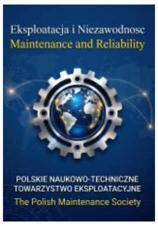

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AI-enabled dependability diagnostics for industrial product lifecycle management

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Abstract

Industrial products increasingly operate as connected cyber-physical technical items whose reliability, maintainability, safety and life-cycle cost depend on IoT monitoring, artificial intelligence and digital twins. This paper develops a software-ready diagnostic method and instrument for assessing organisational and technical readiness for AI-enabled industrial product lifecycle management. The proposed AI-IPLM-RMLCC Diagnostic Engine is derived from a structured synthesis of scientific publications and applied in a diagnostic case study of QUAY BHU Sp. z o.o., a real medium-sized manufacturing enterprise located in Wielkopolska, Poland. It combines operational indicators, maturity levels, implementation-risk scoring, evidence-confidence ratings and composite indices. The instrument helps identify readiness gaps, prioritise risk reduction and link digital deployment to dependability and life-cycle cost outcomes.

Keywords: *artificial intelligence, digital twin, Industrial Internet of Things, predictive maintenance, life-cycle cost*

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Highlights

- A software-ready diagnostic engine is developed for lifecycle decisions.
- Readiness, risk, evidence confidence and life-cycle cost are integrated.
- A real manufacturing case study shows diagnostic output generation.
- Capability indices support industrial AI and digital-twin deployment.
- The instrument can support database, spreadsheet and dashboard use.

1. Introduction

Industrial products are increasingly becoming connected cyber-physical technical items rather than isolated artefacts. Machines, production lines, robotic systems and automation components generate operational data, communicate with other systems and affect reliability, availability, maintainability, safety and life-cycle cost [1–4]. This transformation shifts product lifecycle management (PLM) from documentation-centred engineering control towards monitoring, predictive diagnosis, maintenance support and lifecycle learning. IoT monitoring and digital twins connect operational data with product structure and simulation [5–8]. AI supports anomaly detection, fault diagnosis, remaining useful life (RUL) estimation and predictive maintenance [9–11]. Together, these technologies extend PLM from design and manufacturing to operation, service and modernisation.

Technological availability does not automatically lead to improved reliability or lower life-cycle cost. Industrial applications face barriers related to incomplete data, heterogeneous OT/IT systems, model validation, explainability, cybersecurity, safety accountability and economic justification [12–15]. A pilot model may fail after changes in load profile, asset configuration or sensor quality; a digital twin may also remain a static model rather than a decision-support representation. AI readiness and adoption studies show that organisational preparedness should be assessed together with implementation barriers and evidence quality [16,17]. Thus, a limitation of many AI-readiness assessments is their reliance on declarative survey answers. A firm may report predictive-maintenance readiness while lacking complete failure histories, traceable asset identifiers, documented model validation or reliable downtime-cost data. For reliability and maintenance engineering, readiness should be assessed as an evidence-supported capability condition combining operational indicators, maturity ratings, implementation-risk scores and evidence-confidence ratings.

This paper develops the AI-IPLM-RMLCC Diagnostic Engine, a software-ready instrument for assessing AI-enabled industrial PLM from the perspective of reliability, maintenance and life-cycle cost. It asks what theoretical pillars should support the instrument, how readiness, implementation risk and evidence confidence can be operationalised, and how diagnostic outputs can guide AI, IoT and digital-twin deployment. The contribution is methodological and application-oriented: a structured evidence base is translated into variables, scoring rules, indices, diagnostic profiles and software data fields.

The purpose of this article is therefore to develop a software-ready diagnostic method for assessing AI-enabled dependability in industrial product lifecycle management. The proposed method integrates organisational readiness, implementation risk, evidence quality, IoT-enabled diagnostic data, digital-twin logic and life-cycle cost assessment into a single diagnostic framework for reliability- and maintenance-oriented decision support.

Accordingly, the article addresses the following research questions:

RQ1. How can AI, IoT and digital-twin capabilities be integrated into a software-ready diagnostic framework for industrial product lifecycle management?

RQ2. How can evidence-adjusted readiness assessment distinguish between declared organisational readiness and readiness supported by documented, auditable operational evidence?

RQ3. How can implementation risk and life-cycle cost considerations be incorporated into a diagnostic engine for reliability, maintenance and dependability-oriented decision support?

To improve readability and to facilitate interpretation of the diagnostic architecture, Table 1 summarises the main acronyms and diagnostic indices used throughout the article.

Table 1. Nomenclature. Acronyms and diagnostic indices used in the article.

Acronym/index	Full name	Role in the article
AI-IPLM-RMLCC Diagnostic Engine	AI-enabled Industrial Product Lifecycle Management for Reliability, Maintenance and Life-Cycle Cost Diagnostic Engine	Main software-ready diagnostic artefact proposed in the article
AI	Artificial intelligence	Analytical technologies used for anomaly detection, diagnosis, prognostics and maintenance decision support.
PLM	Product lifecycle management	Lifecycle-oriented management context for engineering, operation, service and modernisation decisions.
IoT / IIoT	Internet of Things / Industrial Internet of Things	Operational data infrastructure connecting sensors, machines, assets and industrial information systems.
PHM	Prognostics and health management	Dependability-oriented analytical stream supporting diagnosis, RUL estimation and maintenance planning.
RUL	Remaining useful life	Prognostic estimate used to support maintenance timing and asset management decisions.
RAMS	Reliability, availability, maintainability and safety	Dependability governance perspective used to assess safe, available and serviceable operation.
LCC	Life-cycle cost	Economic perspective linking reliability, downtime, repair, service, warranty and lifecycle savings.
DRI	Data Readiness Index	Module assessing data completeness, traceability, quality and update frequency.
OTI	OT/IT Integration Index	Module assessing integration between operational technology and information systems.
DTCI	Digital Twin Capability Index	Module assessing digital models, data synchronisation, simulation and decision use.
ARAI	AI Reliability Analytics Index	Module assessing AI use for anomaly detection, diagnosis, RUL and predictive maintenance.
RGI	RAMS Governance Index	Module assessing reliability, availability, maintainability, safety and oversight.
LCCI	Life-Cycle Cost Intelligence Index	Module assessing links between dependability decisions and cost information.
AIRI / nAIRI	AI Implementation Risk Index / normalised AI Implementation Risk Index	Risk module capturing implementation exposure and its normalised interpretation.
ECI	Evidence Confidence Index	Corrective index measuring the evidential strength behind diagnostic scores.
ALRI	AI Lifecycle Readiness Index	Composite readiness index aggregating module-level capability scores.
EARI	Evidence-Adjusted Readiness Index	Composite index adjusting ALRI by evidence confidence.
MTBF / MTTR	Mean time between failures / mean time to repair	Operational validation indicators proposed for future empirical testing.

