Global Electronics Association™

Engineering Virtual Event

Quality AI is Only as Good as Your Data

"Setting Yourself Up for Good AI Outcomes"

Today's Event: Wednesday, May 20, 2026

Time: 1:00 PM ET/12:00 PM CT

Speakers: Warren Scurlock – Chryspac

Linda Hapka – Chryspac

Matt Kownick – Left Hand Engineering

Andrew Steele – FactoryQA

QUALITY AI IS ONLY AS GOOD AS YOUR YOUR DATA

"Capturing Good Quality for Good Outcomes"

1. KNOW THE DATA
2. CAPTURE THE DATA
3. USE THE DATA

TODAY'S EVENT

Wednesday, May 15, 2026 | 1:00 PM EST / 12:00 PM Central

SPEAKERS

Matthew Kownick · Andrew Steele · Linda Hapka · Warren Scurlock

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WELCOME & AGENDA

WHAT WE'LL COVER TODAY

This webinar is designed to give manufacturing professionals a practical foundation for deploying AI in Quality Management. Over the next hour, our four speakers will walk you through each phase of building an AI-ready quality operation — from understanding your data landscape, to capturing it reliably, to putting it to work.

01

KNOW THE DATA

Understand what data exists in your environment, where it lives, and why it matters for AI-driven quality outcomes.

02

CAPTURE THE DATA

Learn proven strategies for collecting clean, consistent, and actionable data on the shop floor and in your systems.

03

USE THE DATA

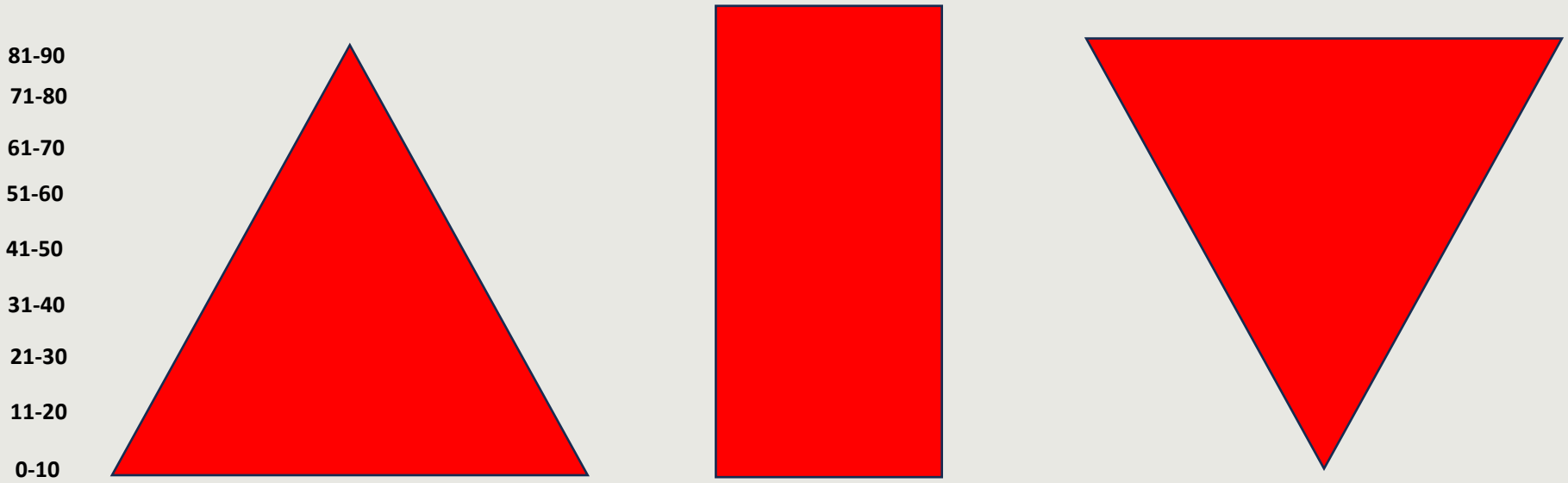
Discover how to transform captured data into work instructions, training, process improvements, and corrective action.

Each section includes speaker commentary and space for real-world experience sharing. Questions are welcome at the end.

What Data is being collected?

Remember how easy it was to hire in 2026?

What's the world look like in 2030?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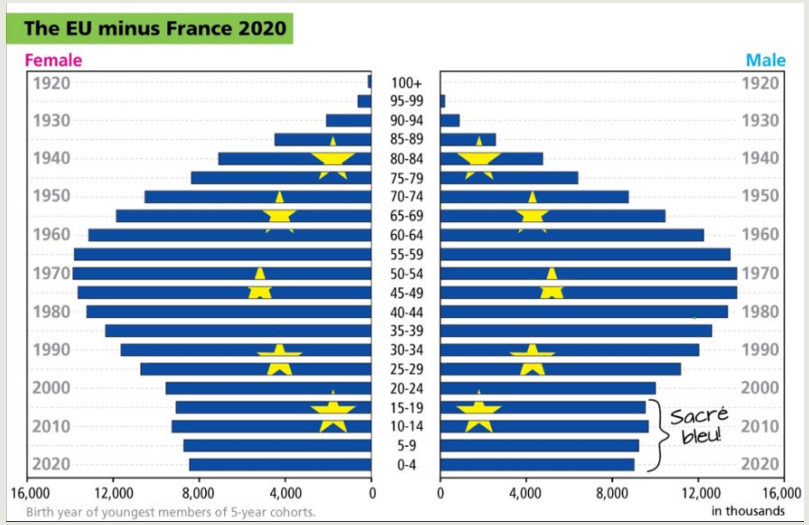

