Proceedings of the Design Society, Volume 6: DESIGN 2026
https://doi.org/10.1017/pds.2026.10605

Reframing AI readiness: a multi-dimensional use case-centered AI readiness framework

Benedikt Müller✉, Daniel Roth and Matthias Kreimeyer

University of Stuttgart, Germany

✉ benedikt.mueller@iktd.uni-stuttgart.de

ABSTRACT: A technology-oriented approach to AI predominates in research and practice, yet despite a high level of technological readiness, projects often fail due to poor domain-specific problem framing and data quality in early-stage AI system development. This contribution conducts an analysis of existing AI-related readiness models, to identify gaps in addressing these factors. The use case-centered AI readiness level framework is proposed on the basis of these findings – a unified, evidence-based model that links problem, data, and technology readiness across planning and implementation stages.

KEYWORDS: artificial intelligence (AI), technology development, socio-technical systems, technology readiness, interdisciplinary AI system development

1. Introduction

Artificial intelligence (AI) is increasingly recognized as a key enabler for transforming product development (PD) by enhancing efficiency, creativity, and decision quality throughout the innovation process (Cooper, 2024). The growing accessibility of AI models and rapid technological progress have made AI development more attainable, even for small and medium-sized enterprises. Despite this advantageous environment, present adoptions within the industry frequently prove ineffective and fail to generate sustainable value. These failures are attributed not to the immaturity of AI technologies themselves, but rather to insufficient process integration, inadequate contextualization, and poor data quality – aspects that ought to be considered on a case-by-case basis in the early stages of AI system development. Successful AI initiatives are consistently characterized by early interdisciplinary collaboration and a shared understanding of objectives and expected outcomes (Lee et al., 2023; Kim et al., 2024). Central to this are well-defined AI use cases, which serve as the conceptual bridge between domain-specific problems and technological implementation (Kirschbaum et al., 2022). Well-formulated use cases – characterized by clear problem definitions, realistic data requirements, and measurable outcomes – help organizations anticipate obstacles such as poor data quality or integration challenges before they impede model development and validation (Lee et al., 2023; Romeo & Lacko, 2025). Their effective formulation requires structured collaboration between domain experts, who contextualize the problem and data environment, and AI experts, who translate these requirements into technically viable solutions; absent such alignment, projects risk being technology-driven rather than need-driven, increasing the likelihood of post-deployment deficiencies. This phenomenon is not uncommon in the context of product development. Companies promptly formulate preliminary concepts for AI applications (e.g., "using AI to generate requirements lists"), yet the structured elaboration and specification of company-specific requirements, data existence, and quality is sub-sequently disregarded in favor of rapid progression to AI developments. To coordinate such complex, interdisciplinary efforts, organizations rely on readiness models to assess progress transparently. The well-established Technology Readiness Level (TRL) framework evaluates technological maturity (Lavin et al., 2022), yet its narrow focus is increasingly questioned in the context of AI system development. Many projects reach high TRL scores but still fail due to poor data quality or vague problem definition – meaning the

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

technology may be ready, but the use case is not. This underscores the need for a use case-centered readiness logic that extends its focus beyond technology to include data and problem perspectives.

1.1. Objectives and research question

Based on a literature review, this study examines whether existing readiness frameworks adequately address the interdisciplinary and multidimensional nature of AI use cases in AI system development. It considers the continuum from AI idea (abstract opportunity) to AI use case (contextualized plan) to AI system/application (technical realization). Understanding readiness along this path is crucial for transparent communication and realistic assessment between domain and AI experts. The aim is to analyze and integrate existing frameworks in order to derive an adapted conceptual readiness logic suited to early-stage AI projects, reflecting both technological and domain-specific challenges. The resulting framework is designed for AI customers and developers in engineering-driven organizations providing a structured basis for assessing and steering AI development projects, enabling informed decision-making across technological feasibility and application domain-specific requirements. Accordingly, the guiding research questions are: ***RQ1: Which dimensions of readiness are relevant for evaluating AI use cases in early-stage system development? RQ2: How can the identified readiness dimensions be operationalized into a framework for assessing AI use cases in early-stage development?***
The remainder of the contribution is structured as follows: Section 2 reviews conceptual foundations and existing readiness approaches in AI system development. Section 3 introduces the adapted conceptual AI use case readiness framework, combining planning and implementation stages into a unified twelve-level structure. Section 4 discusses the theoretical and practical implications of the framework, emphasizing its value for interdisciplinary collaboration and lifecycle alignment. Section 5 concludes with key contributions, limitations, and directions for future research.

2. Related work

This section synthesizes extant research on readiness approaches and AI development lifecycles to derive criteria that must be satisfied by a viable AI-specific readiness framework with a focus extending beyond technology. The text commences with the clarification of conceptual foundations (Section 2.1) and project characteristics (Section 2.2). It then synthesizes requirements specific to AI use cases (Section 2.3) and concludes with a review of existing AI-related readiness approaches (Section 2.4).