2. Theoretical background

2.1. Cyber-physical product lifecycle and data infrastructure

The first theoretical pillar is the cyber-physical view of the industrial product. An industrial product combines mechanical, electrical, software, communication, data and service layers that interact across the lifecycle. Reliability and maintainability therefore depend on physical design, sensor quality, communication continuity, data integrity and the connection between field operation and engineering knowledge [1–3,5]. Cybersecurity and safety accountability extend this view because connected industrial products operate within cyber-physical systems exposed to technical and organizational risks [12,13].

IoT and Industrial IoT provide the data infrastructure for a closed-loop lifecycle. Sensors, controllers, edge devices and data platforms collect condition and event data, but these data become useful for maintenance only when linked to product structure, asset identifiers, operating context and failure history [3-5]. This requirement is consistent with research on digital servitization, lifecycle integration and organisational readiness [18–21]. Digital twins add an interpretive layer to lifecycle data. A digital twin is not a static CAD model or visual dashboard; it should be updated by data from the physical counterpart and support monitoring, simulation, prediction and decision-making [6–8,22]. Digital twin and digital thread studies further show that lifecycle integration requires continuity between product models, operational histories and service decisions [10,23–25]. The distinction between a digital model, digital shadow and operational digital twin is diagnostically important. Fig. 1 summarises how these streams are translated into the diagnostic method, shows how the evidence base is translated into theoretical pillars and then into the AI-IPLM-RMLCC Diagnostic Engine.

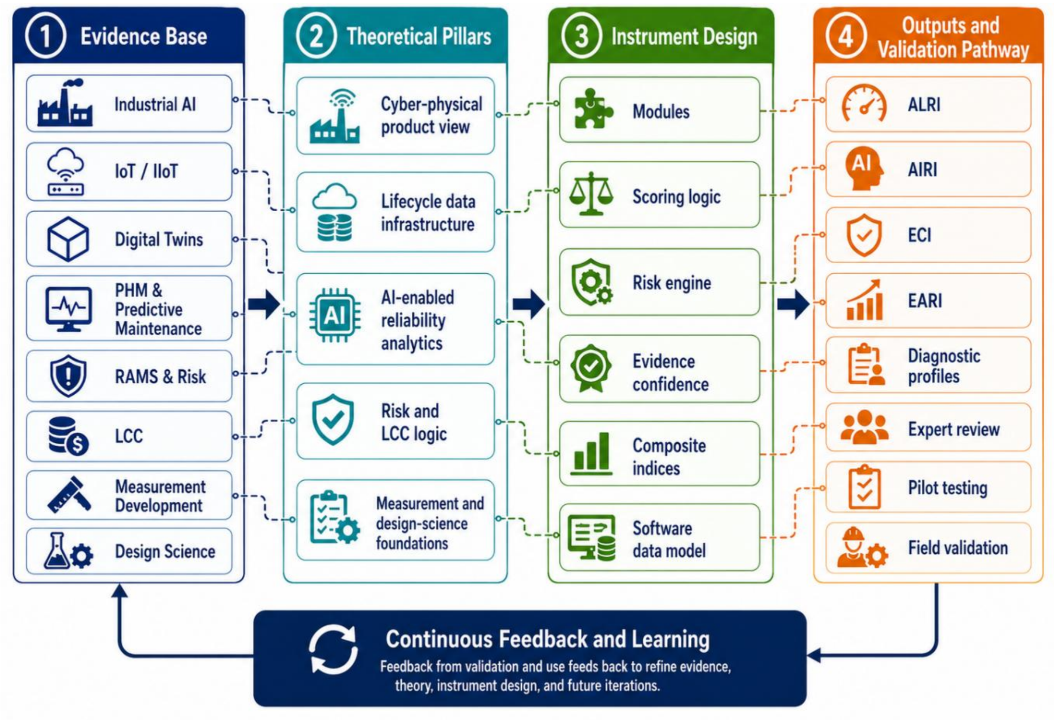

Figure 1. Research logic linking the evidence base, theoretical pillars and the diagnostic engine.

The diagram clarifies the methodological sequence of the study: evidence streams are organised into theoretical pillars and then transformed into diagnostic modules, scoring rules and software-ready outputs.

2.2. Reliability analytics, RAMS and life-cycle cost

The second pillar is AI-enabled reliability analytics and prognostics and health management. AI can support anomaly detection, fault diagnosis, RUL estimation, maintenance scheduling and redesign prioritisation [9–11,26]. Predictive quality, prognostics and predictive maintenance studies show that analytical models must also be operationally useful for engineers and maintenance planners [17,27–30]. Nevertheless, model accuracy alone is insufficient in industrial settings. A model must be robust under changing operating conditions, interpretable for engineers, monitored for drift, connected to maintenance planning and assessed against safety and cost consequences.

Reliability, availability, maintainability and safety (RAMS) provide the dependability-oriented governance layer. RAMS ensures that AI and digital twins are not evaluated only by analytical performance, but also by safe, available and serviceable operation. This is critical when algorithmic recommendations influence inspection intervals, repair-or-replace decisions, spare-parts planning or safety-related interventions.

At instrument-design level, dependability and economic requirements must be converted into measurable variables and formative indices. This requires design-science logic and measurement-development discipline [31–34]. Formative measurement is appropriate because several modules represent distinct capability components rather than interchangeable indicators of a single latent variable [35–37]. Risk logic is also necessary because AI deployment may introduce data-quality, model-drift, cybersecurity, safety and accountability risks [38]. Life-cycle cost links reliability analytics with managerial decisions through avoided failure value, downtime reduction, warranty cost, service cost and lifecycle savings [11,39–42].

Digital-twin maintenance applications extend this logic to model-based asset monitoring and service decisions [24,25,39,40]. Readiness and adoption studies show that organisational capability, maturity and economic justification condition implementation [16,17,20,21,43].

