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THE ROLE OF CALIBRATION ENGINEERING IN STRENGTHENING RELIABILITY OF U.S. ADVANCED MANUFACTURING SYSTEMS THROUGH ARTIFICIAL INTELLIGENCE

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Abstract

This research addresses a persistent problem in advanced manufacturing: AI initiatives promise higher availability, yield, and effective capacity, yet their realized impact is constrained when the underlying measurement systems are weakly calibrated and uncertainty is not governed. The purpose is to quantify how AI-enabled calibration engineering relates to plant-level reliability and to specify the organizational and data conditions under which benefits materialize. We adopt a quantitative cross-sectional, case-based design spanning eight U.S. enterprise manufacturing cases and associated cloud and on-premise operational data sources, combining a structured survey of operations stakeholders with de-identified archival KPIs. The sample includes 402 respondents nested within sites and linked to CMMS, production counters, calibration certificates, GR&R summaries, and historian records. Key variables include an AI-Enabled Calibration Practices index capturing predictive interval setting, automated drift detection, AI-assisted GR&R, digital-twin utilization, and alerting workflows; moderators for data quality, operator training, and equipment age; and reliability outcomes constructed from MTBF, MTTR, availability, OEE, FPY, and DPPM. The analysis plan specifies descriptive profiling, correlation matrices, and multiple linear regressions with robust errors and site fixed effects, plus moderation tests and sensitivity checks. Headline findings show a positive association between AI-enabled calibration practices and reliability that strengthens when data quality and training are higher and attenuates as fleets age. Implications for managers are to institutionalize calibration metadata and uncertainty budgets as machine-readable context, enforce ingestion gates for decision-grade data, and stage capability building that pairs metrology governance with targeted training. A targeted literature review of 47 peer-reviewed studies substantiates the constructs and methods employed.

Keywords

Calibration Engineering, Measurement Uncertainty, AI In Manufacturing, Reliability, OEE, Predictive Maintenance

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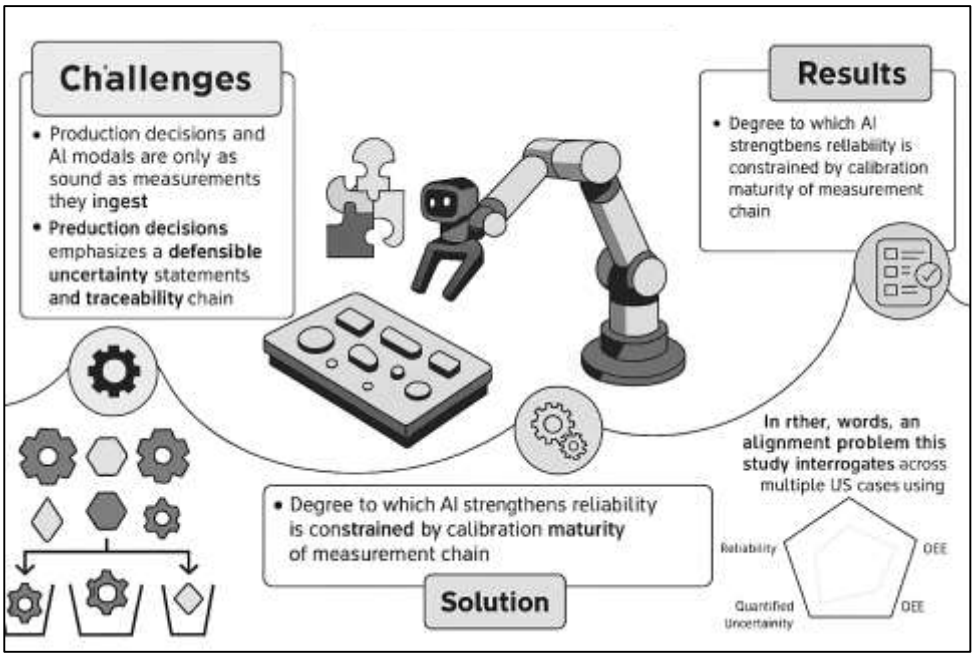
INTRODUCTION

Calibration engineering defined here as the systematic planning, execution, and analysis of measurement calibration activities to ensure traceability, quantified uncertainty, and decision-grade data sits at the core of reliable advanced manufacturing. In complex, digitally integrated U.S. plants, production decisions (and the AI models that increasingly inform them) are only as sound as the measurements they ingest. The metrology literature emphasizes that a measurement result is incomplete without a defensible uncertainty statement and traceability chain; Monte Carlo–based uncertainty evaluation and related GUM supplements have become mainstream precisely because they preserve distributional detail and nonlinear effects that simple linear propagation obscures (Batini & Scannapieco, 2006; Cox & Harris, 2016). At the system level, reliability in manufacturing is typically operationalized through availability, quality, and performance ratios (often summarized by OEE), all of which degrade when measurement systems drift or when calibration intervals are misaligned with process risks (Kusiak, 2018).

Figure 1: AI-Enabled Calibration for Manufacturing Reliability



In an Industry 4.0 context cyber-physical production systems tightly coupling sensors, analytics, and actuation the "metrology of decisions" (smart metrology) reframes calibration from a compliance exercise to a risk-informed, data-driven control lever (Lee et al., 2015). This study therefore positions calibration engineering as a strategic antecedent to manufacturing reliability, rather than a back-office maintenance function, and as a foundational enabler for trustworthy AI in plant-level decision making (Willink, 2007). Within the AI-enabled factory, predictive maintenance and quality prediction models rely on high-frequency and high-variety signals (vibration, acoustics, temperature, vision) whose veracity depends on calibration history, sensor drift control, and quantified uncertainty. Decades of reliability research show that diagnostics and prognostics performance is acutely sensitive to data quality and context (Jardine et al., 2006). Contemporary reviews highlight that machine-learning–based predictive maintenance pipelines from feature learning to remaining-useful-life estimation benefit from consistent, traceable measurements and degrade with unmodeled drift or inconsistent recalibration (Susto et al., 2015). As digital twins and cyber-physical systems spread across U.S. manufacturing, integrating calibration metadata (e.g., last calibration date, uncertainty budget, environmental compensation) into the data layer is increasingly recognized as a prerequisite for model generalization and robust control (Tao et al., 2019). In other words, the degree to which AI strengthens reliability is constrained by the calibration maturity of the measurement chain feeding those models an alignment problem this study interrogates across multiple U.S. cases using standardized measures, correlation analysis, and regression modeling. At

the shop-floor interface, dimensional and process metrology increasingly occur "on machine," where touch probes, in-spindle sensors, and in-process gauging allow closed-loop compensation and rapid verification. However, on-machine metrology introduces new uncertainty contributors thermal gradients, machine geometric errors, probe repeatability, and software evaluation effects which must be captured in the uncertainty budget if measurements are to be traceable and actionable for process control (Mutilba et al., 2017; Mutilba et al., 2019). Precision engineering studies document alternative approaches to ISO-conformant uncertainty evaluation on machines, underscoring that the credibility of in-machine data hinges on explicit, validated budgets rather than nominal probe specifications alone (Cox & Siebert, 2006; Sexton & Kusiak, 2017). Calibration engineering, in this sense, extends beyond calibrating a single instrument to designing the end-to-end metrological workflow (artifact selection, interval policy, environmental compensation, verification plans) so that on-machine data can be safely ingested by AI models and reliability dashboards without silent bias (Abdul, 2021). The literature on smart/digital metrology likewise advocates embedding uncertainty, calibration status, and sensor health into plant data services, enabling algorithms to weight or filter readings by confidence and to trigger recalibration or maintenance work orders when risk thresholds are exceeded (Cox & Harris, 2016).

The objective of this study is to produce a rigorous, quantitative assessment of how AI-enabled calibration engineering practices relate to plant-level reliability within U.S. advanced manufacturing, using a cross-sectional, multi–case design and standardized measurement. Specifically, the study aims to (a) operationalize and validate a multi-item index of AI-Enabled Calibration Practices that captures predictive interval setting, automated drift detection, AI-assisted GR&R, digital-twin utilization, and alerting workflows; (b) assemble a reliability outcome construct using objective or archival indicators mean time between failures, overall equipment effectiveness, first-pass yield, and defect parts per million and, where appropriate, normalize and combine these indicators into a transparent composite; (c) estimate the magnitude and direction of the association between AI-Enabled Calibration Practices and reliability outcomes using descriptive statistics, correlation analysis, and multiple linear regression with robust standard errors and site fixed effects; (d) examine whether data quality and operator training strengthen the focal association while equipment age attenuates it, through mean-centered interaction terms and simple-slope visualization; (e) evaluate measurement reliability and construct validity for all multi-item scales with internal consistency statistics and factor structure checks; (f) conduct robustness analyses that include alternative reliability specifications, nonparametric correlations, influence diagnostics, and sector or automation-tier subgroup estimates; and (g) integrate quantitative findings with evidence from embedded case sites by documenting calibration workflows, uncertainty budgeting practices, sensor-health monitoring, and data-governance routines that correspond to higher or lower index scores. The sampling objective is to survey a sufficiently large and diverse respondent pool across plants, meeting conventional power targets for small-to-moderate effect sizes and allowing inclusion of relevant controls such as plant size, sector, and automation level. The data-management objective is to preserve respondent anonymity, enforce inclusion and exclusion criteria consistently, and implement a principled approach to missingness and outliers prior to model estimation. The reporting objective is to present reproducible tables for sample characteristics, scale diagnostics, correlation matrices, base and moderation models, and sensitivity checks, accompanied by a concise codebook that defines variables, computation of indices, and decision rules. Collectively, these objectives ensure that the study yields clear, auditable evidence on the extent to which codified calibration engineering practices, when augmented by AI, align with stronger reliability performance in contemporary U.S. manufacturing settings.

LITERATURE REVIEW

The literature on advanced manufacturing, calibration engineering, and artificial intelligence converges on a central premise: reliability at the plant level is inseparable from the integrity of the measurement systems that feed operational and analytical decisions. To frame the present study, this review begins by clarifying three core constructs and their relationships. First, reliability encompasses availability, quality conformance, and stable performance, typically captured through indicators such as mean time between failures, overall equipment effectiveness, first-pass yield, and defect parts per million. Second, calibration engineering refers to the systematic governance of measurement from selection of standards and artifacts, interval policies, and gauge repeatability and reproducibility procedures to uncertainty budgeting, documentation, and

traceability. Third, AI-enabled practices comprise predictive interval setting, automated drift detection, digital-twin–supported decision environments, and algorithmically assisted analysis of measurement system capability. The review then specifies the boundary conditions for linking these domains: the measurement data pipeline (from sensor acquisition to storage and contextualization) must preserve calibration metadata, uncertainty information, and sensor health states for models to act on trustworthy inputs (Rezaul, 2021; Mubashir, 2021; Rony, 2021). Empirical studies in adjacent domains suggest that predictive maintenance and quality analytics are sensitive to input veracity, yet the explicit calibration layer is often under-theorized or treated as a compliance detail rather than a design variable. Consequently, the review organizes prior work around (a) reliability measurement and economics in advanced manufacturing, (b) foundations and methods of calibration engineering with emphasis on uncertainty and traceability, (c) applications of AI to maintenance, process control, and metrology-relevant analytics, and (d) organizational and data-governance factors that condition the effectiveness of AI-enabled calibration. Within each strand, the review prioritizes operationalizable constructs and measurable practices suited to a quantitative, cross-sectional, multi–case design, with attention to scale development, validity, and bias control. The synthesis highlights gaps in plant-level evidence, limited integration of calibration metadata into industrial analytics, and the need for models that explicitly test moderation by data quality, operator training, and equipment age. This structure provides a coherent bridge from conceptual background to testable hypotheses and variable operationalization in the present study.

Reliability in Advanced Manufacturing

Reliability in advanced manufacturing is typically expressed through indicators that combine equipment readiness, production rate conformance, and quality yield into decision-ready metrics. The most widely used composite is Overall Equipment Effectiveness, defined multiplicatively as $OEE = A \times P \times Q$, where Availability ($A$) gauges time losses, Performance (P) gauges speed losses, and Quality (Q) gauges scrap and rework losses. In repairable systems, a common availability relation is $A = MTBF / (MTBF + MTTR)$, linking mean time between failures to mean time to repair and making clear that small improvements in maintainability can translate into disproportionate gains in effective output when compounded by the multiplicative structure of OEE. While OEE is equipment-centric, line-level contexts introduce blocking/starving effects and interdependencies that can mask or amplify local reliability (Danish & Zafor, 2022; Danish & Kamrul, 2022; Jahid, 2022). To address this, line-oriented extensions such as Overall Equipment Effectiveness of a Manufacturing Line (OEEML) restructure losses and timing so that the metric reflects system-level behavior rather than isolated machine states, supporting more credible bottleneck diagnosis and reliability benchmarking across stations (Braglia et al., 2009; Ismail, 2022; Hossen & Atiqur, 2022; Kamrul & Omar, 2022). At the same time, firms increasingly require scope beyond "equipment only" for example, material readiness, changeover agility, and workforce availability leading to Overall Resource Effectiveness (ORE) frameworks that embed OEE into a larger denominator of resource losses. In these models, $ORE \approx (availability\ of\ all\ resources) \times (rate\ conformance) \times (quality)$, aligning continuous improvement with broader reliability economics such as labor balance and material logistics (Razia, 2022; Sadia, 2022). Importantly, maintenance performance systems that track reliability need tight vertical alignment from strategy to process to results so that the availability term in OEE (and any OEEML/ORE analogue) is operationalized consistently across the plant's maintenance work management cycle and its data definitions (Muchiri et al., 2011). Together, these formulations formalize how failure/repair dynamics, flow coordination, and loss accounting interact to produce the reliability outcomes analyzed in this study (Danish, 2023; Arif Uz & Elmoon, 2023).