2.1. Conceptual foundations

Readiness is critical when it comes assessing organizational and technological progress in AI system development. **Readiness** describes an organization's preparedness to implement AI-related change and its ability to align technological opportunities with strategic objectives, data assets, and human capabilities (Jöhnk et al., 2021). **Maturity**, in contrast, reflects the degree to which technologies and processes are developed and optimized for effectively deploying and improving AI systems (Reichl & Gruenbichler, 2023). Together, they provide a systematic basis for evaluating capabilities, identifying gaps, and guiding improvement (Becker et al., 2009). Readiness models have been applied as diagnostic and benchmarking tools in innovation and R&D management to support structured assessment and transparent communication (Lavin et al., 2022; Eljasik-Swoboda et al., 2019). In AI system development, these frameworks have evolved beyond purely technological perspectives, emphasizing multi-dimensional readiness by integrating technological, data, organizational, and human factors (Eljasik-Swoboda et al., 2019; Naheed et al., 2025). Successful development depends equally on problem-, data-, and technology-oriented dimensions. Readiness frameworks can provide a common foundation for interdisciplinary collaboration and shared understanding among experts, engineers, and decision-makers. In this contribution, readiness is examined at the level of AI use cases, focusing on project-specific individual applications throughout their conceptual and technical evolution rather than on enterprise-wide adoption maturity. Accordingly, the contribution centers on assessing the content-related and methodological progress of **AI use cases** as the key interface between domain expertise and technical realization, rather than on organizational enablers or strategic preconditions at the enterprise level. Table 1 provides an overview of related terminologies, although the terminology surrounding use cases remains inconsistent: AI is variously seen as a field of study, a capability, or a system (Bawack et al., 2021). Generally, a use case describes how a product or system is applied to achieve a goal (Cambridge Dictionary, 2025). When adapted to AI, it can be understood as a description of how an AI system or AI

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

application operates within a specific context to achieve defined objectives through human-machine interaction. Related definitions (Gerschütz et al., 2023; Kirschbaum et al., 2022) emphasize that use cases integrate problem, data, and technical dimensions but vary in depth and specificity depending on context. In this contribution, the terms AI idea, AI use case, and AI application/system are treated as a continuum: Ideas represent abstract opportunities, use cases are contextualized and domain-specific descriptions, and applications correspond to implemented systems. The AI readiness framework proposed mirrors this logic by assessing progress along this continuum.

Table 1. Comparison of different terminologies

Term	Definition	Source
AI	"<discipline> research and development of mechanisms and applications of AI systems"	[1]
Idea	"a suggestion or plan for doing something"; "an understanding, thought, or picture in your mind"; "a purpose or reason for doing something"	[2]
Use case	"a description of the way someone could use a particular product or system in an effective way, especially a piece of software"	[2]
Concept	"an idea for a new product or a way to sell a product"; "a principle or idea"	[2]
AI application	"Software application with AI functional characteristics and operates in context with its stakeholders' interrelated activities to deliver an intended result"	[3]
AI system	"Engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives"	[1]
Literature: [1] ISO/IEC 22989:2022; [2] Cambridge Dictionary (2025); [3] ISO/IEC 5339:2024		

The existing literature identifies recurring descriptive elements (see Table 2) that pertain to the following: domain context, data properties, system architecture, and organizational conditions. As Kirschbaum et al. (2022) highlight, AI use cases vary in their specificity. General AI use cases describe potential applications at a conceptual level, whereas domain-specific AI use cases provide detailed, context-rich information about technologies, data, and expected results within a specific application domain (company-specific content). The specificity depends on multiple factors, including the AI literacy of involved stakeholders, the domain knowledge of AI experts, and the complexity or sensitivity of the data (Kim et al., 2024). Achieving mutual understanding across these perspectives is crucial for ensuring transparent communication and coherent interdisciplinary collaboration.

Table 2. AI use case-related content

Clustered category	Example contents
Status quo of application domain and context	e.g. Description of the application domain/use case context [1; 2; 4; 5; 7]; Roles and stakeholders [2; 5; 7]; Goals, metrics, and success criteria [6; 7]; Challenges & risks [7]; Problem and need for AI [3; 7]
Status quo of relevant data and data processing	e.g. Dataset & database [1; 4; 5; 6]; Data format & data properties [4; 6]; Data curation & preparation [8]; Data policies & regulation [6]
Technological objective description and AI system architecture	e.g. AI system & functional requirements [5; 8]; AI task & function [7; 8]; Design decisions [1; 4; 8]; User interaction & user story [3; 8]; Integration in processes & IT infrastructures [3; 8]
Organizational and project-related conditions	e.g. Resources, expertise, and budget [3; 6; 7]; Sustainability & long-term impact [8]; Implementation effort [3]; Economic benefit (value) [3]
Literature: [1]: Moosbrugger & Ntoa (2022); [2]: Hupont et al. (2024); [3]: Brakemeier et al. (2023); [4]: Königstorfer (2024); [5]: Müller et al. (2024); [6]: Kim et al. (2024); [7]: Müller et al. (2025b); [8]: Müller et al. (2025c)	

