

Data Pipelines for Industrial AI Design, Integration, and Quality Assurance

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Available online at: <https://doi.org/10.66422/RJMU.ID.70>

Received: 20 May 2026

Revised: 27 June 2026

Accepted: 12 July 2026

Abstract— Industrial artificial intelligence depends not only on advanced algorithms, but also on the unseen data pipelines that feed, organize, validate, and sustain them. This chapter examines how data pipelines shape the design, integration, and quality assurance of AI-driven industrial systems. It explores the movement of data from sensors, machines, production lines, enterprise platforms, and human inputs into structured workflows capable of supporting reliable decision-making. Particular attention is given to data accuracy, interoperability, traceability, governance, and continuous monitoring. The chapter also considers the operational realities of industrial environments, where legacy systems, fragmented data sources, and production pressures often complicate implementation. By linking technical architecture with quality culture, the chapter argues that robust data pipelines are not merely digital infrastructure; they are the foundation upon which trustworthy industrial AI becomes practical, scalable, and meaningful.

Keywords— Industrial AI, data pipelines, quality assurance, smart manufacturing, data integration, predictive analytics, process optimization, industrial quality control.

I. INTRODUCTION

Industrial artificial intelligence is often discussed through the language of algorithms, prediction models, automation, and intelligent decision-making (Mathew et al, 2023). These are, of course, important. A model that can detect a microscopic defect on a production line, predict equipment failure before it becomes visible, or recommend process adjustments in real time can transform the meaning of quality control in manufacturing. Yet behind every successful industrial AI system lies something less glamorous and much less frequently celebrated: the data pipeline. It is the hidden circulatory system of industrial intelligence. It collects, transports, cleans, contextualizes, stores, and prepares data so that machines, models, engineers, and managers can act upon it with confidence. Without a reliable pipeline, AI becomes little more than an impressive surface placed upon a weak foundation.

In industrial environments, data is rarely neat. It emerges from sensors, cameras, programmable logic controllers, supervisory control and data acquisition systems, enterprise resource planning platforms,

maintenance logs, laboratory tests, operator notes, inspection records, and sometimes even handwritten or semi-structured documents. Some of it is continuous and high-frequency; some appears only after manual entry. Some is precise, timestamped, and machine-readable, while other data is incomplete, delayed, duplicated, or trapped inside old systems that were never designed to communicate with contemporary AI platforms. This complexity makes industrial AI different from many other digital applications. In a factory, a refinery, a logistics hub, or a pharmaceutical production facility, data is not simply “available.” It has to be carefully earned, interpreted, aligned, and trusted.

This chapter begins from the belief that data pipelines are not merely technical channels. They are operational structures, quality mechanisms, and governance instruments at the same time. A pipeline determines what kind of data enters the AI system, how that data is transformed, which errors are corrected or ignored, how context is preserved, and how outputs are later traced back to their sources (Pasupuleti, 2025). In

this sense, a data pipeline is never neutral. It quietly shapes the intelligence that follows. If the pipeline excludes certain production variables, the model may fail to notice their influence. If timestamps are misaligned, the model may learn false relationships. If inspection data is inconsistent, defect detection may become unreliable. If data drift is not monitored, yesterday's accurate model may become tomorrow's silent liability.

Quality assurance, therefore, must be understood as part of the data lifecycle rather than as a final checkpoint added after model deployment (Punitha, 2025). Traditional industrial quality control has often focused on product conformity, process stability, inspection methods, standards, and corrective action. AI does not replace these concerns; it deepens them. It introduces new layers of risk and responsibility. The quality of data becomes inseparable from the quality of decisions. The reliability of a prediction becomes linked to the reliability of the pipeline that produced the training environment, the validation dataset, and the real-time input stream. A flawed pipeline can generate confident but misleading AI outputs, and in industrial contexts such outputs may affect production costs, customer safety, regulatory compliance, equipment integrity, and organizational reputation.

The design of industrial AI pipelines also requires a careful balance between technological ambition and practical realism (Vyhmeister et al, 2023). Many organizations are eager to adopt AI, but they may underestimate the effort required to integrate fragmented systems, standardize data definitions, establish data ownership, and create monitoring procedures that continue long after the first model is deployed. The challenge is not simply to build a pipeline that works once in a controlled pilot. The deeper challenge is to build one that survives the heat, noise, interruptions, and compromises of everyday industrial life. Machines are recalibrated. Sensors fail. Operators change shifts. Raw materials vary. Production lines are modified. Market pressures accelerate decision cycles. A useful AI pipeline must be resilient enough to absorb such changes without losing interpretive discipline.

At the same time, the human dimension cannot be pushed aside. Industrial AI pipelines connect machines and models, but they also connect people: data engineers, quality managers, production supervisors, operators, maintenance teams, compliance officers, and senior decision-makers (Jian, 2025). Each group sees quality from a different angle. The engineer may focus on architecture and system latency. The quality officer may be concerned with traceability and audit readiness. The operator may ask whether the AI

recommendation makes sense under real production conditions. The manager may want measurable improvement in efficiency, waste reduction, or defect prevention. A mature pipeline must therefore support not only data movement, but also communication, accountability, and shared understanding.

This chapter examines data pipelines as the backbone of industrial AI design, integration, and quality assurance. It discusses how industrial data is collected and structured, how pipelines connect heterogeneous systems, how data quality is maintained, and how continuous monitoring helps organizations detect degradation before it damages performance. It also reflects on the wider managerial and ethical implications of pipeline design, particularly in relation to trust, transparency, responsibility, and long-term sustainability. The central argument is simple but easily overlooked: industrial AI becomes meaningful only when the data infrastructure beneath it is dependable. The future of AI-enabled quality control will not be determined by algorithms alone. It will be shaped by the disciplined, often invisible work of building pipelines that can carry the weight of industrial reality.

II. FROM RAW SIGNALS TO RELIABLE INTELLIGENCE: THE STRATEGIC ROLE OF DATA PIPELINES IN INDUSTRIAL AI

Industrial AI begins in places that rarely look intelligent at first glance. A vibration sensor attached to a rotating shaft. A thermal camera watching a furnace door. A pressure reading from a hydraulic system. A barcode scan at a packaging station. A short comment typed by an operator at the end of a difficult shift. A defect image captured under uneven lighting. These fragments arrive without poetry, without order, and often without immediate meaning. They are signals before they are knowledge. They are traces of industrial life, not yet intelligence. The work of the data pipeline is to take these scattered traces and make them speak with enough clarity, continuity, and reliability that an AI system can learn from them without being misled.

This is where the real seriousness of industrial AI begins. Not in the elegance of the model, not in the excitement of automation, and not in the polished dashboard displayed to management, but in the long, patient, sometimes messy journey through which data is collected, cleaned, synchronized, contextualized, and transformed. A factory does not naturally produce ready-made datasets. It produces noise, variation, interruptions, and local habits. Machines stop and restart. Sensors drift. Operators improvise. Product batches differ slightly. Maintenance logs may be

written carefully on one day and hurriedly on another. A production line, seen from the distance of a conference presentation, may appear smooth and measurable; seen from inside, it is a living arrangement of metal, software, pressure, fatigue, expertise, and time. Data pipelines must live inside that reality.