2.3. Measurement and design-science foundations

The third pillar is measurement development combined with design science. Design science research constructs and evaluates artefacts that solve relevant organisational problems [31–34]. The proposed engine is such an artefact: it defines constructs, specifies indicators, introduces formulas and generates actionable output profiles. Thus, the instrument is not a purely reflective psychometric scale. Several modules are formative: data readiness, OT/IT integration, digital-twin capability, RAMS governance and life-cycle cost intelligence are distinct capability components rather than interchangeable symptoms of one latent trait [35–37,44,45]. Validation should therefore include expert review, content validity assessment, cognitive interviews, pilot testing and criterion validation.

3. Materials and methods

3.1. Evidence base and instrument development

The study uses a design-science and structured-synthesis approach. The artefact was developed from 45 DOI-indexed publications covering cyber-physical manufacturing, IoT, digital twins, industrial AI, predictive maintenance, PHM, RAMS, life-cycle cost, risk analysis, readiness assessment, measurement development and design science. The evidence base was grouped into literature families, mapped into diagnostic requirements and translated into modules, indicators, scales and software outputs.

Table 2 reports the seven evidence families used to construct the diagnostic engine. It shows that the instrument is not a free-standing checklist: each module is anchored in a specific literature stream, from cyber-physical infrastructure and digital twins to measurement theory and design-science methodology.

Table 2. Evidence base supporting the AI-IPLM-RMLCC diagnostic engine.

Evidence family	Main role in the instrument	Key references
Cyber-physical and smart manufacturing	Defines the industrial product as a connected, data-generating technical item	[1–5]
IoT, IIoT and digital twins	Defines data acquisition, digital representation and lifecycle feedback	[6–8,22,24]
AI maintenance and PHM	Defines diagnosis, prognostics, RUL and predictive maintenance	[9–11,27,30]
Safety, cybersecurity and risk	Defines dependability, safety-critical AI and risk prioritisation	[12,13,15,38]
Servitization, readiness and adoption	Defines organisational and economic implementation conditions	[14,16–19]
Measurement development	Supports construct design, evidence confidence and validation logic	[35–37,44,45]
Design science	Supports the diagnostic engine as a methodological artefact	[31–34]

3.2. Diagnostic architecture and scoring rules

The AI-IPLM-RMLCC Diagnostic Engine consists of six readiness modules: DRI, OTI, DTCI, ARAI, RGI and LCCI. Two complementary modules assess implementation risk and evidence confidence. The composite outputs are ALRI and EARI.

Most capability indicators use a five-level maturity scale: 0 = absent, 1 = local or informal, 2 = partial, 3 = stable and documented, and 4 = integrated, monitored and decision-oriented. Percentage indicators are normalised to 0–100 and binary indicators to 0 or 100. A module score is calculated as a weighted mean of standardised indicators according to Eq. (1):

$$Module_j = \frac{\Sigma(w_i \times x_i)}{\Sigma w_i} \tag{1}$$

where $Module_j$ is the score of readiness module j, x_i is the standardised value of indicator i on the 0–100 scale, w_i is the weight assigned to indicator i, and Σw_i is the sum of weights used in the module.

The default composite readiness index gives slightly higher weights to data readiness, AI reliability analytics, RAMS governance and life-cycle cost intelligence, as shown in Eq. (2):

$$ALRI = 0.18DRI + 0.14OTI + 0.14DTCI + 0.18ARAI + 0.18RGI + 0.18LCCI \tag{2}$$

where: *DRI, OTI, DTCI, ARAI, RGI* and *LCCI* are the six readiness module scores, and the coefficients are default weights that sum to 1.00.

Implementation risk follows a modified failure mode and effects analysis logic. For risk category r, severity, occurrence, difficulty of detection and controllability are scored from 0 to 5. High controllability reduces risk. The adjusted risk score and its normalised form are calculated according to Eqs. (3) and (4):

$$AIRPN_r = S_r \times O_r \times D_r \times (6 - C_r) \tag{3}$$

$$nAIRPN_r = 100 \times \frac{AIRPN_r}{750} \tag{4}$$

where: S_r is severity, O_r is occurrence, D_r is difficulty of detection and C_r is controllability for risk category r. The value 750 is the maximum *AIRPN* on the 0–5 scale, so $nAIRPN_r$ expresses risk on a 0–100 scale.

The aggregated normalised implementation-risk index is calculated as the mean of all normalised risk-category scores according to Eq. (5):

$$nAIRI = mean(nAIRPN_1, \dots, nAIRPN_n) \tag{5}$$

Table 3 gives the interpretation of the normalised risk priority number. This table is used in the diagnostic classification because it converts project-specific risk scoring into a common 0–100 risk scale that can be compared across plants, assets or product families.

Table 3. Normalised AIRPN interpretation.

nAIRPN	Risk level	Interpretation
0	No applicable risk	No relevant exposure identified
0.1–20.0	Low	Risk can be monitored through routine controls
20.1–40.0	Moderate	Mitigation is recommended before scaling
40.1–70.0	High	Risk may threaten operational deployment
70.1–100.0	Critical	Deployment should not proceed without corrective action

Evidence confidence is scored from 0 to 4, where 0 denotes no evidence and 4 denotes auditable or periodically reported data. The Evidence Confidence Index and the Evidence-Adjusted Readiness Index are calculated according to Eqs. (6) and (7):

$$ECI = mean(evidence\ scores)/4 \tag{6}$$

$$EARI = ALRI \times ECI \tag{7}$$

where: *ECI* is the Evidence Confidence Index, *ALRI* is the AI Lifecycle Readiness Index and *EARI* is the Evidence-Adjusted Readiness Index. The divisor 4 reflects the maximum evidence-confidence score.

This adjustment prevents high declarative readiness from being interpreted as verified readiness when supporting evidence is weak. The detailed evidence-confidence scale and minimum implementation data model are provided in Supplementary Material S1, Tables S8 and S9.

