling systems, and edge equipment and autonomously adjust their operating states at the edge. Decisions are executed locally within safety bounds, enabling energy-efficient operation of large-scale physical networks without compromising reliability.

### ISSUE/OPPORTUNITY

Telecom networks consume significant energy, driving both operating costs and carbon exposure. Static energy management wastes power during periods of low demand, as cellular base stations, data centers, and network equipment often run at full capacity regardless of real-time traffic. Edge-deployed IoT sensors, vision-enabled monitoring systems, and wearable devices used by field technicians provide granular visibility into equipment utilization, environmental conditions, and on-site activity. Network operators face growing pressure to meet regulatory sustainability targets while controlling energy costs that represent a major share of operational spend. Physical AI leverages data from edge devices, IoT sensors, and vision-based systems to dynamically adjust network operations in real time, scaling power usage up or down based on actual demand patterns while maintaining service quality and regulatory compliance.

### HOW PHYSICAL AI CAN HELP

#### Edge-level physical arbitration

Physical AI resolves conflicts between competing objectives (energy, performance, safety) locally—e.g., deciding whether to throttle, sleep, or reroute power when conditions degrade.

#### Physical degradation-aware control

AI adapts energy behavior based on equipment age, wear, and thermal stress, reducing long-term physical damage—not just short-term energy use.

#### Sensor-driven micro-actuation

Continuous feedback from temperature, vibration, and load sensors enables fine-grained physical adjustments (fan speeds, power draw, cooling flow) rather than coarse system-wide controls.

#### Human supervision

Operations remain controlled by network engineers who set policies, review AI recommendations, and maintain override authority to help ensure service commitments are met.

### POTENTIAL BENEFITS

#### Extended asset lifespan

Energy decisions informed by physical stress signals may reduce premature component failure across equipment fleets.

#### Scalable cross-site consistency

The same physical control logic can apply across factories, networks, data centers, or plants despite different layouts and equipment mixes.

#### Reduced human intervention in physical tuning

Engineers shift from manual parameter tuning to policy-level oversight as AI handles continuous physical adjustments.

#### Reputational protection

Environmental risk is mitigated as operators demonstrate measurable progress on sustainability goals, protecting brand reputation among environmentally conscious customers and stakeholders.



# Sustainable network operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Physical AI that autonomously adjusts power states, cooling flows, and operating parameters across distributed network infrastructure must perform reliably under all conditions—including equipment aging, unexpected load spikes, and sensor degradation. Incorrect energy adjustments can compromise service quality or accelerate physical wear on the very assets the system is designed to protect.



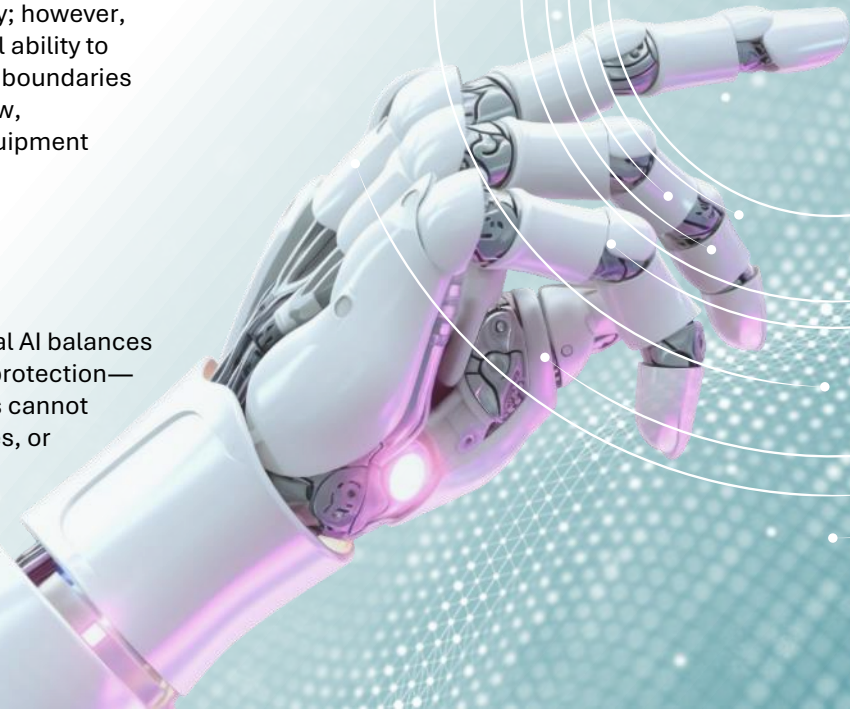
### Responsible and accountable

Network engineers theoretically retain policy-setting and override authority; however, as AI handles increasing volumes of continuous adjustments, the practical ability to review individual decisions is diminished. Organizations must define clear boundaries between autonomous edge actions and decisions requiring engineer review, maintaining clear audit trails to support accountability when service or equipment outcomes are disputed.



### Transparent and explainable

Network engineers setting energy policies need to understand how Physical AI balances competing objectives—energy efficiency, service quality, and equipment protection—and why specific adjustments were made. Without this visibility, engineers cannot calibrate policies effectively, identify misconfigured optimization objectives, or maintain true oversight of systems making continuous physical changes.





