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An integrated sociotechnical reference model for aligning artificial intelligence implementation in organizations

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ABSTRACT

Despite the strategic importance of Artificial Intelligence (AI), organizations struggle to translate ambition into execution. Failures rarely stem from algorithmic shortcomings alone; the deeper issue is misalignment between AI efforts and the broader organizational transformation required to absorb them. Adopting a Design Science Research approach, this study systematically analyzes 45 procedural models, classifying them into five clusters from engineering lifecycles to strategic roadmaps. The analysis reveals disciplinary siloization producing two structural deficiencies: a technocratic bias that sidelines human-centric design, and an internal focus that neglects market responsiveness. To address these gaps, Assembly-Based Method Engineering is applied to construct the Integrated Sociotechnical AI Reference Model (ISAR-M). Embedded decision gates synchronize technical capabilities with organizational readiness across the lifecycle. Expert applicability assessments and scenario-based demonstrations confirm that ISAR-M mitigates temporal asynchrony, offering researchers a structural baseline and practitioners a prescriptive coordination artifact for integrated AI adoption.

Keywords: AI Adoption, Sociotechnical Alignment, Design Science Research, Process Model, AI Governance, Organizational Transformation.

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Ethics declaration: No formal ethics approval or study-specific waiver was obtained prior to data collection. This study did not involve biomedical, clinical, biological, biometric, or sensitive personal data. The only human involvement consisted of voluntary, anonymized expert interviews with professionals in their occupational capacity. The interviews posed no more than minimal risk to participants and did not involve vulnerable groups.

According to the publicly available guidance of the Joint Ethics Committee of the Bavarian Universities of Applied Sciences (GEHBa), student research projects are generally not subject to full ethical review by GEHBa, and expert interviews without particular risk or burden to participants generally do not require a full ethics application. Participation was voluntary, informed consent was obtained verbally from all participants prior to the interviews, and all data were anonymized before analysis and publication. The study was conducted in accordance with applicable institutional guidelines and general ethical principles for research involving human participants.

1 Problem Context and Research Objective

The strategic adoption of Artificial Intelligence (AI), defined in this study as systems capable of learning, reasoning, and acting autonomously (Berente et al., 2021; Lin & Maruping, 2025; Russell et al., 2022), has become a critical determinant of competitiveness for modern enterprises (Krakowski et al., 2022; Lou et al., 2025; Wessel et al., 2025). Despite this widespread recognition, organizations continue to face a significant execution gap. Recent surveys indicate that although approximately three-quarters of firms employ AI in at least one business function, only about one percent have fully integrated it into core workflows in ways that generate significant business value (Meyer, 2023; Singla et al., 2025). This discrepancy varies across industries: adoption maturity is considerably higher in information technology (IT) than in traditional sectors such as manufacturing, logistics or healthcare, suggesting deeper implementation challenges in these domains (Singla et al., 2025; Sira, 2025).

The limited success of AI initiatives is rarely attributable to algorithmic shortcomings alone. Instead, it typically reflects a misalignment between AI efforts and broader strategic, structural, and cultural transformations (Altepost et al., 2024; Tjondronegoro et al., 2022). Effective implementation requires managers to integrate AI technologies with the overall company strategy, data governance, business processes, and workforce capabilities, moving beyond the perception of AI as an isolated IT project (Oluwamola et al., 2024; Smit et al., 2024).

However, the existing body of knowledge primarily addresses what conditions are necessary for AI adoption, rather than how organizations should navigate these conditions over time (Hutzschenreuter & Lă, 2025; Shamsi, 2025). The literature remains dominated by variance-oriented, factor-based studies that conceptualize adoption as a static configuration of determinants, paying comparatively little attention to the temporal, iterative, and sociotechnical dynamics of organizational change (Merhi, 2023; Sanchez-Lengeling et al., 2021; Uren & Edwards, 2023). While these studies identify critical success factors, they often fail to capture the dynamic maturation trajectories required for sustainable AI integration (Gama & Magistretti, 2025; Sira, 2025).

Furthermore, existing procedural models for AI adoption tend to be fragmented, addressing isolated subdisciplines or specific lifecycle phases rather than the holistic transformation, sustained operation, and continuous evolution of AI systems. Consequently, organizational efforts often remain exploratory, focusing on the identification of isolated generative AI use cases across strategic, functional, and operative levels without the guidance of a comprehensive integration framework (Simsek et al., 2024). Technical models, for example, often emphasize engineering and data lifecycles (e.g., De Silva & Alahakoon, 2022; Hasterok & Stompe, 2022), whereas management frameworks prioritize strategic business model innovation but offer limited operational guidance (e.g., Gupta et al., 2024; Reim et al., 2020). This disciplinary siloization has resulted in the absence of a cohesive coordination artifact capable of guiding practitioners across the entire lifecycle (Ruess et al., 2024). Although numerous isolated models exist, current research lacks a systematic, criteria-driven comparison to evaluate their applicability and limitations, a critical prerequisite for identifying suitable approaches or developing improved frameworks. Against this backdrop, this study investigates the following research question:

How can existing process models for introducing artificial intelligence in companies be systematically compared using uniform, central criteria, and how does this comparison inform the development of a consolidated, practice-oriented model for successful AI integration?

To address this inquiry, this paper shifts the analytical focus from isolated adoption factors to a dynamic integration process. Following a Design Science Research (DSR) approach (Hevner et al., 2004), this study employs a methodological cycle of artifact construction and evaluation. The resulting artifact constitutes a theory for design and action (Gregor, 2006). By prescribing specific coordination mechanisms, it moves beyond static factor analysis to actively resolve the sociotechnical misalignment defined in this study. First, we systematically analyze existing procedural models using a uniform set of criteria derived from the literature. Subsequently, drawing on the principles of Assembly-Based Method Engineering (Brinkkemper, 1996; Ralyte et al., 2003), we synthesize a consolidated "best-of-breed" artifact by integrating complementary method chunks from prior research. To complete the DSR cycle, we evaluate the artifact's utility and applicability through informed argument, scenario-based demonstration, and expert applicability assessments (Rosemann & Vessey, 2008). This resulting artifact is designed to serve as a holistic instrument, providing practitioners a structured reference guide to master the complexity of AI implementation. At the same time, it contributes to the academic discourse by harmonizing the fragmented landscape of existing process models into a coherent framework.