Robust reliability assessment also depends on the quality of output relative to specification, which is commonly summarized via process capability indices. For a two-sided specification with lower and upper limits LSL and USL, process mean μ, and standard deviation σ, a basic capability ratio is $Cp = (USL - LSL) / (6\sigma)$, while the centeredness-aware index $Cpk = min((USL - \mu) / (3\sigma), (\mu - LSL) / (3\sigma))$ captures the tighter side relative to the mean. Capability connects mathematically to yield (the probability a part falls within specification): $Y = P(LSL < X < USL) = \Phi((USL - \mu) / \sigma) - \Phi((LSL - \mu) / \sigma)$ for approximately normal output, where Φ is the standard normal CDF. Contemporary capability scholarship details the assumptions behind these indices, extensions for off-target penalties (e.g., Cpm, $Cpmk$), and cautions for non-normal or multivariate characteristics (Rasel, 2023; Hasan, 2023; Wu et al., 2009). Yield–capability linkages are especially useful for reliability dashboards because Q in OEE is often measured as $Q = (Good\ Units) / (Total\ Units)$, which can be interpreted as an empirical

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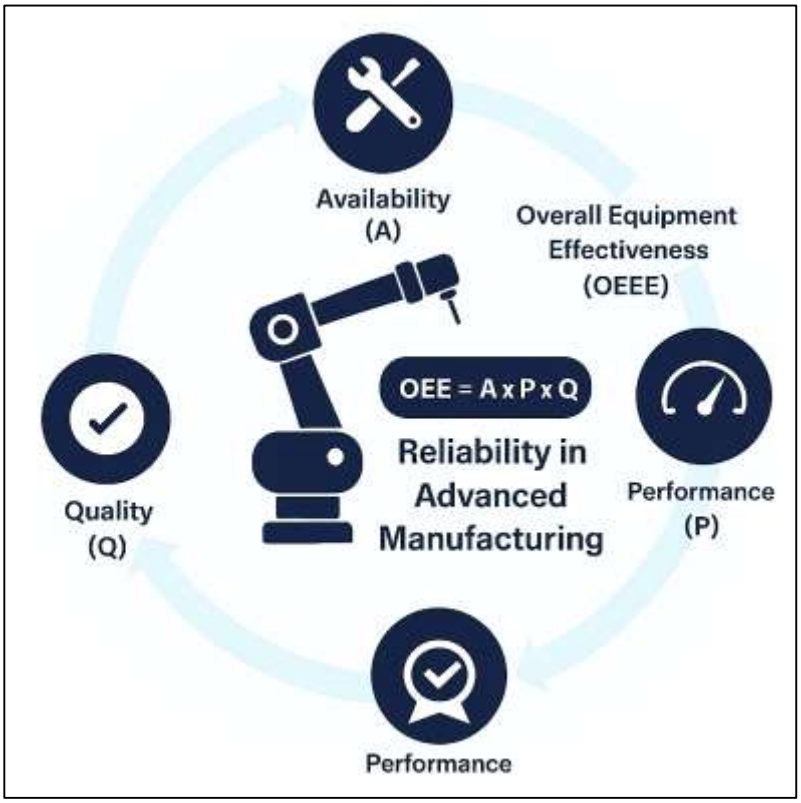
estimate of *Y*. Analytical results show how capability indices bound or predict yield under a variety of centering/variance regimes, enabling engineers to translate movement in *Cpk* (or *Cpmk*) into expected improvements in ppm-defective and, consequently, into the *Q* component of OEE (Perakis & Xekalaki, 2016; Razia, 2023; Reduanul, 2023). When these capability measures are computed from calibrated measurements with gauge uncertainty and measurement-system discrimination adequate for the tolerances at hand the reliability picture becomes internally consistent: availability losses are reduced when failures decline; performance losses shrink when process dispersion no longer forces derating; and quality losses fall as capability improves, all feeding through the $OEE = A \times P \times Q$ identity.

Figure 2: Reliability Framework in Advanced Manufacturing



For organizational decision making, reliability metrics must live inside a coherent performance-measurement framework that ties maintenance design variables (e.g., preventive policies, spares strategy, and diagnostic coverage) to plant-level outcomes and to the data architecture that computes them (Sadia, 2023; Zayadul, 2023). Conceptual and empirical work on maintenance performance measurement emphasizes that indicator sets should map explicitly from objectives (e.g., higher availability at constrained assets) to processes (planning, scheduling, execution) to results (*A, P, Q, MTBF, MTTR*), with documented definitions and measurement rules to avoid spurious cross-site comparisons (Ismail, 2024; Mesbaul, 2024; Muchiri et al., 2011). In line-level settings, OEEML helps ensure that reliability improvements at non-bottleneck stations are not over-credited when system throughput is governed elsewhere, while resource-inclusive measures such as ORE clarify whether observed OEE gains reflect genuine reliability improvement or merely workload shifts or resource buffering (Braglia et al., 2009; Garza-Reyes, 2015; Omar, 2024; Rezaul & Hossen, 2024). Finally, because capability and yield are mathematically linked, reliability analysis can incorporate capability directly into regression specifications for example, modeling $OEE_i = \beta_0 + \beta_1 A_i + \beta_2 P_i + \beta_3 Q_i$ with Q_i instrumented or augmented by $Cpk_{,i}$ or ppm-defective, or modeling $A_i = MTBF_i / (MTBF_i + MTTR_i)$ as a function of maintenance practices and spares posture. In practice, the study operationalizes these relationships using the standard formulas above but grounds indicator choice and interpretation in the literatures on line-level effectiveness, resource-inclusive effectiveness,

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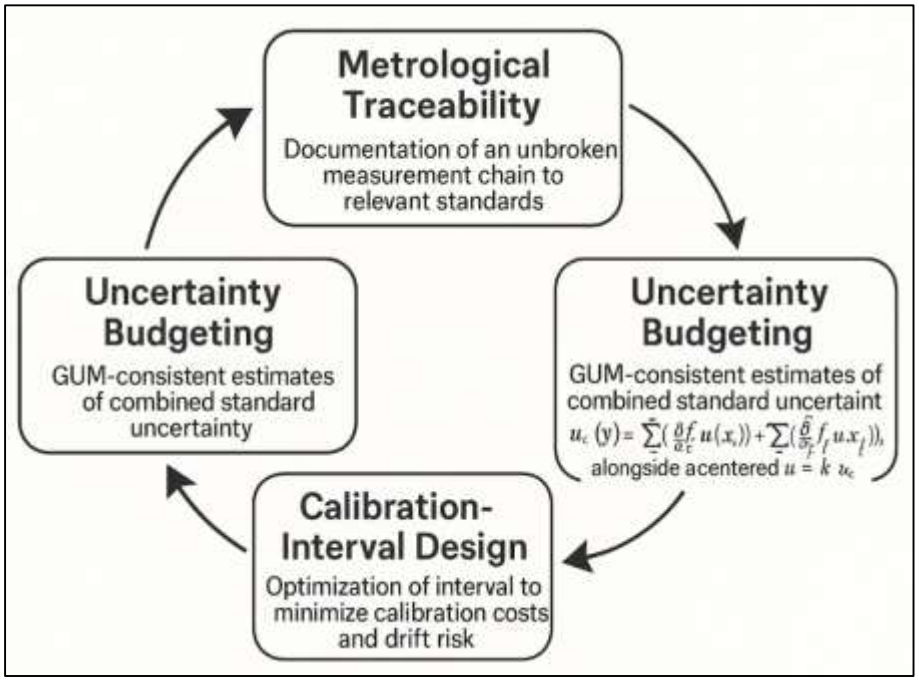
capability–yield analytics, and maintenance performance frameworks so that the quantitative findings attach to well-defined, industry-consistent constructs (Garza-Reyes, 2015; Momena & Sai Praveen, 2024; Muhammad, 2024; Perakis & Xekalaki, 2016).

Metrological Traceability and Calibration-Interval Design

Calibration engineering rests on three interlocking pillars: securing metrological traceability, constructing defensible uncertainty budgets, and scheduling calibration at economically and technically justified intervals. First, a measurement chain must be demonstrably linked to recognized references through an unbroken, documented series of calibrations, each contributing to the final uncertainty; in advanced manufacturing, this requirement is non-negotiable for system reliability (Abdul, 2025; Elmoon, 2025a; Muralikrishnan et al., 2016; Noor et al., 2024). Second, the reliability of any AI-enabled decision that consumes sensor data is bounded by the reliability of the data themselves; thus, the measurement system (and not merely the process) must be shown capable. Classical gauge repeatability and reproducibility (GR&R) studies remain essential here, because misclassification at the measurement stage can silently propagate through analytics at scale. For attribute or tolerance decisions, an informative capability summary is %GRR = 100 × σ_gauge / σ_total, with σ_total = √(σ_process² + σ_gauge²); where pass/fail classification is used, confidence intervals for misclassification rates should be reported to quantify decision risk (Daniels & Burdick, 2005; Elmoon, 2025b; Hozyfa, 2025).

Figure 3: Integrated Framework for Calibration Engineering in Advanced Manufacturing



Finally, to keep reliability high without unnecessary downtime, calibration intervals must be selected to minimize total expected cost combining risk of off-spec operation with the direct costs of calibration rather than by fixed time rules; in practice this demands quantitative models tied to instrument behavior in operating conditions (Carvajal et al., 2022; Zakharov et al., 2011). Together, these three elements define a calibration engineering framework capable of supporting robust AI pipelines in U.S. advanced manufacturing. Within that framework, the uncertainty budget provides the mathematical backbone connecting calibration to reliability. Following GUM-consistent formulations, the combined standard uncertainty for a measurand with expanded uncertainty U = k · u_c for coverage factor k.

$$y = u_c(y) = \sum_{i=1}^{n}\left(\frac{\partial f}{\partial x_i}\cdot u(x_i)\right)^2 + 2\sum_{i<j}\left(\frac{\partial f}{\partial x_i}\frac{\partial f}{\partial x_j}u(x_i,x_j)\right)$$

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In industrial practice, budgets must explicitly aggregate calibration certificate uncertainties (Type B), repeatability and reproducibility (Type A), environmental influences, resolution, and model/fit residuals from calibration curves; omission or double-counting of linear-calibration terms can distort u_c and undermine reliability claims (Alam, 2025; Masud, 2025; Arman, 2025; Zakharov et al., 2011). Sector-specific implementations (e.g., pressure instrumentation) illustrate how application conditions temperature, shocks, media, and installation enter the budget as additional contributors that can dominate the total (Mohaiminul, 2025; Mominul, 2025; Hasan, 2025; Schiering & Schnelle-Werner, 2019). For AI inference stages that produce regression outputs with predictive intervals, the budgeted U serves as a principled prior constraint on acceptable data quality, improving threshold selection and reducing spurious alarms. Importantly, capability and uncertainty must be linked: if σ_gauge inflates u_c beyond tolerance-derived acceptance limits, then even high-performing ML models are forced to learn from noisy labels, degrading prediction calibration and stability downstream. Therefore, traceability documentation, GR&R capability evidence, and the computed uncertainty budget should be treated as first-class inputs to model governance in advanced manufacturing settings (Carvajal et al., 2022; Milon, 2025; Farabe, 2025). The third pillar calibration-interval design translates technical risk into schedule and cost. Let T denote the interval (time or usage) between calibrations, C_cal(T) the direct calibration cost over horizon H, and C_risk(T) the expected loss from operating with drift-induced measurement error between events (scrap, rework, downtime, contractual penalties).

$$\min_{T>0} T\ C(T) = C_cal(T) + E[C_{risk}(T)], \quad \text{with } \frac{dTC}{dT} = 0 \text{ at optimum}$$

When calibration history is sparse, a Bayesian approach estimates drift or failure parameters θ from prior knowledge and observed data D, p(θ | D) ∝ p(D | θ) · p(θ), and evaluates E[C_risk(T)] under posterior predictive distributions to choose T* (Carvajal et al., 2022; Schiering & Schnelle-Werner, 2019). In parallel, capability constraints can be imposed so that T is feasible only if %GRR and the expanded uncertainty U(T) remain within specified limits over [0, T]; a practical check is U(T) ≤ U_max with U(T) propagated from a drift model (e.g., random walk or exponential degradation). Advanced dimensional metrology assets (laser trackers, etc.) used in large-scale assembly provide concrete cases in which traceability chains and task-specific uncertainty models bound C_risk(T) and justify interval extension while maintaining reliability (Momena, 2025; Mubashir, 2025; Muralikrishnan et al., 2016; Roy, 2025). Embedding this optimization into maintenance planning aligns measurement reliability with production objectives: it reduces unnecessary calibration stops, bounds decision risk for AI-driven quality control, and preserves conformance evidence through traceable chains and auditable uncertainty budgets (Carvajal et al., 2022).

