Capability Guide: Data Quality

Data Does Not Need to Be Perfect. It Needs to Be Fit for Purpose.

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Table of Contents

How to use this guide

Read Sections 1 through 3 for the executive view. Use Sections 4 through 7 to build and mature the capability. Use Section 8 to decide what to do next Monday morning.

01 Executive Brief

Data Quality is the organization's ability to make important data accurate, complete, timely, consistent, unique, and fit for purpose.

Quality is the second Data capability because Ownership names who is accountable, and Quality proves whether the data is good enough for the work it supports.

Capability ID	D2 - Data Quality
Domain	Data
Plain-English test	Can the organization prove that the data used for decisions, reporting, automation, and AI is good enough for that use?
Three practical outputs	Data Quality Rules; Data Quality Scorecard; Data Quality Remediation Plan
Primary owner	Business data owners, supported by data stewards, analysts, process owners, technology teams, risk, privacy, security, and Factory teams.
First move	Pick one important data use, identify the critical fields, define simple quality rules, test the data, and decide what must be fixed before use.

Core point of view

Data quality is not about cleaning all data everywhere. It is about knowing which data matters, what good enough means, what defects exist, who must fix them, and whether the data can be trusted for the decision or use case in front of the organization.

The Data domain story is simple: Ownership assigns. Quality proves. Access enables. Flow connects. Insight informs.

2026.08 ALIGNMENT | Quality in the refreshed TIO system

Primary outcome contribution: Intelligence

- Quality includes accuracy, completeness, currency, contradiction, provenance, current-state integrity, and fitness for the intended human, automation, or AI use.
- Knowledge sources and retrieval paths require quality controls, not only structured databases.
- Quality thresholds should be set by the consequence and evidence needs of the work.

Evidence at managed maturity: Quality is defined, owned, applied consistently, measured in operation, reviewed through evidence, and improved without weakening trust, accountability, or Enterprise Autonomy.

First refresh move: Test the freshness, provenance, contradiction, and use fitness of the sources behind one important decision or AI Use Case.

02 The Problem This Capability Solves

Many organizations do not know whether the data they rely on is good enough. They know reports disagree. They know people reconcile numbers before meetings. They know automation breaks. They know dashboards lose credibility. They know AI Use Cases slow down because nobody can stand behind the data.

That is the problem Data Quality solves.

Poor quality used to create bad reports. Now it can feed automation, summaries, recommendations, customer interactions, workforce decisions, risk controls, and executive choices. That makes quality a business confidence issue, not a back-office data issue.

When Data Quality is weak

- Leaders receive conflicting numbers and spend time arguing about which report is right.
- Teams clean data manually because defects are not fixed at the source.
- Automations fail because required fields are missing, duplicated, stale, or inconsistent.
- AI Use Cases stall because nobody can prove the data is fit for purpose.
- Customers, employees, regulators, or partners may be affected by decisions based on unreliable data.
- Transformation work slows down because every new use case becomes a data cleanup project.

> **The practical rule**
>
> Do not try to fix all data everywhere. Start with the data that matters most to strategy, reporting, operations, automation, AI Use Cases, risk controls, customer trust, and transformation work.

03 What this Capability Is

Data Quality makes data trustworthy enough for the purpose at hand. The goal is not perfect data. The goal is fit-for-purpose data.

Fit for purpose means the data is good enough for the decision, report, automation, AI Use Case, customer interaction, employee action, risk control, or operational process it supports.

What Data Quality owns

- Defining what good enough means for priority data.
- Setting quality rules for critical fields and records.
- Checking data against those rules before important use.
- Making defects visible to the right owners and leaders.
- Assigning quality issues for correction at the source where possible.
- Tracking whether data quality is improving over time.
- Setting quality thresholds for reporting, automation, AI Use Cases, and high-value decisions.

What Data Quality does not own

- Cleaning all data everywhere.
- Making every data set perfect.
- A one-time remediation project.
- A technical profiling exercise by itself.
- A data warehouse, data lake, or platform project.
- A technology-only fix without business ownership.
- The final business decision about whether to proceed despite known defects.

Five core behaviors

Behavior	What it means
Define	Agree what good enough means for the specific use of the data.
Check	Test priority data against simple rules and thresholds.
Expose	Make defects, trends, and readiness visible before important use.
Fix	Assign issues to owners and correct the highest-value defects at the source.
Improve	Use quality results to improve rules, systems, processes, training, and decisions.

Boundary rule

Ownership assigns accountability. Quality proves whether the data is fit for use. Access controls safe use. Flow moves data reliably. Insight turns data into decision-quality evidence. Technology provides platforms and tools. Factory uses data in AI Use Cases and transformation work.

04 How the Capability Works

Data Quality should be built into the path from important data to important use. It should not appear after a dashboard, automation, or AI Use Case has already lost trust.