# Data center operations (1/2)

## Anticipatory control of data-center environments

### DESCRIPTION

Physical AI systems may forecast hardware degradation and thermal stress in data centers and coordinate maintenance actions with workload migration to reduce failure risk.

### ISSUE/OPPORTUNITY

In the TMT sector, data centers are complex physical systems where localized issues can quickly cascade across compute, power, and cooling infrastructure. Traditional planning and monitoring struggle to capture the dynamic interplay between workload intensity, thermal behavior, and hardware aging, often reacting only after hotspots, performance degradation, or failures impact service availability. Static thresholds frequently miss early stress signals as servers age, cooling systems lag demand, and power components experience uneven loads. Data center digital twins overlay facilities design, power and cooling systems, and network architecture to simulate “what-if” scenarios, enabling operators to anticipate thermal, capacity, and performance impacts of build-out or configuration changes before making physical interventions. Physical AI enables a shift to predictive, infrastructure-aware operations by continuously analyzing physical signals to anticipate risk earlier. This helps enable operators to proactively migrate workloads, rebalance thermal loads, or schedule targeted maintenance—under strict governance models that keep humans in control—improving resilience, uptime, and energy efficiency at scale.

### HOW PHYSICAL AI CAN HELP

#### Thermal and stress prediction

AI models forecast temperature and load conditions that increase failure risk by analyzing patterns in cooling system performance, compute workload distribution, and environmental factors that create thermal stress on physical infrastructure.

#### Maintenance coordination support

AI assists in aligning physical interventions with operational constraints, helping planners schedule hardware replacement, cooling system maintenance, and infrastructure upgrades during periods that minimize business impact.

#### Guardrailed decision support

AI assists operators rather than acting autonomously.

#### Hardware degradation forecasting

Signals from physical components are used to anticipate end-of-life events, identifying at-risk servers, storage devices, and network equipment. AI assists operators rather than acting autonomously, providing recommendations and analysis while humans retain authority over all actions that could affect availability, performance, or risk exposure.

#### Scenario evaluation

Potential actions are evaluated for risk and impact before execution, modeling the consequences of workload shifts, maintenance windows, or equipment changes to not create new problems while addressing identified risks.

#### Human escalation pathways

Important decisions remain with data-center operators, to help ensure that knowledge and accountability stay with qualified personnel who understand business context and can assess trade-offs that AI systems cannot fully evaluate.

### POTENTIAL BENEFITS

#### Reduced unplanned outages

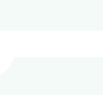
Higher availability through earlier identification and proactive intervention before hardware failures or thermal events may force emergency shutdowns or trigger cascading failures across interconnected infrastructure.

#### Asset longevity

Improved lifecycle management by reducing exposure to stress conditions that accelerate hardware degradation, extending useful equipment life and reducing premature replacement costs.

#### Operational resilience

Better preparedness for incidents through predictive analysis that helps enable advance planning, resource staging, and coordinated response strategies rather than reactive crisis management when failures occur.



# Data center operations (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Physical AI that forecasts hardware degradation and thermal stress must perform reliably across the dynamic interplay of workload intensity, cooling behavior, and equipment aging. A system that misses early stress signals may allow conditions to develop until failures force emergency shutdowns, negating the predictive value that justified deployment.