The strategic role of data pipelines, then, is not merely technical. It is interpretive (Biswas et al, 2022). A pipeline decides what counts as relevant, what must be filtered, what should be preserved, and what relationships between events are worth maintaining. A temperature reading alone may say very little. A temperature reading connected to machine speed, material type, operator shift, ambient humidity, maintenance history, and final inspection results becomes something else entirely. It becomes part of an industrial story. Without this context, AI may detect patterns that are statistically impressive but operationally foolish (Joque, 2022). It may learn from coincidence, amplify hidden errors, or treat temporary disturbances as permanent truths. Industrial AI does

not fail only because models are weak. It often fails because the pipeline has failed quietly before the model ever begins to learn.

Raw industrial data is especially treacherous because it often carries the authority of measurement. Numbers look clean even when their origins are untidy. A sensor reading with three decimal places can feel more trustworthy than a worker's handwritten note, yet that reading may come from a poorly calibrated device installed in the wrong place, operating under conditions never considered in the original system design. A defect label may appear definitive in a dataset, although two inspectors might disagree about the same product under real conditions. A timestamp may seem objective, but if one machine records local time, another logs in server time, and a third loses synchronization after a power interruption, the timeline becomes a trap. The pipeline must notice these hidden fractures. It must ask, again and again: what does this data actually represent?

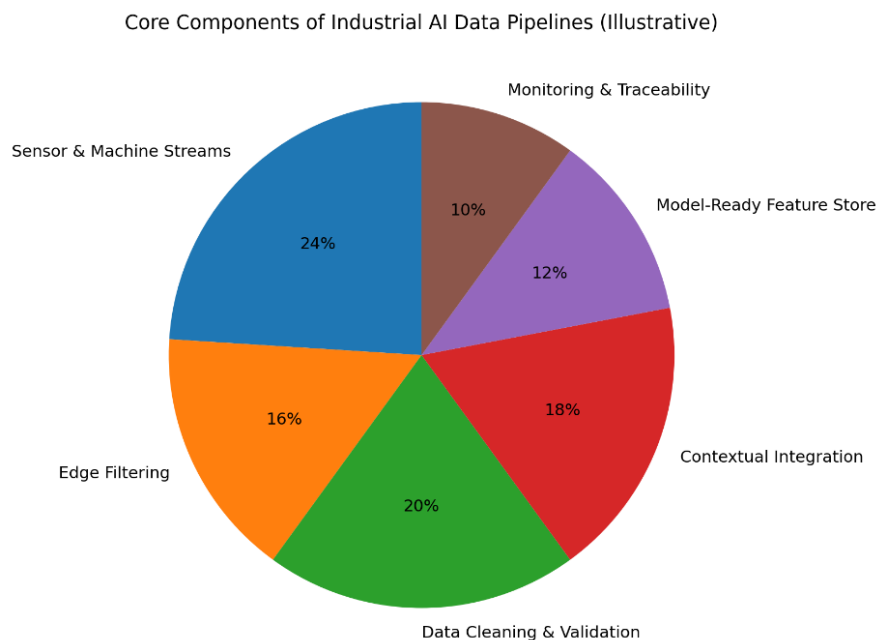


Figure 1 — Core Components of Industrial AI Data Pipelines

This is why data pipelines sit at the heart of quality assurance in industrial AI. Quality control has historically been concerned with the conformity of products and the stability of processes (Khanzada, 2024). AI expands that concern into the digital layer. Now the organization must ask whether the data itself conforms to standards of completeness, accuracy, timeliness, consistency, and traceability. It is no longer enough to inspect the physical product at the end of the line. The informational product must also be inspected:

the dataset, the feature set, the transformation rule, the model input, the feedback loop. A weak pipeline may produce elegant dashboards and confident predictions while quietly corrupting the basis of decision-making. The danger is not always spectacular failure. Sometimes it is a slow, polite decline in reliability, almost invisible until the wrong decision has already been normalized.

A strong pipeline does more than transport data from one system to another. It gives industrial AI a memory (Veluru, 2022). It records where data came from, how it was altered, who approved the transformation logic, which version of a model used it, and how the resulting prediction affected action on the floor. This traceability matters deeply. In industrial quality environments, especially those shaped by regulation, customer audits, safety requirements, and contractual obligations, decisions cannot float without lineage. When an AI system flags a batch as risky, rejects a component, or recommends a process adjustment, the organization must be able to reconstruct the reasoning environment. Not in vague terms. Precisely. Which sensor readings were used? Were any values missing? Was the anomaly detection threshold recently changed? Did the training data include similar production conditions? A pipeline that cannot answer such questions may be fast, but it is not mature.

There is also a cultural dimension here, one that is too often hidden beneath technical vocabulary. Data pipelines force industrial organizations to confront the habits by which they know themselves (Gaddam, 2025). Many factories possess knowledge that lives informally: in the memory of experienced technicians, in unwritten rules about machine behavior, in the quiet judgment of operators who can hear when a process “doesn’t sound right.” AI initiatives sometimes treat such knowledge as outdated or insufficiently scientific. That is a mistake. The best pipelines do not erase human knowledge; they create ways for it to enter the data ecosystem without being flattened into crude categories.

Operator annotations, maintenance explanations, shift observations, and inspection comments can help transform raw signals into meaningful patterns. The challenge is to structure this knowledge without sterilizing it.

Industrial AI also depends on integration across systems that were never designed to cooperate. A typical industrial environment may include legacy control systems, modern IoT platforms, enterprise resource planning software, quality management systems, laboratory information systems, warehouse records, and supplier databases. Each speaks its own dialect. Some use proprietary formats. Some update in real time; others update at the end of the day. Some are rich in detail but poor in accessibility. Others are easy to access but thin in context. The data pipeline becomes a kind of translator moving between these worlds. It must reconcile conflicting identifiers, align production events with inspection outcomes, connect material batches with final product performance, and preserve enough semantic meaning that AI does not

mistake administrative convenience for industrial truth.

The strategic importance of this integration becomes clear when considering predictive quality control. To predict a defect before it happens, AI needs more than defect records (Gezici Geçer & Kolukisa Tarhan, 2025). It needs the conditions that preceded the defect, the process variables that shaped it, the material characteristics that influenced it, and the human or mechanical interventions that may have prevented or intensified it. The pipeline must build this temporal and causal landscape piece by piece. It must join data across time, across equipment, across departments. A defect detected at final inspection may have roots hours earlier in a small temperature fluctuation, a tool nearing wear limits, a rushed maintenance procedure, or a supplier variation that did not seem important at the receiving stage. Reliable intelligence emerges when the pipeline allows these distant signals to meet.

Still, there is a danger in romanticizing the pipeline as if it can solve every industrial problem through better data choreography. Some aspects of production remain ambiguous. Some variables resist measurement. Some decisions involve trade-offs that no model can settle alone.