3.3. Diagnostic case study design

The instrument was applied in a diagnostic case study of QUAY BHU Sp. z o.o., a limited liability company and real medium-sized manufacturing enterprise located in the Wielkopolska region, Poland. The assessment focused on a machine used for cutting industrial belts and was conducted with the proposed AI-IPLM-RMLCC Diagnostic Engine. The purpose of the case study was to examine whether the proposed measurement procedure can be operationalised in an actual industrial context and to demonstrate how module-level readiness scores, implementation-risk exposure, evidence confidence and the final diagnostic profile are produced from structured diagnostic interview data. The company is identified in the article; however, detailed operational records, commercially sensitive information and raw internal documentation are not disclosed. For this reason, the article reports aggregated diagnostic outputs rather than confidential operational data.

The input data were obtained through a structured diagnostic interview and converted into module-level readiness and implementation-risk scores according to the scoring rules of the AI-IPLM-RMLCC Diagnostic Engine. Because separate evidence-level coding was not recorded in the diagnostic form, evidence confidence was conservatively coded as respondent declaration only. Table 5 reports the resulting index values. The same software-facing output record is reproduced in Supplementary Material S1, Table S10, to show how the case-study output can be stored in a spreadsheet, database or dashboard.

4. Results

4.1. Architecture of the diagnostic engine

The result is a modular diagnostic engine for assessing whether an organisation is ready to deploy AI, IoT and digital twins for reliability, maintenance and life-cycle cost improvement. Fig. 2 presents the architecture: operational data, maturity ratings, risk ratings and evidence documentation enter the input layer; module-level readiness, risk and evidence confidence are calculated in the scoring layer; and composite indices, diagnostic profiles and recommendations are produced in the output layer.

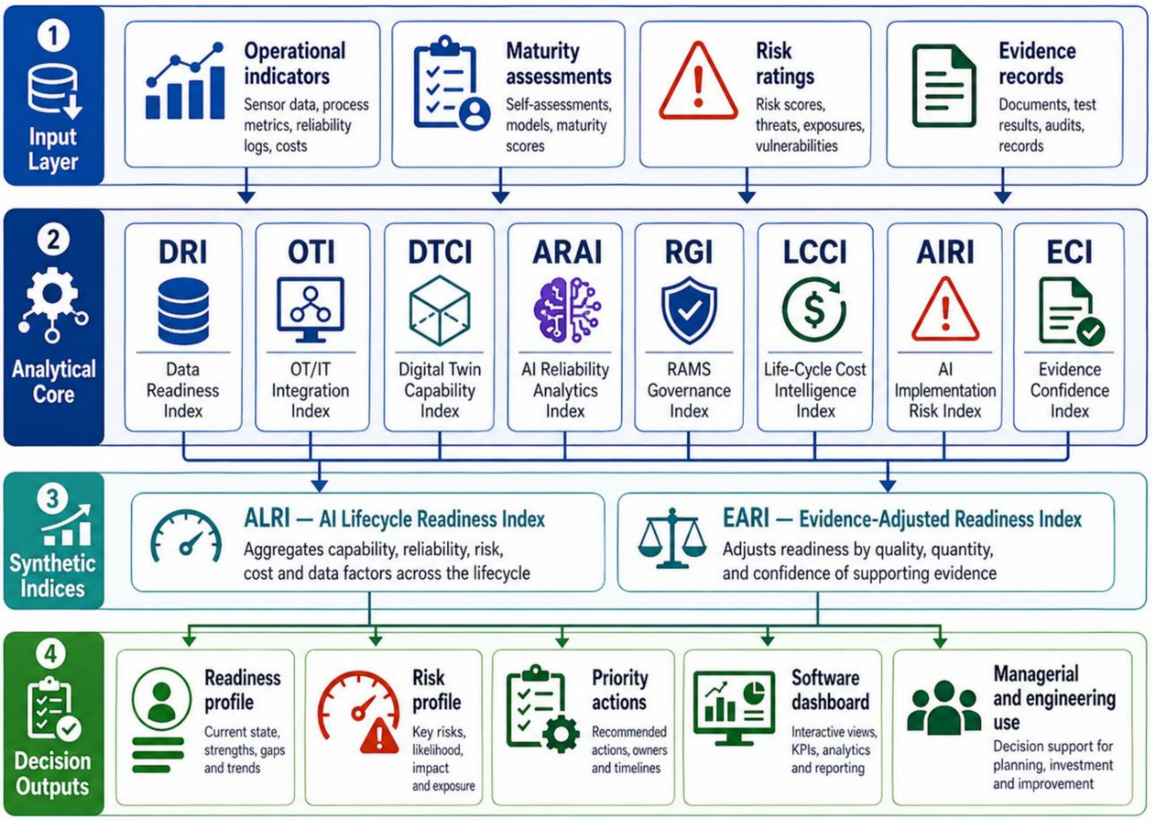

Figure 2. Architecture of the AI-IPLM-RMLCC diagnostic engine.

The structure presented in Fig. 2 is intentionally modular. Industrial organisations differ in asset criticality, data availability, digital-twin maturity and regulatory exposure. A modular design allows the engine to be implemented first as an expert-supported audit tool, then as a spreadsheet or relational database, and finally as a dashboard connected to operational data systems.

The structure of the diagnostic engine is summarised in Table 4. Six modules assess readiness: Data Readiness Index (DRI), OT/IT Integration Index (OTI), Digital Twin Capability Index (DTCI), AI Reliability Analytics Index (ARAI), reliability, availability, maintainability and safety Governance Index (RGI), and Life-Cycle Cost Intelligence Index (LCCI). Two additional modules complement the readiness assessment:

the AI Implementation Risk Index (AIRI) captures implementation exposure, while the Evidence Confidence Index (ECI) evaluates the evidential strength behind the assessment. The two composite measures, AI Lifecycle Readiness Index (ALRI) and Evidence-Adjusted Readiness Index (EARI), integrate these outputs into a final diagnostic profile.

Table 4. Index portfolio of the AI-IPLM-RMLCC diagnostic engine.