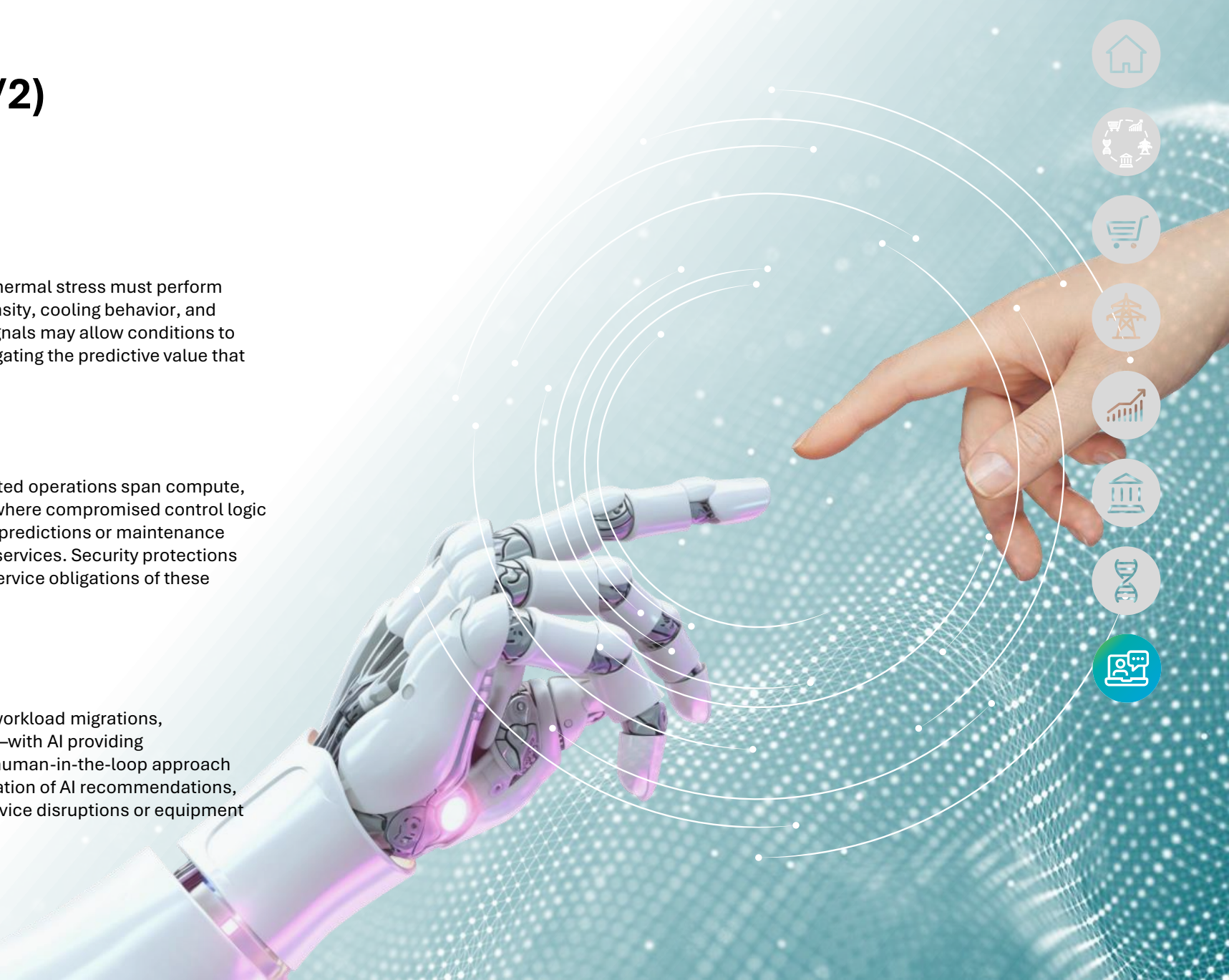
### Safe and secure

Data centers are critical infrastructure whose AI-assisted operations span compute, power, and cooling systems—a broad attack surface where compromised control logic could trigger cascading failures. Manipulated thermal predictions or maintenance scheduling could cause outages affecting dependent services. Security protections must match the operational criticality and customer service obligations of these facilities.



### Responsible and accountable

Humans retain control of all consequential actions—workload migrations, maintenance scheduling, and infrastructure changes—with AI providing recommendations for operator review. However, this human-in-the-loop approach must be adhered to in practice. Consistent documentation of AI recommendations, human decisions, and outcomes is essential when service disruptions or equipment failures require investigation.



# Semiconductor manufacturing orchestration (1/2)

## Fleet-level coordination of fab robots

### DESCRIPTION

Physical AI systems coordinate Collaborative Robot fleets across semiconductor fabrication facilities and adjacent downstream operations (e.g., testing, packing, and quality inspection), dynamically assigning tasks such as transport, inspection, and handling based on production needs.

### ISSUE/OPPORTUNITY

Semiconductor fabrication facilities operate with hundreds of robots performing important tasks, yet traditional systems assign each robot to fixed functions regardless of real-time production needs. Transport robots move wafers between processing stations, inspection robots check for defects, and handling robots load and unload equipment, each following predetermined routes and schedules. When production priorities shift or equipment becomes available ahead of schedule, fixed robot assignments create bottlenecks as idle robots in one area cannot assist with backlogs elsewhere. Facilities purchase additional robots to help enable sufficient capacity for peak demands in each function, driving capital costs higher than necessary if robots could be reassigned dynamically. Quality requirements demand strict contamination control and precise handling, constraining how robots can be redeployed without risking yield loss. In downstream test/pack areas, throughput can fluctuate with shift coverage and attendance, creating avoidable output dips even when equipment capacity exists. Robots and humans work side-by-side at 50/50 ratios during training phases. Humans teach procedures during day shifts; robots maintain operations independently during night shifts and workforce gaps.

The opportunity is fleet-level orchestration that dynamically assigns robots to the highest-priority tasks while respecting cleanroom constraints and quality standards, maximizing throughput with fewer total robots.

### HOW PHYSICAL AI CAN HELP

#### Fleet-level reasoning

AI assigns tasks dynamically across the robot fleet, directing available robots to the highest-priority activities based on current production status and bottleneck locations.

#### Reduced fixed roles

Robots are not task-locked, enabling transport robots to assist with inspection or handling when those functions become bottlenecks, increasing overall fleet utilization.

#### Quality preservation

AI respects fab constraints including contamination zones, handling protocols, and equipment compatibility requirements that protect semiconductor yield and reliability.

#### Throughput-aware coordination

Actions align with production goals, prioritizing movements that accelerate wafers through rate-limiting process steps rather than following rigid predetermined schedules.