Data pipelines are powerful not because they eliminate uncertainty, but because they make uncertainty more visible and manageable (Mitchell et al, 2022). They help distinguish between what is known, what is assumed, what is missing, and what must be investigated further. In a well-designed industrial AI system, the pipeline does not pretend to produce certainty where none exists. It produces disciplined evidence.

The movement from raw signals to reliable intelligence is, in this sense, a movement from accumulation to understanding. Industrial organizations are already surrounded by data, sometimes buried beneath it. The problem is not always scarcity. Frequently, the problem is disorder: too many streams, too little context, too many dashboards, too little trust. A strategic data pipeline imposes shape without oversimplifying. It creates continuity between the physical process and the digital model (Akhund, 2023). It allows quality teams to see not only what happened, but how the evidence was assembled. It gives AI systems the conditions under which learning can become useful rather than decorative.

For industrial leaders, this requires a shift in imagination. Data pipelines should not be treated as invisible plumbing delegated entirely to technical specialists. They are strategic assets tied to

competitiveness, safety, compliance, sustainability, and organizational learning. Investment in pipelines is investment in the organization's capacity to know its own operations more honestly. Poor pipelines create brittle intelligence: quick to impress, easy to distrust, and dangerous under pressure. Robust pipelines create patient intelligence: traceable, adaptable, and capable of improving with use.

The future of industrial AI will depend less on isolated demonstrations of algorithmic brilliance and more on the quiet durability of the systems that feed those algorithms. Raw signals will continue to pour from machines, materials, workers, and environments. Some will be useful. Some will be misleading. Some will matter only when connected to signals far away in time or location. The data pipeline is the disciplined passage between these fragments and the decisions that shape industrial quality. It is where noise is not merely removed, but understood; where information is not merely stored, but made accountable; where intelligence is not simply generated, but earned.

III. DESIGNING INDUSTRIAL DATA ARCHITECTURES: SENSORS, EDGE SYSTEMS, CLOUD PLATFORMS, AND HUMAN OVERSIGHT

Designing an industrial data architecture is not simply a matter of connecting machines to servers and calling the result "smart." That would be a convenient fiction, and perhaps a tempting one, because diagrams of industrial AI systems often look cleaner than the environments they represent. A sensor sends data to an edge device; the edge device filters and processes it; the cloud stores, analyzes, and trains models; dashboards inform managers; decisions return to the factory floor.

On paper, the movement appears graceful. In practice, it is full of friction. The air is dusty, machines vibrate, networks drop, devices age, operators improvise, and production schedules rarely pause politely for digital transformation. Industrial data architecture must be designed for this imperfect world, not for the polished abstraction of a vendor presentation.

At the foundation of such architecture are sensors, the small but decisive instruments through which physical processes become measurable (Kabir, 2025). Temperature, vibration, pressure, torque, humidity, acoustic signals, visual images, energy consumption, flow rates, chemical properties, and countless other indicators form the first layer of industrial intelligence. Yet the sensor is not merely a passive observer. Its placement, calibration, frequency, sensitivity, and

maintenance history all shape the meaning of the data it produces.

A vibration sensor installed too far from the critical bearing may detect motion, but not the motion that matters. A camera exposed to inconsistent lighting may generate images that confuse defect detection models. A temperature probe may function accurately in isolation but fail to represent the thermal behavior of a larger production zone. The architecture begins, then, with a deceptively simple question: what exactly must be known, and where can that knowledge be captured with the least distortion?

This question is strategic because industrial AI does not need all possible data. It needs purposeful data. There is a difference. Many organizations, eager to modernize, collect everything they can, assuming that quantity will eventually mature into insight. Sometimes it does. Often, it produces a swamp: enormous volumes of poorly labeled, weakly contextualized, technically accessible but intellectually vague information. Sensors should not be scattered like decorative technology across a facility. They must be mapped against process logic, defect pathways, risk points, quality requirements, and operational priorities.

A good architecture asks which signals reveal early signs of instability, which measurements support traceability, which variables influence product conformity, and which data streams can realistically be maintained over time. In industrial AI, excessive data without disciplined architecture may become another form of blindness.

Once signals are captured, the edge layer becomes essential. Edge systems sit close to machines and production processes, often within or near the factory environment itself (Vermesan et al, 2022). Their importance has grown because not every industrial decision can wait for distant cloud processing. Some events require immediate response: a pressure spike, a temperature breach, an abnormal vibration pattern, a dangerous motion sequence, a visual defect appearing at high production speed.

Edge computing allows data to be filtered, compressed, analyzed, or acted upon locally before being transmitted elsewhere. It reduces latency, saves bandwidth, and protects operations from the fragility of constant dependence on external connectivity. In quality control, this can be the difference between identifying a defective unit immediately and discovering a pattern of defects after hundreds of products have already moved downstream.

Table 1 — Industrial AI Data Pipeline Layers and QA Responsibilities

Pipeline Layer	Role in Industrial AI	Quality Assurance Focus	Main Risk if Weak
Sensors & PLC/SCADA Inputs	Capture real-time machine and process signals	Calibration, sampling rate, timestamp integrity	Misleading measurements and false process patterns
Edge Processing	Filter, compress, and act near the production line	Latency, local validation, buffering, anomaly screening	Lost early-warning signals or excessive noise
Data Cleaning & Transformation	Convert raw signals into usable, model-ready records	Completeness, deduplication, outlier handling, transformation logs	Clean-looking but distorted datasets
Contextual Integration	Join machine data with batches, shifts, inspections, and maintenance records	Common identifiers, metadata, semantic consistency	AI learns correlations without operational meaning
Feature Store / Model Inputs	Provide controlled, reusable inputs for training and inference	Version control, feature lineage, access governance	Untraceable model behavior and inconsistent predictions
Monitoring & Feedback Loops	Track drift, model performance, overrides, and outcomes	Continuous monitoring, alert thresholds, human review	Silent model decay and reduced trust

The edge layer also performs a quieter function: it protects the cloud from noise. Raw industrial data can be relentless. High-frequency sensors may generate streams so dense that sending every value to a central platform becomes inefficient or even meaningless. Edge devices can remove obvious anomalies caused by communication errors, aggregate readings into meaningful intervals, detect threshold violations, and preserve only the most relevant segments for deeper analysis. Yet this filtering must be handled carefully. If the edge system discards what later turns out to be important, the AI model may never learn the early warning signs of failure. If it simplifies too aggressively, it may erase the subtle variation through which quality problems announce themselves. The edge is not merely a technical buffer; it is an interpretive gatekeeper.

Cloud platforms, by contrast, offer scale, memory, and analytical breadth (Miryala & Gupta, 2023). They allow industrial organizations to integrate data from multiple production lines, plants, suppliers, laboratories, and enterprise systems. They support model training, large-scale storage, advanced analytics, simulation, benchmarking, and collaboration across dispersed teams. In the cloud, isolated process signals can be connected with inspection outcomes, maintenance records, customer complaints, warranty claims, and supply chain data. This wider view is crucial because quality problems are rarely confined to a single machine. A recurring defect may involve raw material variation, equipment wear, environmental conditions, operator training, and subtle changes in production scheduling. The cloud provides the computational and organizational space where these connections can be explored.