Index	Full name	Diagnostic role
DRI	Data Readiness Index	Assesses data completeness, traceability, quality and update frequency
OTI	OT/IT Integration Index	Assesses integration between machines, PLM, MES, ERP, service and quality systems
DTCI	Digital Twin Capability Index	Assesses digital models, data synchronisation, simulation and decision use
ARAI	AI Reliability Analytics Index	Assesses AI use for anomaly detection, diagnosis, RUL and predictive maintenance
RGI	Reliability, Availability, Maintainability and Safety Governance Index	Assesses reliability, availability, maintainability, safety and oversight
LCCI	Life-Cycle Cost Intelligence Index	Assesses links between dependability decisions and downtime, service and warranty costs
AIRI	AI Implementation Risk Index	Assesses implementation exposure across technical, safety, organisational and economic risks
ECI	Evidence Confidence Index	Assesses the evidential strength behind diagnostic scores
ALRI/EARI	Composite readiness indices	Aggregate readiness and adjust it by evidence confidence

Table 5. Case study diagnostic output for a manufacturing enterprise in Wielkopolska, Poland.

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.

Table 3 summarises the index portfolio. The six readiness indices represent the capability base, while AIRI and ECI modify interpretation by risk and evidence. Supplementary Material S1 contains the detailed operational specification: Tables S1–S7 provide indicator catalogues and risk categories, and Tables S8–S10 describe evidence confidence, the software data model and an example output.

4.2. Case study output and diagnostic profile

The diagnostic case study produced an upper-moderate lifecycle readiness profile, but the interpretation changed substantially after evidence adjustment. Table 5 shows strong data readiness, strong reliability, availability, maintainability and safety governance, and very strong life-cycle cost intelligence for conventional maintenance. At the same time, operational-technology/information-technology integration remains moderate, digital-twin capability is still low-to-moderate, and artificial-intelligence reliability analytics are emerging rather than fully operational. The calculated *ALRI* value equals 65.8, while the normalised implementation-risk index remains low at *nAIRI* = 8.5. However, because separate evidence-level coding was not recorded in the diagnostic form, *ECI* was conservatively coded as 0.25. Consequently, *ALRI* is reduced to *EARI* = 16.5. This reduction is important because it shows that a technically promising readiness profile should not be interpreted as verified deployment capability unless the supporting evidence is documented, system-based or auditable.

The same numerical output is repeated in Supplementary Material S1, Table S10, as a software-facing case-study record. Table 5 explains the scientific interpretation of the index values, whereas Table S10 shows the minimum output that can be stored in a spreadsheet, database or dashboard.

Fig. 3 shows the scoring logic behind the case study. Module scores feed into *ALRI*, risk ratings feed into *AIRI*, and evidence ratings feed into *ECI*. *EARI* then reduces readiness when evidence quality is insufficient. Table 6 subsequently translates combinations of readiness and risk into diagnostic profiles.

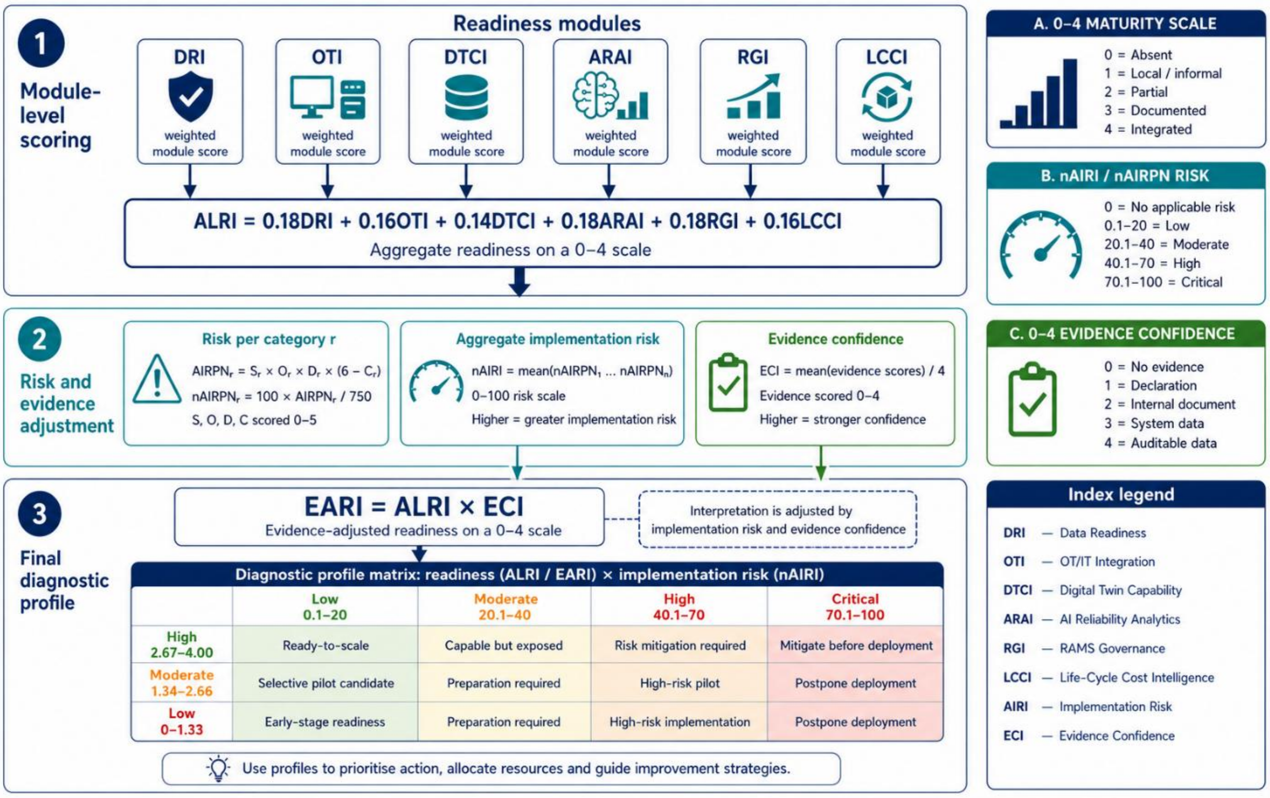

Figure 3. Scoring logic for readiness, implementation risk and evidence adjustment.

Fig. 3 presents the computational logic of the AI-IPLM-RMLCC Diagnostic Engine. The upper layer shows how six readiness modules are aggregated into the AI Lifecycle Readiness Index (*ALRI*). The middle layer introduces two corrective mechanisms: the normalised implementation-risk index (*nAIRI*), derived from risk-category scores, and the Evidence Confidence Index (*ECI*), which captures the strength of documentation supporting the assessment. The lower layer indicates that final diagnostic interpretation emerges from the combined reading of *ALRI, ECI, EARI* and *nAIRI*. In this logic, *EARI* qualifies *ALRI* by reducing the interpretive weight of readiness when the underlying evidence remains weak or insufficiently documented.