#### Human governance

Engineers supervise orchestration, setting production priorities, defining quality constraints, and maintaining oversight of robot assignments to help enable fab safety and yield targets.

#### Remote Enablement

AR-based assistants deliver step-by-step, hands-free fab tool maintenance guidance, enable real-time multilingual troubleshooting using live equipment context, and connect engineers to remote experts.

### POTENTIAL BENEFITS

#### Lower capital intensity

Fewer robots may be required as dynamic assignment enables smaller fleets to handle the same production volumes by eliminating idle capacity in underutilized functional areas.

#### Higher throughput

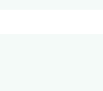
Bottlenecks are reduced through intelligent resource allocation that concentrates robot capacity where production flow is currently constrained, improving wafer cycle times.

#### Operational efficiency

Resources may be better utilized as robots spend more time performing value-adding activities and less time idle, increasing return on expensive automation investments.

#### Quality protection

Standards should be maintained through AI enforcement of contamination protocols, handling procedures, and equipment compatibility rules that prevent quality excursions from dynamic reassignments.



# Semiconductor manufacturing orchestration (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

Fleet-level AI orchestration of robots must perform reliably under real-world production conditions, including equipment changes, yield excursions, and unpredictable robot availability. Orchestration failures that send robots to incorrect zones, create handling conflicts, or violate contamination protocols can directly affect wafer yield in a manufacturing environment where quality failures are extremely costly.



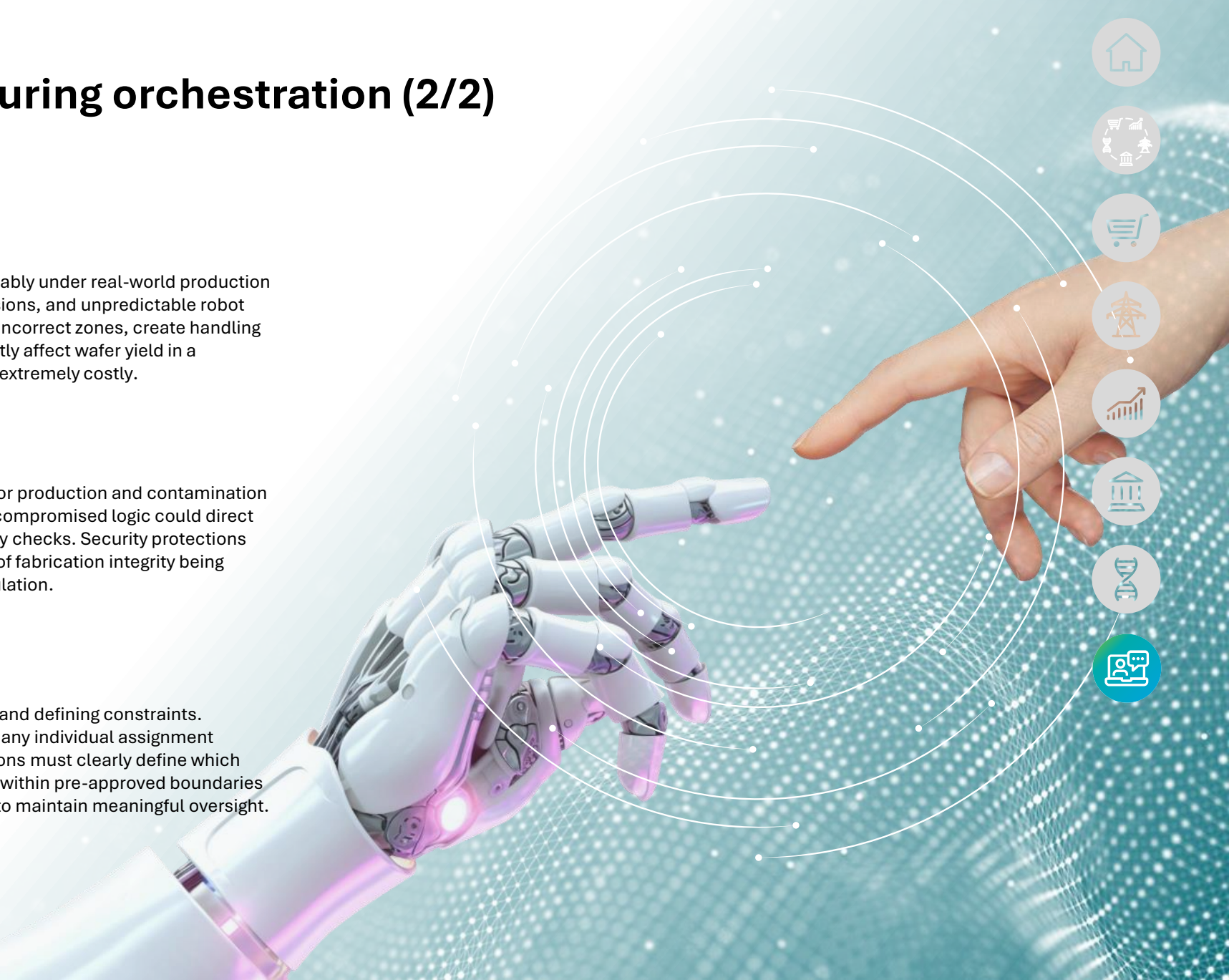
### Safe and secure

Integration of AI robot orchestration into semiconductor production and contamination control systems creates a large attack surface where compromised logic could direct robots to violate contamination zones or bypass quality checks. Security protections must reflect the yield and commercial consequences of fabrication integrity being compromised through unauthorized access or manipulation.