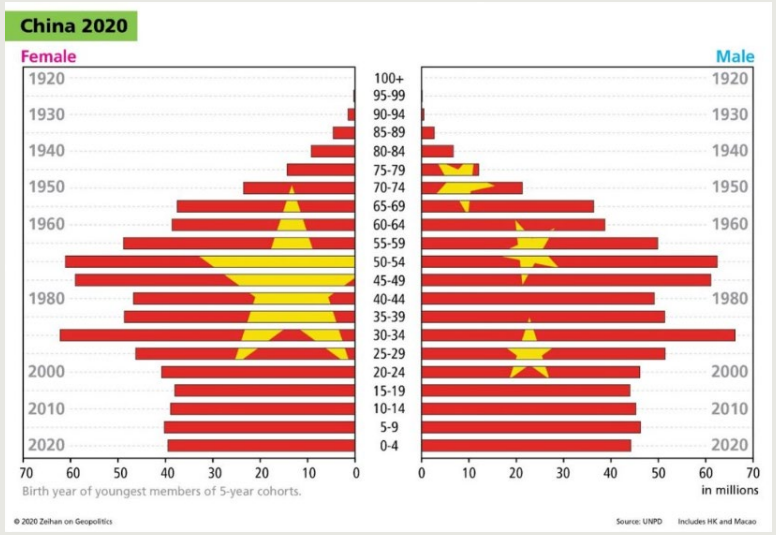

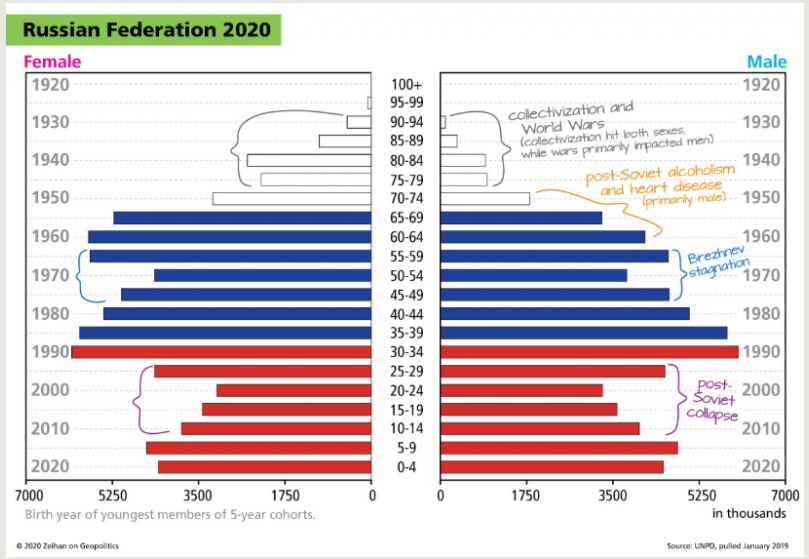

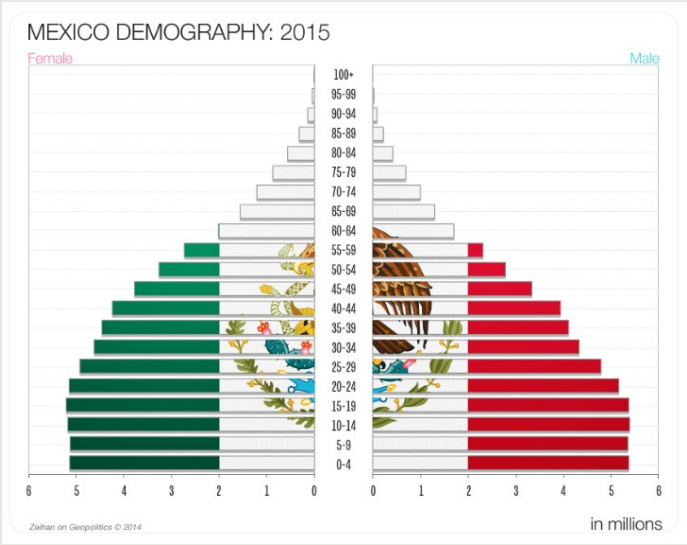

[Peter Zeihan – Powers of Yesterday, Powers of Tomorrow | TLDW (wordpress.com)]

GLASS FACTORY
by Left Hand Engineering

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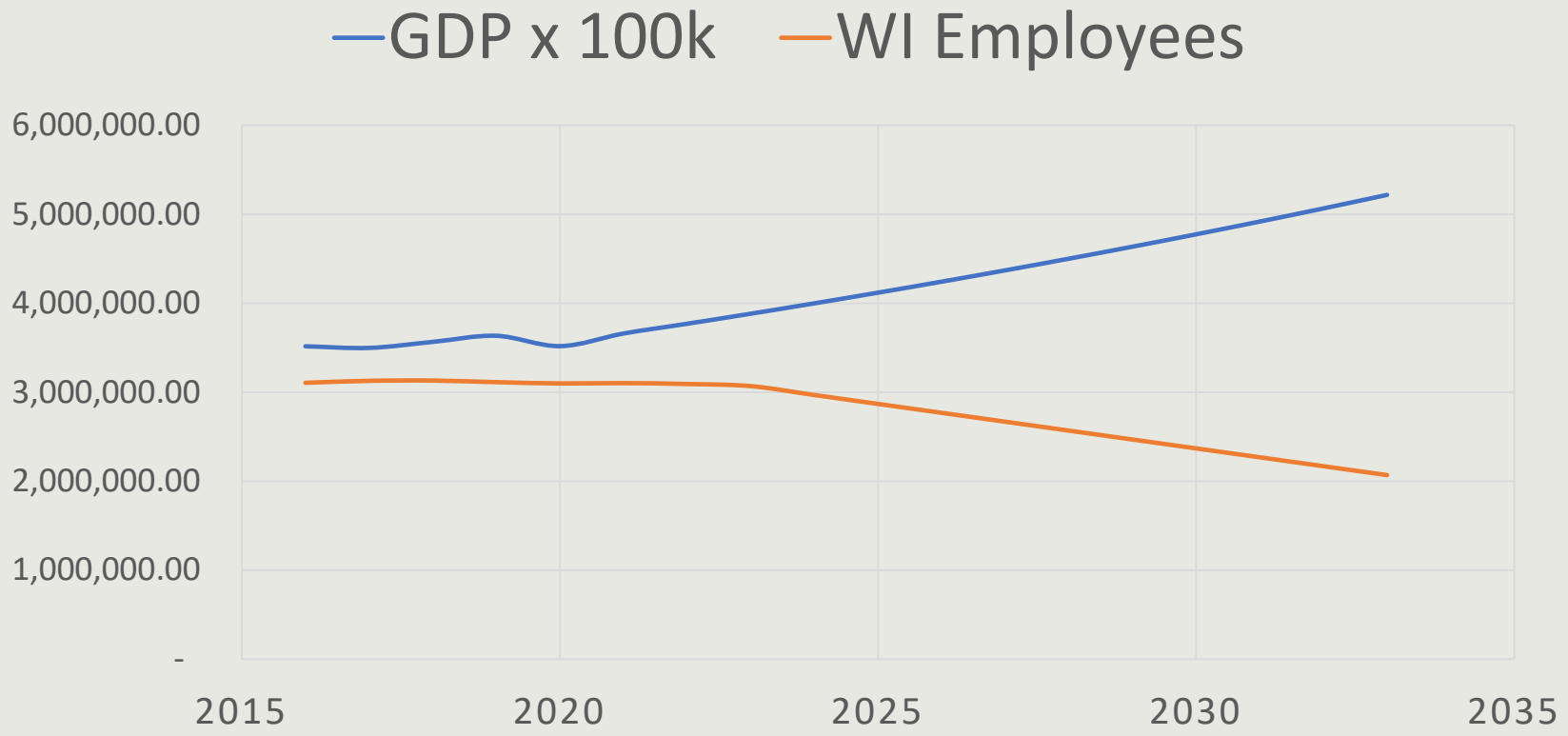