From a methodological perspective, the figure positions the diagnostic engine as more than a maturity model. It integrates capability measurement, risk prioritisation and evidence-based correction within a single decision structure. This matters because an organisation may demonstrate relatively high technical readiness while still lacking auditable evidence, or may face implementation risks that make operational scaling premature. In the case study, this logic explains why an upper-moderate raw readiness score does not automatically support a ready-to-scale profile: *ALRI* = 65.8 is reduced to *EARI* = 16.5 because *ECI* remains low, while *nAIRI* = 8.5 indicates low calculated implementation risk but still calls for qualitative review of selected risk categories.

Table 6. Diagnostic profiles.

ALRI level	nAIRI level	Diagnostic profile	Interpretation
High	Low	Ready-to-scale	Strong readiness and controlled implementation risk
High	High	Capable but exposed	Capabilities exist but risk must be reduced
Medium	Low	Selective pilot candidate	Suitable for focused pilots
Medium	High	Preparation required	Readiness is insufficient for high-risk scaling
Low	Low	Early-stage readiness	Foundational development is needed
Low	High	High-risk implementation	Deployment should be postponed

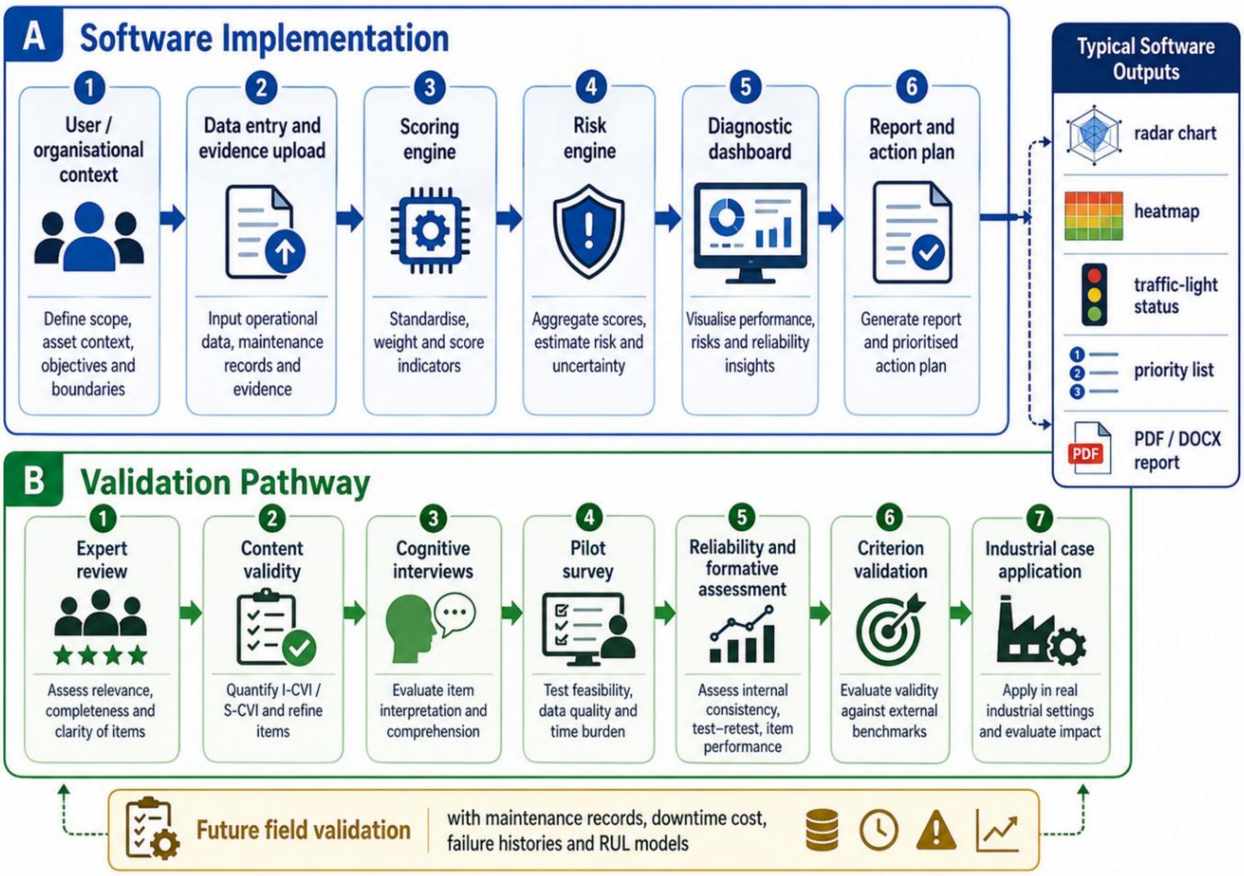

Figure 4. Software implementation and validation pathway of the diagnostic engine.

Table 6 provides the general decision interpretation used by the engine. In the case study, the raw readiness score and the calculated implementation-risk score would suggest pilot potential, because ALRI is upper-moderate and nAIRI is low. However, the low Evidence Confidence Index substantially reduces the evidence-adjusted readiness score. For this reason, the final profile is interpreted as evidence-constrained early-stage readiness rather than as a ready-to-scale or selective-pilot profile. The recommended response is therefore evidence strengthening and controlled preparation: documentation of evidence levels, validation of analytical models, improved OT/IT integration and systematic recording of lifecycle cost effects. The matrix provides a simplified decision interpretation based on readiness and normalised implementation risk; when ECI is low, the final diagnostic profile should be interpreted through EARI rather than through ALRI alone.

4.3. Software implementation pathway

The diagnostic engine can be implemented as a relational database, spreadsheet-based diagnostic tool, web application or dashboard module. From a software perspective, the instrument should operate as a structured decision-support system rather than a static checklist. The input layer contains information on the assessed organisation, industry, product family, asset type, artificial intelligence use case and criticality level. The measurement layer stores readiness indicators, maturity scores, operational metrics and evidence-confidence ratings. The risk layer stores severity, occurrence, detection difficulty and controllability ratings for each implementation-risk category. The output layer generates module scores, composite indices, readiness-risk profiles and prioritised recommendations. Fig. 4 summarises the implementation and validation workflow and separates implementation from validation. Implementation starts with context configuration, data and evidence collection, and calculation of readiness, risk and evidence-adjusted scores. Validation should compare outputs with expert judgement and operational outcomes such as downtime, failure frequency, maintenance cost, MTBF, MTTR and RUL prediction performance. The minimum data model and example output are given in Supplementary Material S1, Tables S9 and S10.

