Supplementary Material S1[1]

Detailed indicator catalogue, risk categories, evidence-confidence scale and software implementation fields for:

AI-enabled dependability diagnostics for industrial product lifecycle management: a software-ready method integrating IoT, digital twins and life-cycle cost

This supplementary material provides the operational specification of the AI-IPLM-RMLCC Diagnostic Engine. The main manuscript presents the conceptual architecture, scoring logic and validation pathway; the tables below provide item-level definitions intended for software implementation, replication and future validation.

This supplementary material should be read together with the scoring logic and diagnostic interpretation presented in the main manuscript. Readiness indicators use a 0–4 maturity logic unless otherwise specified. Implementation-risk dimensions use a 0–5 diagnostic scale and are normalised to the 0–100 nAIRPN/nAIRI scale. Evidence confidence uses a 0–4 scale and is converted into ECI by dividing the mean evidence score by 4.

Table S1. Data Readiness Index indicators.

Code	Indicator	Scale	Data type
DRI_1	Share of critical assets covered by condition monitoring	0–100%	quantitative
DRI_2	Completeness of maintenance records	0–100%	quantitative
DRI_3	Completeness of failure history	0–100%	quantitative
DRI_4	Share of data linked to unique asset/product identifiers	0–100%	quantitative
DRI_5	Frequency and stability of data updates	0–4	maturity
DRI_6	Existence of automated data validation rules	0/1	binary
DRI_7	Systematic monitoring of sensor drift	0–4	maturity

Note: Scores use the common maturity logic unless otherwise specified: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, 4 = integrated, monitored and used for decisions.

Table S2. Operational Technology and Information Technology Integration Index indicators.

Code	Indicator	Scale
OTI_1	Integration of machines and sensors with data platforms	0–4
OTI_2	Integration of product lifecycle management with manufacturing execution and enterprise resource planning systems	0–4
OTI_3	Integration of quality data with service data	0–4
OTI_4	Availability of application programming interfaces or standardised interfaces	0–4
OTI_5	Standardisation of product and asset identifiers	0–4
OTI_6	Cross-functional data flow between departments	0–4
OTI_7	Integration of Internet of Things data into decision dashboards	0–4

Note: Scores use the common maturity logic unless otherwise specified: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, 4 = integrated, monitored and used for decisions.

Table S3. Digital Twin Capability Index indicators.

Code	Indicator	Scale
DTCI_1	Existence of a digital model of product, process or asset	0–4
DTCI_2	Automatic update of the model with operational data	0–4
DTCI_3	Connection between model and operating history	0–4
DTCI_4	Ability to run what-if simulations	0–4
DTCI_5	Use of the model for failure prediction	0–4
DTCI_6	Use of the model for service or maintenance decisions	0–4
DTCI_7	Model update after product or asset configuration change	0–4

Note: Scores use the common maturity logic unless otherwise specified: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, 4 = integrated, monitored and used for decisions. Digital representation maturity may also be interpreted as: 0 = no model, 1 = digital model, 2 = digital shadow, 3 = operational digital twin, 4 = decision-oriented digital twin.

Table S4. Artificial Intelligence Reliability Analytics Index indicators.

Code	Indicator	Scale
ARAI_1	Use of artificial intelligence for anomaly detection	0–4
ARAI_2	Use of artificial intelligence for fault diagnosis	0–4
ARAI_3	Use of artificial intelligence for failure prediction	0–4
ARAI_4	Use of artificial intelligence for remaining useful life estimation	0–4
ARAI_5	Use of artificial intelligence for predictive maintenance scheduling	0–4
ARAI_6	Validation of artificial-intelligence models before operational use	0–4
ARAI_7	Monitoring of model drift	0–4
ARAI_8	Explainability of artificial-intelligence recommendations	0–4

Note: Scores use the common maturity logic unless otherwise specified: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, 4 = integrated, monitored and used for decisions.

[1] As the submission system did not provide a separate upload field for supplementary material, Supplementary Material S1 has been included at the end of the manuscript file after the References. It contains the detailed indicator catalogue, implementation-risk categories, evidence-confidence scale, minimum software data model and case-study diagnostic output.

Table S5. Reliability, Availability, Maintainability and Safety Governance Index indicators.

Code	Indicator	Scale
RGI_1	Defined reliability requirements for artificial-intelligence-enabled lifecycle projects	0–4
RGI_2	Defined availability requirements	0–4
RGI_3	Defined maintainability requirements	0–4
RGI_4	Defined safety requirements	0–4
RGI_5	Analysis of artificial-intelligence impact on safety	0–4
RGI_6	Human-in-the-loop for safety-critical decisions	0–4
RGI_7	Auditability of artificial-intelligence-supported decisions	0–4
RGI_8	Procedure for suspending or withdrawing artificial-intelligence models	0–4

Note: Scores use the common maturity logic unless otherwise specified: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, 4 = integrated, monitored and used for decisions.

Table S6. Life-Cycle Cost Intelligence Index indicators.

Code	Indicator	Scale
LCCI_1	Known cost of one hour of downtime	0/1
LCCI_2	Recording of repair costs	0–4
LCCI_3	Recording of warranty costs	0–4
LCCI_4	Recording of spare-parts costs	0–4
LCCI_5	Linking failure costs to assets or product families	0–4
LCCI_6	Evaluation of artificial-intelligence projects using life-cycle cost logic	0–4
LCCI_7	Use of repair-versus-replace analysis	0–4
LCCI_8	Estimation of avoided failure value	0–4

Note: Scores use the common maturity logic unless otherwise specified: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, 4 = integrated, monitored and used for decisions. Avoided failure value may be estimated as $AFV = P_f \times C_f \times P_d$ (8), where P_f is the estimated probability of failure, C_f is the expected cost of failure and P_d is the probability of successful detection or prevention.