2023- Rev/Employee = $126,544

2030- Rev/Employee = $201,644

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What Data is being collected?

Companies will have to leverage their systems to gain efficiencies

GLASS FACTORY
by Left Hand Engineering

What Data is being collected?

What are you measuring today?

Can you clearly define this?

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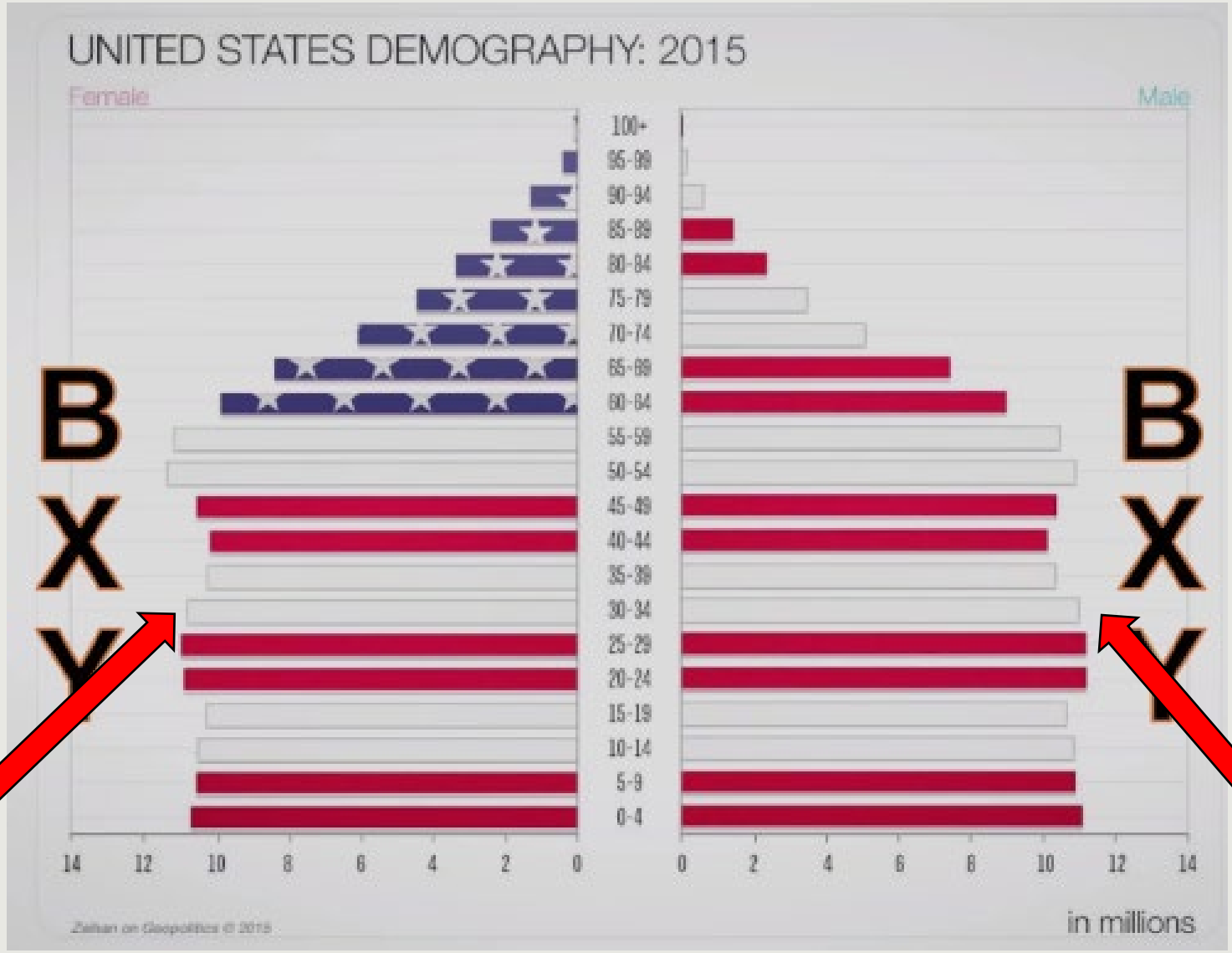
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SETTING THE STAGE

WHY DATA QUALITY IS THE FOUNDATION OF AI IN MANUFACTURING

THE CORE PROBLEM

AI systems — no matter how sophisticated — will only produce reliable outputs if the data fed into them is accurate, complete, and well-structured. In manufacturing, poor data quality leads to false alerts, missed defects, and costly rework. Garbage in, garbage out is not a cliché — it is a fundamental engineering truth.

THE OPPORTUNITY

Manufacturers who invest in data quality before deploying AI gain a compounding advantage. Clean data enables predictive quality, reduces scrap and warranty costs, and accelerates continuous improvement cycles. The organizations seeing the best ROI from AI are not those with the fanciest algorithms — they are the ones with the most disciplined data practices.