Figure 4 clarifies that the proposed engine should be understood both as a software artefact and as a measurement instrument requiring empirical validation. The software workflow enables data entry, scoring and profile generation, whereas the validation pathway links diagnostic outputs with expert judgement and operational indicators such as downtime, failure frequency, maintenance cost, MTBF, MTTR and RUL prediction performance. This separation strengthens the methodological logic of the article by showing that implementation feasibility and measurement validity are related but distinct evaluation criteria.

5. Conclusion

This article developed the AI-IPLM-RMLCC Diagnostic Engine, a software-ready diagnostic instrument for assessing readiness and implementation risk in AI-enabled industrial product lifecycle management from the perspective of reliability, maintenance and life-cycle cost. The proposed engine integrates six readiness indices, an implementation-risk index, an evidence-confidence index and two composite readiness measures. Its main contribution is the transformation of a dependability-oriented conceptual framework into an operational diagnostic architecture that can be implemented in a spreadsheet, relational database, web application or decision-support dashboard.

The diagnostic case study conducted in a real medium-sized manufacturing enterprise in Wielkopolska, Poland, shows how the instrument converts structured interview data into module-level scores, composite indices and an interpretable diagnostic profile. The case demonstrates that raw lifecycle readiness and calculated implementation risk do not provide a sufficient basis for deployment decisions when the supporting evidence is weak. In the analysed enterprise, raw lifecycle readiness is upper-moderate and calculated implementation risk is low, but low evidence confidence substantially reduces the evidence-adjusted readiness score. The final profile should therefore be interpreted as evidence-constrained early-stage readiness rather than as verified deployment capability.

This finding has an important methodological implication. The proposed instrument does not only measure whether an organisation declares readiness for AI, IoT or digital-twin deployment. It also tests whether such readiness is supported by documented, system-based or auditable evidence. This distinction is particularly relevant in reliability and maintenance contexts, where premature scaling of weakly evidenced digital solutions may lead to false confidence in predictive models, insufficiently controlled maintenance recommendations and underestimated operational risk.

The study is limited by the use of a single diagnostic case study rather than multi-site field validation. Moreover, the default weights used in the composite readiness index require further calibration in different industrial sectors, especially in safety-critical and asset-intensive environments. Future research should validate the instrument across multiple plants, product families and asset classes using maintenance records, sensor data, downtime costs, failure histories, remaining useful life models and expert evaluations. Such validation would allow the AI-IPLM-RMLCC Diagnostic Engine to develop from a theoretically grounded and case-applied diagnostic artefact into a robust tool for evidence-based deployment of AI, IoT and digital twins in reliability-oriented industrial lifecycle management.

References

1. Lee J, Bagheri B, Kao HA. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters* 2015; 3: 18-23. https://doi.org/10.1016/j.mfglet.2014.12.001.
2. Kusiak A. Smart manufacturing. *International Journal of Production Research* 2018; 56(1-2): 508-517. https://doi.org/10.1080/00207543.2017.1351644.
3. Xu LD, He W, Li S. Internet of Things in industries: A survey. *IEEE Transactions on Industrial Informatics* 2014; 10(4): 2233-2243. https://doi.org/10.1109/TII.2014.2300753.
4. Yang H, Kumara S, Bukkapatnam STS, Tsung F. The Internet of Things for smart manufacturing: A review. *IISE Transactions* 2019; 51(11): 1190-1216. https://doi.org/10.1080/24725854.2018.1555383.
5. Barrios P, Danjou C, Eynard B. Literature review and methodological framework for integration of IoT and PLM in manufacturing industry. *Computers in Industry* 2022; 140: 103688. https://doi.org/10.1016/j.compind.2022.103688.
6. Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine* 2018; 51(11): 1016-1022. https://doi.org/10.1016/j.ifacol.2018.08.474.
7. Tao F, Zhang H, Liu A, Nee AYC. Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics* 2019; 15(4): 2405-2415. https://doi.org/10.1109/TII.2018.2873186.
8. Fuller A, Fan Z, Day C, Barlow C. Digital twin: Enabling technologies, challenges and open research. *IEEE Access* 2020; 8: 108952-108971. https://doi.org/10.1109/ACCESS.2020.2998358.
9. Carvalho TP, Soares FAAMN, Vita R, Francisco RP, Basto JP, Alcalá SGS. A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering* 2019; 137: 106024. https://doi.org/10.1016/j.cie.2019.106024.
10. Hu Y, Miao X, Si Y, Pan E, Zio E. Prognostics and health management: A review from the perspectives of design, development and decision. *Reliability Engineering & System Safety* 2022; 217: 108063. https://doi.org/10.1016/j.ress.2021.108063.
11. Compare M, Antonello F, Pinciroli L, Zio E. A general model for life-cycle cost analysis of condition-based maintenance enabled by PHM capabilities. *Reliability Engineering & System Safety* 2022; 224: 108499. https://doi.org/10.1016/j.ress.2022.108499.
12. Wang Y, Chung SH. Artificial intelligence in safety-critical systems: A systematic review. *Industrial Management & Data Systems* 2022; 122(2): 442-470. https://doi.org/10.1108/IMDS-07-2021-0419.
13. Harkat H, Mustapha A, Maamar Z. Cyber-physical systems security: A systematic review. *Computers & Industrial Engineering* 2024; 189: 109891. https://doi.org/10.1016/j.cie.2024.109891.
14. Peres RS, Jia X, Lee J, Sun K, Colombo AW, Barata J. Industrial artificial intelligence in Industry 4.0-Systematic review, challenges and outlook. *IEEE Access* 2020; 8: 220121-220139. https://doi.org/10.1109/ACCESS.2020.3042874.
15. Puthanveettil Madathil A, Luo X, Liu Q, Walker C, Madarkar R, Qin Y. A review of explainable artificial intelligence in smart manufacturing. *International Journal of Production Research* 2025; 63(23): 8654-8697. https://doi.org/10.1080/00207543.2025.2513574.
16. Jöhnk J, Weißert M, Wyrtki K. Ready or not, AI comes-An interview study of organizational AI readiness factors. *Business & Information Systems Engineering* 2021; 63(1): 5-20. https://doi.org/10.1007/s12599-020-00676-7.
17. Uren V, Edwards JS. Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management* 2023; 68: 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588.
18. Frank AG, Mendes GHS, Ayala NF, Ghezzi A. Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technological Forecasting and Social Change* 2019; 141: 341-351. https://doi.org/10.1016/j.techfore.2019.01.014.
19. Paiola M, Gebauer H. Internet of Things technologies, digital servitization and business model innovation in BtoB manufacturing firms. *Industrial Marketing Management* 2020; 89: 245-264. https://doi.org/10.1016/j.indmarman.2020.03.009.
20. Schumacher A, Erol S, Sihn W. A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia CIRP* 2016; 52: 161-166. https://doi.org/10.1016/j.procir.2016.07.040.
21. Mittal S, Khan MA, Romero D, Wuest T. A critical review of smart manufacturing and Industry 4.0 maturity models: Implications for small and medium-sized enterprises. *Journal of Manufacturing Systems* 2018; 49: 194-214. https://doi.org/10.1016/j.jmsy.2018.10.005.
22. Semeraro C, Lezoche M, Panetto H, Dassisti M. Digital twin paradigm: A systematic literature review. *Computers in Industry* 2021; 130: 103469. https://doi.org/10.1016/j.compind.2021.103469.