Königstorfer and Thalmann (2022) further demonstrate that documentation practices vary by organizational readiness and risk perception. Across domains, a lack of standards and testing procedures remains a major barrier to adoption. Nonetheless, comprehensive documentation is recognized as a

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

central enabler for transparency, traceability, and ethical accountability in AI projects, an aspect equally relevant for AI applications in product development. **Conceptual distinctions**: A reviewed body of literature reveals persistent ambiguities regarding readiness in AI system development, particularly in defining evidence of progress, relevant artifacts, and criteria for achievement. Existing approaches use different dimensions and assessment criteria, underscoring the need for a standardized, reliable conceptual framework. Moreover, AI use cases vary in specificity - from general concepts to domain-specific implementations - depending on interdisciplinary team competencies and contextual knowledge maturity, resulting in different levels of readiness across projects and domains.

2.2. AI system development project and process model characteristics

AI system development projects differ fundamentally from conventional IT or software projects due to their high complexity, data dependency, and continuous experimentation (Müller et al., 2025a; Martins, 2023). The development process is inherently iterative and feedback-driven, requiring ongoing model refinement, validation, and adaptation as new data and insights emerge (ISO/IEC 22989:2022). Uncertainty is inherent, as outcomes can vary significantly between experimental and production environments (Martins, 2023). Effective execution depends on managing dynamic interactions between humans, data, and machines within an evolving learning system (ISO/IEC 22989:2022). Moreover, AI projects are inherently interdisciplinary, involving AI specialists, data engineers, and domain experts, supported by management, IT, and regulatory stakeholders (ISO/IEC 22989:2022; Müller et al., 2024). Domain experts provide contextual framing, goal definition, and relevance assessment, while AI experts focus on model design, data preparation, and validation (Müller et al., 2024; Luley et al., 2023). Early and structured stakeholder involvement is therefore critical to align technological feasibility with domain needs and to ensure meaningful solutions (Müller et al., 2025a), underscoring the necessity of cross-functional communication and shared conceptual frameworks. Several lifecycle models structure AI system development. ISO/IEC 22989 (2022) outlines a comprehensive AI system life cycle spanning data preparation, model training, validation, deployment, and operation. Complementary deep learning and end-to-end frameworks emphasize technical iteration and DevOps-based processes (Müller et al., 2024), yet often underrepresent preceding conceptual and organizational phases. Addressing this gap, Brakemeier et al. (2023) highlight industrial early phases -preparation, ideation, assessment, and prioritization - while Müller et al. (2025a) integrate conceptual and technical perspectives into a holistic lifecycle model centered on the AI use case as the interface between exploration and realization. Across this lifecycle, stakeholder information and transparency requirements evolve: pre-modeling stresses representativeness and contextual clarity, modeling emphasizes accuracy and robustness, and post-modeling requires interpretability, usability, and performance evaluation (IEEE Std 2894-2024). These shifting demands reinforce the need for structured mechanisms to coordinate activities and communicate progress. **Project characteristics**: AI system development follows an end-to-end continuum from initial idea to defined use case and implemented application, structured across the phases of pre-modeling, modeling, and post-modeling. Each phase entails distinct objectives and information requirements, from conceptual framing and data preparation to validation and operational learning. The process is inherently iterative, characterized by feedback loops and stage transitions as models evolve. Typically, domain experts lead ideation and problem framing, while AI experts drive technical realization, focusing on efficiency and scalability. Depending on implementation strategy - enterprise-ready, self-developed, or hybrid - progress across readiness levels may be nonlinear. These characteristics necessitate frameworks that accommodate iteration, interdisciplinary roles, and stage-specific readiness assessment.

2.3. Requirements for readiness approaches in the context of AI use cases

Building on the conceptual distinctions (Section 2.1) and the specific characteristics of AI system development projects (Section 2.2), this section derives requirements for readiness approaches tailored to AI use cases. AI use cases constitute the central unit of analysis, as they connect abstract AI ideas with concrete system implementations. They vary in their specificity – from general (conceptual, transferable) to domain-specific (context-rich, operational) – and in their lifecycle phases (pre-modeling, modeling, post-modeling). Their description integrates problem, data, technology, and organizational facets (cf. Table 2) to ensure transparent and verifiable progression across stages (cf. Naheed et al., 2025). Challenges typically arise from unclear problem framing, limited data/information accessibility due to the lack of interdisciplinary collaboration in the early stages, and insufficient coordination between domain and AI experts. Accordingly, readiness approaches should help structure and question the interdisciplinary collaboration, ensuring that each stage of development

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

builds on transparent and verifiable foundations. They are diagnostic and guiding instruments that assess the current state and indicate improvement paths (Reichl & Gruenbichler, 2023). From a methodological standpoint, a viable readiness approach for AI use cases should therefore meet the following core criteria:

1. First, it must be use case-centric and stage-aware, guiding the transition from an initial AI idea to a domain-specific use case and integrated AI application – all while aligning assessment criteria with the respective lifecycle phases of pre-modeling, modeling, and post-modeling.
2. Second, it must be multidimensional, capturing application domain contexts, related data aspects, and technology implications (cf. Müller et al., 2025a).
3. Third, it should remain role-explicit and literacy-sensitive, clarifying the contributions of domain experts, data specialists, and AI engineers (cf. Kim et al., 2024).
4. Fourth, it must be evidence-based, linking each level to tangible artifacts such as data profiles, method cards (cf. Müller et al., 2025c), or validation reports that allow traceability of decisions.
5. Fifth, the framework should be actionable, providing clear criteria for progress assessment.
6. Finally, it needs to be comparable and adaptable, enabling organizations to benchmark projects while remaining flexible to specific domain conditions.

Design implication: The derived core criteria imply a two-part structure: planning levels ensure complete (domain-specific) specification and feasibility before any technical implementation, while implementation levels follow TRL logic. This implication guides our model choice and evaluation in Section 2.4, also providing direct motivation for the adapted conceptual framework in Section 3.

2.4. AI-related readiness approaches

Readiness approaches assess the development stage and implementation capability of technologies or project states. In the context of AI, several frameworks adapt or extend established concepts such as Technology Readiness Levels (TRLs) to address AI-specific characteristics. Figure 1 summarizes the key frameworks identified in the literature to establish a conceptual understanding and evaluates their applicability to AI system development projects against the core criteria defined in Section 2.3.

The TRL framework developed by NASA measures the maturity of technologies across nine levels, ranging from the identification of basic principles to operational use (cf. Meystel et al., 2003). In the context of AI, TRL has been applied to classify and benchmark the maturity of AI technologies (Martínez-Plumed et al., 2020). Its strengths lie in its standardized evidence logic and comparability across domains. However, it remains technology-centric, with limited consideration of data quality or application domain context in individual domain-specific AI use cases.

The TRL for machine learning systems (MLTRL) by Lavin et al. (2022) extends the TRL concept to ML pipelines with levels ranging from 0 (first principles) to 9 (deployment). It integrates aspects such as data readiness, validation, robustness, and continuous monitoring through gated reviews and artifact documentation (e.g., MLTRL cards). MLTRL strengthens use case centricity, multidimensionality (technology and data, but not problem orientations), and evidence linkage, but addresses organizational and human factors only indirectly. The approach is particularly relevant for managing the technical maturation and deployment readiness of ML-based AI use cases and only transferable to other AI approaches (e.g., LLMs) to a limited extent, which restricts its industrial applicability.

Eljasik-Swoboda et al. (2019) propose a multidimensional AI and data readiness model that evaluates an organization's ability to develop and deploy AI innovations. The framework introduces six specific dimensions – specification readiness (AI), algorithmic readiness (AI), data existence readiness, data legal readiness, data format and quality readiness, and expert knowledge readiness (data) – each with defined maturity levels. It supports gap analysis and action planning, fulfilling multidimensionality but lacking a consistent cross-level scale for comparability, actionability, and artifact traceability.

The three approaches differ fundamentally in scope and application. While the general TRL focuses on technology maturity, MLTRL extends this to the ML pipeline and operational environment. In contrast, AI and data readiness refers to an organization's capability to effectively implement and derive value from AI. Across these approaches, the evolution of AI-related readiness concepts reflects a gradual shift from technology maturity toward socio-technical and data-driven readiness. However, no single framework fully captures the iterative, interdisciplinary, lifecycle-, and use case-oriented nature of AI system development. A consolidated, stage-sensitive framework - combining evidence logic of MLTRL with multidimensional orientation of AI and data readiness - appears essential for supporting consistent assessment along the AI idea-use case-application continuum.