80%

OF AI PROJECT FAILURES

are attributed to poor data quality, not algorithmic shortcomings

3X

ROI MULTIPLIER

for manufacturers who standardize data collection before AI deployment

$12B

ANNUAL COST

of poor data quality in U.S. manufacturing (Industry estimates)

SECTION 1 OF 3

KNOW THE DATA

Before any AI model can be trained or quality system can be optimized, your team must develop a deep, systematic understanding of what data you already have — and what you're missing.

KNOW THE DATA

WHAT TO LOOK FOR: THE DATA LANDSCAPE

Most manufacturers are sitting on more data than they realize — but it is scattered, inconsistent, and often untrusted. The first step is conducting an honest inventory of the data types present in your operation.

PROCESS & MACHINE DATA

Temperature, pressure, cycle times, machine OEE, sensor outputs, SPC readings. This is often the richest and most underutilized data set in a manufacturing environment.

QUALITY INSPECTION RECORDS

Dimensional reports, visual inspection results, first-article data, incoming inspection logs. Often housed in spreadsheets or paper-based systems — prime candidates for digitization.

NONCONFORMANCE & DEFECT DATA

NCR logs, scrap rates, rework hours, warranty returns. These data sets are invaluable for training AI models to detect early warning signals.

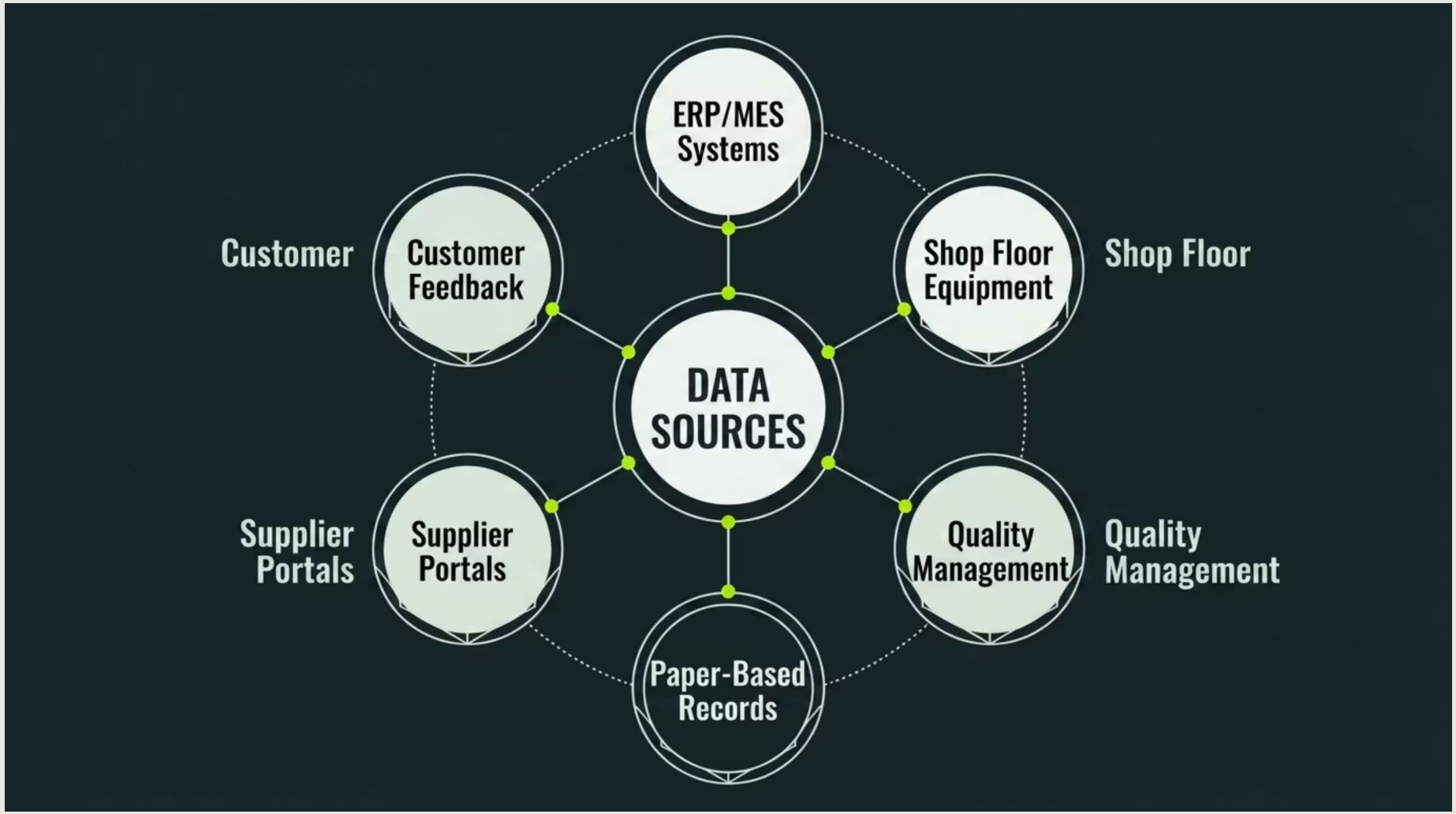
SUPPLIER & MATERIAL DATA

Certificates of conformance, material lot traceability, supplier scorecards, incoming quality trends. Supplier variation is frequently an invisible root cause of downstream defects.

KNOW THE DATA

WHERE TO LOOK: MAPPING YOUR DATA SOURCES

Data in a manufacturing operation rarely lives in one place. Understanding the physical and digital geography of your data is essential before any AI implementation can begin.



⚠ A common pitfall: teams assume data in the ERP is authoritative. In practice, the most accurate quality data is often still on paper at the machine level. Always audit the source, not just the system.

KNOW THE DATA

WHEN TO LOOK: DATA TIMING AND RELEVANCE

REAL-TIME DATA

Collected at the point of production — sensor readings, in-line inspection results, operator entries. This is the most valuable data for AI-driven process control but requires robust capture infrastructure. The value of real-time data degrades quickly: a temperature spike logged 30 minutes after it occurred cannot drive a real-time correction.