The remainder of this paper is structured as follows: Section 2 outlines the theoretical background, followed by the research design in section 3. Section 4 through 6 analyze the model landscape to provide a structural overview

and identify coverage gaps based on key adoption determinants derived. Section 7 details the construction of the Integrated Sociotechnical AI Reference Model (ISAR-M) using Assembly-Based Method Engineering. Section 8 evaluates the artifact through analytical and empirical methods. Section 9 discusses the theoretical contributions related to sociotechnical parallelism and managerial implications, and section 10 concludes with limitations and avenues for future research.

2 Theoretical Background

This section demonstrates the need for a consolidated procedural model by showing that static frameworks, while useful for benchmarking organizational capability levels, cannot account for the transition between them. Because they lack a temporal logic that orchestrates mutual adaptation, they offer no guidance on how technology and organization should evolve together. A process-oriented model is therefore required to actively synchronize both dimensions over time.

2.1 Sociotechnical Complexity of AI Adoption

To understand why traditional IT adoption models often fall short in the context of AI, one must first delineate the specific nature of AI through the lens of Sociotechnical Systems (STS) theory. While AI is formally defined as "[...] the science and engineering of making intelligent machines and computer programs" (McCarthy, 2007), its organizational adoption cannot be treated as a mere technical upgrade. STS theory postulates that organizations consist of two distinct but interacting subsystems: a technical subsystem, comprising tools, tasks, and formal processes, and the social subsystem, encompassing people, roles, norms, and authority structures (Bostrom & Heinen, 1977). The central axiom of this framework is the principle of joint optimization (Trist, 1981), which holds that organizational performance is maximized only when both subsystems are mutually aligned rather than when technical efficiency is pursued at the expense of social coherence (Sarker et al., 2019).

AI challenges these principles because it fundamentally differs from deterministic IT tools (Clegg, 2000; Grisold et al., 2025; Tanriverdi & Akinyemi, 2025). While traditional software executes predefined rules, AI systems exhibit probabilistic behavior and varying degrees of autonomy (Bosch et al., 2020; Hutzschenreuter & Lã, 2025; Lee et al., 2023). This autonomy introduces a reciprocal dependency: the technical artifact continues to evolve after deployment through learning processes, thereby exceeding the static boundaries of legacy systems (Altepost et al., 2024; Benbya et al., 2021; Kerschbaum & Dachs, 2024).

This dynamic creates sociotechnical misalignment. As stable organizational routines collide with emergent AI capabilities (Sira, 2025), the adoption process shifts from a one-time integration effort to a state of continuous organizational adaptation (AlSheibani et al., 2018). In this study, sociotechnical misalignment is defined as a temporal asynchrony in which the technical maturity of AI systems outpaces the organizational maturity required to effectively absorb and govern them (Leonard-Barton, 1988; Mikalef & Gupta, 2021). This condition manifests in breakdowns of routines, decision rights, accountability structures, and workforce capabilities, ultimately impeding the sustainable integration of AI.

2.2 Limitations of Static Variance Theories

Despite the inherently dynamic nature of AI implementation, current Information Systems research predominantly rely on variance theories to explain AI adoption. This paradigm seeks to identify independent variables (antecedents) that account for variance in a dependent variable (typically adoption intention). Established frameworks, such as the Technology-Organization-Environment (TOE) framework (Tornatzky et al., 1990) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), successfully isolate static antecedents like competitive pressure, performance expectancy, or data readiness (Oliveira & Martins, 2011; Rane et al., 2024; Venkatesh et al., 2003). However, these models treat the implementation process as a black box, positioned between input factors and the eventual adoption decision (Lee et al., 2023).

Maturity models such as Capability Maturity Model Integration (CMMI) or the Artificial Intelligence Maturity Model (AIMM) offer a complementary perspective by benchmarking an organization's current capability level (AlSheibani et al., 2019; CMMI Product Team, 2002). Yet, they share a fundamental limitation: they are descriptive rather than prescriptive. While they define the characteristics of each maturity stage, they do not explain how organizations transition from one level to the next or which mechanisms drive such progression (Röglinger et al., 2012).

Both variance theories and maturity models therefore focus on static states and antecedent conditions, lacking the temporal and evolutionary dimension required to understand the dynamic complexity of AI implementation (Sira, 2025). To capture the iterative interplay between technology and organizational transformation, research must shift from a factor-centric variance perspective toward dynamic process theories that explain the sequence, mechanisms, and mutual adaptations unfolding during implementation (Lee et al., 2023; Mohr, 1982).

2.3 Procedural Models as Coordination Artifacts

To overcome the explanatory limitations of variance theory and maturity models in capturing sociotechnical complexity (Lee et al., 2023), this research adopts a process-theoretical perspective that conceptualizes procedural models as coordination artifacts (Haefner et al., 2023). Unlike factor-based approaches that merely identify antecedents of success, procedural models prescribe the sequence of interdependent activities required to transform inputs into outcomes (Sira, 2025). Theoretically, they operate as boundary objects that structure collaboration across heterogeneous actors, mitigate sociotechnical tensions, and reduce complexity by organizing activities into a coherent temporal order (Okhuysen & Bechky, 2009; Ven et al., 1976). In the context of AI adoption, such a model addresses the inherent tension within the Human-Task-Technology (HTT) triad. It provides a mechanism to align the technical subsystem (data, algorithms, infrastructure) with the social subsystem (routines, roles, governance), thereby enabling the sociotechnical integration required for successful implementation (Star & Griesemer, 1989; Weber et al., 2023).

Despite the theoretical necessity of such coordination mechanisms, the current landscape fails to provide a cohesive boundary object for AI integration (Ruess et al., 2024). A disciplinary divide persists: technical models often overlook organizational embedding and social implications of algorithms, while strategic roadmaps tend to ignore the probabilistic, iterative and experimental nature of AI engineering (De Silva & Alahakoon, 2022; Rai et al., 2026). As a result, a persistent gap exists in both research and practice: scholarship lacks a unified coordination framework, and practitioners are left without an end-to-end guidance instrument to steer transformation efforts (Kerschbaum & Dachs, 2024; Weber et al., 2023). This study aims to bridge this gap by synthesizing these fragmented perspectives into an integrated procedural model that connects strategic intent with operational implementation, thereby offering a comprehensive coordination artifact for AI adoption.

3 Research Design

This section outlines the research design and methodological procedures employed to systematically derive, develop, and evaluate the consolidated AI adoption process model.

3.1 Research Design Overview

To address the absence of a holistic AI adoption process model, this study is guided by the Design Science Research (DSR) paradigm (Hevner et al., 2004). DSR is appropriate because the research objective extends beyond describing AI adoption phenomena; it aims to generate prescriptive knowledge in the form of an artifact, a consolidated procedural model that responds to the practical challenge of fragmented and insufficient implementation guidance.