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

	Technology-centered readiness without use case logic	*Stage-aware for machine learning (ML) – but model-focused*	*Multi-dimensional checklist without project guidance*	*Use case-centered, multidimensional, and project-accompanying AI maturity*
	TRL (NASA-derived, applied to AI) [1], [2]	**MLTRL** (TRL4ML) [3]	**AI & Data Readiness** [4]	**Use case-centered AI Readiness** [this contribution]
1) Use case-centric & stage-aware	**(0)** Stage-aware for technology, but not use case-centric across idea–use case–application continuum.	**(0)** Stage-aware for ML (transfer to other AI approaches limited), not use case-centric; non-linear paths acknowledged.	**(0)** Has "specification readiness" and links across phases, but not a full pre/model/post lifecycle (LC).	**(+)** Use case-centric stage awareness, independent of AI approaches (e.g., ML, LLM, AI agents); full pre/model/post LC.
2) Multi-dimensional (problem/data/techn.)	**(0)** Technology-centric; data/problem/organization largely out of scope, no use case-centric specifications.	**(0)** Integrates data readiness in technical pipeline. Problem-orientation only in MLTRL 1, not use case-centric.	**(+)** Six dimensions incl. data existence & quality, expert knowledge, algorithmic (techn.)/specification (problem).	**(+)** Consideration of dim. acc. to [4], emphasis of relevant use case-related considerations along the continuum.
3) Role-explicit & literacy-sensitive	**(-)** No explicit role/literacy guidance; centered on the working object, technology.	**(0)** References evolving working groups, but roles/literacy not formalized.	**(0)** Captures "expert knowledge readiness", yet roles/literacy not systematically mapped.	**(0)** Lead roles (domain vs. AI) and exemplary content requirements along continuum.
4) Evidence-based (artifacts)	**(0)** Leveled techn. evidence logic incl. e.g. PoC, prototypes, operational demos. No use case-related artifacts.	**(+)** Gated reviews, MLTRL Cards, ethics checklists, documented deliverables.	**(0)** Levels and a navigator tool exist, but artifact linkage less formal than MLTRL.	**(+)** Assignment of typical artifacts and content evidence per level.
5) Actionable (progress criteria)	**(0)** Supports step-by-step advancement, but mainly technological maturation.	**(+)** Clear deliverables, reviews, and methods for moving levels.	**(0)** Useful for gap analysis/work packages, no sequence/ connections; used in projects.	**(+)** Consideration of the full idea–use case–application continuum.
6) Comparable & adaptable	**(+)** Standardized nomenclature enabling cross-technology comparison; used to benchmark AI maturity, but no use case focus.	**(+)** Promotes shared nomenclature and reuse across domains, but primary focus is ML systems (less organizational tailoring).	**(0)** Heterogeneous scales and the need for normalization impair comparability; nevertheless adaptable.	**(+)** Supports comparability between domain-specific AI use cases; artifacts adaptable to companies/application domain requirements.

Legend: **(+)** = fulfilled; **(0)** = partially fulfilled; **(-)** = not covered

References: [1] Meystel et al. (2003); [2] Martínez-Plumed et al. (2020); [3] Lavin et al. (2022); [4] Eljasik-Swoboda et al. (2019)

Figure 1. Comparison and assessment of AI-related readiness approaches

Another use of TRL is demonstrated by Uren and Edwards (2023), who empirically reposition TRL from a technology lens to the project as unit of analysis. They propose an adoption model that complements People–Process–Technology with Data in order to capture socio-technical readiness as well as technological progress. Utilizing TRL as a reference framework in interviews, they identify stage-specific success factors: in TRL 2–4, exploratory prototyping with realistic data and early end-user involvement supports effective problem framing; in TRL 5–7, bridging the lab-to-operations gap requires access to operational data, governance structures, and expert judgment; and at TRL 9, integration with the organization's MIS and alignment between developers and business functions become decisive. The study's practical implication is to build a bridge - that is, to form cross-functional teams and develop data/technology skills - to sustain operational AI. Theoretically, it argues that people, process, and data readiness are co-requirements with technology readiness for successful adoption.

2.5. Interim summary

The literature underscores that technology-centric readiness alone is an insufficient predictor of AI project success. Effective assessment must consider the entire AI use case, combining multidimensional readiness. It must also treat the AI idea–use case–application continuum as a continuous, evidence-based path. Existing models each cover parts of this path; none spans it end-to-end with actionable checkpoints. This provides motivation for a unified framework that (i) finishes domain-specific planning before implementation and (ii) considers technological readiness as one part of the holistic AI use case.

3. Conceptual development of an adapted AI readiness framework

The development of the proposed use case-centered AI readiness framework follows a conceptual design approach aimed at integrating and extending existing readiness approaches for the specific context of AI system development. It follows the structure of TRL adapted to AI (cf. Martínez-Plumed et al., 2020), extends the multidimensional perspective of the AI and data readiness (Eljasik-Swoboda et al., 2019), and integrates methodological features of the MLTRL (Lavin et al., 2022), such as evidence-based documentation. The focus is on the progression from nascent ideas, through the formulation of general use cases and subsequent domain-specific specifications, to the implementation of applications. While established approaches such as TRL, MLTRL, and AI & Data Readiness (cf. Section 2.4) primarily assess technological maturity, pipeline robustness, or data prerequisites, they remain largely technology-

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

centric and underrepresent early problem framing and domain-oriented planning phases that precede technical implementation. In contrast, the present framework shifts the evaluative focus from technology readiness to use case maturity (cf. Figure 1). Readiness is conceptualized as the progressive coherence of problem, data, and system within a specific application context. Rather than asking whether a technology is deployable, the framework examines whether an AI use case is contextually grounded, systematically specified, and operationally implementable. The proposed framework is guided by three conceptual design principles: **Continuity**, ensuring a logical transition from idea exploration to continuous operation across the full AI life cycle; **interdisciplinarity**, providing a shared structure that enables collaboration between domain and AI experts (typical outputs guide domain experts to assign progress), and **transparency**, linking every readiness level to tangible artifacts and typical outputs that document progress and decision rationale. An overview of the eleven levels, including corresponding readiness dimensions, typical outputs, and methodological support, is provided in Figure 2.