HISTORICAL DATA

Archived records from past production runs, audits, and quality events. This forms the training dataset for predictive models. The depth and consistency of historical data directly determines model accuracy.

KEY TIMING QUESTIONS TO ASK

- How fresh does this data need to be to drive a decision?
- Are there seasonal or shift-based patterns in our defect data?
- When in the process does the defect actually originate vs. when it is detected?
- How far back does our clean, consistent historical data actually go?
- Are we capturing data at the right frequency for the variation we are trying to detect?

Tip: Detection lag — the gap between when a defect is created and when it is found — is one of the biggest blind spots in traditional quality systems. AI can help close this gap dramatically.

KNOW THE DATA

HOW TO LOOK: CONDUCTING A DATA AUDIT

A structured data audit gives your team a repeatable methodology for assessing data readiness. This is not a one-time exercise — it should become part of your quality management cadence.

STEP 1: IDENTIFY

1

List every data source across the value stream. Include systems, people, machines, and paper logs.

2

STEP 2: ASSESS

Evaluate each source for completeness, accuracy, consistency, timeliness, and accessibility.

STEP 3: PRIORITIZE

3

Rank data sources by impact on quality outcomes and feasibility of improvement.

4

STEP 4: DOCUMENT

Create a data map — a living document that shows what data exists, where it lives, and who owns it.

STEP 5: ACT

5

Close the highest-priority gaps before deploying any AI tools. Fix the foundation first.

KNOW THE DATA

WHY IT MATTERS: THE BUSINESS CASE FOR DATA AWARENESS AWARENESS

Understanding your data is not just a technical prerequisite for AI — it is a strategic business capability. Organizations that have mapped their data landscape make faster decisions, resolve quality escapes more quickly, and build more effective supplier relationships.

FASTER ROOT CAUSE ANALYSIS

When you know where your data lives and trust its accuracy, troubleshooting time drops dramatically. Teams spend less time searching for evidence and more time solving problems.

AI READINESS

Every hour spent understanding your data is an hour saved during AI implementation. Models trained on well-understood data are more accurate and require far less retraining.

CULTURAL SHIFT

A team that understands its data becomes a data-driven team. This mindset shift is often more valuable than any individual AI application you deploy.

SECTION 2 OF 3

CAPTURE THE DATA

Knowing what data you need is only half the battle. The harder challenge — and the one where most manufacturers struggle — is building reliable, consistent systems and habits for capturing it at the source.

CAPTURE THE DATA

HOW MANUFACTURERS CAPTURE DATA TODAY

Before we can improve data capture, we need to be honest about how it actually happens on most shop floors today. The reality is a patchwork of methods — some digital, some analog — that have accumulated over decades without a unified strategy.

PAPER FORMS & INSPECTION SHEETS

Operators record measurements, inspection results, and process parameters by hand on printed forms. Data is often stored in binders, filed by date, and rarely analyzed systematically.

SPREADSHEETS

Excel is the universal fallback. Data is manually keyed in from paper, or entered directly. Spreadsheets are flexible but fragmented — every department has their own version, with no enforced structure or validation.

STANDALONE SOFTWARE SILOS

Many plants use dedicated software for specific functions (a CMM system, a gage management tool, an ERP module) that don't talk to each other. Data lives in isolated islands.

VERBAL & TRIBAL KNOWLEDGE

A significant portion of quality knowledge is never formally captured at all. It lives in the heads of experienced operators and engineers — and walks out the door when they retire.

None of these methods are inherently wrong — but together, they create a data environment that is fragmented, inconsistent, and largely inaccessible to AI systems.

CAPTURE THE DATA

WHY TRADITIONAL DATA CAPTURE FAILS AI

AI systems are only as good as the data they are trained and operated on. The legacy capture methods most manufacturers rely on introduce specific, compounding problems that make AI deployment unreliable — or impossible.

THE CORE PROBLEMS

- **No Structure at the Source** — Free-text fields, inconsistent naming, and ad hoc formats mean AI models cannot reliably parse or learn from the data without expensive preprocessing.
- **Transcription Errors** — Every time data moves from paper to spreadsheet to system, errors are introduced. A dataset with even 5% transcription error rate is unreliable for AI training.
- **Incomplete Records** — Paper forms and spreadsheets rarely enforce mandatory fields. Missing values create gaps that break time-series models and skew statistical analysis.
- **No Timestamps or Traceability** — AI models need to understand when and where data was captured. Paper records often lack precise timestamps, shift IDs, or machine identifiers.
- **Siloed & Inaccessible** — Data locked in binders, local spreadsheets, or disconnected systems cannot be aggregated for AI analysis without a major manual effort.

THE DOWNSTREAM IMPACT

These are not just data hygiene issues — they have direct business consequences. When AI models are trained on flawed data, they produce flawed predictions. A defect detection model trained on inconsistently coded defect records will misclassify defects. A predictive maintenance model trained on incomplete sensor logs will miss failure patterns. The cost of bad data compounds over time.

⚠ Attempting to deploy AI on top of legacy data capture systems is one of the most common — and most expensive — mistakes in manufacturing AI projects.

CAPTURE THE DATA

BETTER WAYS TO CAPTURE DATA IN MANUFACTURING

Modern data capture is not just about going paperless — it is about designing systems that produce structured, traceable, AI-ready data at the point of production. Here are the methods that leading manufacturers are using today.

DIGITAL FORMS AT THE POINT OF WORK

Tablet or PC-based forms deployed directly at workstations replace paper and eliminate transcription. Mandatory fields, drop-down menus, and validation rules enforce data quality at entry.

BARCODE & QR CODE SCANNING

Scanning part numbers, work orders, and operator IDs at the point of capture links every data record to its full production context automatically — no manual entry required.

AUTOMATED SENSOR & MACHINE DATA

IoT-connected equipment, CMMs, and in-line gauges feed measurement data directly into quality systems in real time. No human transcription, no delay, no error.

INTEGRATED QUALITY MANAGEMENT SYSTEMS (QMS)

Purpose-built QMS platforms (e.g., FactoryQA) provide structured, validated data capture with built-in traceability, audit trails, and integration to ERP/MES systems.