### Responsible and accountable

Engineers supervise orchestration by setting priorities and defining constraints. However, dynamic fleet orchestration generates too many individual assignment decisions for engineers to review each one. Organizations must clearly define which assignment decisions can be executed autonomously within pre-approved boundaries and which require human validation before execution to maintain meaningful oversight.



# Ultra-low-latency network protection (1/2)

## Enabling safety-critical instant response through device intelligence

### DESCRIPTION

In telecom networks, next-generation Physical AI embeds GPU (graphics processing units) based intelligence directly at the edge within base stations, network equipment, cameras, and sensors to help enable real-time threat detection without relying on centralized processing. By analyzing signals locally in milliseconds, these systems can identify physical and network threats such as site tampering, unauthorized access, equipment anomalies, or service-impacting attacks, and autonomously take immediate protective actions isolating affected assets, triggering failover, or adjusting operating parameters before issues propagate across the network, while keeping human operators in the oversight loop.

### ISSUE/OPPORTUNITY

In telecom environments, critical safety and security decisions should be made in milliseconds to prevent physical damage, service disruption, or harm to personnel. For example, AI-enabled wearables worn by field technicians at cell sites can continuously monitor proximity to live equipment, restricted zones, or hazardous conditions and trigger immediate alerts or automatic equipment shutdowns if unsafe behavior is detected without relying on network connectivity. Extending this model to the network itself, Physical AI embedded directly into base stations, edge devices, and security sensors can autonomously detect threats such as site tampering, unauthorized access, or abnormal signal behavior and take instant protective actions, including isolating affected network elements, denying access, or activating failover paths. By eliminating transmission latency and enabling on-device decision-making, telecom operators can contain threats at the edge before they cascade across interconnected networks, while retaining human oversight for escalation and compliance.

### HOW PHYSICAL AI CAN HELP

#### On-camera AI processing

Lightweight AI models run directly on smart cameras, processing video streams locally and making threat detection or safety decisions without network transmission, achieving response times under 10 milliseconds enabling intervention that is essentially instantaneous.

#### Device-embedded threat recognition

In telecom networks, AI embedded in edge devices such as site cameras, base stations, and access sensors detects physical and network threats in real time. By processing data locally, these systems can autonomously isolate affected assets, deny access, or trigger failover containing threats instantly without waiting for centralized analysis, while retaining human oversight.

#### Instantaneous alert and action systems

On-device processing enables immediate triggering of alerts, alarms, or automated safety responses (e.g., crane shutdowns, access denials) at machine-speed rather than network-limited speeds, ensuring protective actions occur fast enough to prevent incidents.

### POTENTIAL BENEFITS

#### Life-saving response times

Eliminating transmission latency can help enable AI systems to detect and respond to threats or safety violations fast enough to prevent incidents, potentially saving lives in security and industrial safety applications where milliseconds matter.

#### Network-independent operation

On-device processing can help enable important safety systems function even during network outages or connectivity issues, maintaining protection under conditions without dependence on network infrastructure availability.

#### Scalable safety infrastructure

Distributed intelligence on individual devices can avoid the bandwidth and processing bottlenecks of centralized systems, enabling organizations to deploy comprehensive safety monitoring across large facilities without infrastructure constraints or centralized processing limitations.



# Ultra-low-latency network protection (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Robust and reliable

AI making autonomous protective decisions within milliseconds must perform with extremely high reliability. A false positive that shuts down a cell site or denies access to a field technician creates operational disruption; a false negative that misses a genuine threat allows the incident it was designed to prevent. Both failure modes carry immediate operational consequences.