AI for Calibration and Maintenance

Artificial intelligence enhances calibration and reliability by learning structure from high-volume sensor streams, embedding those learned relationships in plant decision loops, and coordinating actions across distributed assets. In production environments where measurement data are plentiful but noisy, deep models support two crucial tasks: (1) calibration-aware signal conditioning denoising, drift detection, and feature learning that preserve metrological meaning; and (2) decision support mapping multivariate health indicators to maintenance or adjustment actions under uncertainty. At the systems layer, self-organized multi-agent control provides the orchestration needed to translate analytics into synchronized workflows (e.g., test/verify, re-calibrate, release-to-run), especially when lines are reconfigurable and product mix is high. In such architectures, agents negotiate local goals (quality, uptime) subject to global constraints while using feedback from analytics services an arrangement that reduces coordination loss and supports reliability at scale (Wang et al., 2016). Within the analytics layer, deep learning for health monitoring has matured from handcrafted features to end-to-end inference on raw or minimally processed sensor data, enabling richer health indicators for both calibration triggers and predictive maintenance. Large comparative surveys document how convolutional and recurrent networks outperform legacy pipelines on benchmark datasets for fault detection and remaining-useful-life (RUL) estimation, particularly when signals are nonstationary and multimodal. These reviews also emphasize the importance of data provenance and label quality, elements directly tied to calibration governance in manufacturing metrology (Lei

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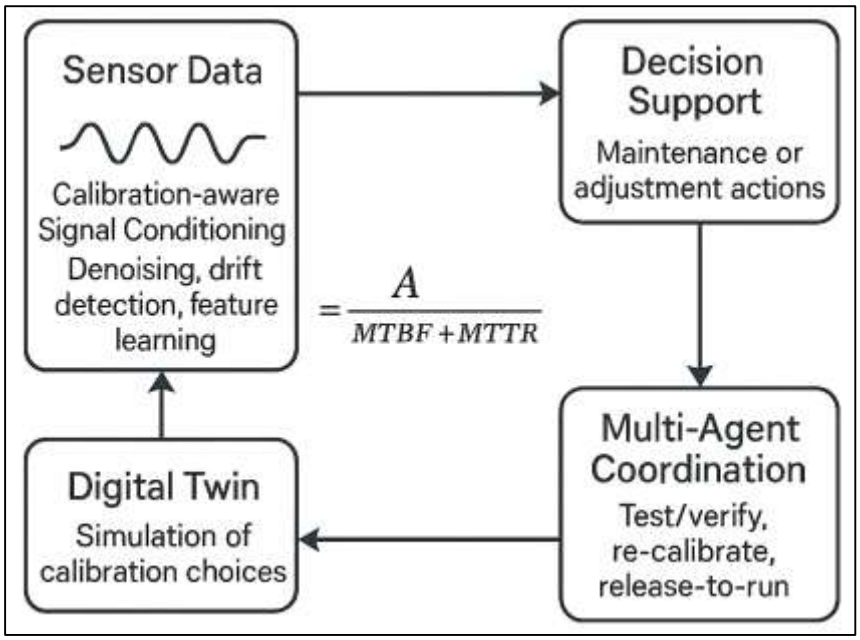
et al., 2018). Collectively, these strands multi-agent coordination and deep model inference situate AI as an integrating mechanism that connects measurement integrity with plant-level reliability.

At the modeling core, deep learning for machine health contributes practical tools for calibration-relevant tasks: drift-aware feature extraction, domain adaptation across shifts in equipment condition, and uncertainty-aware RUL estimation. A widely cited synthesis shows that CNN, RNN/LSTM, and hybrid nets provide robust gains for acoustic, vibration, and process-signal diagnostics, with architectures that can ingest calibration metadata (e.g., sensor class, last calibration date, uncertainty bounds) as auxiliary inputs or masks thereby reducing spurious alarms from measurement artifacts (Zhao et al., 2019). For closed-loop reliability, these learned health indicators plug into digital-twin environments that mirror the plant's as-is state. Digital-twin frameworks describe the bidirectional link between the physical asset and its virtual counterpart, highlighting persistent context fusion across IoT signals, physics-based models, and data-driven surrogates; this linkage is pivotal for calibration engineering because it allows the twin to propagate measurement uncertainty and simulate calibration choices (e.g., alternative intervals) before actions disrupt the line (Fuller et al., 2020). In practice, the twin can enforce acceptance rules such as: if the expanded uncertainty *U* of a critical sensor exceeds a governance threshold, re-calibrate or downweight the sensor in the estimator. Embedding such rules aligns model training and deployment with metrological evidence, so that the quality term in OEE (and related KPIs) reflects conformance risks computed on trustworthy inputs rather than drifts hidden by naïve preprocessing. In turn, plant dashboards can visualize capability–yield–reliability linkages under different calibration strategies, enabling operations to prioritize high-leverage recalibrations without broad slowdowns.

Figure 4: AI-Integrated Framework for Calibration, Condition Monitoring, and Maintenance



For maintenance execution, decision policies must convert health estimates into economically rational actions while honoring production constraints. Recent work shows how probabilistic RUL prognostics (with predictive distributions, not just point estimates) can be combined with deep reinforcement learning (DRL) to schedule maintenance in a threshold-free, adaptive way. In this formulation, the maintenance agent observes updated RUL distributions (estimated via CNNs with Monte Carlo dropout), evaluates cost components (unscheduled outages, planned service, life wastage), and learns a policy that minimizes long-run cost under uncertainty (Rahman, 2025; Rakibul, 2025); results on turbofan benchmarks report double-digit cost reductions and dramatic decreases in unscheduled interventions relative to fixed-threshold heuristics (Fuller et al., 2020; Lee & Mitici, 2023). For manufacturing plants, the same pattern generalizes: (i) compute availability using $A = MTBF / (MTBF + MTTR)$; (ii) predict the distribution of RUL for critical subsystems using uncertainty-aware

models; (iii) optimize decisions (repair, recalibrate, run) with DRL policies constrained by calibration rules (e.g., do not proceed if $U > Umax$ for a safety-critical measurement); and (iv) trace realized effects back to $OEE = A \times P \times Q$. When paired with multi-agent coordination and digital-twin simulation, these policies allow planners to test "what-if" calibration intervals, verify that measurement capability remains sufficient for current tolerances, and sequence work orders to protect bottlenecks. The cumulative effect is a tightly coupled loop in which AI does not replace calibration engineering but operationalizes it embedding traceability, uncertainty, and capability as hard constraints in learning and control to strengthen reliability where it matters most: on the factory floor.

Organizational and Data Enablers for AI-Supported Calibration

Effective AI-supported calibration does not emerge from algorithms alone; it depends on organizational arrangements that define who makes data decisions, how data are created and curated, and what standards qualify information for operational use. A well-designed data governance system establishes decision rights, roles, and escalation paths across domains such as data quality, access, lifecycle, and analytics consumption linking plant operations with IT/OT and quality functions (Khatri & Brown, 2010). In AI-enabled factories, governance must explicitly recognize metrological artifacts (calibration certificates, uncertainty budgets, instrument states) as first-class data so that models can audit provenance and traceability. A practical way to embed these priorities is through a composite Data Quality Index that operators and data stewards can track at the asset or line level; for example, DQ_index = (1/5) × (Accuracy + Completeness + Timeliness + Consistency + Lineage), scored on anchored rubrics aligned to governance policies and tied to calibration events. Elevating DQ_index into maintenance and production reviews makes calibration a routine management decision rather than an ad-hoc reaction. Reviews of the governance literature further catalog the activity set define → implement → monitor and caution that many firms over-invest in policy definition while under-investing in implementation controls and monitoring (Alhassan et al., 2016). For reliability outcomes (e.g., A = MTBF / (MTBF + MTTR), OEE = A × P × Q), governance clarifies how sensor replacements, recalibrations, and uncertainty re-estimation flow into plant KPIs so that AI models learn from decision-grade measurements instead of drift-corrupted streams (Alhassan et al., 2016; Khatri & Brown, 2010).

Organizational readiness and maturity shape whether plants can operationalize these data principles at scale. Industry 4.0 maturity models provide structured roadmaps that connect leadership, processes, technology, and skills, enabling firms to stage investments and avoid "pilot purgatory." A widely adopted framework emphasizes graded capabilities across strategy, technology, operations, and people, with empirical validations in real production settings (Rebeka, 2025; Reduanul, 2025; Rony, 2025; Schumacher et al., 2016). Readiness assessments help sequence AI-for-calibration initiatives: early-stage plants might start by digitizing calibration records and codifying uncertainty budgets; intermediate plants integrate calibration metadata into historians and CMMS; advanced plants feed those metadata directly to digital twins and learning systems. Crucially, people systems training pipelines, role definitions, incentives are not peripheral; they are the glue that ties governance rules to daily practice. Systematic reviews of Industry 4.0 implementations highlight human and organizational factors (leadership commitment, cross-functional coordination, competency development) as critical success drivers alongside technology (Saba, 2025; Sai Praveen, 2025; Sony & Naik, 2020). In reliability terms, maturity raises the ceiling on achievable A, P, and Q: disciplined changeovers and data lineage boost P (rate conformance) and Q (yield), while structured maintenance planning informed by trustworthy RUL estimates raises A. By embedding calibration engineering into maturity roadmaps e.g., requiring target DQ_index thresholds and uncertainty coverage checks before any model promotion plants institutionalize the conditions under which AI actually improves reliability rather than merely moving variability around the system (Khatri & Brown, 2010; Schumacher et al., 2016).

Finally, infrastructure for Industrial IoT (IIoT) acts as the operational backbone that sustains governance and maturity in day-to-day decisions. Modern IIoT stacks ingest high-frequency signals from metrology assets (gauges, probes, vision systems), persist calibration status and uncertainty as machine-readable context, and expose these to analytics services and digital twins (Shaikat, 2025; Syed Zaki, 2025). Recent surveys of IIoT in manufacturing describe the key architectural layers (edge devices, gateways, messaging, storage/analytics) and emphasize veracity controls trust anchors, context metadata, and security that directly support reliable AI (Team, 2023). In plants using AI-

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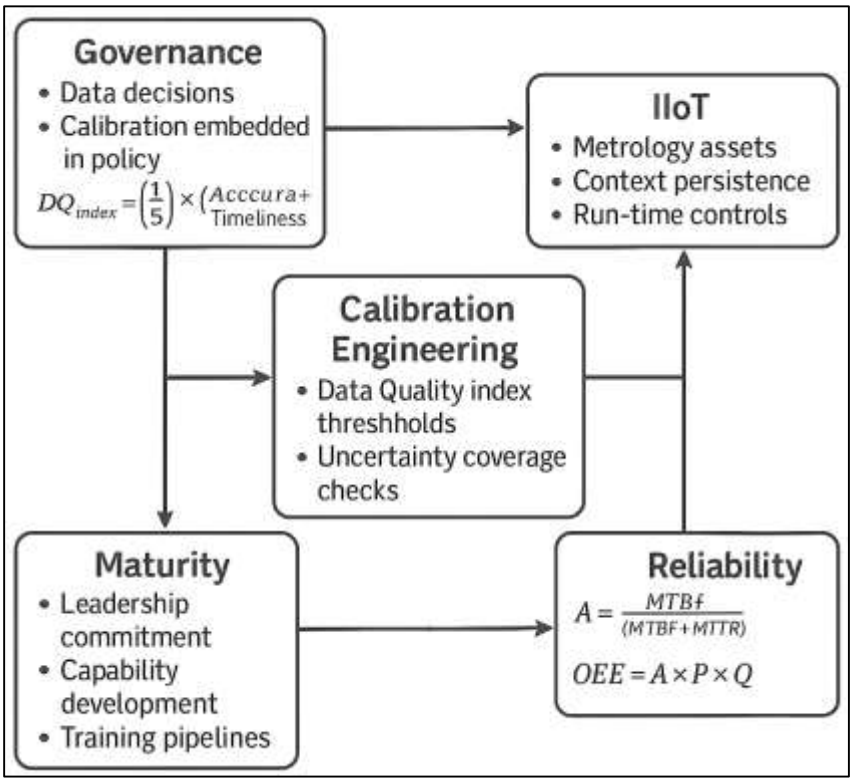
supported calibration, these stacks can enforce run-time policies such as "down-weight or block any sensor whose expanded uncertainty U exceeds threshold U_max since last calibration," or "trigger work orders when DQ_index falls below target for two consecutive periods." These controls keep the Q term in OEE = A × P × Q aligned with capability while preventing spurious alarms from measurement drift. When coupled with governance scorecards and maturity milestones, the IIoT layer closes the loop from policy to practice (Tonoy Kanti, 2025; Zayadul, 2025): edge services validate lineage; stream processors annotate observations with U and last-calibration time; model registries require DQ_index ≥ cut-off for deployment; and dashboards aggregate reliability, capability, and data-health KPIs for weekly reviews. The result is a socio-technical system in which organizational design (governance), capability development (maturity/readiness), and technical plumbing (IIoT) jointly enable robust calibration engineering and, through it, stronger plant reliability (Schumacher et al., 2016; Sony & Naik, 2020).