Figure 2. Proposed use case-centered AI readiness level (UCAIRL)

The framework comprises eleven levels (UCAIRL 0–10) that form a continuous pathway from the conceptual AI idea to the operational AI application. It is structured along the AI idea-use case-application continuum and merges planning and implementation phases into a traceable approach:

- **UCAIRL 0–1 (AI idea)**: Early exploratory stages where theoretical foundations, initial ideas of AI utilization, and problem hypotheses are formulated and linked to data existence readiness.
- **UCAIRL 2–3 (General AI use case)**: Transition from abstract ideas to general use case formulation. At these levels, the problem, data context, and technological concept are consolidated, and algorithmic feasibility is validated under controlled laboratory conditions.
- **UCAIRL 4–5 (Domain-specific AI use case)**: Refinement toward domain-specific application scenarios. These stages cover proof-of-concept validation, legal and data quality readiness, and demonstration of AI capabilities in realistic environments. The result is a context-specific AI solution with verified robustness and traceability under company-specific requirements.
- **UCAIRL 6–10 (Domain-specific AI application)**: Implementation-related levels that reflect progression consistent with MLTRL, from prototype adaptation (UCAIRL 6) through integration and qualification (UCAIRL 7–8) to deployment and operation (UCAIRL 9–10). These levels address scaling, monitoring, and continual learning within the product development application environment.

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

To illustrate the logic of the UCAIRL, the framework is applied to the ReqGPT use case based on Schiller et al. (2025), a fine-tuned large language model designed to generate structured requirements lists from historical product development documents. The vignette demonstrates how an initially observed efficiency gap in early-phase requirements engineering (UCAIRL 0) evolves into a formalized AI concept with defined objectives and data readiness considerations (UCAIRL 1). Experimental validation under controlled conditions confirms technical feasibility and establishes a reproducible ML pipeline (UCAIRL 2–3), thereby positioning the current state of development at UCAIRL 3, corresponding to a validated general AI use case. Crucially, the example highlights the stage-aware and iterative nature of AI system maturation: deficiencies observed during pilot deployment in a domain-specific environment (e.g., missing regulatory constraints or terminology inconsistencies) would trigger structured switchbacks to earlier stages for targeted refinement. This non-linear progression reflects established system engineering principles in MLTRL (cf. Lavin et al., 2022). The vignette is intended as a conceptual illustration of maturity transitions rather than as empirical evidence of industrial deployment beyond laboratory validation.

The proposed framework thus offers a stage-sensitive, interdisciplinary, and evidence-based navigation tool that supports transparent collaboration between domain and AI experts. It enables consistent assessment across the full life cycle – from ideation to sustained operation – while maintaining alignment with the logic of existing readiness concepts. It should be emphasized that the AI readiness framework represents a conceptual proposition derived from literature synthesis rather than an empirically validated model. Its practical validation remains the subject of future research.

4. Discussion

This study introduces an integrated readiness logic that places AI use case readiness on an equal footing with technological maturity. The proposed UCAIRL framework merges planning and implementation stages into a single continuum, ranging from idea exploration to operational deployment. Levels 0–5 (idea to domain-specific AI use case) cover conceptual and detailed specification – clarifying problem, data, and algorithmic feasibility – while UCAIRL 6–10 follow a MLTRL-consistent trajectory tailored to AI systems, encompassing application/system development, validation, integration, and operation. Each level is defined by concise indicators and verifiable artifacts (e.g., application domain, data, and use case cards; validation reports; deployment documentation) that enable transparent decision-making and reproducible assessment across interdisciplinary teams. The framework addresses a long-recognized limitation of existing TRL-based approaches: AI projects often achieve high technological maturity at a time when they are still not ready for adoption due to deficiencies in problem framing, data quality, or organizational preparedness. By centering readiness on the AI use case – the bridge between domain requirements and technical realization – the framework provides a mechanism to reduce late reworking, strengthen interdisciplinary alignment, and prioritize resource allocation. Accordingly, RQ1 is answered through a multidimensional view of readiness encompassing problem-related, data, technical, and organizational dimensions, while RQ2 is addressed through level-specific indicators that operationalize shared understanding and structured decision quality.

Theoretical implications: The framework extends the conceptual scope of TRL theory by embedding multidimensional and socio-technical perspectives into readiness assessment. Rather than equating maturity with technical performance, readiness is reconceptualized as a phase-sensitive, evidence-linked construct that integrates the interplay between problem definition, data readiness, technical realization, and organizational adoption. This expansion situates the model within the lifecycle logic of ISO/IEC 22989:2022 and aligns it with the explainability principles of IEEE 2894-2024. By assigning auditable artifacts to each level, the framework operationalizes transparency and traceability – enhancing the validity of the construct and the comparability of maturity judgments. It thereby transforms TRL from a unidimensional measure of technological progress into a multidimensional, interdisciplinary readiness instrument that reflects the entire AI system life cycle.