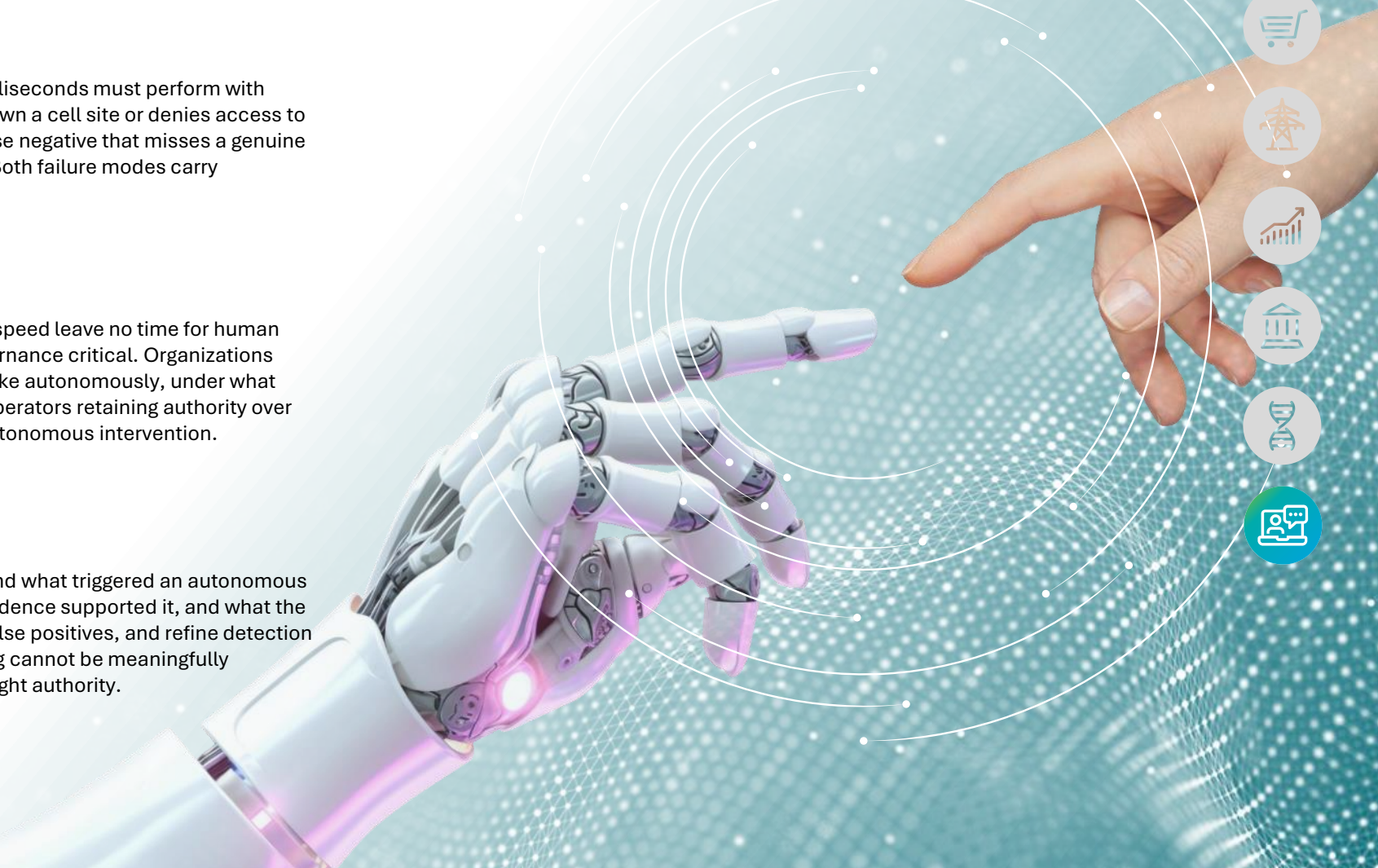
### Responsible and accountable

Autonomous protective actions executed at machine speed leave no time for human review before execution, making pre-deployment governance critical. Organizations must define precisely which actions the system can take autonomously, under what conditions, and with what constraints—with human operators retaining authority over escalation, investigation, and recovery following an autonomous intervention.



### Transparent and explainable

Human operators in the oversight loop must understand what triggered an autonomous protective action—what threat was detected, what evidence supported it, and what the system did—to assess appropriateness, investigate false positives, and refine detection policies. Systems acting without explainable reasoning cannot be meaningfully supervised even when humans nominally retain oversight authority.



# Robotic quadrupeds for stadium operations and sports broadcasting (1/2)

## Agile, AI-driven mobility for live events and complex venues

### DESCRIPTION

Physical AI-powered robotic quadrupeds are being deployed in sports venues to support stadium operations and live broadcasting. These mobile robots combine sensors, cameras, and remote-control capabilities to navigate physical environments, assist security teams with monitoring, and capture stable, dynamic visual content for live sports coverage without disrupting on-ground activities.

### ISSUE/OPPORTUNITY

Large sports venues face operational challenges related to real-time monitoring, safety oversight, and immersive fan engagement. Security teams often need early visibility into crowded or hard-to-access areas without increasing human risk.

Simultaneously, broadcasters seek innovative ways to capture engaging visuals while maintaining stability and reliability in dynamic environments.

Physical AI systems present an opportunity to extend human capabilities through mobile robotic platforms that operate on the ground, interact safely with surroundings, and deliver real-time visual intelligence and coverage.

### HOW PHYSICAL AI CAN HELP

#### Intelligent mobile surveillance

AI-enabled perception allows robotic quadrupeds to navigate venue perimeters, monitor movement patterns, and provide continuous visual feedback, supporting preventive monitoring and operational awareness across large physical spaces.

#### Remote operation and assisted autonomy

On-device processing enables AI-supported control systems help operators guide robots through complex terrain, relay audio-visual information, and perform initial assessments before human teams intervene.

#### Computer vision-based situational detection

Computer vision models process live video feeds to identify unusual activity or objects, to help enable faster alerts and informed decision-making while maintaining human oversight of critical actions.

#### Edge-based execution for reliability

Core perception and mobility decisions run locally on the robot, to help enable continued operation even under network congestion or partial connectivity loss.