Still, cloud-centered architecture brings its own vulnerabilities. Industrial data may contain commercially sensitive process knowledge,

intellectual property, supplier information, production volumes, or safety-related records. Moving such data into cloud environments raises questions of cybersecurity, ownership, jurisdiction, access control, and regulatory compliance. The architecture must define not only where data is stored, but who is allowed to see it, modify it, export it, or use it to train models (Kreuzberger et al, 2023). A careless cloud strategy can turn industrial AI into a security liability. A thoughtful one can create a controlled environment where data remains usable without becoming exposed. Encryption, identity management, role-based permissions, audit trails, and governance policies are not administrative decorations; they are part of quality assurance itself.

The most mature industrial data architectures usually combine sensors, edge systems, and cloud platforms in layered arrangements rather than treating one level as superior to the others. Some data should remain local. Some should travel upward. Some should be summarized. Some must be archived in its raw form because future investigations may require it. Real-time control may belong at the edge, while long-term model refinement may belong in the cloud. Quality dashboards may draw from both. Regulatory records may require stable repositories with strict traceability (O’Sullivan et al, 2025). The art lies in deciding what belongs where, and why. A poorly designed architecture may send too much data to the cloud, overburdening networks and creating unnecessary exposure. Another may keep too much at the edge, limiting organizational learning. Balance is not a slogan here; it is an engineering and managerial discipline.

Human oversight is the layer that prevents the architecture from becoming technically impressive but operationally foolish. Industrial AI systems do not exist in empty digital space. They intervene in

workplaces where people have responsibilities, habits, frustrations, and deep practical knowledge. Operators often notice irregularities before dashboards do, though they may describe them in language that does not fit neatly into databases. Maintenance technicians understand the difference between a harmless vibration and a worrying one because they have listened to machines for years. Quality inspectors may know that a defect category is too broad, or that certain borderline cases require contextual judgment. If the architecture excludes these voices, it may produce intelligence that is formally correct and practically shallow.

Human oversight should not be reduced to emergency intervention after automation fails (Johnsen & Park, 2025). It must be designed into the architecture from the beginning. This means creating channels for annotation, correction, feedback, and disagreement. When an AI system flags a defect, users should be able to confirm, challenge, or refine the classification. When a predictive model warns of equipment failure, maintenance teams should be able to document whether the warning matched physical evidence. When operators override a recommendation, the reason should not vanish into informal conversation; it should become part of the learning system. Such feedback loops help prevent AI from drifting away from industrial reality. They also build trust, because people are more likely to rely on systems that allow their expertise to matter.

This human role is particularly important in environments where data quality is uneven. A model may interpret missing values as random absence, while a human may know that missing values always occur during a specific shift change or cleaning procedure. A dashboard may show rising defect rates, while a supervisor may understand that a new inspection standard has changed how defects are recorded. A cloud model may detect a correlation between machine speed and product failure, while experienced personnel may recognize that machine speed is only a proxy for a deeper issue in material handling. Architecture must allow such interpretation to enter the system. Otherwise, AI becomes trapped in its own formalism.

Designing industrial data architecture also requires attention to standards and interoperability (Alabadi et al, 2022). Industrial facilities often contain equipment from different manufacturers, installed at different times, using different communication protocols. Without common data models, naming conventions, metadata practices, and interface standards, integration becomes a patchwork of fragile connections. This fragility may not be visible during a pilot project, but it becomes costly when the system expands. A sensor

called “Temp_01” in one line, “T-Furnace-A” in another, and “HeatZonePrimary” elsewhere may confuse teams and algorithms alike unless semantic consistency is established. Naming is not trivial. Metadata is not clerical. These small disciplines carry the architecture’s long-term intelligibility.

There is also the question of resilience. Industrial AI architecture must survive disruption. Networks fail. Cloud services may experience delays. Edge devices may require updates. Sensors may malfunction. Cyberattacks may target connected systems. Power interruptions may corrupt data streams. A serious architecture anticipates failure rather than pretending it can be avoided entirely. It includes redundancy, fallback modes, local buffering, recovery procedures, validation checks, and clear responsibilities when systems behave unexpectedly. In quality control, resilience is more than uptime. It is the ability to maintain confidence in decisions when conditions are strained.

The architecture, finally, should remain open to evolution. Industrial systems change. New products are introduced, production lines are reconfigured, regulations shift, suppliers change, and quality expectations become more demanding. A rigid architecture may serve the first AI application but block the next five. A flexible architecture, built with modular components and clear governance, allows organizations to adapt without rebuilding everything from scratch. This matters because industrial AI is not a single project with a neat endpoint. It is an expanding capability. The architecture must support learning, revision, and scale.

To design industrial data architecture well is to respect both the physics of production and the politics of organizational knowledge. Sensors translate physical events into data. Edge systems bring intelligence close to action. Cloud platforms widen the analytical horizon. Human oversight anchors the entire structure in judgment, responsibility, and lived experience. None of these layers is sufficient alone. Together, they form the conditions under which industrial AI can move beyond experimentation and become trustworthy quality infrastructure.

The deeper point is this: architecture is never just architecture. It is a statement about what an organization believes quality requires (Ågren et al, 2022). If it values speed without traceability, the system will show it. If it values automation without human sense-making, the system will show it. If it values data volume without meaning, the system will show it too. But when industrial data architecture is designed with care, it becomes something more

enduring than a digital upgrade. It becomes a disciplined way of seeing the factory, listening to its signals, preserving its memory, and allowing intelligence—machine and human—to meet where quality is actually made.

IV. QUALITY ASSURANCE IN THE DATA LIFECYCLE: ACCURACY, TRACEABILITY, VALIDATION, AND CONTINUOUS MONITORING

Quality assurance in industrial AI does not begin when a model produces its first prediction (Msakni et al, 2023). It begins much earlier, almost invisibly, at the moment a signal is captured, named, timestamped, stored, transferred, cleaned, joined with other records, and prepared for interpretation. This may sound like a technical sequence, and in one sense it is. Yet beneath that sequence lies a deeper question: can the organization trust the informational world it is building around its physical operations? In traditional industrial quality control, attention often settles on materials, machinery, inspection results, process capability, and conformity to specifications. In AI-supported quality control, these concerns remain, but they are joined by another layer of responsibility: the quality of data itself.

This shift is not minor. It changes the center of gravity. If data becomes the raw material of artificial intelligence, then flawed data is not simply an inconvenience; it is a defective input entering the decision-making system. A mislabeled image, a missing sensor value, a duplicated inspection record, a distorted timestamp, or an undocumented transformation can travel quietly through the pipeline and reappear later as a confident recommendation. The danger is that digital errors often look clean. They arrive in tables, dashboards, charts, and probability scores. They carry the visual discipline of precision, even when their foundations are unstable. Industrial AI, for all its sophistication, remains vulnerable to this old and rather human problem: believing what appears orderly.