VISION & AI-ASSISTED INSPECTION

Camera-based inspection systems capture defect images and classification data automatically, creating rich labeled datasets that can be used to train and improve AI models over time.

The right combination of these methods depends on your production environment, volume, and existing infrastructure. You do not need all five — start with the one that addresses your biggest data quality gap.

CAPTURE THE DATA

MAKING THE TRANSITION: FROM LEGACY TO AI-READY CAPTURE

The gap between where most manufacturers are today and where they need to be for AI is real — but it is bridgeable. The key is a phased, pragmatic approach that delivers value at each step rather than waiting for a complete transformation.

01

AUDIT YOUR CURRENT STATE

Before changing anything, document what you have. Map every data capture touchpoint: what is recorded, how, by whom, and where it goes. Identify the highest-volume and highest-impact data streams first.

02

PRIORITIZE ONE HIGH-VALUE PROCESS

Do not try to modernize everything at once. Select one process where data quality problems are causing the most pain — a chronic defect, a customer complaint, a recurring scrap issue — and focus your first effort there.

03

DESIGN FOR STRUCTURE FROM DAY ONE

When replacing a paper form or spreadsheet, resist the urge to replicate it digitally. Redesign the form with controlled fields, mandatory entries, standardized codes, and automatic timestamps. This is your chance to fix structure problems at the source.

04

PILOT, VALIDATE, AND REFINE

Run the new capture method in parallel with the old one for a defined period. Compare data quality, completeness, and operator feedback. Refine before expanding.

05

EXPAND SYSTEMATICALLY AND BUILD THE CULTURE

Once the pilot proves value, roll out to adjacent processes. Involve operators in each new deployment. Show teams how their captured data is being used. Data capture culture is built one success story at a time.

WHAT TO EXPECT

- Initial resistance from operators used to existing methods
- A temporary dip in data volume as old habits change
- Rapid improvement in data quality within 60–90 days of a well-run pilot
- Growing organizational confidence in the data

COMMON MISTAKES TO AVOID

- Digitizing bad processes instead of redesigning them
- Skipping operator involvement in form design
- Launching too broadly before validating the approach
- Treating the transition as an IT project rather than an operations project

CAPTURE THE DATA

STRUCTURING DATA FOR AI CONSUMPTION

Even well-captured data can be unusable by AI systems if it is structured poorly. How you define fields, categories, and codes has a direct impact on model performance.

DATA STRUCTURE BEST PRACTICES

- **Use controlled vocabularies:** Drop-down menus over free text wherever possible. Free text is nearly impossible to use for machine learning without significant preprocessing.
- **Standardize defect codes:** A consistent defect taxonomy across products, shifts, and plants enables cross-functional pattern detection.
- **Link records with unique IDs:** Part numbers, lot numbers, work order IDs, and operator IDs must be consistently applied to allow traceability and correlation analysis.
- **Time-stamp everything:** Date and time of capture, not just date of entry, are critical for time-series analysis and shift-pattern detection.

THE COST OF POOR STRUCTURE

Consider a defect code field where operators can type anything. Over time, you will find entries like "scratch," "Scratch," "SCRATCH," "light scratch," "minor scratch," and "scr." These are all the same defect — but to an AI model, they look like six different things. Normalizing this field alone can take weeks of data cleaning effort and still produce an imperfect dataset.

⚠ Fix structure problems upstream — at the point of capture. Cleaning messy data downstream is expensive and never fully successful.

CAPTURE THE DATA

BUILDING A DATA CAPTURE CULTURE ON THE SHOP FLOOR

Technology and process redesign will only take you so far. The most sophisticated digital form is worthless if operators do not trust it, understand it, or have time to use it. Sustaining AI-ready data capture over time requires a culture shift — and that starts with leadership.

INVOLVE OPERATORS IN FORM DESIGN

Operators who help design capture forms are far more likely to use them correctly. They also know what is actually feasible to record at the pace of production. Their input is not optional — it is essential.

CLOSE THE LOOP VISIBLY

Show operators how the data they capture gets used. When people see their input driving a process improvement or preventing a customer return, data entry transforms from a burden into a contribution.

RECOGNIZE AND REINFORCE

Celebrate teams and individuals who demonstrate excellent data discipline. Quality data capture should be recognized as a skilled behavior — not taken for granted or treated as an administrative task.

LEAD FROM THE TOP

When managers and engineers actively use and reference captured data in daily decisions, they signal that data capture is valued — not just an audit requirement. Culture follows behavior, not policy.

Speaker Note: Share your experience with cultural resistance to data capture. What worked to turn skeptics into advocates?

SECTION 3 OF 3

USE THE DATA

You have mapped your data, cleaned it, and built reliable capture systems. Now comes the payoff: putting that data to work to drive real quality improvements, smarter decisions, and a continuously learning organization.

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SECTION 3 OF 3

WHAT AI CAN DO WITH YOUR QUALITY DATA

AI tools can act on your quality data in several distinct ways — understanding these capability categories helps you match the right tool to the right problem.

ANALYZE

Find patterns, anomalies, and trends across large datasets, identifying root causes, predicting failures, and optimizing processes.

DRAFT

Automatically generate written content such as quality reports, corrective action plans, or standard operating procedures from structured data inputs.

CREATE

Build new documents, work instructions, and forms using intelligent templates, ensuring accuracy and adherence to specific guidelines.

IMPORT & EXTRACT

Pull structured data from unstructured sources like PDFs, technical drawings, scanned documents, or handwritten notes, making it machine-readable.

AUDIT & COMPARE

Check documents, processes, or products against predefined standards, specifications, or historical records to ensure compliance and identify deviations.

SUMMARIZE & SYNTHESIZE

Condense large volumes of quality records into actionable insights, providing quick overviews and highlighting critical information for decision-makers.

A SUMMARY OF AI TOOLS FOR QUALITY MANAGEMENT

Not all AI tools are created equal — and the landscape is evolving rapidly. Here is a practical overview of the major categories of AI tools relevant to manufacturing quality teams, helping you match the right solution to the right problem.