As illustrated in Figure 1, the research follows a sequential cycle comprising seven steps based on the design cycle proposed by Takeda et al. (1990). This framework was selected as it represents a seminal and widely adopted standard in DSR, offering a rigorous and transparent structure for artifact development in Information Systems research. The process begins with the **(0) Problem Definition** (see section Problem Context and Research Objective) to pinpoint the specific research gap, followed by a **(1) Literature Research** to identify existing procedural models. These findings facilitate the **(2) Development of a Criterion Catalogue**, which serves as the analytical lens for the subsequent **(3) Comparative Analysis of the existing Models**. The results of this analysis guide the **(4) Model Development**, where complementary elements are synthesized into a consolidated artifact. The resulting model undergoes (5) Evaluation, assessing its utility and applicability. Finally, the study derives (6) Implications and Future Work, outlining contributions for both researchers and practitioners and identifying the next iteration's (0) Problem Definition, consistent with DSR's iterative nature and its emphasis on continuous refinement of the knowledge base.

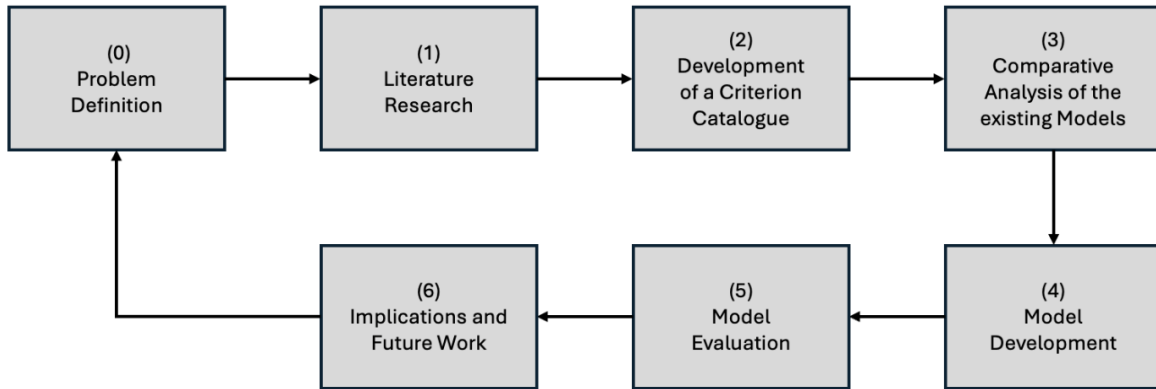


Fig. 1 Research design following the DSR cycle of Takeda et al. (1990)

3.2 Identification of Procedural Models

Constituting Step 1 of the research cycle, this phase focuses on identifying existing approaches to AI implementation within the knowledge base. To establish a robust comprehensive foundation, a systematic literature search was conducted in November 2025 following the guidelines of Webster and Watson (2002). The databases Scopus, IEEE Xplore, the AIS eLibrary (AISEL), and ScienceDirect were queried using the English keywords "AI Adoption", "AI Implementation", "AI Process Model", "AI Procedural Model" and "AI Roadmap", as well as their German equivalents. To ensure completeness and mitigate selection bias, the initial search was complemented by a backward search, examining the reference lists of the identified publications, and a forward search, analyzing subsequent citations of seminal works. Given the high volume of search results, AI tools (SciSpace, ScopusAI) were used to filter titles and abstracts based on predefined inclusion criteria (see Step 2 Derivation of Key Adoption Determinants). All AI-suggested inclusions were manually validated against the full text to prevent hallucination, misclassifications, or the omission of relevant studies.

Strict exclusion criteria were applied to ensure that the resulting corpus adequately reflects the temporal complexity of AI adoption. Consequently, Technology Acceptance Models, static maturity models, and unstructured lists of criteria were filtered out. Only models defining explicit sequential logic, such as phases or steps, were retained, yielding a final corpus of 45 procedural models. The filtering and classification of these models followed the Systematic Mapping Approach described by Petersen et al. (2008). This methodology provides a high-level overview of a research area by categorizing individual studies into a systematic map. It employs a multi-stage classification scheme, where a keywording process is used to develop a consistent taxonomy, enabling the identification of thematic clusters and structural patterns within the literature. Applying this lens allowed the research field to be systematically organized, and the procedural models were categorized according to their thematic focus and level of granularity. The final selection is presented in Table 6, while Figure 2 illustrates the underlying process.

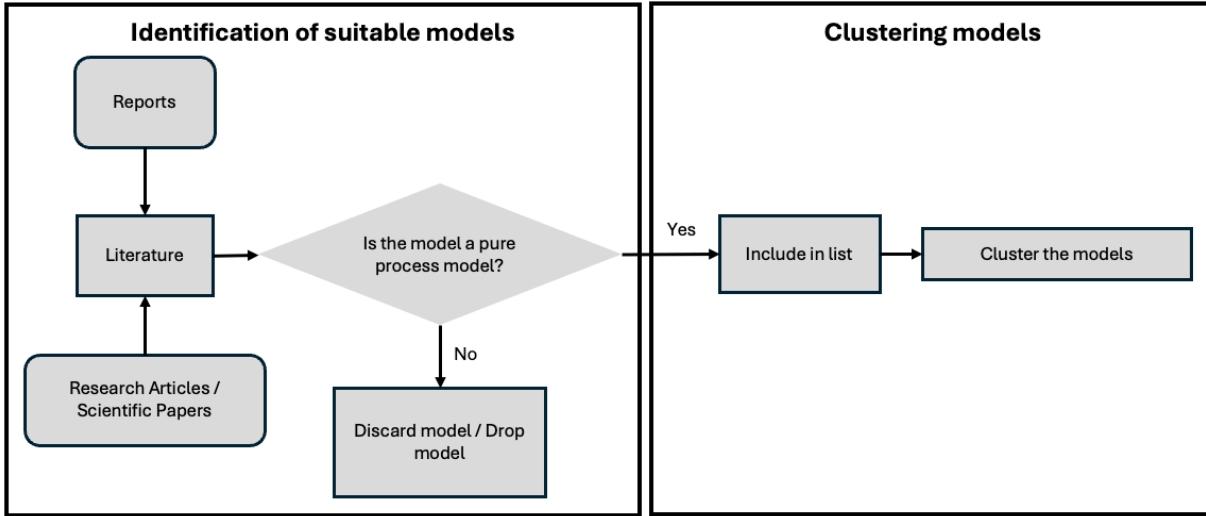


Fig. 2 Selection process for the final corpus of 45 procedural AI adoption models