Accuracy is the first visible demand in the data lifecycle, but it is also one of the most misunderstood (Zhang et al, 2022). In industrial settings, accuracy does not mean only that a value is numerically correct. It means that the value correctly represents the process condition it claims to represent. A sensor may record temperature accurately at its point of contact while failing to capture the thermal variation that actually affects product quality. A camera may produce high-

resolution images that are useless because the lighting angle hides surface defects. An operator may enter the right defect code according to the available menu, while still knowing that the menu does not quite fit what happened. Accuracy, then, is not a narrow technical property. It is a relationship between measurement, context, meaning, and use.

This is why data accuracy must be managed across the full lifecycle rather than checked only at the point of collection. Calibration records, sensor placement, sampling frequency, environmental conditions, data entry procedures, and inspection standards all shape the reliability of industrial data. If a pressure sensor drifts gradually over several weeks, the pipeline may continue to receive values without interruption, and yet the meaning of those values has changed. If inspectors apply defect categories differently across shifts, the dataset may become internally inconsistent while still appearing complete. If one production line uses automated recording and another relies on manual entry, comparisons between them may reflect recording practices as much as production reality. Quality assurance must look for these quiet distortions, because they rarely announce themselves with dramatic failure (Boswell et al, 2024).

Traceability adds another layer of discipline. In a mature industrial AI environment, data should not move through the system like anonymous water through a pipe. It should carry its lineage. The organization should know where it came from, when it was captured, which device or person created it, what transformations were applied, which rules governed those transformations, and which models or decisions later depended on it. This is not bureaucratic fussiness. It is the foundation of accountability.

When an AI model recommends rejecting a batch, adjusting a parameter, or scheduling urgent maintenance, the organization must be able to reconstruct the path from raw evidence to final output. Without traceability, the system may still function, but it cannot be properly trusted. Traceability is especially important in regulated or high-risk industries, where quality decisions may affect safety, compliance, customer contracts, and legal responsibility. Suppose a model flags a production anomaly that later becomes linked to a customer complaint. Investigators must be able to ask precise questions. Which data streams informed the model? Were any values imputed?

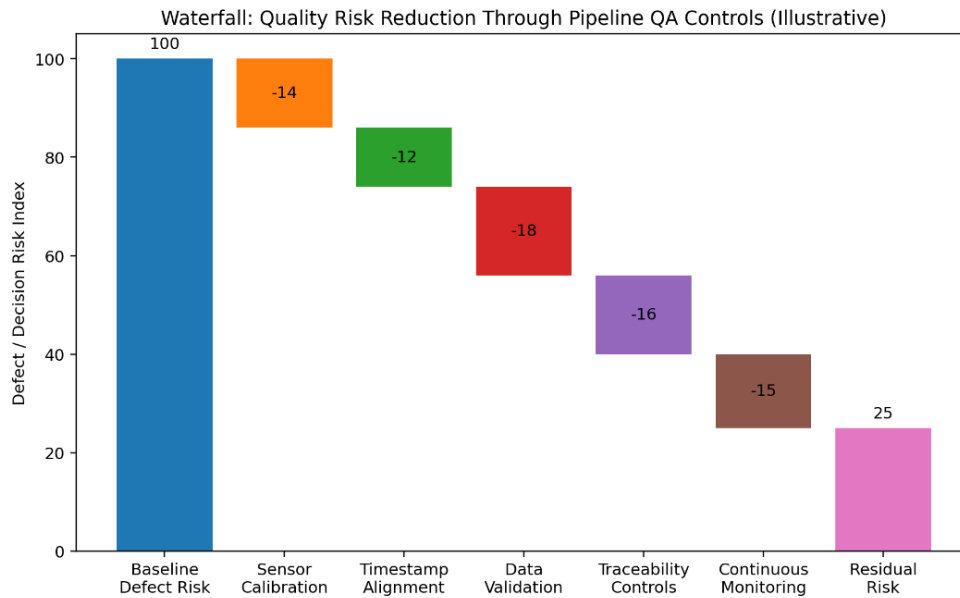


Figure 2 — Waterfall: Quality Risk Reduction Through Pipeline QA Controls

Was the relevant sensor recently recalibrated? Did the model use the current version of the defect classification scheme? Was the operator's override recorded? Was the training dataset representative of the product variant involved? These questions are not signs of distrust toward AI. They are signs of serious quality culture. A system that cannot answer them is not yet ready to carry the weight of industrial decision-making.

Validation, meanwhile, is often discussed as if it were a single phase before deployment: train the model, test the model, approve the model, move on. That mindset is too thin for industrial AI (Ayyat et al, 2025). Validation must be treated as an ongoing relationship between data, model, process, and outcome. At the data level, validation asks whether the data is complete, consistent, plausible, timely, and aligned with operational definitions. At the model level, it asks whether predictions remain reliable across different products, machines, shifts, suppliers, and environmental conditions. At the process level, it asks whether the AI output actually improves quality decisions rather than merely producing impressive performance metrics in isolation.

There is a delicate distinction here. A model can perform well in a controlled validation environment and still struggle in production. The training data may have been collected during stable conditions, while actual production includes interruptions, rare defects, unusual batches, maintenance periods, and human workarounds (Chukwunweike et al, 2024). The validation set may contain examples that resemble the past more than the future. Some defects may be underrepresented because they are rare, newly

emerging, or inconsistently labeled. A high accuracy score, taken alone, can be strangely comforting and dangerously incomplete. Industrial validation must ask harder questions: what kinds of errors does the model make? Which errors are acceptable? Which are costly? Which are unsafe? Which are hidden by aggregate metrics?

For quality assurance, this means validation should include both statistical testing and practical review (Kirwan, 2022). Engineers, operators, inspectors, and quality managers should examine model outputs in relation to real production cases. False positives and false negatives must be interpreted not only as numbers, but as operational events. A false positive may slow production, increase inspection workload, and gradually weaken trust. A false negative may allow defective products to pass unnoticed. In some contexts, one type of error is far more serious than the other. The acceptable balance depends on product risk, customer expectations, regulatory requirements, and the organization's tolerance for disruption. AI validation, in this sense, is not simply mathematical. It is managerial, ethical, and industrial.

Continuous monitoring is the discipline that keeps validation alive after deployment. This is where many systems either mature or decay. Industrial environments are not static, and neither are their data patterns. Model drift, data drift, sensor degradation, process changes, new raw materials, revised specifications, seasonal conditions, operator turnover, maintenance interventions, and equipment aging can all weaken the connection between past learning and present reality. A model that performed well six months ago may now be learning from a world that no

longer exists. If no one is watching, the decline may be slow enough to feel normal.

Monitoring must therefore include the pipeline, the data, the model, and the outcome. It is not enough to check whether the system is running (Mattila, 2024). A running system can still be wrong. Data distributions should be examined for unexpected shifts. Missing values should be tracked. Sensor patterns should be compared against calibration and maintenance records. Model confidence should be watched for unusual inflation or collapse. Prediction outcomes should be compared with later inspection results, customer feedback, rework rates, scrap levels, downtime, and corrective action records. In stronger systems, alerts are not limited to machine failures; they also signal informational weakness. The pipeline itself becomes inspectable.