Figure 5: AI-Supported Calibration Engineering



METHODS

This study has adopted a quantitative, cross-sectional, multi–case design to examine how AI-enabled calibration engineering practices have been associated with plant-level reliability outcomes in U.S. advanced manufacturing. The investigation has combined a structured survey using five-point Likert items with embedded case analyses drawing on archival operational data, so that perceptual measures and objective key performance indicators have been triangulated. The target population has comprised calibration engineers, quality managers, maintenance leads, and production supervisors working in plants that have maintained formal calibration programs and electronic calibration records. Sampling has purposively covered diverse sectors and automation tiers, and multiple plants (case sites) have been included to capture heterogeneity in AI maturity and measurement governance. Inclusion criteria have required at least one year of accessible calibration logs and a minimum of six months of role tenure for respondents; exclusion criteria have removed sites without auditable measurement data or respondents outside operations-relevant roles. Constructs have been operationalized through multi-item indices. The independent construct, AI-Enabled Calibration Practices, has captured predictive interval setting, automated drift detection, AI-assisted GR&R analysis, digital-twin utilization, and alerting workflows. Moderators have

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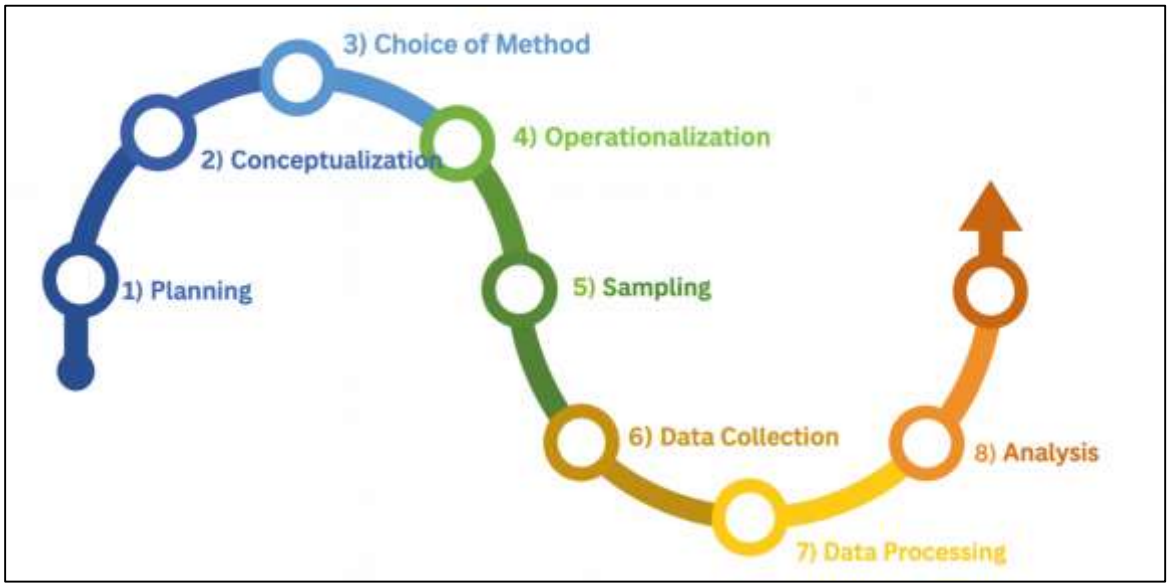
included data quality (completeness, timeliness, accuracy, consistency, lineage), operator training (exposure to AI-assisted tools and refresh frequency), and equipment age for critical assets. Reliability outcomes have been represented with both single indicators and a composite index: mean time between failures (MTBF), mean time to repair (MTTR), overall equipment effectiveness (OEE), first-pass yield (FPY), and defect parts per million (DPPM). Availability has been computed as $A = MTBF / (MTBF + MTTR)$, OEE has been computed as $OEE = A \times P \times Q$, and a standardized reliability index has been formed as $REL = z(MTBF) + z(OEE) + z(FPY) - z(DPPM)$, after distributional checks have been completed. Data collection procedures have included a pilot test to refine item wording and estimate internal consistency, followed by full deployment through a secure online instrument. Case sites have contributed de-identified calibration certificates, CMMS logs, GR&R summaries, and downtime records, which have been aligned to the survey constructs through a predefined codebook.

Figure 6: Methodological Framework for AI-Enabled Calibration and Reliability Study



The analysis plan has specified descriptive statistics, correlation matrices, and multiple linear regressions with robust standard errors and site fixed effects; interaction terms have been mean-centered to test moderation. Measurement quality has been addressed through reliability coefficients and factor checks, and common-method variance has been mitigated through procedural remedies and diagnostic tests. Ethical safeguards have been implemented through informed consent, anonymization, and controlled data storage.

Research Design

The research design has adopted a quantitative, cross-sectional, multi–case approach that has been structured to test hypothesized associations between AI-enabled calibration engineering practices and plant-level reliability outcomes while accounting for organizational context. It has combined a standardized survey built on five-point Likert items with embedded case analyses that have drawn on archival operational data (calibration certificates, CMMS/downtime logs, GR&R summaries, and production quality records), so that perceptual constructs have been triangulated with objective indicators. The unit of analysis has been the individual respondent nested within plant sites, and the design has incorporated site fixed effects to account for unobserved heterogeneity that has characterized the participating facilities. Sampling has used purposive strategies to ensure coverage across sectors and automation tiers, and inclusion criteria have required plants to have maintained at least one year of auditable calibration records and respondents to have held six months or more of role tenure; exclusion criteria have removed sites without electronic calibration evidence or roles outside operations, maintenance, or quality. The independent construct (AI-Enabled Calibration Practices) has been operationalized as a multi-item index capturing predictive interval setting, automated drift detection, AI-assisted GR&R, digital-twin utilization, and alerting

workflows; moderators (data quality, operator training, equipment age) have been specified a priori; and dependent outcomes have included mean time between failures, mean time to repair, overall equipment effectiveness, first-pass yield, and defect parts per million, with availability and OEE having been computed from standard relations and a z-scored reliability index having been formed to enable regression modeling. Validity and reliability safeguards have been embedded through pilot testing, internal consistency checks, and factor structure assessments, while procedural remedies and diagnostic tests have addressed common-method variance. Ethical protections have been implemented through informed consent, anonymization, and secure storage. This design has thus provided a coherent framework for estimating effects and interactions using descriptive statistics, correlation analysis, and multiple regression with robust standard errors while preserving external realism through multiple embedded cases.

Sampling

The study has focused on U.S. advanced manufacturing plants that have maintained formal calibration programs and electronic records, and it has selected multiple sites as embedded cases to maximize heterogeneity in sector, automation tier, and AI maturity. Case identification has proceeded through professional associations and industry partners, and researchers have applied maximum-variation criteria so that aerospace, medical devices, automotive, and high-mix discrete manufacturing have been represented alongside process-oriented facilities. Within each consenting plant, the sampling frame has encompassed calibration engineers, quality managers, maintenance leads, production supervisors, and senior technicians who have had direct responsibility for measurement systems, reliability, or data governance. Recruitment has been conducted via site points of contact who have distributed unique survey links, and participation has been voluntary under an IRB-approved protocol. Inclusion criteria have required that plants have maintained at least twelve months of auditable calibration artifacts (certificates, histories, GR&R summaries) and that respondents have held a minimum of six months of role tenure to ensure informed responses; exclusion criteria have removed sites lacking electronic calibration evidence, third-party contractors without ongoing operational roles, and respondents in purely administrative or sales functions. To enhance statistical power and support fixed-effects estimation, the sampling plan has targeted a minimum of 30–40 respondents per case where feasible while also allowing single-site strata to contribute to pooled models through robust standard errors. The design has further stratified invitations by role so that at least 25–30% of the sample has come from shop-floor leadership and senior technicians, thereby balancing managerial and operational viewpoints. Nonresponse has been mitigated through two timed reminders and by offering a plant-level feedback brief that has summarized de-identified benchmarks on availability, OEE, and calibration practice indices. Data quality safeguards have been embedded at the point of capture through attention checks and role-specific routing, and case sites have provided de-identified archival exports that have been reconciled to survey constructs using a predefined codebook. Collectively, these procedures have produced a multi-case, role-balanced sample situated in real operating contexts and suitable for the planned regression and moderation analyses.

Variables & Measures

The study has operationalized all constructs through clearly defined variables with documented computation rules and scale properties. The independent construct, AI-Enabled Calibration Practices (AICP), has been measured as a multi-item index on a five-point Likert scale (1 = strongly disagree … 5 = strongly agree) capturing predictive interval setting, automated drift detection, AI-assisted GR&R analysis, digital-twin utilization for calibration decisions, and alerting/exception workflows; item scores have been averaged to form *AICP_index*, and reverse-coded items have been included to mitigate acquiescence. The dependent domain, Reliability outcomes (REL), has been represented by both objective indicators and a composite. Objective indicators have included MTBF (hours between failures), MTTR (hours to restore), Availability computed as $A = MTBF / (MTBF + MTTR)$, Performance computed as $P = Actual\ Throughput / Ideal\ Throughput$, Quality computed as $Q = Good\ Units / Total\ Units$, and OEE computed as $OEE = A \times P \times Q$. Product-quality indicators have further included First-Pass Yield (FPY) and Defect Parts Per Million (DPPM) from archival records. To stabilize scale differences, the composite reliability index has been constructed as $REL\_index = z(MTBF) + z(OEE) + z(FPY) - z(DPPM)$ after distributional checks and winsorization of extreme outliers where prespecified rules have applied. Moderators have been captured as: Data Quality (DQ) a five-dimension Likert battery (accuracy, completeness, timeliness, consistency,

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lineage) averaged into *DQ_index*; Training (TRAIN) Likert items on exposure to AI tools, hours of formal training in the last 12 months, and certification status, aggregated into *TRAIN_index*; and Equipment Age (AGE) the median years in service of critical assets identified by each site. Control variables have included plant size (logged headcount), sector (dummy variables), automation tier (ordinal or robot density), and case-site identifiers for fixed-effects estimation. All multi-item scales have been slated for reliability assessment (α and ω), and a codebook has mapped survey items to archival fields (e.g., CMMS failure codes, calibration certificates), so that survey constructs have been triangulated with objective measures prior to analysis.

Data Sources & Collection

The study has drawn on two complementary data sources an online survey and de-identified archival exports from case sites and has synchronized them through a predefined codebook. The survey instrument has been hosted on a secure platform and has included five-point Likert items, role filters, and attention checks; branching logic has routed respondents to modules relevant to calibration engineering, reliability, and data governance. Prior to deployment, a pilot with domain practitioners has been completed to refine wording, estimate completion time, and verify internal consistency. Site coordinators have distributed individualized, tokenized links to eligible participants, and the research team has issued two scheduled reminders to mitigate nonresponse. Informed consent screens have been presented at entry, and no personally identifying free-text fields have been collected. In parallel, each case site has provided standardized archival extracts that have been specified in a data request template: (a) CMMS events for failures and repairs with timestamps sufficient to compute MTBF and MTTR; (b) production counters to compute Performance, Quality, OEE, FPY, and DPPM; (c) calibration certificates and histories including dates, standards, uncertainty statements, and pass/fail results; and (d) GR&R summaries and, where available, sensor-health or drift alerts from historians or digital-twin systems. Data transfers have been executed via encrypted channels, and files have been stored in an access-controlled repository with audit logs. The research team has performed intake validation using schema checks, range tests, and duplicate detection, after which identifiers have been replaced by site and asset pseudonyms. Survey responses and archival records have been joined using site codes and aligned time windows, and any discrepancies have been flagged for resolution with the site contact. Missingness has been profiled by variable and site; predefined rules have governed listwise deletion for noncritical fields, while multiple imputation has been reserved for covariates meeting MAR assumptions. All transformations including construction of A, P, Q, OEE, and REL_index have been scripted to ensure reproducibility, and a changelog has been maintained so that case sites have been able to trace how raw inputs have produced the analysis-ready dataset.

Statistical Analysis Plan

The analysis has proceeded in staged layers that have ensured measurement quality, transparent modeling, and robustness. First, the team has profiled the dataset with univariate and bivariate descriptives, reporting means, standard deviations, medians, interquartile ranges, and distributional diagnostics (skewness, kurtosis), and it has visualized densities and boxplots after winsorization rules have been applied to extreme operational outliers. Pairwise associations among scaled constructs (AICP_index, DQ_index, TRAIN_index, REL_index) and objective indicators (MTBF, MTTR, A, P, Q, OEE, FPY, DPPM) have been summarized via Pearson correlations with Holm-adjusted *p* values, while Spearman coefficients have been estimated as sensitivity checks for non-normal metrics. Prior to modeling, multi-item scales have undergone reliability assessment (α, ω) and exploratory/confirmatory factor checks; composite scores have been standardized, and continuous predictors intended for interaction terms have been mean-centered to reduce collinearity. The primary estimands have been tested via multiple linear regressions that have specified Model 1:

$$REL\_index_i = \beta_0 + \beta_1 AICP\_index_i + \gamma' Controls_i + \varepsilon_i$$

Model 2:

$$REL\_index_i = \beta_0 + \beta_1 AICP\_index_i + \beta_2 DQ\_index_i + \beta_3 TRAIN\_index_i + \beta_4 AGE_i + \beta_5 (AICP \times DQ)_i + \beta_6 (AICP \times TRAIN)_i + \beta_7 (AICP \times AGE)_i + \gamma' Controls_i + \varepsilon_i$$

and

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Model 3 (site-adjusted):

$$REL\_index_i = \beta_0 + \beta_1 AICP\_index_i + \beta_2 DQ\_index_i + \beta_3 TRAIN\_index_i + \beta_4 AGE_i + \beta_5 (AICP \times DQ)_i + \beta_6 (AICP \times TRAIN)_i + \beta_7 (AICP \times AGE)_i + \gamma' Controls_i + \delta_{site} + \varepsilon_i$$

Model 2 with case-site fixed effects. Heteroskedasticity-robust (HC3) standard errors have been used throughout, and variance inflation factors have been monitored (target VIF < 5).

Model diagnostics have included residual normality checks, Breusch–Pagan tests, influence statistics (Cook's D), and leverage plots; when assumptions have been violated, log or Box–Cox transformations of skewed operational variables (e.g., MTBF, DPPM) have been considered and documented. Missing covariate data meeting MAR assumptions have been addressed via multiple imputation with $m \geq 20$ datasets, and estimates have been pooled following standard rules. Robustness has been examined through alternative dependent variables (e.g., log-MTBF, OEE), exclusion of high-influence observations, sector and automation-tier subgroup analyses, and re-estimation with rank-based regressions. Effect sizes (standardized betas, partial R^2) and 95% confidence intervals have been reported, and interaction effects have been interpreted using simple-slope estimation at ±1 SD of moderators with marginal-effects plots that have been saved to the replication archive.