Tool Category	Example Tools	Best Used For
Large Language Models (LLMs)	e.g., ChatGPT, Claude, Gemini	Drafting, summarizing, and analyzing text-based quality records (e.g., non-conformance reports, customer feedback).
Document AI / OCR Platforms	e.g., Microsoft Azure Document Intelligence, Google Document AI	Extracting structured data from unstructured sources like technical drawings, forms, scanned documents, and handwritten notes.
Quality Management System (QMS) AI Add-ons	e.g., ETQ, MasterControl, Qualio (AI features within)	Automating CAPA workflows, enhancing audit management processes, ensuring compliance tracking, and intelligent document routing.
Computer Vision / Inspection AI	e.g., Cognex, Landing AI	Automated visual inspection, real-time defect detection on production lines, and quality control of manufactured goods.
Analytics & BI Platforms with AI	e.g., Power BI Copilot, Tableau AI	Identifying trends, creating interactive dashboards, generating predictive quality metrics, and deeper data exploration.

SECTION 3 OF 3

HOW TO SELECT THE RIGHT AI TOOL

Choosing the wrong AI tool wastes time and budget. Use these criteria to evaluate and select the solutions that genuinely fit your quality team's actual needs and deliver tangible value.

DEFINE THE PROBLEM FIRST

Start with a specific quality challenge, not a technology. What decision do you need to make faster? What task takes too long? What critical data is currently unused?

ASSESS YOUR DATA READINESS

A tool is only as good as the data you feed it. Confirm you have sufficient volume, structure, and cleanliness for the intended use case before committing to any solution.

EVALUATE INTEGRATION REQUIREMENTS

Will the tool connect seamlessly to your existing QMS, ERP, or MES? Standalone solutions requiring manual data export often create new, inefficient bottlenecks.

CONSIDER YOUR TEAM'S CAPABILITY

Some tools demand data science expertise, while others are designed for quality engineers. Match tool complexity to your team's current skills and their training capacity.

START WITH A BOUNDED PILOT

Before full deployment, run a time-limited pilot on a single product line or process. Define clear success criteria in advance and rigorously measure against them.

> The best AI tool is the one your team will actually use consistently — adoption matters more than capability on paper.

SECTION 3 OF 3

AI IN ACTION: REAL EXAMPLES FOR QUALITY

These are not hypothetical use cases — they are practical applications quality teams are deploying today. Each example shows what the AI does, what data it needs, and what the output looks like, providing a clear roadmap for integrating AI into your quality management processes.

ANALYZE NCRS & DRAFT ROOT CAUSES / CORRECTIVE ACTIONS

Feed nonconformance records into an LLM. The AI analyzes patterns across NCRs, identifies likely root causes based on historical data, and drafts a structured 8D or corrective action report for engineer review.
Input → structured NCR records with defect codes, part numbers, process steps, and prior corrective actions.
Output → a pre-populated CAPA report ready for human review and approval.

AUDIT QMS DOCUMENTS AGAINST STANDARDS

Upload your quality procedures, work instructions, or control plans alongside the relevant standard (ISO 9001, IATF 16949, AS9100, etc.). The AI compares clause by clause, flags gaps, and generates an audit-ready gap analysis report.
Input → current QMS documents in PDF or Word format, target standard text.
Output → a gap analysis matrix with specific clause references and recommended remediation actions.

BALLOON & EXTRACT DATA FROM ENGINEERING DRAWINGS

Use Document AI or OCR tools to automatically identify and extract balloon callouts, GD&T tolerances, material specifications, and revision history from engineering drawings.
Input → engineering drawings in PDF or image format.
Output → a structured inspection plan or first article inspection (FAI) checklist populated directly from the drawing.

DEVELOP DOCUMENT DRAFTS

Provide AI with a product specification, process description, or existing legacy document. The AI generates a first draft of a work instruction, control plan, PFMEA, or quality procedure in your organization's format.
Input → product/process specs, existing templates, relevant standards.
Output → a structured draft document ready for SME review, reducing authoring time by 60-80%.

▸ Show query

Most and least productive employee where productivity is compared to the target rate for the 'Box Set' project

For the 'Box Set' project, [redacted] is the most productive employee with an actual parts per hour rate of 3.79 and a productivity ratio of 1.26. In contrast, [redacted] is the least productive employee with an actual parts per hour rate of 1.20 and a productivity ratio of 0.40.

▾ Show data (2 rows)

Actual Parts Per Hour	Category	First Name	Last Name	Productivity Ratio	Target p
3.785262938505403	Highest	[redacted]		1.2617543128351343	3
1.2	Lowest			0.4	3

▸ Show query

Top 10 customers by revenue

Send

Top 10 customers by revenue

The top 10 customers by revenue are led by [redacted] with $1,442,450.48 in revenue, followed by [redacted] with $981,013.54, and [redacted] with $532,302.46. The total revenue from these top 10 customers includes $450,563.02 from [redacted] $363,165.09 from [redacted], $350,473.37 from [redacted] $338,080.51 from [redacted] $304,256.53 from [redacted] $248,140.06 from [redacted] and $220,122.81 from [redacted].

▾ Show data (10 rows)

Customer	Revenue
[redacted]	1442450.481
	981013.5402992239
	532302.463
	450563.019
	363165.092
	350473.36833333335
	338080.511
	304256.53
	248140.06
	220122.81

Ask anything...

Send

GETTING STARTED: WHAT YOU NEED TO DO

Deploying AI in quality management is not a solo effort — it requires the right people, the right preparation, and a structured approach to getting started. Here is how to move from interest to action.

WHO NEEDS TO BE INVOLVED

- **Quality Manager or Director:** Executive sponsor and decision-maker.
- **Quality Engineers:** Primary users and subject matter experts.
- **IT / Data Team:** Data access, integration, and security.
- **Operations / Production:** Process knowledge and change management.
- **Compliance / Regulatory:** Ensure AI outputs meet audit and regulatory requirements.

Note: You do not need a dedicated AI team — start with the people you already have.

WHAT NEEDS TO BE DONE

1. Identify 1-2 high-value use cases to pilot.
2. Audit your data for the selected use case — is it structured, accessible, and sufficient?
3. Select a tool appropriate for the use case and team capability.
4. Define success metrics before you start (time saved, error rate reduction, CAPA cycle time, etc.).
5. Establish a human review process — AI outputs should always be reviewed before action.
6. Document your process and results for future scaling.