3.3 Derivation of Key Adoption Determinants

Aligning with Step 2 (Development of a Criteria Catalogue) of the research cycle shown in Figure 1, this section develops the evaluative framework referred to as Key Adoption Determinants (KADs), which serve as the foundation for the subsequent comparative analysis. Following the principles of Design Science Research (Hevner et al., 2004), the derivation of these criteria is grounded in a clear methodological distinction between the environment (problem space) and the knowledge base (solution space). Accordingly, the evaluation criteria were derived exclusively from studies on AI adoption barriers and success factors, rather than from characteristics of existing procedural models (Peffer et al., 2007). Drawing on the quality dimensions of Lindland et al. (1994), general structural attributes including graphical syntax or formal role definitions were deliberately excluded to ensure that the framework prioritizes semantic validity. This separation safeguards the independence of the evaluation metric and prevents tautological reasoning, where an artifact is assessed based on criteria it implicitly defines (Brocke et al., 2020). By anchoring the criteria in the problem space, the resulting benchmarks reflect the empirical realities and necessities of organizational practice, independent of existing solution artifacts (Gregor & Hevner, 2013).

The identification of determinants followed the same systematic literature review protocol described before (Webster & Watson, 2002), with the search strategy adapted to the thematic focus on adoption challenges. The databases were queried using the keywords “AI Adoption Barriers”, “AI Success Factors”, “AI Adoption Challenges”, “AI Adoption Success Factors”, and “AI Adoption Enablers”, including their German equivalents.

To systematically extract and categorize the determinants, a qualitative content analysis following Mayring & Fenzl (2014) was applied. Using inductive category formation, raw text segments were condensed into generalized categories of barriers and enablers. This process was supported by a Large Language Model for initial extraction and thematic pre-sorting. To ensure scientific rigor, all papers were subsequently read in full, and every AI-suggested category was manually validated. Regardless of whether they were framed as negative (barriers) or positive (enablers), all identified concepts were interpreted as functional requirements within the problem space that the target artifact must address.

To transform this inventory into a consolidated evaluative framework, a multi-stage validation process was applied (see Figure 3). First, to ensure external validity and avoid anecdotal findings, the identification process followed the guidelines for systematic mapping (Petersen et al., 2008) combined with a concept-centric validation (Webster & Watson, 2002). All identified factors were subjected to a frequency analysis to assess their prevalence across the literature (Kitchenham et al., 2009). A determinant was included in the final framework only if it was reported as significant in three independent studies (Jeyaraj et al., 2006). This cross-study triangulation ensures that the criteria represent generalized organizational challenges rather than context-specific anomalies (Okoli & Schabram, 2010).

Second, the validated determinants were translated into procedural requirements using a logic of prescription derivation (Gregor, 2006). Validated success factors were converted into active process steps (e.g., Top Management Support necessitates a Strategic Alignment Phase). Their temporal placement was guided by the AI lifecycle phases

(Conception, Development, Production) proposed by De Silva and Alahakoon (2022) whose 19-stage decomposition integrates technical AI taxonomies with organizational risk considerations and reflects the iterative nature of AI-data dependencies. Within this structure, we applied a logic of precedence: we analyzed functional dependencies to ensure that necessary inputs (e.g., data availability) serve as prerequisites for subsequent process steps (e.g., model training). Conversely, barriers were transformed through logical inversion into mitigation requirements (e.g., the barrier Algorithmic Bias dictates the necessity for an Ethical Validation Step).

Building on the factor aggregation approaches of AlSheibani et al. (2019) and Radhakrishnan and Chattopadhyay (2020), this study extends their focus on static readiness by operationalizing determinants into dynamic procedural requirements. Drawing on Uren and Edwards (2023), the resulting framework transforms static success factors into actionable steps that support the continuous, iterative nature of AI implementation (Haefner et al., 2023; Weber et al., 2023).

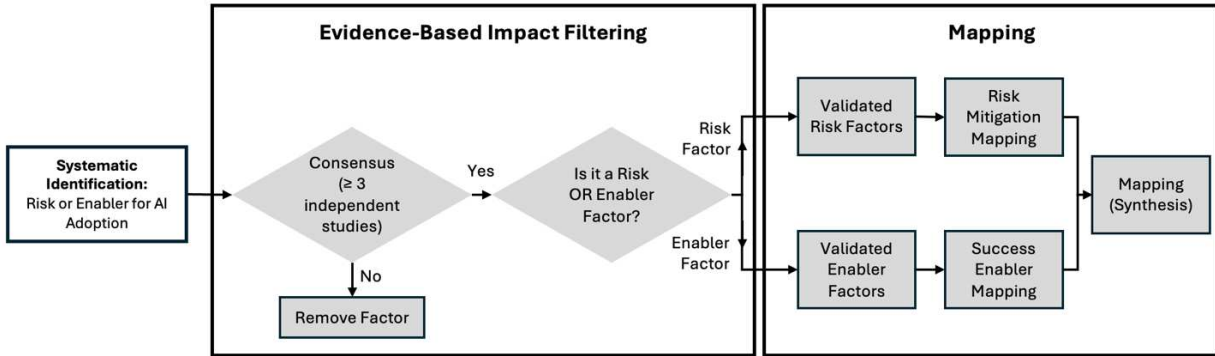


Fig. 3 Multi-stage derivation process for Key Adoption Determinants (KADs)

3.4 Comparative Analysis and Model Development

The consolidated model was constructed following the principles of Assembly-Based Method Engineering (Brinkkemper, 1996; Ralyte et al., 2003). This hybrid approach integrates proven method chunks from existing literature with theoretically deduced components, thereby leveraging the rigor of prior studies rather than designing the artifact from scratch. Consequently, the consolidated artifact constitutes an improvement design contribution, explicitly building upon and extending the existing knowledge base (Gregor & Hevner, 2013).