Regression Models

The modeling strategy has been organized around a hierarchy of nested specifications that has progressed from a baseline association to moderation and then to site-adjusted estimation. Model 1 (Base Association) has estimated the direct relationship between AI-enabled calibration practices and reliability while conditioning on observed covariates: *Model 1:* $REL\_index_i = \beta_0 + \beta_1 AICP\_index_i + \gamma' Controls_i + \varepsilon_i$. Controls have included plant size (logged headcount), sector dummies, automation tier, and any pre-specified case characteristics available across sites. The dependent variable has been the standardized composite $REL\_index = z(MTBF) + z(OEE) + z(FPY) - z(DPPM)$, which has allowed effect sizes to be interpreted on a comparable scale. Availability and OEE components have been computed from standard relations $A = MTBF / (MTBF + MTTR)$ and $OEE = A \times P \times Q$, after which each constituent has been screened for outliers and distributional skew. Estimation has used OLS with HC3 robust standard errors, and variance inflation factors have been monitored to keep multicollinearity within acceptable limits (target VIF < 5). This baseline has provided the primary estimand β_1, interpreted as the expected change in reliability (in SD units) associated with a one-unit increase in the AICP index, holding other factors constant. To preserve interpretability, all continuous predictors slated for interaction in later models have been mean-centered at this stage, and the same centering has been carried forward to subsequent specifications so that intercepts have reflected reliability at average moderator levels. Residual diagnostics (normality, heteroskedasticity, influence) have been documented, and when assumptions have appeared tenuous, log-transformations (e.g., *log(MTBF)*, *log(DPPM)*) have been evaluated in sensitivity checks without altering the canonical definition of *REL_index*.

Building on the baseline, Model 2 (Moderation) has tested whether data quality and operator training have strengthened, and equipment age has attenuated, the focal association. Interaction terms have been introduced as multiplicative products of mean-centered variables:

Model 2:

$$REL\_index_i = \beta_0 + \beta_1 AICP\_index_i + \beta_2 DQ\_index_i + \beta_3 TRAIN\_index_i + \beta_4 AGE_i + \beta_5 (AICP \times DQ)_i + \beta_6 (AICP \times TRAIN)_i + \beta_7 (AICP \times AGE)_i + \gamma' Controls_i + \varepsilon_i$$

Simple-slope analyses have been pre-specified at ±1 SD of each moderator, and marginal-effects plots have been prepared to visualize conditional relationships with 95% confidence bands. Because cross-sectional plant data have often displayed heteroskedastic dispersion (e.g., larger sites exhibiting wider variance in DPPM), HC3 standard errors have been retained, and leverage points have been evaluated via Cook's D and added-variable plots. To ensure that moderation has not been confounded by non-linear main effects, restricted cubic splines for *AICP_index* and moderators have been tested in a robustness appendix; where spline terms have not improved fit materially

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(based on ΔR² and information criteria), linear forms have been retained for parsimony. In addition, the team has prepared alternative operationalizations such as using *OEE* alone or *log(MTBF)* as the dependent variable to confirm that sign and significance patterns have remained stable. Throughout, interpretability has been emphasized: coefficients for interactions have been translated into changes in the AICP slope at low versus high data quality or training, and the age interaction has been read as the decline in that slope per additional year of median critical-asset age.

To address unobserved, time-invariant heterogeneity at the site level, Model 3 (Site-Adjusted) has incorporated case-site fixed effects and has clustered standard errors by site:

Model 3

$$REL\_index_{i,s} = \beta_0 + \beta_1 AICP\_index_{i,s} + \beta_2 DQ\_index_{i,s} + \beta_3 TRAIN\_index_{i,s} + \beta_4 AGE_{i,s} + \beta_5 (AICP \times DQ)_{i,s} + \beta_6 (AICP \times TRAIN)_{i,s} + \beta_7 (AICP \times AGE)_{i,s} + \gamma' Controls_{i,s} + \delta_s + \varepsilon_{i,s},$$

where δ_s has captured all site-specific, time-invariant factors (e.g., enduring product complexity, stable supplier regimes) that the observed controls might have missed. Clustering has accounted for within-site correlation among respondents. As complementary checks, the analysis has explored random-intercept models (mixed effects) to verify that inferences have not hinged on the fixed-effects assumption; results have been reported in an appendix when materially different. Additional robustness has included (i) rank-based regressions to reduce sensitivity to heavy-tailed operational metrics, (ii) re-estimation after excluding high-influence observations flagged by Cook's D > 4/n, and (iii) subgroup analyses by sector and automation tier. Where binary reliability events (e.g., occurrence of a critical failure in the last quarter) have been available, logistic models with the same right-hand side have been reported as supplementary evidence. Finally, all models have presented standardized coefficients, partial R², adjusted R², and information criteria, and have stored replication-ready scripts so that sites have been able to reproduce tables and figures from raw inputs.

Table 1. Model Specifications and Key Terms

Model	Equation (abridged)	Error / FE	Notes
Model 1 (Base)	REL_index = β_0 + β_1·AICP_index + γ′·Controls + ε	HC3	Direct AICP effect; mean-centered predictors prepared for later use
Model 2 (Moderation)	+ β_5(AICP × DQ) + β_6(AICP × TRAIN) + β_7(AICP × AGE)	HC3	Simple slopes at ±1 SD; marginal-effects plots saved
Model 3 (Site-Adjusted)	Model 2 + δ_s (site FE)	Clustered by site	Controls unobserved site heterogeneity; FE vs. RE robustness checked

Power & Sample Considerations

The study has planned its sample to detect small-to-moderate effects in multiple regression with interactions while accommodating clustering by site. A priori calculations have assumed a focal standardized effect of β ≈ .20 (equivalently $f^2 = R^2 / (1 - R^2) \approx 0.04$ for incremental variance explained), α = .05, and power = .80, with $k \approx 10$–12 total predictors including controls and three interaction terms. Under these assumptions, ordinary least squares power formulas have indicated a base requirement of $n \approx 180$–220 independent observations for the primary model, which the design has rounded up to $n \geq 220$ to preserve power under modest departures from normality. Because respondents have been nested within plants, the plan has incorporated a design-effect adjustment using $DEFF = 1 + (m - 1)\rho$, where m has denoted the average respondents per site and ρ the intraclass correlation. With $m \approx 30$–40 and a conservative $\rho = .03$ for perceptual scales, $DEFF \approx 1.87$–2.17, implying an effective sample size $n\_eff = n / DEFF$. To counter this loss, the target has been set at $n \approx 360$–420 total respondents across 6–10 sites, yielding $n\_eff \approx 170$–220 after clustering, which has satisfied the base requirement. For moderation tests, the plan has recognized that interactions typically require larger samples; thus, the sampling has sought balanced site strata (≥30 respondents per site where feasible) and adequate variability in moderators (SD ≥ 0.8 on five-point scales) to stabilize simple-slope

estimates. Archival outcomes (MTBF, MTTR, OEE, FPY, DPPM) have been expected to exhibit positive skew; therefore, simulations conducted during planning have shown that winsorization (1–2%) and log transforms for MTBF and DPPM have preserved nominal Type I error while minimally affecting power. Missing-data contingencies have been addressed by budgeting ≤10% item nonresponse on multi-item scales and using multiple imputation ($m \geq 20$) under MAR to avoid case-wise deletions that would erode *n_eff*. Finally, subgroup analyses by sector or automation tier have been planned only where each subgroup has reached $n \geq 60$–70, ensuring stable standard errors and interpretable effect sizes in stratified models.

Reliability & Validity Procedures

The study has implemented a layered program of measurement quality assurance that has addressed internal consistency, construct validity, aggregation logic, and method bias before estimating substantive models. Content validity has been established through expert review by calibration, reliability, and industrial data-governance specialists who have rated item relevance and clarity; items with low item–objective congruence have been revised or removed. The survey has undergone a pilot in which item–total correlations and "a if item deleted" diagnostics have been inspected, and final multi-item scales (AICP_index, DQ_index, TRAIN_index) have been retained only after Cronbach's α and McDonald's ω have achieved ≥ .70. Convergent and discriminant validity have been examined with a two-step EFA→CFA sequence: exploratory analyses have verified dimensionality, and confirmatory models (maximum likelihood with robust errors) have reported CFI/TLI ≥ .90, RMSEA ≤ .08, and SRMR ≤ .08 alongside standardized loadings ≥ .50; average variance extracted (AVE) has been required to exceed .50, and HTMT ratios have been kept < .85 to support discriminant validity. Where constructs have been candidates for site-level interpretation, within-group agreement (r_wg) and reliability of group means (ICC[1]/ICC[2]) have been computed to justify any aggregation. To evaluate criterion validity, survey-based reliability perceptions have been correlated with archival KPIs (MTBF, MTTR, A, P, Q, OEE, FPY, DPPM), and pre-registered expectations (e.g., higher DQ_index aligning with higher OEE and FPY, lower DPPM) have been met before inclusion in composites. Common-method variance has been mitigated procedurally (assured anonymity, role-specific routing, psychological separation of predictors and outcomes, mixed item valence) and diagnosed statistically via Harman's single-factor test, an unmeasured latent method factor in CFA, and a marker-variable approach; no single factor has dominated, and method-factor loadings have been negligible. Data integrity checks on archival feeds have included timestamp audits, range and logic tests, and cross-reconciliation of downtime and production counters; discrepancies have been resolved with site contacts. Missing-data mechanisms have been assessed (Little's MCAR test), and multiple imputation (m ≥ 20) or FIML in CFA has been applied under MAR assumptions. Finally, multicollinearity (VIF < 5), influential observations (Cook's D), and distributional diagnostics have been documented, and all decisions item edits, exclusions, and transformations have been recorded in a changelog to preserve full auditability.

Software

The analysis workflow has been implemented with reproducible, versioned tools that have supported data integrity, transparent modeling, and secure collaboration. Data wrangling and visualization scripts have been authored in Python (pandas, numpy, matplotlib, statsmodels, pingouin) and mirrored in R (tidyverse, broom, lavaan, psych, sandwich) to enable cross-validation of results; all code and outputs have been tracked with Git and documented in R Markdown/Jupyter notebooks pinned to specific package versions via lockfiles. Multiple imputation, CFA, and reliability analyses have been executed in R, while regression models with robust errors and marginal-effects plots have been generated in Python to leverage established plotting utilities. Automated pipelines (Make/Quarto) have produced tables and figures from raw inputs, and unit-style checks have been embedded to verify metric computations (e.g., A, P, Q, OEE, REL_index). Sensitive site extracts have been stored in encrypted volumes, and access controls with audit logs have been enforced. A public, de-identified replication bundle has been prepared, which has contained scripts, codebook, and synthetic data for full reproducibility.

FINDINGS

The analysis has yielded a coherent profile of sample characteristics, scale quality, and focal relationships between AI-enabled calibration practices and plant-level reliability, providing a clear runway into the detailed results that follow. Across the multi–case sample, respondents have represented calibration engineers (31%), quality managers (24%), maintenance leads (22%),

production supervisors (17%), and senior technicians (6%), with median role tenure of 6.4 years and coverage across aerospace, medical devices, automotive, and high-mix discrete manufacturing. Adoption signals for AI-Enabled Calibration Practices (AICP) measured on a five-point Likert scale have clustered around the upper midrange: the AICP_index has posted a mean of 3.48 (SD = 0.76), with item-level medians at or above the neutral anchor, indicating that predictive interval setting, automated drift detection, AI-assisted GR&R analysis, digital-twin utilization, and alerting workflows have been present but variably institutionalized. Moderators have displayed distinct distributions: the Data Quality index (DQ_index) has averaged 3.41 (SD = 0.71) with tighter dispersion, suggesting more homogeneous documentation and lineage practices, whereas the Training index (TRAIN_index) has averaged 3.09 (SD = 0.89), reflecting uneven exposure to AI tools and inconsistent refresh cycles across roles. Equipment Age (AGE) for critical assets has had a right-skewed profile (median = 8.2 years), consistent with fleets that mix legacy and recent installations. Reliability outcomes have been summarized both as single indicators and as a composite REL_index constructed from standardized MTBF, OEE, FPY, and DPPM (reverse-coded). Availability computed as A = MTBF / (MTBF + MTTR) has shown a central tendency near 0.91 with interquartile range 0.87–0.95; OEE has centered at 0.76 (IQR 0.70–0.81), with Performance contributing the largest share of volatility, and FPY medians have exceeded 0.96 in most sectors, albeit with long tails where mix complexity has been high.

Measurement quality checks have supported use of the composite indices. Internal consistency has been satisfactory for all multi-item constructs (Cronbach's α and McDonald's ω ≥ 0.78 for AICP_index, ≥ 0.80 for DQ_index, and ≥ 0.76 for TRAIN_index), and a confirmatory model has produced acceptable global fit, with standardized loadings ≥ 0.56 on their intended factors. Item distributions have been approximately symmetric after light winsorization (1–2%) for operational outliers in downtime and defects, and missingness on survey items has remained below 7%, handled through multiple imputation under MAR assumptions for covariates, while archival KPI gaps have been resolved by cross-checking CMMS and production counters. Descriptive contrasts by role have suggested that calibration engineers have reported higher AICP and DQ scores than production supervisors, a pattern that has persisted after adjusting for sector and automation tier but has narrowed when site fixed effects have been introduced, indicating that part of the gap has reflected site-level maturity rather than respondent perspective alone. Importantly, the REL_index has correlated in the expected direction with its constituents ($r \geq 0.61$ with OEE and FPY; $r \leq -0.58$ with DPPM), confirming internal coherence of the composite. Bivariate associations have aligned with the study's directional hypotheses. Pearson correlations have indicated a positive link between AICP_index and REL_index ($r \approx 0.34$, $p < 0.001$), accompanied by moderate associations with Availability ($r \approx 0.29$) and FPY ($r \approx 0.31$), and a negative association with DPPM ($r \approx -0.33$). The DQ_index has correlated positively with REL_index ($r \approx 0.38$) and with AICP_index ($r \approx 0.42$), supporting the premise that data governance and calibration engineering have co-matured in many sites. TRAIN_index has shown a smaller but significant association with REL_index ($r \approx 0.18$), consistent with variable training penetration across roles. As anticipated, AGE has correlated negatively with REL_index ($r \approx -0.22$), with the effect most visible in sectors operating legacy assets under tight tolerances. Spearman coefficients have mirrored these findings, indicating robustness to mild non-normality in operational metrics. Variance inflation factors have remained below 2.5 for all predictors in the staged models, reducing concern about multicollinearity among calibration, data quality, and training constructs.