### POTENTIAL BENEFITS

#### Enhanced operational visibility

Mobile robots can extend monitoring reach across stadium environments without increasing direct human exposure.

#### Improved safety support

Early situational awareness can help enable informed responses before deploying personnel into uncertain conditions.

#### Richer audience experience

Dynamic, ground-level visuals can add engaging perspectives while maintaining broadcast stability and reliability.



# Robotic quadrupeds for stadium operations and sports broadcasting (2/2)

## MANAGING RISK AND PROMOTING TRUST



### Private

Quadrupeds with cameras and sensors in public sports venues continuously capture video covering large numbers of spectators who have not consented to robotic surveillance. Organizations must define clear policies on what is recorded, how long footage is retained, what prevents repurposing for individual tracking, and how this monitoring is disclosed to event attendees.



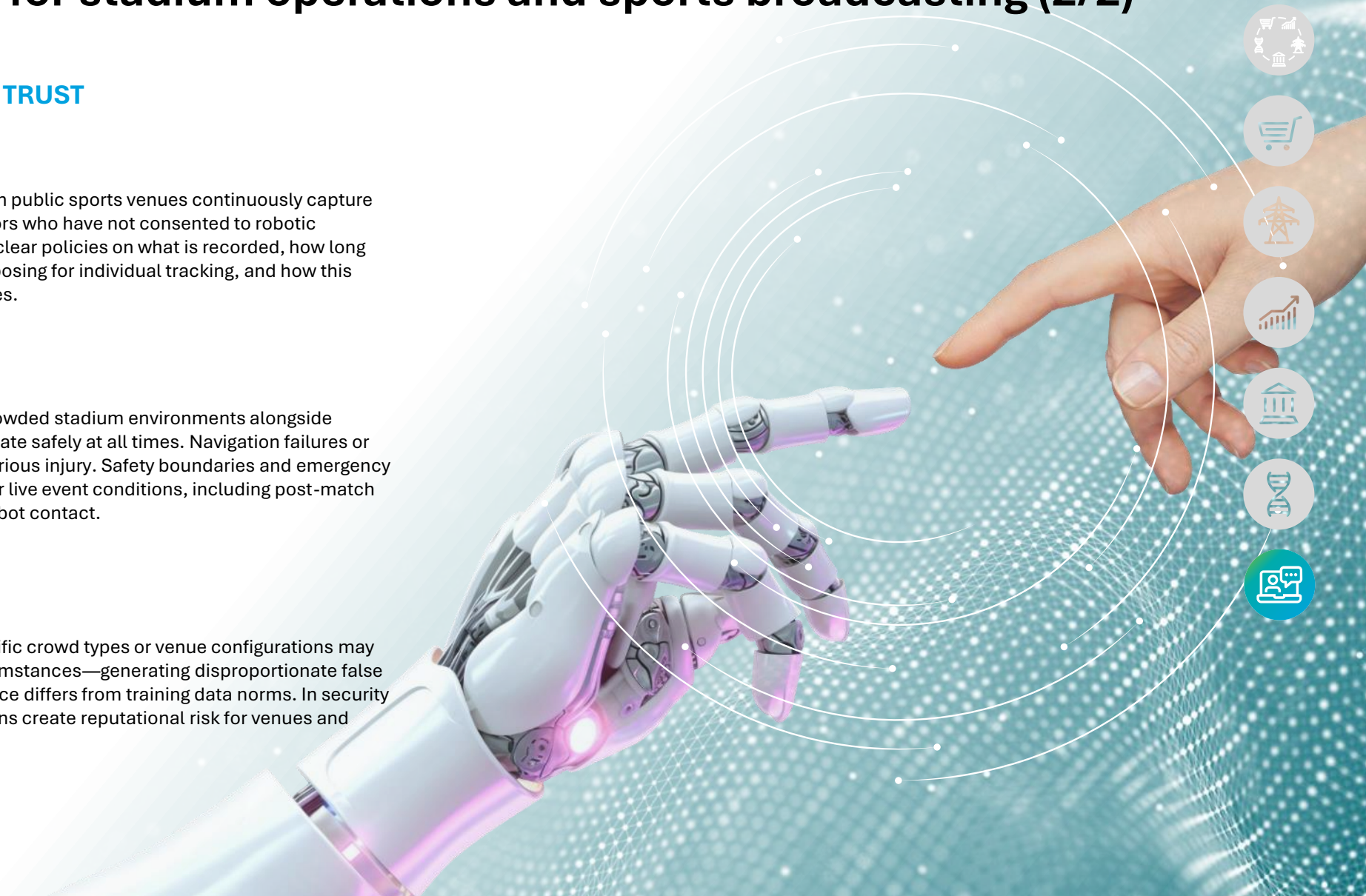
### Safe and secure

Quadruped robots navigating densely crowded stadium environments alongside spectators, staff, and athletes must operate safely at all times. Navigation failures or loss of control in a crowd could cause serious injury. Safety boundaries and emergency stop capabilities must be validated under live event conditions, including post-match crowd surges and unexpected human-robot contact.