To operationalize this assembly process, the procedure began with Component Identification via Compliance Mapping. A criteria-based comparative analysis (see Table 8) was executed to identify constituent components by mapping procedural models from the systematic literature review against the KADs. This mapping followed an AI-augmented protocol for initial thematic pre-alignment, which was subsequently subjected to a rigorous manual verification by the authors to ensure the semantic accuracy and theoretical consistency of each mapping. Adhering to a concept-centric approach (Webster & Watson, 2002), this mapping functioned as a deductive category application using the KADs as the coding frame. In line with the imperative that artificial intelligence systems require actionable design principles formulated as prescriptive statements to guide practical implementation (Herath Pathirannehelage et al., 2025), models were categorized as fully compliant if they provided actionable steps, partially compliant if they mentioned the factor without steps, and not compliant if they omitted the factor. Only fully compliant procedural phases, defined as offering concrete and actionable steps, were selected as candidate method chunks for the consolidated artifact.

Building on these results, the study employed a Dual-Backbone Integration strategy. We selected the two most comprehensive frameworks, Wendt (2025) and Kutzias et al. (2023), as the structural backbone. These models were chosen because they complement each other to conceptually satisfy all compliance criteria (see Table 7). However, while this dual backbone provides broad structural coverage, it lacks operational depth in several areas. The broader model landscape remains highly fragmented, with effective execution protocols dispersed across niche models. To address the fragmentation, the dual backbone was treated strictly as a governance container. The primary design value lies in systematically enriching this backbone with the fully compliant method chunks identified during the mapping phase.

To reconcile conflicting or overlapping content across the corpus of fully compliant method chunks, and to avoid constructing an incoherent artifact, specific prioritization rules were applied. Drawing on Assembly-Based

Method Engineering, we established three governing rules to harmonize distinct method chunks into a unified, logically consistent artifact (Brinkkemper, 1996; Ralyte et al., 2003).

Rule A Granularity Check (Operational Viability): Following Brinkkemper's (1996) distinction between atomic fragments and meaningful chunks, a component was eligible for integration only if it provided operational interpretability rather than high-level abstraction. Priority was given to chunks with explicit procedural specifications and concrete outputs, such as the Strategic Foresight Report, ensuring that the final model constitutes an actionable specification rather than a descriptive taxonomy relative to the backbone.

Rule B Association Strategy (Syntactic Interoperability): Adhering to the Association Strategy (Ralyte et al., 2003), syntactic interoperability was guaranteed by defining explicit bridges between heterogeneous chunks. A chunk was integrated only if its output logically served as a mandatory input for the subsequent step. For instance, the Investment Decision Gate requires specific validated inputs, such as the Business Case and Value-Risk Matrix, generated in the preceding phase, thereby maintaining a coherent logical chain of evidence (Harmsen et al., 1994).

Rule C Integration Strategy (Contextual Harmonization): Following the Integration Strategy (Ralyte et al., 2003), we harmonized overlapping method fragments. To resolve friction between the backbone and specific chunks, we applied Unification and Transformation operators to ensure the merged artifact maintains internal consistency. This rule addresses both under-specification (by grounding abstract concepts in templates) and over-specification (by abstracting overly technical tasks), thereby preserving adaptability across diverse organizational contexts while maintaining methodological coherence.

The unified baseline was refined using Assembly-Based Method Engineering, drawing specifically on the Integration and Association strategies (Ralyte et al., 2003). To operationalize these strategies, we applied specific operators to systematically harmonize the identified method chunks:

- **Retention (Selection):** Applied to satisfy the Selection Strategy (Ralyte et al., 2003). While Ralyte et al. (2003) defines Cancellation operators for removing inadequate elements, we utilized Retention to explicitly select and preserve core backbone steps that satisfied Rule A (e.g., Infrastructure Audit) without modification.
- **Merge (Unification & Transformation):** Applied to execute the Integration Strategy (Rule C). We utilized Unification operators to align terminology and Transformation operators to refine abstract backbone steps by integrating instrumental tools (e.g., merging Opportunity Ranking with the Value-Risk Matrix).
- **Insertion (Addition):** Triggered where the backbone exhibited a coverage deficit regarding a validated adoption factor. Distinct chunks, such as Mock-up Workshops, were inserted to address human-centricity gaps. Consonant with Rule B, these insertions were strictly validated to ensure logical connectivity to the Risk Assessment Report and subsequent design decisions.

3.5 Model Evaluation

Consistent with the framework for Evaluation in Design Science (FEDS) (Venable et al., 2016), the artifact was subjected to a dual-validation process combining analytical and empirical methods. The analytical component consisted of an Informed Argument to assess structural integrity. Drawing on the Structure and Goal Criteria of Prat et al. (2015), the authors examined whether the assembled method chunks form a coherent, non-contradictory sequence. This assessment ensured that the integration of previously fragmented elements preserved internal consistency and methodological rigor. To evaluate practical utility and reduce the risk of theoretical complexity, a preliminary Applicability Check (Rosemann & Vessey, 2008) was conducted as the empirical component. Practitioners were selected through purposive sampling for individual, in-depth interviews, targeting experts responsible for both the operationalization and strategic integration of AI across organizations with varying maturity levels. Although the sample size (N=3) is limited, the panel was deliberately composed to triangulate distinct sociotechnical perspectives. Participants ranged from start-up founder deploying AI agents to strategic leads in departments such as HR or Transformation (see Table 1). All three participants were chosen for their active involvement in AI integration. Their experience spans both internal strategic alignment and external solution architecture. This direct exposure ensures a high level of proficiency regarding the technical and organizational challenges of AI, validating their suitability as expert sources for this formative feedback loop. The evaluation followed a structured, multidimensional protocol (Abbasi et al., 2024; Larsen et al., 2025) assessing the artifact along three key dimensions: (1) structural validity and cognitive grasp, (2) detailed phase-specific logic (spanning Evaluate, Design, Realize, and Operate), and (3) pragmatic utility with respect to efficiency and business impact.

Table 1 External Evaluators

ID	Role	Employees	Industry / Maturity*	Focus Area
E1	HR Lead	> 100.000	Automotive (Maturity: 3/5)	Evaluate & Design
E2	CEO & Co-Founder	<10	AI Tech Start-up (Maturity: 4/5)	Evaluate & Design
E3	Product Owner (AI)	>100.000	Insurance (Maturity: 3-4/5)	Design & Realize

*Note: Maturity reflects how the respondent rates the organization's digital/AI readiness on a scale from 1 (Low) to 5 (High).

4 The AI Adoption Model Landscape

The Systematic Literature Review yielded a corpus of 45 procedural models for AI adoption. Examination of this corpus reveals a rapidly evolving research field characterized by high specialization. Rather than converging toward a unified standard, the landscape has fragmented into distinct research streams driven by technological shifts, organizational needs, and regional priorities.