This idea may feel unusual at first, but it is entirely consistent with quality thinking. If a production process requires control charts, audits, sampling plans, and corrective actions, why should the data process be exempt? The data lifecycle is a production process of its own. It produces datasets, features, predictions, classifications, and recommendations. These outputs influence physical decisions. They should be governed with comparable seriousness. Data quality thresholds, anomaly checks, validation routines, version control, change management procedures, and audit logs become the digital equivalents of industrial quality safeguards.

Still, continuous monitoring should not create a culture of mechanical suspicion in which every variation becomes a crisis. Industrial processes breathe. Some variation is normal, even healthy. The task is not to eliminate every fluctuation but to distinguish meaningful change from ordinary noise. This requires technical systems, yes, but also human judgment. A sudden change in defect detection rates might indicate model drift; it might also indicate a new inspection policy, a different product mix, a material substitution, or a temporary production experiment. Monitoring systems can identify the signal, but interpretation often requires people who know the shop floor and its recent history. A good monitoring regime invites investigation rather than jumping too quickly to blame.

One of the more subtle risks in data lifecycle quality assurance is overcleaning. Industrial data is messy because industrial life is messy. Cleaning is necessary, but excessive cleaning can erase valuable evidence. Outliers may be errors, but they may also be early signs of failure. Missing values may be accidental, but they may also reveal moments when a sensor stopped responding under specific process conditions.

Inconsistent labels may reflect poor procedure, but they may also expose ambiguity in the quality standard itself. The pipeline must not become so obsessed with neatness that it removes the very irregularities AI is supposed to learn from. Quality assurance should refine data without sanitizing reality beyond recognition.

Documentation matters here more than many people like to admit. Transformation rules, data definitions, labeling guidelines, validation criteria, retraining schedules, threshold changes, and model versions should be recorded in language that can be understood beyond the data science team (Sharma et al, 2025). When knowledge lives only in code, or worse, in the memory of one specialist, the organization becomes fragile. Documentation is not glamorous, but it is a form of institutional memory. It allows future teams to understand why a pipeline was designed in a certain way, why certain variables were included or excluded, and why a model behaved differently before and after a specific update. In quality assurance, what cannot be explained often cannot be defended.

There is also an ethical undertone running through the data lifecycle. Industrial AI systems may influence worker evaluation, production pressure, safety decisions, and resource allocation. If the data is inaccurate or poorly governed, people may be judged by systems that misunderstand the conditions of their work. An operator may appear responsible for quality variation that actually originated in supplier inconsistency or equipment wear. A shift may seem less efficient because its data entry practices are more complete and honest than others. Data quality, then, is not only about better predictions. It is about fairness inside the organization. Poor data can distort accountability.

The broader lesson is that quality assurance in the data lifecycle requires humility (Sargiotis, 2024). It asks organizations to admit that digital systems are not automatically objective, that measurement is never detached from context, and that AI confidence does not equal industrial truth. This humility is not weakness. It is a strength, because it prevents careless trust. It encourages organizations to build systems that can be questioned, audited, corrected, and improved.

A reliable industrial AI pipeline is not one that never encounters error. Such a system does not exist. Reliability comes from the ability to detect error, trace it, understand it, respond to it, and prevent its repetition where possible. Accuracy gives data its immediate credibility. Traceability gives it accountability. Validation gives AI its tested legitimacy (Ranjitsingh & Rao, 2025). Continuous monitoring gives the whole

system a chance to remain alive in changing conditions. Together, these practices transform the data lifecycle from a hidden technical sequence into a disciplined quality framework.

In the end, the question is not whether industrial AI can process data quickly. It can. The more serious question is whether the data deserves to be processed, whether the transformations preserve meaning, whether the model has been tested against the world it claims to serve, and whether the organization continues to watch after deployment with enough patience and honesty. Quality assurance in the data lifecycle is the quiet work that makes these questions answerable. Without it, industrial AI may still look powerful. With it, industrial AI can become trustworthy.

V. OPERATIONAL IMPACT AND FUTURE DIRECTIONS: BUILDING TRUSTWORTHY, SCALABLE, AND RESILIENT INDUSTRIAL AI PIPELINES

The operational impact of industrial AI pipelines is best understood not through the language of novelty, but through the quieter language of consequence (Lu & Cheng, 2025). A pipeline that works well does not merely move data from one platform to another; it alters the tempo of industrial decision-making. It changes how early a defect can be seen, how quickly a maintenance risk can be understood, how confidently a process variation can be interpreted, and how responsibly an organization can act before waste, downtime, or unsafe conditions expand into something larger. In this sense, the value of a data pipeline is not hidden in its architecture alone. It appears in the daily behavior of the production system: fewer surprises, sharper interventions, better memory, and a more disciplined relationship between evidence and action.

One of the most immediate operational effects is the movement from reactive quality control to anticipatory quality assurance. Traditional inspection often discovers problems after they have already travelled through part, or all, of the production process. AI pipelines can shift attention upstream. By connecting machine signals, material data, inspection histories, environmental conditions, and operator feedback, they make it possible to detect fragile patterns before they become visible defects. A slight drift in vibration, a small rise in energy consumption, an unusual combination of temperature and speed, a repeated operator adjustment that never appears in formal reports—such signals may look insignificant alone. When placed within a pipeline that preserves context and compares them against historical outcomes, they may become early warnings. The operational gain is not only technical; it is economic, environmental, and

managerial. Less scrap. Less rework. Less unplanned downtime. Less blind decision-making under pressure.

Yet this impact depends on trust, and trust is not created by accuracy percentages alone. Industrial teams do not trust AI because a dashboard looks sophisticated or because a vendor claims predictive power. They trust it when it behaves consistently, when its recommendations can be investigated, when its mistakes are acknowledged rather than hidden, and when people can understand enough of its reasoning environment to judge whether action is warranted. A trustworthy pipeline must therefore make evidence visible. It should allow a quality manager to trace a prediction back to its data sources, a maintenance engineer to see whether a warning reflects genuine equipment behavior, and an operator to challenge an alert that ignores practical conditions on the line. Trust grows when the system is not arrogant. It should not speak as an oracle. It should speak as a disciplined assistant, one that offers evidence, remembers context, and remains open to correction.

This is where operational impact and organizational culture meet. A pipeline may be technically sound, but if the people around it feel excluded, monitored unfairly, or forced to obey unexplained recommendations, its value will shrink. Industrial AI cannot be simply installed into a workplace as if human trust were an automatic by-product of computation (Banerjee, 2025). Workers need to know how data is collected, how alerts are generated, how feedback is used, and whether the system is designed to support improvement or assign blame. If every AI output becomes a managerial weapon, people will respond defensively. They may avoid entering uncomfortable truths, ignore warnings, or create informal workarounds. A resilient AI pipeline is not built only with software; it is built with credible governance, shared language, and the assurance that human expertise remains respected.