The simplest operating model is:

Quality operating flow

Pick the use -> identify the data -> define the rules -> check the data -> expose defects -> decide fitness -> fix what matters -> improve at the source.

The work in practice

- Start with a real use, such as a board metric, customer report, automation, AI Use Case, regulatory report, or operational dashboard.
- Identify the critical data fields and records that must be trusted for that use.
- Define simple quality rules, such as required fields, valid values, duplicate checks, timeliness, linkage, and consistency.
- Test the data through sampling, profiling, reconciliation, user review, or source-system checks.
- Review the defects with the business owner, data owner, process owner, and technology owner.
- Decide whether the data is ready, ready with limits, or not ready for the intended use.
- Assign the most important defects for remediation and track whether they are fixed.
- Update the rules and source process when the same defect keeps recurring.

Example

A mid-sized field services company wants to use service ticket, technician, invoice, and client data to create an AI-enabled operations dashboard showing service performance, margin leakage, and client opportunities.

The team identifies critical fields such as client ID, work order ID, technician ID, open date, close date, labour hours, parts cost, invoice amount, service location, and ticket status. They define simple quality rules. Every closed ticket must have a close date. Every invoice must link to a valid work order. Every technician record must have an active status. Every dashboard margin calculation must use the same definition.

The first test finds missing close dates, duplicate client records, invoices without linked work orders, and inconsistent status values. Operations, Finance, and Technology agree which defects block the dashboard, which can be tolerated with a warning, and which must be fixed at the source.

Quality gives leaders confidence that the dashboard, automation, or AI Use Case is not built on unreliable data.

05 Outputs, Evidence, and Measures

Data Quality should produce a small number of useful outputs. More profiling does not mean more trust. Three outputs are enough to start and mature the capability.

Output	Purpose	Quality standard
Data Quality Rules	Define what good enough means for priority data, fields, records, reports, automations, and AI Use Cases.	Rules are simple, specific, owned, testable, and tied to real business use.
Data Quality Scorecard	Show whether priority data is ready, limited, or not ready for important use.	The scorecard shows defects, trends, thresholds, owners, impact, and readiness decisions.
Data Quality Remediation Plan	Assign the most important defects for correction and prevent repeat defects where possible.	The plan names issue, source, owner, impact, action, due date, status, and evidence of closure.

Evidence that the capability exists

- Documented quality rules for priority data.
- A current quality scorecard used in decisions.
- Named owners for quality rules and defect resolution.
- Known thresholds for important reports, automations, and AI Use Cases.

Evidence that the capability is used

- Data is checked before important reports, dashboards, automations, and AI Use Cases go live.
- Defects are reviewed with business and technology owners.
- Remediation actions are assigned and tracked.
- Readiness decisions are recorded as ready, ready with limits, or not ready.

Assessment crosswalk

Use this guide with the TIO Capability Model and Maturity Assessment Tool. Scores should be supported by evidence that quality rules, scorecards, remediation, and readiness decisions are used in real work. A one-time cleanup effort is not the same as a mature Quality capability.

Useful measures

Measure	What it tells leaders
Critical-field completeness	Whether required fields are populated enough for the intended use.
Duplicate rate	Whether records such as customers, vendors, products, assets, or employees are being counted more than once.

Measure	What it tells leaders
Timeliness	Whether the data arrives or updates in time for the decision or workflow.
Consistency	Whether the same definition or value is used across reports, systems, and teams.
Defect aging	How long known issues stay unresolved.
Remediation closure rate	Whether assigned fixes are being completed.
Use-case readiness	Whether data is ready, ready with limits, or not ready for a report, automation, AI Use Case, or decision.
Recurring defect rate	Whether the same issues keep returning because the source process is not fixed.

06 Maturity: 0 to 5

Use the maturity model to score Data Quality honestly. A high score requires evidence that quality is defined, checked, used in decisions, improved at the source, and connected to value.

Level	What it looks like	Evidence	Next move
0 - Absent	Data quality is not meaningfully managed. Defects are discovered through complaints, reconciliations, failed reports, or broken work.	No quality rules, no scorecard, no owner for defects, no remediation rhythm.	Pick one priority data use and identify the fields that must be trusted.
1 - Initial	Some teams check or clean data, but work depends on individual effort and local spreadsheets.	Ad hoc checks, manual cleanup, team-specific definitions, recurring disputes.	Define simple quality rules for the first priority data set.
2 - Repeatable	Basic rules and checks exist for priority data. Defects are visible and assigned for correction.	Rules, basic scorecard, defect log, named owners, remediation actions.	Connect quality checks to reports, automations, and AI Use Case readiness.
3 - Defined	Quality is documented, owned, communicated, and used consistently for priority data.	Standard rule format, scorecard cadence, thresholds, owner decisions, source fixes.	Measure trends and use quality evidence in governance, risk, Factory, and leadership decisions.
4 - Managed	Quality is measured and managed. Leaders understand trends, recurring issues, value impact, and readiness for important use.	Trend reports, defect aging, closure rates, use-case readiness, value and risk linkage.	Use quality learning to improve systems, workflows, ownership, access, and source processes.
5 - Optimized	Quality continuously improves and helps the organization adapt faster, trust data more, and scale AI and automation with confidence.	Continuous improvement rhythm, fewer repeat defects, strong readiness evidence, faster trusted delivery.	Keep quality rules current as strategy, systems, work, data use, and AI capability change.