Practical implications: From an applied perspective, the framework provides actionable guidance for planning and managing AI projects in industrial product development contexts. Early readiness gates (UCAIRL 0–5) serve as checkpoints for verifying conceptual clarity, data availability, and stakeholder alignment before resource-intensive modeling begins. Integration of supporting methods facilitates structured risk identification and informed go/no-go decisions. During implementation, the standardized

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

documentation and gated reviews allow teams to track progress across technical and organizational dimensions, promoting accountability and comparability across project portfolios.

5. Conclusion, limitations, and future research needs

This contribution presents the use case-centered AI Readiness Level (UCAIRL 0–10) as a conceptual framework derived from existing AI-related readiness models. The UCAIRL introduces an integrated readiness logic that completes domain-specific planning before implementation and then follows a TRL-consistent trajectory through deployment and operation. By operationalizing multidimensional readiness - problem, data, technology, and organizational - through concise, evidence-linked artifacts, the framework supports shared understanding and disciplined decision-making across interdisciplinary teams. The UCAIRL extends the traditional TRL paradigm by framing readiness as an integrative property of systems, data, and context rather than a purely technological measure. It thereby improves the theoretical robustness and practical applicability of maturity assessment for AI development. For practitioners, it provides a lightweight structure that enhances comparability, portfolio governance, and accountability, especially in data-intensive or regulated domains. As a conceptual framework, the proposed UCAIRL require empirical validation. Future work should therefore focus on (i) expert interviews and workshops to test completeness, usefulness, and usability, (ii) comparative studies featuring the UCAIRL and traditional TRL assessments, and (iii) development of domain-specific indicators and gate criteria calibrated to regulatory risk classes. Longitudinal analyses – such as pilot-to-production conversion rates or time-to-value – can further clarify the practical benefits. In addition, integrating digital documentation tools with traceability features and linking readiness levels to governance and compliance mechanisms offer promising avenues for responsible AI adoption.

References

Bawack, R. E., Fosso Wamba, S., & Carillo, K. D. A. (2021). A framework for understanding artificial intelligence research: insights from practice. *Journal of Enterprise Information Management*, 34(2), 645–678. https://doi.org/10.1108/JEIM-07-2020-0284

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Developing Maturity Models for IT Management: A Procedure Model and its Application. *Business & Information Systems Engineering*, 1(3), 213–222. https://doi.org/10.1007/s12599-009-0044-5

Brakemeier, H., Gebert, P., Hartmann, P., Schamberger, M. &, Waldmann, A. (2023). Applying AI: How to find and prioritize AI use cases. appliedAI Initiative GmbH. https://www.appliedai.de/en/insights/how-to-find-andprioritize-ai-use-cases

Cambridge Dictionary. (2025). Dictionary English. https://dictionary.cambridge.org/dictionary/english/

Cooper, R. G. (2024). The Artificial Intelligence Revolution in New-Product Development. *IEEE Engineering Management Review*, 52(1), 195–211. https://doi.org/10.1109/EMR.2023.3336834

Eljasik-Swoboda, T., Rathgeber, C., & Hasenauer, R. (2019). Assessing Technology Readiness for Artificial Intelligence and Machine Learning based Innovations: Proceedings of the 8th International Conference on Data Science, *Technology and Applications*, 281–288. https://doi.org/10.5220/0007946802810288

Gerschütz, B., Goetz, S., & Wartzack, S. (2023). AI4PD—Towards a Standardized Interconnection of Artificial Intelligence Methods with Product Development Processes. *Applied Sciences*, 13(5), 3002. https://doi.org/10.3390/app13053002

Hupont, I., Fernández-Llorca, D., Baldassarri, S., et al. (2024). Use case cards: a use case reporting framework inspired by the European AI Act. *Ethics Inf Technol* 26, 19. https://doi.org/10.1007/s10676-024-09757-7

IEEE Standards Association. (2024). IEEE Guide for an Architectural Framework for Explainable Artificial Intelligence (IEEE Std 2894-2024). IEEE SA.

International Organization for Standardization. (2022). Information technology - Artificial intelligence - Artificial intelligence concepts and terminology (ISO/IEC 22989:2022). ISO. https://www.iso.org/standard/81120.html

International Organization for Standardization. (2024). Information technology - Artificial intelligence - Guidance for AI applications (ISO/IEC 5339:2024). ISO. https://www.iso.org/standard/74296.html

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, 63(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Kim, D. H., Shin, H., Yadgarova, S., Son, J., Subramonyam, H., & Kim, J. (2024). AINeedsPlanner: A Workbook to Support Effective Collaboration Between AI Experts and Clients. *Designing Interactive Systems Conference*, 728–742. https://doi.org/10.1145/3643834.3661577

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press

Kirschbaum, J., Posselt, T., & Roth, A. (2022). Use-Case-based Innovation for Artificial Intelligence - An ontological Approach. In *Association for Information Systems (AIS) (Eds.), Proceedings of the Thirtieth European Conference on Information Systems (ECIS 2022)* (pp. 1–7). Timi oara, RO.