Table S7. Artificial Intelligence implementation risk categories.

Code	Risk category	Example risk
R1	Data quality risk	Missing values, poor labels, sensor drift
R2	Integration risk	Disconnected operational-technology/information-technology systems
R3	Model drift risk	Declining accuracy after operating changes
R4	Cybersecurity risk	Data manipulation or attack-induced failure
R5	Safety risk	Artificial-intelligence recommendation affects safety-critical decision
R6	Organisational resistance risk	Engineers do not trust or use the system
R7	Return-on-investment uncertainty risk	Benefits are not measurable or not captured
R8	Supplier dependency risk	Dependence on external platforms or black-box models
R9	Regulatory risk	Unclear accountability or certification implications
R10	Explainability risk	Model outputs cannot be interpreted or audited

Note: Each risk category should be scored using four dimensions: severity, occurrence, difficulty of detection and controllability. Each dimension is scored on a 0–5 diagnostic scale, where 0 denotes absence or non-applicability and 5 denotes the maximum level. Missing or undocumented information should not be coded as 0; it should be captured separately through the Evidence Confidence Index. $AIRPN_r$, $nAIRPN_r$ and nAIRI are calculated according to Eqs. (3), (4) and (5). The interpretation of nAIRPN follows the normalised 0–100 risk scale reported in the main manuscript.

Table S8. Evidence confidence scale.

Score	Evidence level	Interpretation
0	No evidence	The answer is unsupported
1	Respondent declaration	The answer is based on self-report only
2	Internal document	The answer is supported by procedures, reports or documentation
3	System data	The answer is supported by data from operational systems
4	Auditable data	The answer is supported by periodically reported or auditable data

Note: Evidence confidence is used to adjust readiness interpretation and prevent unsupported declarations from being treated as verified capability. ECI is calculated according to Eq. (6).

Table S9. Minimum software data model.

Table	Key fields	Purpose
Project	project_id, industry, asset_type, criticality, AI_use_case	Defines diagnostic context
IndicatorScore	project_id, module, indicator_code, raw_value, standardised_score, weight	Stores readiness indicators
RiskScore	project_id, risk_code, severity, occurrence, detection_difficulty, controllability, AIRPN, nAIRPN	Stores risk assessment
EvidenceRecord	project_id, indicator_code, evidence_level, evidence_source, evidence_date	Stores documentation quality
OutputProfile	project_id, DRI, OTI, DTCI, ARAI, RGI, LCCI, ALRI, nAIRI, ECI, EARI, profile	Stores final diagnosis

Note: This minimum data model can be implemented in a spreadsheet, relational database, web application or audit dashboard. The nAIRPN and nAIRI fields support the normalised 0–100 risk interpretation used in the main manuscript.

Table S10. Case-study diagnostic output.

This table reports the software-facing output for the diagnostic case study described in the main manuscript.

Output	Value	Diagnostic interpretation
DRI	**80.7**	Strong data readiness. The machine has high condition-monitoring coverage, complete failure-history coding, strong linkage with production orders and frequent data updates. Remaining weaknesses concern sensor-drift monitoring and the need to clarify the meaning of critical machine components.
OTI	**57.1**	Moderate operational-technology/information-technology integration. The machine shows some integration with data platforms and dashboards, and strong standardisation of identifiers, but integration with MES, ERP or PLM remains limited.
DTCI	**32.1**	Low-to-moderate digital twin capability. A digital representation exists mainly at the product or process-model level, but automatic updating, connection with operating history, simulation and predictive use remain weak.
ARAI	**43.8**	Emerging artificial-intelligence reliability analytics. AI-supported diagnosis and explainability are relatively stronger, but remaining useful life estimation, predictive maintenance scheduling, model validation and model-drift monitoring are still weak.
RGI	**81.3**	Strong reliability, availability, maintainability and safety governance. Classical dependability requirements and human oversight are well developed, although auditability and withdrawal procedures for AI-supported decisions remain less mature.
LCCI	**90.6**	Very strong life-cycle cost intelligence for conventional maintenance. Downtime cost, repair costs, warranty or complaint costs, spare-parts costs, repair-versus-replace logic and avoided-failure thinking are largely present, although AI projects are still weakly evaluated through life-cycle cost logic.
ALRI	**65.8**	Upper-moderate lifecycle readiness. The organisation is close to a high-readiness profile, but the result is limited by weak digital twin capability and still-developing AI reliability analytics.
ECI	**0.25**	Low evidence confidence. Because the updated interview form does not include separate evidence-level coding, the responses were conservatively treated as respondent declarations.
EARI	**16.5**	Low evidence-adjusted readiness. The raw readiness level is substantially reduced because the supporting evidence has not yet been documented or audited.
nAIRI	**8.5**	Low normalised implementation risk. The risk profile is low on average, but several categories, especially supplier dependency, regulatory risk and explainability risk, require qualitative review because high controllability scores strongly reduce their calculated risk values.
Profile	**Evidence-constrained early-stage readiness**	Based on raw ALRI and low nAIRI, the case could be treated as a selective pilot candidate. After evidence adjustment, however, the safer classification is early-stage readiness, meaning that documentation, evidence coding and validation should precede operational scaling.

Note: Readiness indicators were converted to a 0–100 scale before aggregation. Because the interview form did not include separate evidence-level coding, ECI was conservatively coded as 0.25, corresponding to respondent declaration only. If internal documents, system data or auditable records are later attached to the diagnostic record, ECI and EARI should be recalculated. The nAIRI value reflects the numerical risk ratings provided in the interview; high controllability scores reduce the calculated risk for supplier dependency, regulatory risk and explainability risk.