### Fair and impartial

Computer vision models trained on specific crowd types or venue configurations may perform less accurately in different circumstances—generating disproportionate false positives for individuals whose appearance differs from training data norms. In security monitoring applications, biased detections create reputational risk for venues and event operators.



# Trustworthy AI™ in the Physical World

## Deloitte's Trustworthy AI™ framework highlights six important characteristics for AI system:

These dimensions apply to different forms of AI; however, Physical AI amplifies the consequences of getting them wrong because the impacts are physical too. While a flawed recommendation from a software algorithm might produce a bad decision, a flaw in a Physical AI system could stop a production line, damage equipment, injure a worker, or (in high-stakes use cases such as surgical robotics or autonomous vehicles) directly threaten human life.

### Robust and reliable

Physical AI systems should perform consistently across dynamic, unpredictable environments—conditions that are far more variable and challenging than the controlled data environments in which models are typically trained.

### Safe and secure

Sensor failures, edge cases, and adverse conditions can cascade quickly into real-world physical harm. Security vulnerabilities are equally consequential: a compromised autonomous robot or a manipulated control system is not just a data breach; it's a physical threat.

### Respectful of privacy

Privacy is a large and growing concern with Physical AI systems, many of which are equipped with cameras, microphones, and environmental sensors that could continuously collect data about people, workplaces, and public spaces. The data governance obligations attached to these systems are substantial and vary significantly across jurisdictions.

### Transparent and explainable

With Physical AI, decisions often happen in milliseconds and the reasoning behind an action may be difficult to audit after the fact. Organizations deploying Physical AI need to invest in the monitoring infrastructure and logging systems that create accountability, not just for regulatory purposes, but to build the operational confidence that allows human workers to trust and collaborate effectively with AI-driven systems.

### Responsible and accountable

When a Physical AI system causes harm, accountability should be clearly traceable—to the organization that deployed it, the team that designed it, and/or the humans who supervised it. Where that chain is unclear, organizations often face slower adoption, higher risk exposure, and increased regulatory scrutiny as major markets move to clarify expectations.

### Fair and impartial

Physical AI trained on narrow datasets struggles to generalize across environments, increasing the risk of biased behavior, unequal access, and physical harm. World models are the differentiator: by simulating the physical world with cause-and-effect reasoning, they enable machines to anticipate outcomes, adapt to unfamiliar conditions, and act safely beyond their training data—turning brittle automation into resilient, context-aware intelligence.

Trustworthy AI™ should not be viewed as a compliance checklist or barrier to progress, but as a catalyst for responsible widespread deployment. As such, it represents a design philosophy that should be embedded from the earliest stages of system development and revisited continuously as systems are deployed, updated, and expanded into new environments.

# Conclusion



Recall the world you were invited to picture earlier: autonomous robots tackling the hardest jobs in a distribution center; drones patrolling hundreds of miles of remote infrastructure; AI-assisted surgical systems enabling super-human levels of precision; and smart machines making people's everyday lives better. Not long ago, these visions were science fiction. Today, they are realistic use cases.

Even more important, the use cases in this dossier are just a starting point, not a ceiling. They represent the Physical AI applications that organizations are beginning to envision and deploy today. However, the fuller picture—the one that may define competitive advantage over the next decade and beyond—has not yet been drawn. Physical AI is a genuinely new frontier, and its most transformative applications are likely ones that have yet to be imagined.

This is both the challenge and the opportunity. The risk for most organizations is not that they may fail to adopt Physical AI—it's that they may adopt it too narrowly. That they should use it to automate existing processes rather than reimagine them. That they may ask "how does AI-enable what can already be done?" rather than "what becomes possible that was not possible before?" Organizations that ask the second question—and pursue it with rigor, creativity, and a clear focus on value creation—are the ones that should not just keep pace with disruption but drive it. Realizing this future may require more than imagination—it may demand disciplined investment choices, clear ROI models, and thoughtful trade-offs across Capex and Opex, so that reimagined possibilities can move from pilots to scaled, value-creating Physical AI deployments.

Physical AI does not just offer a more efficient version of the world we already operate in. It helps to enable a world that is fundamentally better and different. The challenge now is to imagine and build it.



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## End Notes

1. [\[2506.06580\] AI Simulation by Digital Twins: Systematic Survey, Reference Framework, and Mapping to a Standardized Architecture](#)
2. [Physical AI in retail supply chains: From the dashboard to the warehouse floor - Automated Warehouse](#)
3. [AI in manufacturing: Transforming engineering, production and supply chains – Tecnomatix](#)
4. [Robotic bricklayers, the new workmates in construction crews](#)
5. [Managing explanations: how regulators can address AI explainability](#)
6. [Sustainability of public finances in OECD countries | OECD](#)
7. [Guardrails Don’t Kill Innovation, They Fuel It in Safety-Critical Sectors – ADAICO](#)
8. [McKinsey study: Potential of automation by sector](#)
9. [Reducing unnecessary lab testing in the ICU with artificial intelligence – PMC](#)
10. [Data center sustainability | Deloitte insights](#)