Königstorfer, F. (2024). A comprehensive review of techniques for documenting artificial intelligence. *Digital Policy, Regulation and Governance*, 26(5), 545–559. https://doi.org/10.1108/DPRG-01-2024-0008

Königstorfer, F., & Thalmann, S. (2022). AI Documentation: A path to accountability. *Journal of Responsible Technology*, 11, 100043. https://doi.org/10.1016/j.jrt.2022.100043

Lavin, A., *et al.* (2022). Technology readiness levels for machine learning systems. *Nature Communications*, 13(1), 6039. https://doi.org/10.1038/s41467-022-33128-9

Lee, M. C. M., *et al.* (2023). The implementation of artificial intelligence in organizations: A systematic literature review. *Information & Management*, 60(5), 103816. https://doi.org/10.1016/j.im.2023.103816

Luley, P.-P., Deriu, J. M., Yan, P., Schatte, G. A., & Stadelmann, T. (2023). From Concept to Implementation: The Data-Centric Development Process for AI in Industry. *2023 10th IEEE Swiss Conference on Data Science (SDS)*, 73–76. https://doi.org/10.1109/SDS57534.2023.00017

Martínez-Plumed, F., Gómez, E., Hernández-Orallo, J. (2020). *AI Watch: Assessing Technology Readiness Levels for Artificial Intelligence*, EUR 30401 EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-76-22987-2, doi:10.2760/15025, JRC122014

Martins, M. R. (2023). Project Management Evolution: From Traditional IT Implementations to AI-Driven Projects. *International Journal of Scientific Research and Management (IJSRM)*, 11(07), 5011–5028. https://doi.org/10.18535/ijsrm/v11i07.em03

Meystel, A., Albus, J., Messina, E., & Leedom, D. (2003). *Performance measures for intelligent systems: Measures of technology readiness*. Gaithersburg, MD: National Inst of Standards and Technology.

Moosbrugger, J., & Ntoa, S. (2022). A Unified Framework to Collect and Document AI-Infused Project Exemplars. In J. Y. C. Chen *et al.* (Eds.), *HCI International 2022 – Late Breaking Papers: Interacting with eXtended Reality and Artificial Intelligence* (Vol. 13518, pp. 407–420). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-21707-4_29

Müller, B., Roth, D., & Kreimeyer, M. (2024). Survey of the Role of Domain Experts in Recent AI System Life Cycle Models. *Proceedings of NordDesign 2024*, 256–265. https://doi.org/10.35199/NORDDESIGN2024.28

Müller, B., Roth, D., & Kreimeyer, M. (2025a). KI-Adaption in der Produktentwicklung: Ansätze und Vorgehen aus wissenschaftlicher und praktischer Perspektive. *Zeitschrift Für Wirtschaftlichen Fabrikbetrieb*, 120(s1), 44–50. https://doi.org/10.1515/zwf-2024-0158

Müller, B., Roth, D., & Kreimeyer, M. (2025b). From theory to practice: derivation of the application domain card for supporting AI system development. *Proceedings of the Design Society*, 5, 1903–1912. https://doi.org/10.1017/pds.2025.10204

Müller, B., Roth, D., & Kreimeyer, M. (2025c). AI System Development for SMEs: The AI Use Case Card as a Practical Method. In K. Hölzle *et al.* (Eds.), *Stuttgarter Symposium für Produktentwicklung SSP 2025* (pp. 376–387). Fraunhofer IAO. https://doi.org/ https://doi.org/10.18419/opus-16366

Naheed, S., Pinto, R., & Pirola, F. (2025). A Preliminary multidimensional AI readiness assessment model for SME's. *Procedia Computer Science*, 253, 774–783. https://doi.org/10.1016/j.procs.2025.01.139

Reichl, G., & Gruenbichler, R. (2023). Maturity Models for the Use of Artificial Intelligence in Enterprises: A Literature Review. *19th International Scientific Conference on Industrial Systems*, 486–502. https://doi.org/10.24867/IS-2023-VP1.1-5_07341

Romeo, E., & Lacko, J. (2025). Adoption and integration of AI in organizations: a systematic review of challenges and drivers towards future directions of research. Kybernetes. https://doi.org/10.1108/K-07-2024-2002

Schiller, K. A., Haddad, M.-S., & Seibel, A. (2025). ReqGPT: a fine-tuned large language model for generating requirements documents. *Proceedings of the Design Society*, 5, 2741–2750. https://doi.org/10.1017/pds.2025.10288

Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

https://doi.org/10.1017/pds.2026.10605 Published online by Cambridge University Press