Scalability introduces another layer of difficulty. Many industrial AI projects succeed as pilots because pilots are protected environments (Ziakkas et al, 2025). They focus on one line, one machine, one defect type, or one carefully selected dataset. The real test begins when the system must expand across plants, products, shifts, suppliers, and operational cultures. What worked beautifully in one facility may falter in another where machines are older, labels differ, network stability is weaker, or inspection criteria are interpreted differently. Scaling is not copying. It is translation. Each new context asks whether the pipeline's assumptions still hold: Are the data definitions compatible? Are the sensors comparable? Are the production rhythms similar? Are the human workflows

aligned? Are the model thresholds still appropriate? Without this questioning, organizations may scale fragility instead of intelligence.

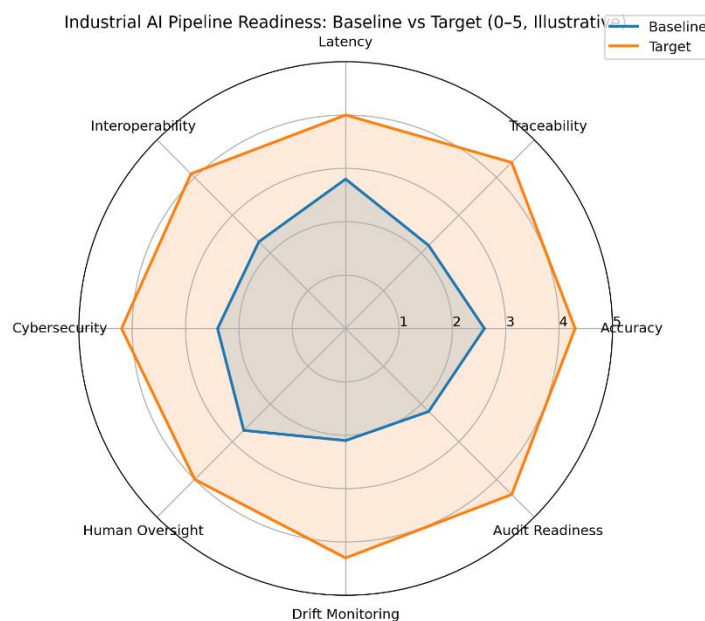


Figure 3 — Industrial AI Pipeline Readiness: Baseline vs Target

A scalable pipeline must therefore be modular, governed, and semantically coherent. Modularity allows components to be reused, replaced, or adapted without breaking the entire structure. Governance ensures that data ownership, access rights, documentation, validation, and change control do not dissolve as the system grows (Maheshwari, 2025). Semantic coherence may sound abstract, but it is painfully practical. A defect category must mean the same thing across locations, or at least the differences must be documented. A production batch must be identifiable across procurement, manufacturing, inspection, and customer service systems. A machine state must not be called by five names in five databases without a mapping logic. At small scale, such inconsistencies can be managed by memory and improvisation. At large scale, they become structural noise.

Resilience, meanwhile, is the ability of the pipeline to continue serving the organization when conditions are imperfect. And conditions will be imperfect. Sensors fail. Networks slow down. Cloud services become temporarily unavailable. Models drift. Product specifications change. Cybersecurity threats evolve. Staff turnover removes local knowledge. New equipment is installed beside old equipment that refuses to disappear. A brittle pipeline expects the world to remain stable. A resilient pipeline expects disruption and designs for recovery. It buffers data

locally when connectivity is weak, flags suspicious input rather than swallowing it silently, maintains version histories, supports fallback procedures, and makes it clear who must act when the system becomes uncertain.

This last point matters more than it may first appear. An AI pipeline should not only produce predictions; it should also know how to express uncertainty. Industrial decisions often become dangerous when uncertainty is disguised as confidence. A model that has moved outside its training conditions should not continue speaking with the same authority. A pipeline receiving incomplete or abnormal data should not produce outputs as if nothing has changed (Chaudhari & Charate, 2025). The future of trustworthy industrial AI will depend heavily on systems that can say, in effect, “This recommendation is weak because the data is incomplete,” or “This case differs significantly from the conditions under which the model was validated.” Such humility, embedded into technical design, may become one of the most valuable features of mature industrial AI.

The operational future will also be shaped by the growing relationship between AI pipelines and digital twins. As factories develop richer virtual representations of machines, processes, and production flows, pipelines will no longer feed only predictive models; they will feed simulated environments where

decisions can be tested before being applied physically. This opens important possibilities. A process adjustment could be evaluated in a virtual space before affecting real production. Maintenance scenarios could be compared. Quality risks could be explored under different material or environmental

conditions. Yet digital twins will only be as reliable as the pipelines that sustain them. A virtual factory built on poor data becomes a beautiful illusion. It may look advanced while misrepresenting the process it claims to mirror.

Table 2 — 12-Month Implementation Roadmap for Industrial AI Data Pipelines

Phase	Focus	Key Activities	Evidence / Deliverables
Q1	Pipeline Discovery & Governance	Map data sources, owners, formats, risks, and regulatory requirements	Data-source inventory; ownership matrix; risk register
Q2	Architecture & Integration Design	Define edge/cloud roles, identifiers, metadata rules, storage layers, and access controls	Reference architecture; integration plan; cybersecurity controls
Q3	Quality Assurance & Validation	Implement checks for accuracy, completeness, lineage, drift, and model input validity	QA rules; validation scripts; audit trail; model-input checklist
Q4	Monitoring, Scaling & Improvement	Deploy dashboards, feedback loops, retraining triggers, and cross-site scaling procedures	Monitoring dashboard; retraining policy; lessons-learned report

Edge intelligence will also become more central. As production environments demand faster responses, more analysis will occur close to the machine rather than in distant cloud platforms. This does not mean the cloud will disappear. It means industrial AI will become more distributed. Some decisions will need immediate local action, while others will require broader historical analysis across sites. The challenge will be coordination: ensuring that edge models, cloud models, quality systems, and human feedback remain aligned. If each layer evolves separately, the organization may end up with fragmented intelligence, where local systems optimize one part of the process while weakening the whole. Future pipelines must therefore support synchronization as well as speed.

Sustainability is another future direction that should not be treated as decorative. Industrial AI pipelines can help reduce waste, energy consumption, unnecessary rework, and inefficient resource use (Qudus, 2025). They can reveal where processes consume more than they should, where defects create hidden environmental costs, and where maintenance strategies can extend equipment life. At the same time, AI infrastructure itself consumes energy and requires digital resources. A responsible future will ask not only whether pipelines improve productivity, but whether their benefits justify their computational and material costs. The strongest industrial AI strategies will connect quality improvement with environmental responsibility, treating efficiency not as a narrow financial measure but as part of a broader ethic of industrial stewardship.

Cybersecurity will become inseparable from quality assurance. As machines, models, operators, and quality systems become more connected, the boundary between digital vulnerability and physical risk becomes thinner (Hughes & Robinson, 2024). A manipulated data stream could mislead a model. A

compromised sensor could hide dangerous process behavior. Unauthorized access to production data could expose intellectual property or enable sabotage. Future pipelines must be designed with security as a structural principle, not as a patch applied after integration. Authentication, encryption, network segmentation, anomaly detection, access governance, and incident response must belong to the architecture from the beginning. In connected industrial environments, a secure pipeline is a quality requirement.