A qualitative assessment of the identified models highlights four developments that define the current state of research. First, the field exhibits a non-linear temporal trajectory. While foundational work dates back to Chapman (2000), the field has witnessed a significant recent surge, with over 75% of models published between 2023 and 2025. This acceleration marks a shift from early theoretical concepts to urgent, practice-oriented guidance driven by widespread organizational pressure to operationalize AI. Second, a clear regional divergence is observable: while international models frequently prioritize technical speed and automation (e.g., De Silva & Alahakoon, 2022; Lamba & Kaur, 2024), frameworks from the DACH region predominantly adopt a sociotechnical perspective emphasizing collaborative design and human-centric integration (e.g., Harlacher et al., 2023; Ruess et al., 2024). This divergence indicates differing institutional priorities and regulatory environments. Third, the nature of technology has necessitated a shift in procedural guidance from building models (traditional Data Science) (e.g., Chapman, 2000; Hasterok & Stompe, 2022) to integrating pre-trained services and system orchestration (e.g., Weinberg, 2025; Wildhirt et al., 2025), reflecting the industry-wide transition toward service-based AI ecosystems. Finally, the target audience has democratized, moving from exclusive, resource-intensive frameworks for large enterprises (e.g., Haefner et al., 2023; Oluwamola et al., 2024) to pragmatic, resource-sensitive adoption paths specifically tailored for SMEs (e.g., Hussain & Rizwan, 2024; Werner & Schmalenbach, 2024). This shift mirrors the broader diffusion of AI capabilities across organizational sizes and sectors.

To capture this differentiated landscape, the 45 models were organized into clusters (see Table 9). Given the field's heterogeneity, statistical clustering was unfeasible. Instead, a qualitative content analysis approach was employed (Krippendorff, 2019). Specifically, models were coded and grouped based on their primary stated objective, target audience, and dominant theoretical lens (Miles et al., 2014). To ensure reliability and minimize subjective bias, an iterative coding process was conducted, mapping the models and resolving any thematic discrepancies through structured consensus-building. This systematic categorization yielded five distinct, largely non-overlapping clusters that map the current discourse.

Cluster 1: The Strategic Perspective (Management & Governance)

Models in this cluster, such as Reim et al. (2020) and Gupta et al. (2024), view AI adoption primarily through a business and management lens. They emphasize strategic alignment, business model innovation, and organizational readiness, often drawing on established frameworks like TOE. These models are effective in clarifying the strategic rationale for AI adoption, yet they frequently abstract away from the technical realities of implementation. As a result, they offer robust governance structures but limited operational guidance for practitioners.

Cluster 2: The Engineering Perspective (Technical Lifecycle)

Rooted in foundational data mining methodologies like the Cross-Industry Standard Process for Data Mining (CRISP-DM; Chapman, 2000), this cluster focuses on the construction and validation of technical artifacts. Modern

iterations, such as the Process Model for AI Systems Engineering (PAISE; Hasterok & Stompe, 2022) and the AI Life Cycle by De Silva & Alahakoon (De Silva & Alahakoon, 2022), provide granular guidance on the software development process, data pipelines, and model architecture. However, by emphasizing technical rigor, these frameworks frequently underestimate organizational inertia and the challenges of embedding AI systems into non-technical workflows.

Cluster 3: The Sociotechnical Perspective (Human-Centric)

Acknowledging that successful adoption depends as much on people as on algorithms, this cluster focuses on organizational culture and the human-in-the-loop. Contributions by Ruess et al. (2024) and Stowasser & Suchy (2020) stress participatory design and change management to foster workforce acceptance. Concepts like "Convivial AI" (Dusdal et al., 2023) further emphasize a symbiotic relationship between humans and machines. While essential for trust, these models risk becoming detached from the technical imperatives required for scalable deployment.

Cluster 4: SME-Specific Adoption

Distinguished by a focus on resource constraints and lower digital maturity, this cluster offers pragmatic entry points for smaller organizations. Unlike broad strategic models, approaches like FAIGMOE (Weinberg, 2025) and the roadmap by Sánchez et al. (2025) offer pragmatic, step-by-step maturity pathways. Other examples, such as Werner & Schmalenbach (2024), address the specific transition needs of the German SMEs. While highly practical, these models remain context-bound and therefore less applicable to larger or more digitally advanced organizations.

Cluster 5: Domain-Specific Implementation

The final cluster comprises models tailored to highly regulated sectors where generic frameworks fall short. In healthcare, for instance, van der Vegt et al. (2023) propose the SALIENT framework for clinical implementation, while Kim et al. (2023) focus on organizational governance within health systems. These models place strong emphasis on compliance, safety protocols, and domain-specific stakeholder management, reflecting the stringent requirements of their respective fields.

The coexistence of these clusters demonstrates that the knowledge required for AI adoption is currently distributed across specialized perspectives. While strategic models define the "**Why**", engineering models define the "**How**", and sociotechnical approaches address the "**Who**" none offer a complete picture independently. Furthermore, while SME- and domain-specific models provide valuable contextual guidance, their narrow focus inherently excludes a vast majority of generalized enterprise scenarios. Because a successful transformation requires the integration of strategy, technology, and people into a coherent and broadly universally applicable structure, the following section derives a unified set of Key Adoption Determinants (KADs) to synthesize these disparate perspectives.

5 Key Adoption Determinants for Successful AI Implementation

Based on the qualitative content analysis (Mayring & Fenzl, 2014) methodology, this section defines the consolidated Key Adoption Determinants of both risk factors and success enablers. The analysis yielded ten non-redundant determinants that constitute the necessary criteria for successful AI adoption. These determinants were subsequently aggregated into four overarching dimensions, **Technology & Data, Organization & Strategy, Human-Centricity, and Environment**. The dimensions emerge directly from the content structure of the KADs and provide a coherent framework for integrating the diverse perspectives identified in the preceding cluster analysis.

5.1 Dimension I: Technology & Data

This dimension captures the technical prerequisites for trustworthy AI, distinguishing hard assets from the broader organizational context (Hangl et al., 2022; Heimberger et al., 2024).

- **Determinant 1: Data Availability & Quality:** High-performing AI models are predicated on the availability of high-quality, unbiased data. Empirical studies consistently show that inadequate or biased data is one of the most common reasons for AI initiatives to fail during early development or pilot phases (Madanchian & Taherdoost, 2025). *Criterion for Comparison:* A procedural model must include explicit steps for Data Readiness Assessment, mandating the evaluation of data completeness, accuracy, and consistency prior to model training (Ayinaddis, 2025; Kavak & Rusu, 2025).
- **Determinant 2: Data Governance, Security & Privacy:** Beyond quality, organizations must ensure that data is handled within a robust governance framework. Security breaches, unclear ownership, and insufficient privacy safeguards significantly reduce organizational willingness to adopt AI (Aljarboa, 2024). *Criterion for Comparison:* To be compliant, the model must explicitly mandate a dedicated Governance Layer that enforces

cybersecurity protocols, privacy-preserving techniques (e.g., anonymization), and transparent data ownership structures (Hangl et al., 2022; Heimberger et al., 2024).