07 How to Build and Mature the Capability

Start light. Build only what helps people define quality, check priority data, expose defects, assign fixes, and decide whether data is fit for use. Add more structure only when scale, risk, customer exposure, regulation, system complexity, or AI use requires it.

Minimum viable Data Quality capability

- One accountable Quality lead for priority data work.
- One list of priority data uses that matter most now.
- One set of critical fields for each priority use.
- One simple rule set for what good enough means.
- One scorecard showing defects, trends, thresholds, and readiness.
- One remediation plan with owners and dates.
- One review rhythm that connects quality to decisions, AI Use Cases, reports, and transformation work.

First 30 days

- Choose one important use: a key report, dashboard, automation, AI Use Case, regulatory report, or customer-facing output.
- Name the business data owner, process owner, analyst, technology contact, and decision owner.
- Identify the 10 to 20 fields that matter most for that use.
- Write simple quality rules for completeness, validity, uniqueness, timeliness, consistency, and linkage.
- Run the first quality check and review the defects with the owners.
- Decide whether the data is ready, ready with limits, or not ready for the intended use.

First 90 days

- Create the first Data Quality Scorecard for priority data.
- Build the first remediation plan and assign owners for the highest-impact defects.
- Track defect aging, closure, and repeat defects.
- Add quality checks to the intake path for dashboards, automations, and AI Use Cases.
- Agree which defects must be fixed at the source, not manually cleaned downstream.
- Review quality results in the relevant leadership, governance, risk, Factory, or transformation rhythm.

First 12 months

- Expand rules and scorecards to the most important data domains.
- Connect quality evidence to the TIO assessment, AI Use Case pipeline, Evidence Gates, and value reviews.
- Reduce recurring defects by changing source processes, system controls, training, and ownership routines.
- Use quality trends to prioritize data, technology, and workflow improvements.
- Refresh rules as new decisions, systems, automations, AI Use Cases, and regulatory obligations emerge.

Scale	How to keep it practical
Owner-led enterprise	Start with the numbers and records the owner relies on most. Do not build a large data program.
Managed enterprise	Use simple rules, named owners, and a monthly review for reports, operations, finance, customers, and AI experiments.
Mid-sized enterprise	Build scorecards and remediation plans around priority data domains, AI Use Cases, and transformation work.
Large enterprise	Standardize quality rules, ownership, scorecards, remediation, and decision thresholds across major domains and platforms.
Large distributed enterprise	Use common standards, local accountability, enterprise scorecards, and clear escalation for high-risk or external-facing data use.

08 TSLA Support and First Moves

TSLA helps leaders build Data Quality as a practical trust capability, not as a data cleanup campaign. The work is designed to be clear enough for executives, useful enough for managers, and strong enough to support trusted reporting, automation, AI Use Cases, and transformation work.

Where TSLA can help

- Data Quality and AI Readiness Assessment.
- Priority data selection and critical-field mapping.
- Data Quality Rules design.
- Data Quality Scorecard design.
- Data Quality Remediation Plan and owner rhythm.
- Quality checks for AI Use Cases, dashboards, automations, and Evidence Gates.
- Executive Thought-Partnership on data confidence, risk, and value decisions.

What to do Monday morning

- Pick one important report, dashboard, automation, AI Use Case, or decision that depends on trusted data.
- Name the business owner, data owner, process owner, analyst, and technology contact.
- List the critical fields that must be trusted for that use.
- Write one simple quality rule for each critical field.
- Run the first quality check using sampling, profiling, reconciliation, or expert review.
- Label the data as ready, ready with limits, or not ready for the intended use.
- Assign the top five defects to owners and start a remediation log.
- Review the results in the next leadership, governance, Factory, or transformation meeting.

Closing thought

Quality is not perfection. Quality is confidence. The organization needs to know when data is good enough to use, when it needs limits, and when it is not ready yet.

A Source Note

This guide is part of the TIO Library. It is aligned to the TIO Framework, the TIO Data Capability Domain Master, the TIO Capability Model and Maturity Assessment Tool, and the approved 8-section Capability Guide structure used for the Governance, Risk, Transformation, and Data Ownership Capability Guides.

It is written as a practical executive guide. It is not a technical data-management standard, legal opinion, privacy assessment, cybersecurity review, or professional assurance report. Organizations should apply their own policies, obligations, accountabilities, and professional review where required.