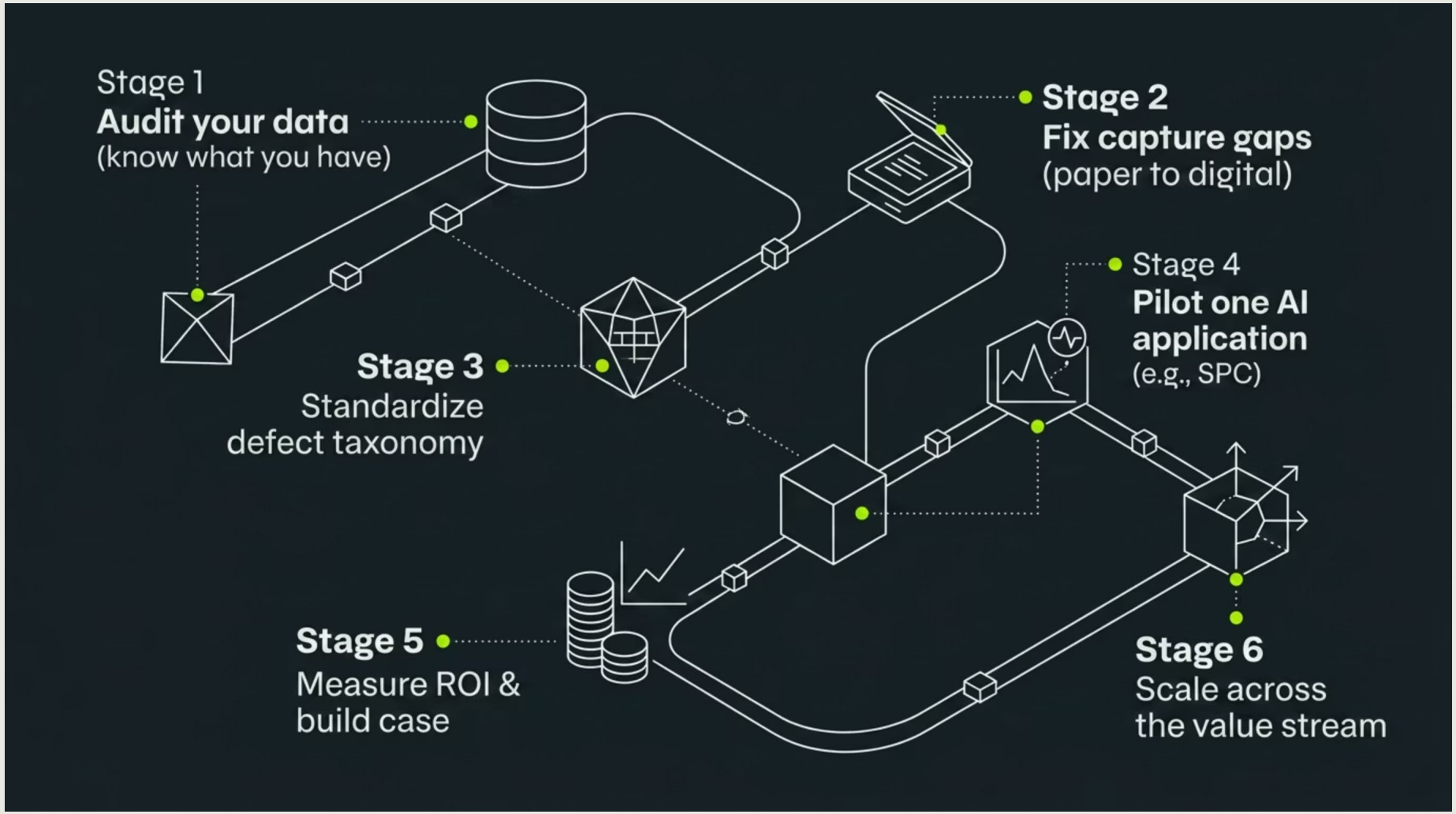
HOW TO GET STARTED WITH A

Most enterprise AI tools offer free trials or sandbox environments. Start with a 30-60 day pilot on a single use case. Use real data from a completed project so you can validate AI outputs against known outcomes. Involve 2-3 quality engineers as pilot users. Collect structured feedback weekly. At the end of the trial, present results to leadership with a clear go/no-go recommendation backed by data.

BRINGING IT TOGETHER

GETTING STARTED: A PRACTICAL ROADMAP FOR MANUFACTURERS

You do not need to transform everything at once. The most successful AI quality implementations start small, prove value quickly, and expand systematically. Here is a practical starting point regardless of where you are today.



The organizations that succeed with AI in quality do not start with the biggest, most complex use case. They start with the most painful, best-documented problem — and they win there first.

BRINGING IT TOGETHER

KEY TAKEAWAYS: KNOW, CAPTURE, USE

KNOW YOUR DATA

Map every data source across your value stream. Understand what you have, where it lives, how fresh it is, and whether it can be trusted. Do this before selecting any AI tool.

CAPTURE IT RELIABLY

Invest in digital capture at the source. Validate your measurement systems. Design forms and workflows that make accurate data entry the path of least resistance for your operators.

USE IT TO DRIVE ACTION

Connect your data to decisions. Use AI to find patterns, accelerate root cause analysis, improve work instructions, and verify corrective action effectiveness. Close the loop — always.

> AI does not replace quality expertise — it amplifies it. The engineers and leaders in this room are the ones who understand the process deeply enough to ask the right questions of the data. That combination — domain expertise plus AI — is the real competitive advantage.

Q&A & CLOSING

THANK YOU FOR ATTENDING

Thank you all for joining today's webinar on AI and data quality in manufacturing. We hope the frameworks and experiences shared today give you practical tools you can bring back to your organizations this week.

REQUEST THE PDF SLIDES

If you would like a copy of today's presentation materials, reach out to us directly. We are happy to share the slide deck along with any supporting resources referenced today.

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STAY CONNECTED

Questions that did not get answered today? Challenges you would like to discuss further? Our speakers are available for follow-up conversations. Reach out anytime — we are here to help manufacturers succeed with AI-driven quality.

We welcome your feedback on today's session. Your input helps us make future webinars even more relevant and useful.