- **Determinant 3: IT Infrastructure & Technical Interoperability:** Legacy systems, fragmented architectures, and insufficient infrastructure maturity frequently slow or block AI adoption (Espina-Romero et al., 2024; Saghiri et al., 2022). Interoperability is necessary but not sufficient; organizations also require scalable infrastructure (e.g., cloud/edge capabilities) to avoid technical debt and prevent the formation of new data silos (Lim & Seng, 2024). *Criterion for Comparison:* A procedural model must include explicit steps for assessing Infrastructure Readiness and mapping architectural integration points (APIs, shared data models, and middleware) to the existing IT landscape (Kondratenko et al., 2023).

5.2 Dimension II: Organization & Strategy

This dimension integrates the financial business case with the organizational flexibility required for effective AI implementation (Ayinaddis, 2025; Marocco et al., 2024).

- **Determinant 4: Executive Sponsorship & Financial Viability:** Financial constraints in AI initiatives typically reflect insufficient executive sponsorship and strategic alignment rather than a genuine lack of capital (Oldemeyer et al., 2025). High implementation become barriers only when disconnected from long-term strategic prioritization (Ayinaddis, 2025). *Criterion for Comparison:* The model must mandate top-management anchoring and dedicated budgeting, ensuring a transparent cost-benefit logic throughout the project lifecycle (Nguyen et al., 2024).
- **Determinant 5: Perceived Relative Advantage (Business Value):** While Determinant 4 addresses costs, this determinant evaluates utility. Ambiguous expectations regarding AI's relative advantage over existing methods frequently lead to project discontinuation (Mathagu, 2024). Perceived relative advantage consistently emerges as the strongest predictor of adoption in TOE-based research (Apostoaie et al., 2025; Lim & Seng, 2024). *Criterion for Comparison:* The model must incorporate a structured Value Check Phase to quantify operational benefits (e.g., efficiency gains, risk reduction), replacing generic innovation narratives with measurable KPIs (Khanfar et al., 2024; Merhi, 2023).
- **Determinant 6: Structural Agility & Data-Driven Processes:** AI generates continuous, data-driven insights that rigid organizational structures cannot effectively absorb (Altepost et al., 2024; Weber et al., 2023). Success depends on the organization's dynamic capability to adjust roles, workflows, and decision rights in response to AI-enabled insights (Heimberger et al., 2024). *Criterion for Comparison:* The model must require an adaptive process architecture, capable of rapidly reconfiguring workflows and reallocating decision authority to match AI-enabled insights (Nair et al., 2024).

5.3 Dimension III: Human-Centricity

This dimension conceptualizes AI adoption primarily as a human challenge, integrating capability, willingness, and usability (Ivchik, 2024; Kelm & Johann, 2025).

- **Determinant 7: Workforce Competence:** The knowledge gap operates in two directions: insufficient skills hinder deployment (Ali & Khan, 2025), while systematic competence development fuels adoption readiness and reduces resistance (Lopez-Garcia et al., 2024). Tool acquisition alone is ineffective without foundational digital literacy (Ayinaddis, 2025). *Criterion for Comparison:* The model must mandate competence assessments and targeted upskilling programs that address technical, analytical, and interpersonal skill domains (Rasdi & Baki, 2025).
- **Determinant 8: Cultural Acceptance & Trust (XAI):** Beyond skills, psychological factors shape willingness to adopt AI. Algorithm aversion, job-security concerns, and perceived unfairness are central barriers (Ivchik, 2024; Tangi et al., 2023). Domain-specific analyses further confirm that overcoming this algorithm aversion requires transparent communication and validation regarding the quality and reliability of AI-generated outcomes (Gebert et al., 2025). Trust is strongly influenced by the opacity of algorithmic decision-making (Marocco et al., 2024). *Criterion for Comparison:* The model must operationalize change management and Explainable AI (XAI). Culture must be treated as a design variable, requiring transparency about how AI-supported decisions are generated (Alasmari, 2024; Silbernagl et al., 2024).
- **Determinant 9: Human-Centric Design (UX):** Adoption falters when technically robust systems are paired with unintuitive or cognitively demanding interfaces (Heimberger et al., 2024; Kelly et al., 2023). Consistent with TAM/UTAUT findings, perceived ease of use is a decisive adoption driver (Kim et al., 2023; Lee et al., 2023). *Criterion for Comparison:* The model must require participatory prototyping and ergonomic interface design to

reduce entry barriers and enable trustworthy interaction, particularly for non-technical users (Hangl et al., 2022; Song et al., 2025).

5.4 Dimension IV: Environment

This dimension captures the external boundary conditions defining the organization's license to operate (Jena et al., 2024).

- **Determinant 10: Responsible AI & Regulatory:** Distinct from data privacy concerns, this determinant focuses on the ethical behavior and legal compliance of the AI models themselves. Legal uncertainty and ethical risks including algorithmic discrimination or lack of accountability constitute hard barriers to sustainable adoption (Daly et al., 2025; Trivedi, 2021). Moreover, the absence of transparent guidelines undermines the stakeholder trust required for scaling (Merhi, 2023). *Criterion for Comparison:* To be compliant, the model must integrate a Responsible AI Framework that operationalizes fairness (bias testing) and algorithmic accountability alongside strict adherence to regulatory standards such as the EU AI Act (Huang et al., 2024; Nigmatov & Pradeep, 2023).
- **Determinant 11: Market Responsiveness:** External competitive pressure shapes the urgency of AI adoption (Aljarboa, 2024). Firms in high-velocity markets adopt AI to survive, whereas those in more static environments tend to lag behind (Merhi & Harfouche, 2023). *Criterion for Comparison:* The model must include an environmental scanning mechanism to benchmark internal velocity against industry standards, thereby informing the strategic timing of AI initiatives (Patnaik & Bakkar, 2024; Sechabe & Malatji, 2025).