23. Lehner C, Wurst J, Burkhardt J, Glaessgen E, Lachmayer R. Digital twin and digital thread within the product lifecycle management. *Procedia Computer Science* 2024; 232: 2165-2174. https://doi.org/10.1016/j.procs.2024.02.104.
24. van Dinter R, Tekinerdogan B, Catal C. Predictive maintenance using digital twins: A systematic literature review. *Information and Software Technology* 2022; 151: 107008. https://doi.org/10.1016/j.infsof.2022.107008.
25. Errandonea I, Beltrán S, Arrizabalaga S. Digital twin for maintenance: A literature review. *Computers in Industry* 2020; 123: 103316. https://doi.org/10.1016/j.compind.2020.103316.
26. Tercan H, Meisen T. Machine learning and deep learning based predictive quality in manufacturing: A systematic review. *Journal of Intelligent Manufacturing* 2022; 33(7): 1879-1905. https://doi.org/10.1007/s10845-022-01963-8.
27. Zio E. Prognostics and health management (PHM): Where are we and where do we need to go in theory and practice. *Reliability Engineering & System Safety* 2022; 218: 108119. https://doi.org/10.1016/j.ress.2021.108119.
28. Ucar A, Karakose M, Kırımça N. Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Applied Sciences* 2024; 14(2): 898. https://doi.org/10.3390/app14020898.
29. Jardine AKS, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing* 2006; 20(7): 1483-1510. https://doi.org/10.1016/j.ymssp.2005.09.012.
30. Lei Y, Li N, Guo L, Li N, Yan T, Lin J. Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing* 2018; 104: 799-834. https://doi.org/10.1016/j.ymssp.2017.11.016.
31. Hevner AR, March ST, Park J, Ram S. Design science in information systems research. *MIS Quarterly* 2004; 28(1): 75-105. https://doi.org/10.2307/25148625.
32. Gregor S, Hevner AR. Positioning and presenting design science research for maximum impact. *MIS Quarterly* 2013; 37(2): 337-355. https://doi.org/10.25300/MISQ/2013/37.2.01.
33. Peffers K, Tuunanen T, Rothenberger MA, Chatterjee S. A design science research methodology for information systems research. *Journal of Management Information Systems* 2007; 24(3): 45-77. https://doi.org/10.2753/MIS0742-1222240302.
34. Venable J, Pries-Heje J, Baskerville R. FEDS: A framework for evaluation in design science research. *European Journal of Information Systems* 2016; 25(1): 77-89. https://doi.org/10.1057/ejis.2014.36.
35. Boateng GO, Neilands TB, Frongillo EA, Melgar-Quiñonez HR, Young SL. Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health* 2018; 6: 149. https://doi.org/10.3389/fpubh.2018.00149.
36. Diamantopoulos A, Winklhofer HM. Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research* 2001; 38(2): 269-277. https://doi.org/10.1509/jmkr.38.2.269.18845.
37. MacKenzie SB, Podsakoff PM, Podsakoff NP. Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly* 2011; 35(2): 293-334. https://doi.org/10.2307/23044045.
38. Liu HC, Liu L, Liu N. Risk evaluation approaches in failure mode and effects analysis: A literature review. *Expert Systems with Applications* 2013; 40(2): 828-838. https://doi.org/10.1016/j.eswa.2012.08.010.
39. Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology* 2020; 29: 36-52. https://doi.org/10.1016/j.cirpj.2020.02.002.
40. Madni AM, Madni CC, Lucero SD. Leveraging digital twin technology in model-based systems engineering. *Systems* 2019; 7(1): 7. https://doi.org/10.3390/systems7010007.
41. de Jonge B, Scarf PA. A review on maintenance optimization. *European Journal of Operational Research* 2020; 285(3): 805-824. https://doi.org/10.1016/j.ejor.2019.09.047.
42. Si XS, Wang W, Hu CH, Zhou DH. Remaining useful life estimation: A review on the statistical data driven approaches. *European Journal of Operational Research* 2011; 213(1): 1-14. https://doi.org/10.1016/j.ejor.2010.11.018.
43. Ghobakhloo M, Iranmanesh M, Vilkas M, Grybauskas A, Amran A. Drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs: A systematic review and transformation roadmap. *Journal of Manufacturing Technology Management* 2022; 33(6): 1029-1058. https://doi.org/10.1108/JMTM-12-2021-0505.
44. Lynn MR. Determination and quantification of content validity. *Nursing Research* 1986; 35(6): 382-385. https://doi.org/10.1097/00006199-198611000-00017.

45. Polit DF, Beck CT. The content validity index: Are you sure you know what is being reported? Critique and recommendations. *Research in Nursing & Health* 2006; 29(5): 489-497. https://doi.org/10.1002/nur.20147.