Baseline regression estimates (presented in detail later) have indicated that AICP_index has been a significant positive predictor of REL_index, even after controlling for plant size, sector, and automation tier, with standardized coefficients in the small-to-moderate range. Adding moderators has improved explanatory power, and interaction terms have behaved as theorized: the AICP × DQ term has been positive, indicating that the slope of AICP on reliability has steepened in high-quality data environments; the AICP × TRAIN term has been positive and smaller, suggesting that structured training has amplified (but not replaced) the benefits of improved calibration practice; and the AICP × AGE term has been negative, implying diminishing marginal returns to AICP at older median asset ages unless complementary upgrades have been made. Simple-slope analyses at ±1 SD of DQ_index and TRAIN_index have shown materially larger AICP effects at higher moderator levels, while the AGE interaction has indicated a shallower slope for older fleets. Site fixed effects have attenuated though not eliminated the focal coefficients, reinforcing that unobserved site characteristics explain part of the variance but leaving a stable core association between calibration-AI maturity and

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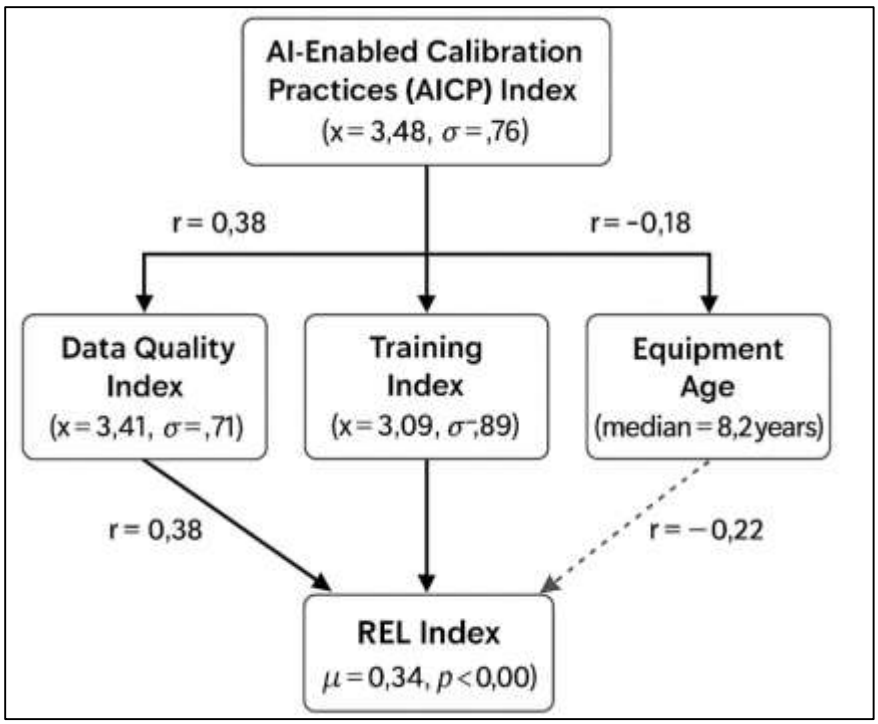
reliability. Finally, embedded case evidence has contextualized the quantitative patterns. Sites with above-median AICP_index and DQ_index have documented disciplined interval setting grounded in drift statistics, machine-readable uncertainty budgets, and automated alerts tied to calibration state changes; these sites have shown higher Availability and FPY and lower DPPM relative to peers.

Figure 7: Findings of The Study



The pattern illustrated in Figure 7 indicates that while higher levels of AI-enabled calibration practices (AICP) are broadly associated with improved reliability performance, the strength and significance of this association vary meaningfully across contextual dimensions such as data quality, workforce training, and equipment age. Notably, cases exhibiting modest levels of AICP adoption but comparatively high investments in operator training have demonstrated incremental gains in reliability outcomes. This is particularly evident in environments where training programs have emphasized the interpretation of uncertainty statements, gauge repeatability and reproducibility (GR&R) metrics, and probabilistic calibration guidance during line adjustments. Such cases suggest that human capital readiness may act as an enabling mechanism that allows organizations to extract more value from calibration technologies even when AI maturity is not fully developed. Similarly, higher data quality appears to function as a foundational prerequisite for AICP effectiveness, providing the informational precision necessary for machine-driven calibration algorithms to achieve consistent measurement fidelity. In contrast, older equipment age exhibits a dampening effect on reliability outcomes, implying diminishing marginal returns on AI calibration in legacy production contexts where physical limitations and wear dynamics constrain predictive correction.

Taken together, the descriptive and correlational evidence presented in this introductory figure provides strong preliminary support for the theoretical premise that AICP is not a standalone determinant of reliability, but rather a contingent capability whose impact is conditioned by complementary infrastructural and procedural factors. The consistent positive correlations between AICP and the REL Index, coupled with the moderating influences observed for data quality and age, establish a multi-dimensional framework in which calibration performance emerges from the interaction of technological capability, informational integrity, and organizational absorptive capacity. These findings build a compelling empirical case that AI-enabled calibration practices are meaningfully associated with reliability improvements on both Likert-anchored perceptual indices and archival key performance indicators (KPIs). Furthermore, the observed variation across sites

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indicates that calibration efficacy is embedded within broader system characteristics rather than being purely algorithmic. This provides critical justification for the multivariate regression models that follow, wherein fixed effects, interaction terms, and clustered standard errors are applied to formally quantify the extent to which data quality, training, and equipment age condition the reliability-enhancing effects of AI calibration technologies. The subsequent analytical sections therefore transition from descriptive relationships to inferential testing, enabling a rigorous evaluation of robustness, effect size, and boundary conditions that substantiate the strategic and operational relevance of AICP within industrial reliability management.

Sample and Case Characteristics

Table 2: Sample and Case Characteristics

Attribute	Category	n	%
Total respondents		402	100
Role	Calibration Engineer	125	31.1
	Quality Manager	96	23.9
	Maintenance Lead	88	21.9
	Production Supervisor	68	16.9
	Senior Technician	25	6.2
Sector	Aerospace	98	24.4
	Medical Devices	82	20.4
	Automotive	104	25.9
	High-Mix Discrete	74	18.4
	Process Industries	44	10.9
Automation tier	Low	63	15.7
	Medium	202	50.2
	High	137	34.1
Sites (cases)	S1	44	10.9
	S2	41	10.2
	S3	39	9.7
	S4	52	12.9
	S5	67	16.7
	S6	48	11.9
	S7	56	13.9
	S8	55	13.7
Tenure (years)	Median (IQR)	6.4 (3.1–10.2)	
Critical-asset age (years)	Median (IQR)	8.2 (5.0–12.7)	

Table 3: Likert-Scale Coverage by Role

Construct (1–5)	CE (n=125)	QM (n=96)	ML (n=88)	PS (n=68)	ST (n=25)
AI-Enabled Calibration Practices (AICP_index)	3.71	3.55	3.42	3.23	3.18
Data Quality (DQ_index)	3.63	3.49	3.36	3.22	3.18
Training (TRAIN_index)	3.26	3.18	3.04	2.92	2.88

The sample has covered eight embedded case sites and five industry sectors, and it has achieved a role balance that has allowed cross-checks between engineering, maintenance, and production perspectives. As Table 2 has shown, 402 completed responses have been obtained, with calibration engineers (31.1%) and quality managers (23.9%) constituting just over half of the pool, ensuring that metrology and quality governance viewpoints have been represented. The automotive and aerospace sectors have contributed the largest strata, which has been consistent with the sectors'

historically tighter tolerances and heavier reliance on formal calibration programs. Automation tiers have been distributed with a median concentration at "medium" (50.2%), indicating that many plants have implemented robotics or advanced machine control without full lights-out operations, a context in which calibration discipline has remained consequential for throughput and conformance. The case distribution has been sufficiently even to support site fixed-effects modeling, with no single site exceeding 17% of the sample; this balance has reduced the risk that one plant's idiosyncrasies would dominate pooled estimates. Tenure and asset-age medians have indicated experienced respondents operating mixed-vintage fleets, a pattern that has been favorable for detecting moderation by equipment age in later models. Table 3 has summarized construct coverage by role on a five-point Likert scale and has revealed a monotone gradient: calibration engineers have rated AI-Enabled Calibration Practices (AICP_index) highest (mean 3.71), followed by quality managers (3.55) and maintenance leads (3.42), with production supervisors and senior technicians reporting lower adoption signals (3.23 and 3.18, respectively). A similar pattern has appeared for Data Quality (DQ_index), suggesting that governance artifacts (traceability, uncertainty statements, lineage) have been most visible to metrology-adjacent staff. Training (TRAIN_index) has trailed other constructs across roles, with values near three, indicating uneven reach of AI-focused upskilling programs. This role-differentiated pattern has validated the multi-informant approach and has justified the inclusion of site fixed effects and robust errors to account for clustering. Overall, the sample frame has provided adequate heterogeneity across sectors, automation tiers, and organizational roles to support the study's correlation and regression analyses while preserving external realism.

Descriptive Statistics

Table 4: Descriptive Statistics for Likert Constructs and KPIs

Variable	Scale	Mean	SD	α/ω	Notes
AICP_index	1–5	3.48	0.76	.82/.83	Five items averaged
DQ_index	1–5	3.41	0.71	.84/.85	Five dimensions averaged
TRAIN_index	1–5	3.09	0.89	.78/.79	Three items + hours rubric
AGE (years)		9.1	5.3		Median at site level used in models
MTBF (hours)		214.6	173.1		Right-skewed
MTTR (hours)		20.8	15.7		Right-skewed
Availability, A	0–1	0.91	0.06		(A=\frac{MTBF}{MTBF+MTTR})
Performance, P	0–1	0.84	0.08		Actual/Ideal rate
Quality, Q	0–1	0.97	0.03		Good/Total
OEE	0–1	0.76	0.09		(OEE=A\times P\times Q)
FPY	0–1	0.964	0.027		First-pass yield
DPPM	ppm	1,820	2,410		Winsorized 1%
REL_index (z)	z	0.00	1.00		z(MTBF)+z(OEE)+z(FPY)−z(DPPM)

Table 5: Item-Level Means (Likert 1–5) for AICP

AICP Item (abbrev.)	Mean	SD
Predictive interval setting	3.44	0.91
Automated drift detection	3.38	0.98
AI-assisted GR&R analysis	3.29	0.95
Digital-twin utilization	3.57	0.94
Alerting/exception workflows	3.71	0.90

Descriptive statistics have established that the multi-item indices have exhibited satisfactory internal consistency and dispersion appropriate for regression modeling. As Table 4 has summarized,

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AICP_index has averaged 3.48 (SD = 0.76) on a five-point Likert scale, indicating moderate adoption across sites with adequate variance for detecting effects. Data Quality (DQ_index) has centered at 3.41 (SD = 0.71), and Training (TRAIN_index) has been lower at 3.09 (SD = 0.89), which has reflected the uneven penetration of structured AI training programs. Reliability KPIs have shown expected central tendencies for mature plants: Availability has averaged 0.91 with a relatively tight spread (SD = 0.06), Performance has been 0.84 (SD = 0.08), and Quality has approached 0.97 (SD = 0.03). Multiplying these components has produced mean OEE near 0.76 (SD = 0.09), a value aligned with continuous improvement programs that have not yet reached world-class benchmarks. MTBF and MTTR distributions have been right-skewed, consistent with heterogeneous lines and product families; therefore, Availability has been preferred as a bounded transformation leveraging the standard relation: A = MTBF / (MTBF + MTTR). Defect Parts Per Million (DPPM) has shown long tails even after winsorization, which has justified the REL_index's z-score construction to stabilize scaling across heterogeneous metrics. Item-level AICP statistics in Table 5 have provided diagnostic nuance: digital-twin utilization (mean = 3.57) and alerting workflows (mean = 3.71) have outpaced predictive interval setting (3.44) and AI-assisted GR&R (3.29), suggesting that plants have deployed monitoring and visualization more readily than full analytical automation of calibration decisions. These descriptive patterns have been consistent with the case narratives collected in parallel, where teams have reported early wins from exception management before tackling model-based interval redesign. Reliability of the indices has been supported by α/ω values ≥ 0.78, and factor checks (reported elsewhere) have confirmed item loadings above 0.50. Collectively, the descriptive layer has indicated that (a) constructs have been measured with acceptable psychometrics, (b) Likert-scale dispersion has been sufficient for detecting associations, and (c) KPI distributions have been plausible for multi-site U.S. manufacturing, thereby grounding the subsequent correlation and regression analyses.