The human future of industrial AI is perhaps the most delicate issue. Automation will expand, but the need for judgment will not disappear. Instead, human roles may shift toward interpretation, oversight, exception handling, system improvement, and ethical responsibility. Operators may become active contributors to AI feedback loops. Quality professionals may need stronger data literacy. Engineers may need to understand not only machines, but also model behavior and data governance. Managers may need to learn that AI outputs are not shortcuts around accountability (Collina et al, 2023). This requires training, but also a different organizational attitude. People should not be treated as obstacles to automation. They are the living context that allows automation to remain sensible.

The long-term success of industrial AI pipelines will depend on whether organizations can resist two opposite temptations (Park et al, 2024). The first is technological naivety: the belief that AI will automatically solve quality problems once enough data is collected. The second is defensive skepticism: the belief that industrial complexity is too messy for AI to handle responsibly. Both positions miss the harder, more interesting truth. AI pipelines can create enormous operational value, but only when they are designed with patience, validated with honesty,

monitored continuously, and integrated into the human and material realities of production.

A trustworthy, scalable, and resilient pipeline is not a finished object. It is a living infrastructure. It must learn, adapt, and remain open to revision. It must carry data without stripping away meaning. It must support automation without silencing human insight. It must scale without losing local sensitivity. It must remain resilient without pretending failure is impossible. Such pipelines will not merely strengthen industrial quality control; they will change how industrial organizations understand themselves. They will make factories more legible, decisions more accountable, and quality less dependent on late discovery.

The future of industrial AI, then, will not be decided by the most dazzling algorithm alone (Ahmed et al, 2022). It will be decided by the less theatrical, more demanding work of building pipelines that can endure real production life. Heat, noise, urgency, variation, uncertainty, human judgment, machine fatigue, shifting standards—all of it. The pipeline that can carry intelligence through these conditions without becoming brittle is the pipeline that will matter. And perhaps that is the most honest measure of industrial AI: not whether it can impress in controlled demonstrations, but whether it can remain useful, trustworthy, and humane when the factory refuses to behave like a diagram.

VI. CONCLUSION

Data pipelines are frequently treated as background infrastructure, something technical teams build so that AI models can function. This chapter has argued for a broader and more serious understanding. In industrial AI, the data pipeline is not a secondary component. It is the condition that makes intelligent quality control possible. It determines whether data can be trusted, whether models can be validated, whether predictions can be explained, and whether decisions can be connected back to the material realities of production. A sophisticated algorithm may attract attention, but the pipeline decides whether that algorithm can live responsibly inside an industrial environment.

The movement from traditional quality control to AI-supported quality assurance is not merely a change in tools. It is a change in how organizations perceive defects, variation, risk, time, and responsibility. Instead of waiting for faults to appear at the end of the production process, industrial AI promises earlier detection, predictive awareness, adaptive control, and continuous learning. Yet this promise depends on the quality of the data journey. Raw signals must be captured accurately. Data must be cleaned without losing meaning. Information from different machines and systems must be integrated in ways that preserve

context. Models must be trained on representative datasets, tested against real industrial conditions, and monitored after deployment. Each stage is vulnerable to distortion. Each stage requires care.

One of the most important lessons is that data quality is not a one-time achievement. It is a continuous discipline. In industrial settings, conditions change constantly. Equipment ages. Sensors drift. Suppliers vary. Production targets shift. New products are introduced. Maintenance practices evolve. Even a well-designed AI system can weaken if the pipeline feeding it is not monitored and renewed. For this reason, quality assurance must extend beyond the inspection of final products or even the validation of AI models. It must include the ongoing evaluation of data flows, metadata, transformation rules, access controls, model inputs, and feedback loops. The pipeline itself becomes an object of quality management.

The chapter has also shown that integration is one of the most demanding aspects of industrial AI. Many factories and industrial organizations do not begin with clean, unified, modern data ecosystems. They begin with legacy machines, disconnected databases, uneven documentation practices, and systems built at different moments for different purposes. To integrate these elements is not simply to connect software platforms. It is to negotiate between historical layers of industrial practice. It requires technical skill, but also patience, institutional memory, and a willingness to understand why existing systems developed as they did. A rushed pipeline may produce quick demonstrations, but fragile results. A thoughtful pipeline may take longer to design, yet it gives AI the stability needed to become genuinely useful.

Trust remains central. Workers and managers will not rely on AI simply because it is advanced. They will rely on it when its outputs are consistent, explainable, traceable, and visibly connected to production experience. Data pipelines help create this trust by preserving lineage, recording transformations, enabling audits, and making it possible to investigate why a recommendation was made. When a defect is flagged, when a machine is predicted to fail, or when a process adjustment is suggested, the organization must be able to ask: Where did this conclusion come from? What data supported it? Was the data complete? Has anything changed in the process? Without such questions, AI can become a black box placed inside another black box—the factory itself.

The human role, therefore, does not disappear. In fact, it becomes more important. Industrial AI pipelines require human judgment at every level: deciding which

variables matter, interpreting unusual patterns, resolving conflicts between data and experience, setting thresholds for action, and determining when automated recommendations should be questioned. Quality assurance has always depended on disciplined observation, professional responsibility, and practical wisdom. AI adds speed and analytical power, but it does not remove the need for human accountability. The strongest industrial systems will not be those that simply automate decision-making, but those that create a productive relationship between data, machines, and human expertise.

Looking ahead, the future of industrial AI will likely involve more edge computing, real-time analytics, digital twins, autonomous inspection systems, and self-optimizing production environments. These developments will increase the importance of pipeline design rather than reduce it. As data becomes faster, larger, and more distributed, organizations will need stronger standards for interoperability, cybersecurity, governance, and ethical use. They will also need to avoid the temptation to treat AI implementation as a fashionable technological upgrade. The real transformation lies deeper. It lies in building industrial cultures where data is handled with seriousness, where quality is designed into digital systems from the beginning, and where AI is judged not only by its novelty but by its reliability under pressure.

Ultimately, data pipelines remind us that intelligence is not born at the moment of prediction. It is assembled gradually, through countless decisions about collection, cleaning, labeling, storage, integration, validation, and monitoring. Industrial AI succeeds when these decisions are made carefully and responsibly. It fails when they are neglected, hidden, or assumed to be purely technical matters. For quality control, this distinction is decisive. A reliable pipeline can help transform scattered industrial data into usable knowledge, and usable knowledge into better processes, safer products, reduced waste, and more resilient organizations. In that sense, the pipeline is more than infrastructure. It is the quiet architecture of trust upon which the next generation of industrial quality assurance will depend.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest.

Funding

The authors received no financial support for this book review.

Human Participants

This paper does not involve human participants.

Originality Note

The authors confirm that the manuscript is their original work, and if others' works are used, they are properly cited/quoted.

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