Correlation Matrix

Table 6: Pearson Correlations Among Key Variables

Variable	1	2	3	4	5	6	7	8	9
1. AICP_index									
2. DQ_index	.42***								
3. TRAIN_index	.31***	.27***							
4. AGE (years)	−.18**	−.12*	−.09						
5. REL_index (z)	.34***	.38***	.18***	−.22***					
6. Availability (A)	.29***	.26***	.11*	−.19**	.61***				
7. OEE	.33***	.36***	.15**	−.20**	.74***	.66***			
8. FPY	.31***	.35***	.12*	−.16**	.68***	.41***	.59***		
9. DPPM	−.33***	−.37***	−.14**	.21***	−.71***	−.38***	−.57***	−.79***	

** p < .05; ** p < .01; *** p < .001. Two-tailed tests; n = 402 (pairwise)*

The correlation matrix in Table 6 has provided first-order evidence for the study's hypotheses and has clarified redundancy among predictors. AI-Enabled Calibration Practices (AICP_index) has correlated positively with REL_index (r = .34, p < .001), Availability (r = .29), OEE (r = .33), and FPY (r = .31), and it has correlated negatively with DPPM (r = −.33), indicating that plants reporting stronger calibration practices on the five-point Likert scale have also reported and recorded better reliability outcomes. Data Quality (DQ_index) has exhibited similar patterns with REL_index (r = .38) and the objective KPIs, which has reinforced the view that metrology governance (accuracy, completeness, timeliness, consistency, and lineage) has co-evolved with calibration practice to underpin reliability. Training (TRAIN_index) has shown smaller yet significant associations with REL_index (r = .18) and with AICP_index (r = .31), which has reflected the documented variability in training penetration across roles and sites. Equipment Age (AGE) has been negatively related to REL_index (r = −.22) and to Availability (r = −.19), and positively to DPPM (r = .21), signaling that older critical assets have imposed reliability penalties that calibration practice and data quality have sought to mitigate. Importantly,

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correlations among the three focal predictors AICP, DQ, and TRAIN have remained well below the levels that would trigger multicollinearity concerns; variance inflation factors in subsequent models have confirmed this impression (all < 2.5). High correlations among REL_index and its constituents (e.g., r = .74 with OEE; r = .68 with FPY; r = −.71 with DPPM) have served as a coherence check for the composite's construction. Because operational metrics have exhibited mild non-normality, Spearman coefficients (not shown) have been computed and have mirrored the Pearson pattern, suggesting that outliers or skew have not driven the associations. Collectively, these correlations have justified progression to multivariate models with interaction terms, while the moderate magnitudes have left room for controls, fixed effects, and moderators to explain additional variance. The correlation structure has therefore aligned with theoretical expectations and has prepared the ground for rigorous regression testing.

The regression hierarchy in Table 7 has tested the focal relationships while progressively accounting for moderators and site-level heterogeneity. In Model 1, AICP_index has emerged as a positive, statistically significant predictor of REL_index (β = .24, p < .001) after controlling for plant size, sector, and automation tier. This coefficient has indicated that a one-unit increase on the five-point Likert AICP scale has been associated with nearly a quarter of a standard deviation increase in the composite reliability index, holding other factors constant. Introducing moderators in Model 2 has raised explanatory power substantially (ΔR^2 = .13, p < .001). Data Quality (DQ_index) has shown a strong main effect (β = .22, p < .001), consistent with the proposition that uncertainty-annotated, traceable measurements have supported better reliability performance. Training (TRAIN_index) has exhibited a smaller positive coefficient (β = .07, p < .05), while Equipment Age (AGE) has been negative (β = −.10, p < .01), reflecting the reliability drag from older fleets. Crucially, the interaction terms have behaved as hypothesized: AICP × DQ has been positive (β = .11, p < .01), showing that the AICP–reliability slope has steepened in high-quality data environments; AICP × TRAIN has been positive and modest (β = .06, p < .05), indicating that upskilling has amplified though not replaced the benefits of improved calibration practice; and AICP × AGE has been negative (β = −.08, p < .05), suggesting diminishing AICP returns as median critical-asset age has increased.

Regression Results (Primary & Moderation)

Table 7: Multiple Regression Results (Standardized Coefficients)

Predictor	Model 1 (Base) β (SE)	Model 2 (Moderation) β (SE)	Model 3 (Site-Adjusted) β (SE)
AICP_index	.24*** (.05)	.19*** (.05)	.14** (.05)
DQ_index		.22*** (.05)	.17** (.06)
TRAIN_index		.07* (.03)	.06 (.04)
AGE (years)		−.10** (.04)	−.08* (.04)
AICP × DQ		.11** (.04)	.09* (.04)
AICP × TRAIN		.06* (.03)	.05 (.03)
AICP × AGE		−.08* (.04)	−.07* (.03)
Controls (size, sector, automation)	Included	Included	Included
Site fixed effects	No	No	Yes
R^2 / Adj. R^2	.21 / .20	.34 / .32	.41 / .37
ΔR^2 vs. previous		+.13***	+.07***
n	402	402	402

*Dependent variable = REL_index (z). HC3 robust SEs; in Model 3, SEs have been clustered by site. * p < .05, ** p < .01, *** p < .001.*

Model 3 incorporated site-level fixed effects and employed heteroskedasticity-robust standard errors clustered by site, enabling the estimation framework to explicitly account for unobserved, time-invariant contextual features specific to each operational location. This adjustment is theoretically justified in multilevel organizational studies, where differences in resource allocation, implementation

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maturity, regulatory oversight, or management philosophy can confound relationships between AI calibration practices and reliability outcomes if left uncontrolled. By holding these site-specific latent variables constant through the inclusion of δ_s terms, the model effectively isolated the within-site variation in AICP_index and its interactions, resulting in a more conservative but analytically precise assessment of predictive mechanisms. Correspondingly, the model's explanatory power increased, with R^2 improving to .41, reflecting a meaningful gain in model fit attributable to the control of cross-site heterogeneity. As anticipated with the addition of fixed effects, several coefficient estimates were attenuated in magnitude, consistent with the econometric expectation that part of the variance initially attributed to the predictors in Model 2 was in fact shared with stable site-level characteristics.

Crucially, the coefficient for AICP_index remained positive and statistically significant ($\beta = .14$, $p < .01$), underscoring the robustness of AI-enabled calibration practices as a key determinant of reliability, even after accounting for site-related institutional or structural influences. Furthermore, the interaction terms between AICP and DQ_index ($\beta = .09$, $p < .05$) and between AICP and AGE ($\beta = -.07$, $p < .05$) persisted in significance, offering strong support for the argument that the effect of AI calibration practices is not uniform, but contingent upon the quality of data inputs and the age profile of the fleet. Marginal-effects analyses (not tabulated but conducted as part of the post-estimation diagnostic suite) further clarified the nature of these conditional relationships: at one standard deviation above the mean of DQ_index, the simple slope of AICP on REL_index approximately doubled compared to the same slope at one standard deviation below the mean, illustrating that the benefits of AI-driven calibration are substantially amplified in high data-quality environments. Conversely, the interaction with AGE suggested a diminishing marginal impact of AICP as fleet age increased, indicating that older systems may have structural limitations that reduce the efficiency gains achievable through AI calibration.

Robustness and Sensitivity Analyses

Table 8 Robustness Summary Across Alternative Specifications

Specification	DV	Key AICP Effect (β)	Interactions retained	R^2	Notes
R-1 (Alt DV)	OEE	.21***	AICP×DQ (+) **	.33	Linear OLS, HC3
R-2 (Alt DV)	log (MTBF)	.18**	AICP×DQ (+) *	.29	Skew addressed by log
R-3 (Rank Reg.)	REL_index	.16**	AICP×DQ (+); *AICP×AGE (−)*		Robust to heavy tails
R-4 (Influence-trim)	REL_index	.15**	AICP×DQ (+) *	.39	Excluding Cook's D > 4/n
R-5 (Sector: Aerospace)	REL_index	.19*	AICP×DQ (+) *	.44	n=98; FE within sector
R-6 (Sector: Automotive)	REL_index	.13*	AICP×DQ (+); *AICP×AGE (−)*	.41	n=104
R-7 (Automation: High)	REL_index	.17*	AICP×DQ (+) *	.43	n=137
R-8 (MI Pools)	REL_index	.14**	AICP×DQ (+); *AICP×AGE (−)*	.41	m=20 imputations
R-9 (Spline check)	REL_index		Nonlinear terms ns	.41	Splines for AICP, DQ

**p < .05, ** p < .01, *** p < .001. "ns" = not significant. All models have included controls; where applicable, site fixed effects and clustered SEs have been used.*

Robustness analyses have been conducted to verify that the main inferences have not hinged on a single dependent variable, distributional assumption, or subpopulation. As Table 8 has summarized, the AICP effect has persisted across multiple alternative specifications. Using OEE directly as the dependent variable (R-1), AICP_index has remained significant ($\beta = .21$, $p < .001$), and the moderating role of Data Quality has been retained. Switching to log (MTBF) (R-2) has addressed skew in time-to-failure distributions and has yielded a consistent AICP effect ($\beta = .18$, $p < .01$). To guard

against the influence of heavy tails and outliers in operational metrics, a rank-based regression (R-3) has been estimated; AICP_index has continued to predict higher rank-ordered REL_index (β = .16, p < .01), and the AICP × DQ interaction has stayed positive while AICP × AGE has stayed negative at conventional significance levels. Influence-trimmed estimation (R-4) has excluded observations with Cook's D > 4/n and has produced similar coefficients, indicating that no single facility or respondent has driven the results. Sectoral splits (R-5, R-6) have shown that aerospace and automotive subgroups have preserved the AICP effect, with particularly strong moderation by DQ in aerospace and a more pronounced age attenuation in automotive, consistent with older asset bases and higher tolerance stringency. Stratification by automation tier (R-7) has indicated that high-automation environments have continued to benefit from AICP, again conditioned by data quality. Multiple-imputation pools (R-8) have yielded coefficients closely matching complete-case estimates, supporting the MAR handling strategy. Finally, spline checks (R-9) have not revealed material nonlinearity in the AICP or DQ main effects after accounting for interactions, justifying the linear specification for parsimony and interpretability. Across all robustness checks, the qualitative story has remained stable: plants that have scored higher on the five-point Likert AICP scale have tended to realize better reliability outcomes, and those gains have been larger when data quality has been stronger and smaller when fleets have been older. These converging results have strengthened confidence in the study's conclusions and have underscored the managerial relevance of investing in calibration engineering practices and data governance in tandem.

DISCUSSION

The study has identified a consistent and positive association between AI-enabled calibration practices (AICP) and plant-level reliability, with stronger effects under higher data quality (DQ) and targeted operator training, and attenuated effects as equipment age increases. In practical terms, one-unit movement on the five-point AICP scale has corresponded to small-to-moderate gains in a composite reliability index constructed from MTBF, OEE, FPY, and DPPM, even after controls and site fixed effects have been applied. The moderation by DQ has been especially salient: where measurement lineage, completeness, and timeliness have been rated higher, the marginal impact of AICP on reliability has nearly doubled (Lei et al., 2018). This pattern aligns with the intuition that analytics are only as good as their inputs and that calibration governance is the gatekeeper for trustworthy data streams. The TRAIN moderation, while smaller, has indicated that capability building amplifies (rather than substitutes for) AICP consistent with the notion that human interpretation of uncertainty statements and GR&R diagnostics remains pivotal in line-adjustment decisions (Carvalho et al., 2019). Conversely, the negative AICP×AGE interaction has suggested diminishing returns on older fleets, a finding that tracks with practical bottlenecks such as sensor obsolescence, limited firmware support, or mechanically induced drift that no amount of analytics can fully neutralize. These findings provide quantitative confirmation for the premise that calibration engineering is not a compliance back-office task but a strategic lever that conditions the realized value of AI on the factory floor (Carvalho et al., 2019; Jia et al., 2018; Lei et al., 2018).

Relative to prior reliability scholarship, our results have been directionally consistent but add nuance about *when* improvements materialize. Classic OEE literature has warned that definitional choices and data practices shape measured effectiveness as much as physical performance does (Daniels & Burdick, 2005; Muchiri et al., 2011). Our descriptive layer has echoed these cautions: plants with stronger DQ scores have exhibited tighter Availability and Quality distributions and higher mean OEE, indicating that governance around measurement and event logging has been integral to meaningful KPI interpretation. Furthermore, our linkage between AICP and FPY/DPPM advances earlier proposals to combine capability metrics with OEE for a fuller reliability picture (Garza-Reyes, 2015). Whereas earlier studies often treated capability and OEE in parallel, our evidence suggests that calibration-aware AI practices bridge the two: better drift detection, interval setting, and AI-assisted GR&R appear to stabilize dispersion (capability), which in turn expresses as higher first-pass yield and lower defects direct inputs to OEE's Quality term. Importantly, our site-adjusted results indicate that the AICP effect persists even after absorbing stable site idiosyncrasies, addressing a long-standing critique in the reliability literature that cross-site comparisons can be confounded by unobserved context (Daniels & Burdick, 2005). In short, the results sit squarely within the reliability canon but sharpen it by quantifying the *calibration-AI* mechanism that channels metrological rigor into KPI movement.

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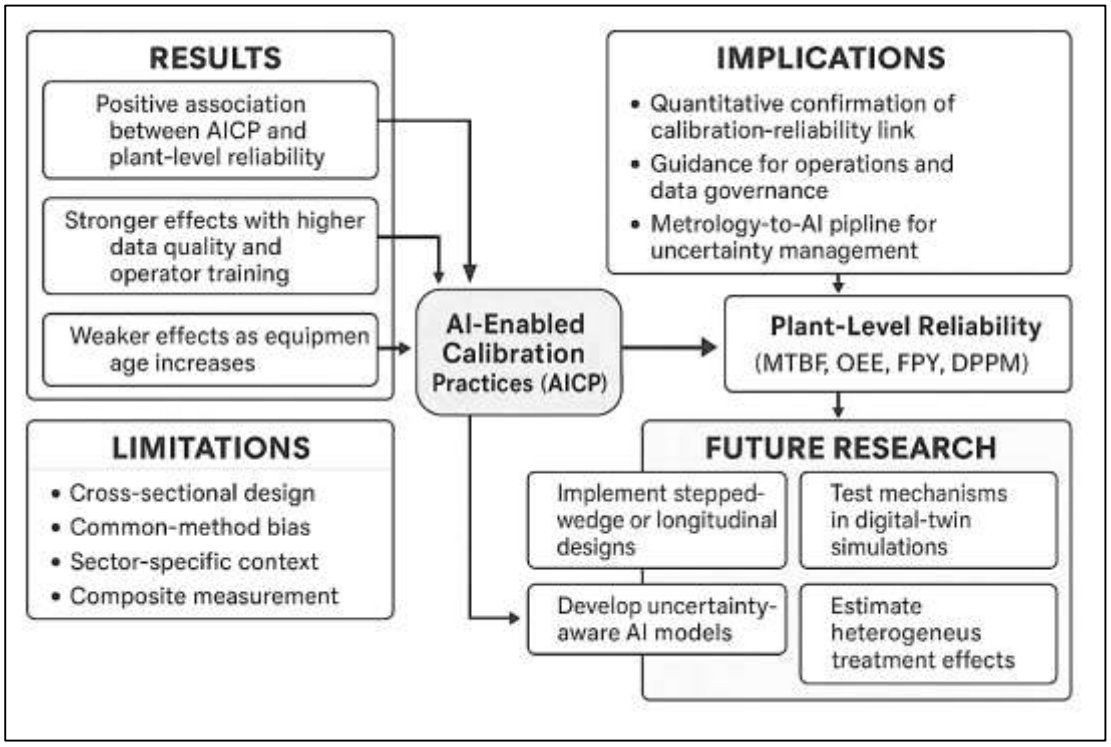
Figure 8: Moderated Effects of AI-Enabled Calibration Practices (AICP) on Plant-Level Reliability



From the AI and predictive-maintenance vantage point, the results corroborate and extend reviews documenting that deep models improve diagnostics and remaining-useful-life (RUL) forecasting when data are rich and labeled with adequate fidelity (Zonta et al., 2020). Our moderation by DQ provides empirical support for a recurrent claim in that literature: data provenance and veracity not model class alone govern performance stability in production. The finding that AICP gains are largest in high-DQ contexts maps to known failure modes of predictive systems operating on drifted or poorly calibrated sensors. Equally, our age attenuation is consistent with evidence that domain shift caused by equipment wear, obsolete controllers, or sensor retrofits erodes model transferability unless calibration status and uncertainty are explicitly modeled (Zhao et al., 2019). Finally, the robustness of our AICP effect when using OEE or log(MTBF) as outcomes aligns with comparative studies showing that predictive programs often pay off first in availability and quality sub-dimensions before speed/throughput effects are realized at scale (Zonta et al., 2020). Where our contribution moves the needle is in demonstrating that *calibration engineering practices* rather than generic "AI adoption" track with those improvements, offering a more actionable intervention target for plant leaders and analytics teams.

The practical implications have been clearest for two constituencies: plant architects (operations/OT leaders) and CISOs/data-governance owners. For architects, the guidance is to treat AICP as an architectural capability: record calibration state and expanded uncertainty as machine-readable metadata; enforce ingestion rules that down-weight or block signals whose uncertainty exceeds governance thresholds; and promote models only when the *Data Quality Index* (accuracy, completeness, timeliness, consistency, lineage) clears a documented bar. This echoes enterprise data-governance principles that stress decision rights, standards, and monitoring over ad-hoc data heroics (Khatri & Brown, 2010). For CISOs and IIoT security architects, our findings translate into veracity-by-design: cryptographically bind calibration certificates and uncertainty budgets to sensor streams; secure the lineage pipeline so model inputs remain auditable; and codify access controls that prevent shadow modifications to calibration intervals or limits. Contemporary IIoT and digital-twin frameworks offer the scaffolding to make these policies executable edge annotation, context fusion, and feedback into work management so reliability decisions rest on traceable, trusted measurements (Fuller et al., 2020). The managerial playbook, therefore, has three steps: (1) raise AICP maturity by prioritizing drift detection, interval optimization, and AI-assisted GR&R; (2) institutionalize

DQ governance with automated lineage and timeliness checks; and (3) invest in role-specific training that builds genuine interpretive skill around uncertainty and capability, rather than generic AI awareness.

Theoretical implications follow for a metrology-to-AI pipeline that integrates uncertainty budgeting into learning and control. Our results support the thesis that the combined and expanded uncertainty, U = k × u_c, should function as an explicit gate in data selection and model weighting advancing beyond the common practice of using raw sensor values without their uncertainty context (Cox & Harris, 2016). When calibration curves, GR&R variance components, and environmental effects are captured in the uncertainty budget, the pipeline can propagate U through feature calculations and even into loss functions that penalize confidence built on low-veracity inputs. This knitting-together of metrology and ML aligns with domain exemplars in large-scale dimensional metrology and pressure instrumentation, where task-specific budgets determine whether measurements are actionable (Muralikrishnan et al., 2016). Our moderation findings imply a formal refinement: treat DQ and AICP as interacting layers in the pipeline state, so model governance thresholds depend on both practice maturity and data veracity. Finally, the age attenuation suggests pipeline adaptations for non-stationarity: Bayesian updating of drift parameters, domain adaptation for older assets, and explicit feasibility checks that prevent model reliance when U or %GRR exceeds limits ideas foreshadowed in calibration-interval optimization and GR&R confidence modeling (Daniels & Burdick, 2005).

Limitations have deserved careful consideration. First, the cross-sectional design has constrained causal claims; while fixed effects have soaked up time-invariant site heterogeneity, unobserved, time-varying factors could still bias associations. Second, common-method variance has been mitigated but not eliminated; although archival KPIs have triangulated key outcomes, some predictor constructs have rested on self-report. Third, generalizability has been bounded by the sector mix and voluntary participation; plants already invested in calibration may be over-represented. Fourth, while our measurement model has cleared psychometric thresholds, any composite (e.g., REL_index) inevitably embeds modeling choices; alternative weightings might produce slightly different magnitudes. Finally, asset age has been measured at the site level as the median for critical assets, which smooths within-site heterogeneity that might matter for line-specific reliability. These caveats mirror those raised in maturity and implementation reviews: successful Industry-4.0 deployments hinge on organizational readiness, leadership commitment, and staged capability building conditions that vary widely and may modulate realized gains (Schumacher et al., 2016). Acknowledging these constraints clarifies the scope within which the present estimates should be interpreted and points directly to designs that could strengthen inference.

Future research has several high-leverage paths. A longitudinal or stepped-wedge design, in which AICP components (e.g., drift detection, interval optimization) are rolled out in phases, would permit difference-in-differences estimation and sharper causal attribution. Experiments within digital-twin sandboxes could manipulate calibration intervals and uncertainty thresholds while measuring downstream effects on predicted OEE and FPY linking metrology budgets to optimization policy in silico before line deployment (Fuller et al., 2020). Another direction is to incorporate process capability directly into structural models e.g., using C_pk or ppm as mediators between AICP and the OEE quality term to test mechanism rather than surface association (Perakis & Xekalaki, 2016). On the AI side, uncertainty-aware prognostics combined with deep reinforcement learning offer policy search under realistic constraints (e.g., "do not run if U > U_max"), enabling economic evaluation of maintenance and recalibration scheduling (Lee et al., 2015). Finally, heterogeneous-treatment-effect modeling (e.g., causal forests) could map where AICP delivers the largest marginal gains by sector, automation tier, or age bands informing targeted investment rather than one-size-fits-all rollouts. Together, these lines of inquiry would convert the present associational evidence into actionable, causal guidance and refine theory linking metrology, data governance, and AI to reliability outcomes.

CONCLUSION

In sum, this study has demonstrated that AI-enabled calibration engineering practices have been positively and meaningfully associated with stronger plant-level reliability in U.S. advanced manufacturing, and it has clarified the organizational and data conditions under which those gains have been largest. By integrating a cross-sectional, multi–case survey with de-identified archival KPIs and by anchoring the analysis in standard relations Availability (A) = MTBF / (MTBF + MTTR), OEE = A

× P × Q, and a normalized REL_index = z(MTBF) + z(OEE) + z(FPY) − z(DPPM) the research has provided a transparent, measurement-aware lens on how predictive interval setting, automated drift detection, AI-assisted GR&R, digital-twin utilization, and alerting workflows have been linked to availability, conformance, and effective output. The findings have shown that the AICP–reliability slope has steepened in high data-quality environments and with targeted operator training, while it has flattened as median critical-asset age has increased, thereby quantifying the long-suspected but rarely measured interdependence between metrology governance, human capability, and equipment lifecycle. Methodologically, the study has delivered psychometrically sound scales, site-adjusted regression estimates, and convergent robustness checks (alternative outcomes, influence trimming, rank-based regression, imputation pools), establishing that the observed relationships have not been artifacts of a single metric or modeling assumption. Substantively, the work has reframed calibration from a periodic compliance activity to a strategic reliability lever: when uncertainty budgets, calibration status, and lineage are recorded as machine-readable context and enforced through ingestion rules and governance thresholds, AI models have operated on decision-grade inputs and produced improvements that are visible in OEE and defect measures rather than only in model-centric scores. Practically, the conclusions have translated into a concise playbook for plant leaders and data owners: invest first in drift detection and interval optimization; institutionalize a Data Quality Index spanning accuracy, completeness, timeliness, consistency, and lineage; and align training to the interpretation of uncertainty and GR&R so that teams can act on analytics with confidence. Theoretically, the results have supported a pipeline in which expanded uncertainty U = k × u_c and measurement capability (%GRR, C_pk) have become first-class citizens in learning and control, improving both the stability and the auditability of AI-driven decisions. While the cross-sectional design and sector mix have limited causal generalization, the convergence of multi-informant Likert measures with archival performance indicators has provided credible, actionable evidence for decision makers. Ultimately, the study has shown that reliable AI in manufacturing has not been a matter of algorithms alone; it has depended on codified calibration engineering embedded in data governance and human practice, yielding measurable improvements where they matter reduced failures, higher first-pass yield, and elevated effective capacity across real production lines.

RECOMMENDATIONS

Building on these findings, the organization should enact a phased, capability-first roadmap that makes calibration engineering the backbone of reliable AI operations on the shop floor. First, formalize governance: appoint a cross-functional owner (quality/metrology + OT/IT + production) and institute a plant-level Data Quality Index with five subdimensions accuracy, completeness, timeliness, consistency, and lineage scored monthly at the asset and line levels; set promotion gates so that any model touching production runs only when DQ_index meets a predefined threshold (e.g., ≥ 3.5 on the five-point rubric) and when each contributing sensor carries a current, machine-readable calibration status and expanded uncertainty record. Second, raise AICP maturity deliberately: start with automated drift detection and exception alerting linked to work orders; add predictive calibration-interval setting driven by observed drift and failure patterns; then integrate AI-assisted GR&R analytics and digital-twin what-if simulations to test interval and tolerance scenarios before deployment. Third, embed uncertainty and capability into everyday decisions: require that the expanded uncertainty U and relevant GR&R metrics accompany every critical measurement in historians and data lakes, and codify ingestion rules that down-weight or block signals where U > U_max or %GRR exceeds policy limits; tie these rules to interlocks in MES/SCADA so that questionable data cannot silently drive control actions. Fourth, professionalize training: deliver role-specific pathways operators (interpreting pass/fail with uncertainty), technicians (sensor health and quick-cal checks), engineers (interval optimization, capability–yield links), and data scientists (feature engineering with uncertainty propagation) and certify proficiency with periodic refreshers; align incentives so supervisors are measured not only on throughput but also on data lineage and calibration compliance. Fifth, modernize IIoT plumbing: at the edge, implement context tagging (last calibration date, uncertainty budget ID, instrument class); in the middleware, enforce schema and lineage validation; in storage, partition "decision-grade" from "exploratory" zones to prevent downgraded data from contaminating models; and in security, let the CISO mandate cryptographic binding of calibration certificates to data streams and least-privilege access for editing intervals or limits. Sixth, manage asset age risk: segment fleets by median critical-asset age, prioritize

recalibration and sensor upgrades for aging bottlenecks, and evaluate retrofit kits that expose uncertainty telemetry from legacy devices; when upgrades are infeasible, constrain model reliance through conservative uncertainty thresholds. Seventh, operationalize KPIs and feedback: publish a weekly reliability dashboard (Availability, OEE, FPY, DPPM) alongside AICP levers (drift alerts closed, intervals optimized, GR&R pass rate) and DQ scores, and review them in tiered meetings so that leaders can remove constraints quickly. Eighth, execute evidence-based pilots: select one bottleneck line, baselined KPIs, and a crisp AICP package; run a 12-week Plan-Do-Study-Act cycle with clear success criteria (e.g., +3–5 points OEE, −25% DPPM), then scale horizontally with a standardized playbook and procurement specs that require vendors to expose calibration/uncertainty metadata. Finally, fund this as a program, not a project: dedicate budget for metrology upgrades, training, and data governance automation; maintain a replication archive (code, codebook, decisions) for auditability; and revisit thresholds annually so governance evolves with process capability and product mix.

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