While these eleven KADs form a holistic framework, they can be grouped into general IT implementation factors and AI-specific imperatives. Standard prerequisites such as Strategic Sponsorship (Determinant 4) and IT Infrastructure (Determinant 3) remain universally critical for any digital transformation. However, the probabilistic nature and partial autonomy of machine learning systems fundamentally reshape several other determinants. For example, although Human Centric Design (Determinant 9) is a common IT requirement, AI specific phenomena like algorithm aversion shift the focus from mere usability toward fostering trustworthy human-AI interaction. Likewise, the opaque decision-making of these systems introduces unique challenges that render concepts like Explainable AI (Determinant 8) and Responsible AI (Determinant 10) mandatory rather than optional.

6 Gap Analysis of Procedural Models for AI Adoption

The comparative analysis of the 45 identified procedural models against the eleven Key Adoption Determinants (KADs) reveals a research landscape characterized by substantial methodological heterogeneity. As illustrated in the heatmap visualization in Figure 4, the maturity levels of existing artifacts vary considerably, underscoring a domain in which specialized frameworks tend to address isolated sub-problems rather than supporting a comprehensive, end-to-end transformation approach.

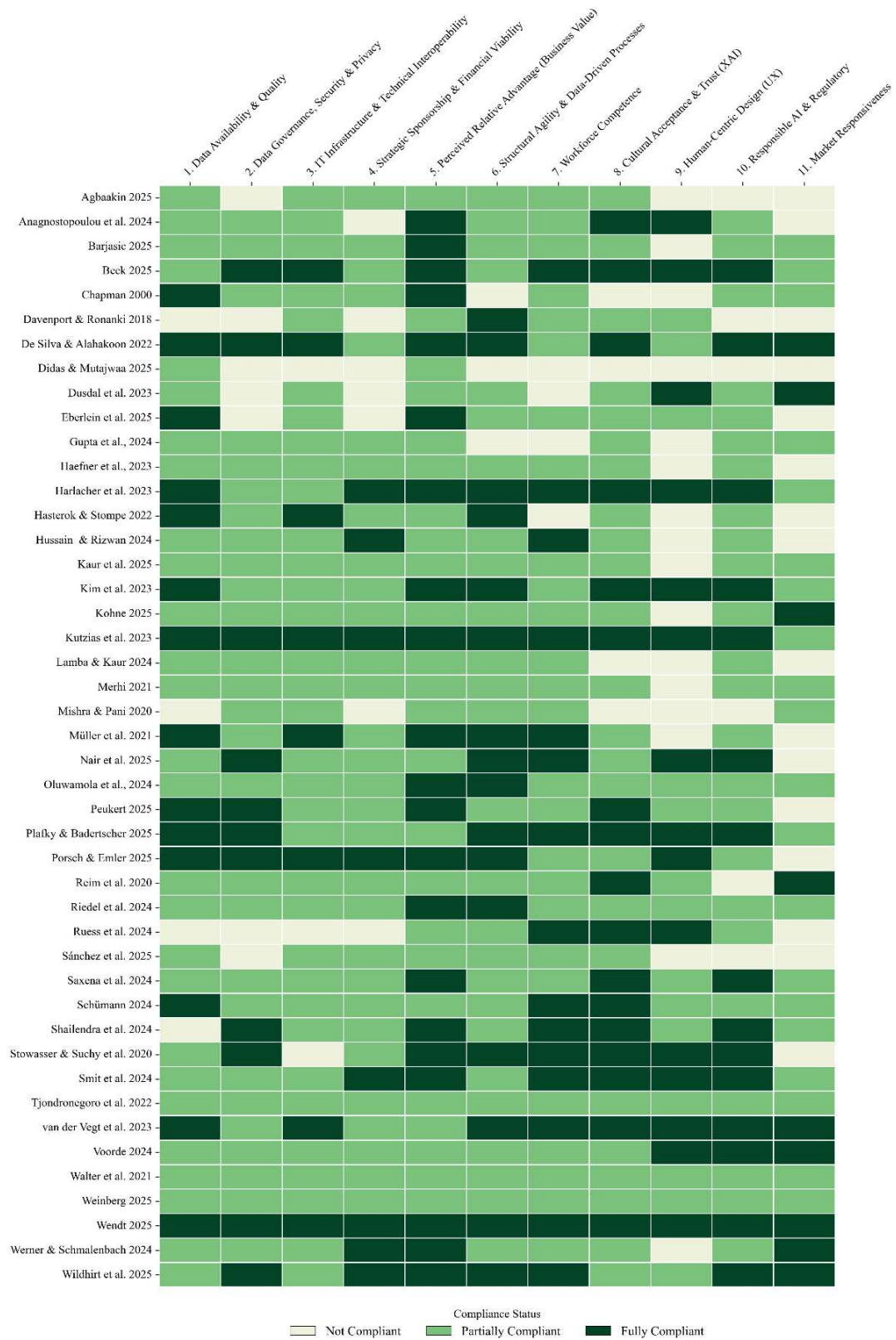


Fig. 4 Comparative compliance analysis of 45 AI process models across 13 Key Adoption Determinants

Analysis shows that only two models achieve a coverage rate above 90 percent (Kutzias et al., 2023; Wendt, 2025). Within this subset, the framework by Wendt (2025) serves as a primary reference point by covering all identified determinants, while the model by Kutzias et al. (2023) follows closely with 95 percent coverage. This comprehensive scope reflects their complementary theoretical foundations: Wendt (2025) represents the strategic-management orientation of the first cluster, whereas Kutzias et al. (2023) embody the sociotechnical perspective of the third cluster. A qualitative in-depth examination reveals a critical trade-off between thematic breadth and methodological specialization. While the foundational concept by Wendt (2025) provides the strategic architecture, our evaluation captures its full operational depth by integrating the exhaustive WhitegloveAI practitioner's guide (James et al., 2025), which is collectively tracked as Wendt (2025) throughout our visualizations. Conversely, the research field remains fragmented, with highly specialized and methodologically rigorous execution protocols often confined to narrow, domain-specific models. Several models with lower overall coverage nevertheless contain precise, fully compliant method chunks that provide concrete, operationalizable guidance for individual determinants. For this reason, Wendt (2025) and Kutzias et al. (2023) form the structural backbone of the synthesis. The construction process systematically integrates complementary method chunks from the wider corpus to close the operationalization gap and enhance the practical applicability of the resulting model.

6.1 Areas of Scientific Consensus

The analysis reveals several domains in which scientific consensus has solidified despite the overall methodological heterogeneity of existing AI adoption models. A first area of agreement concerns the centrality of Business Value (KAD5). 100 percent of the investigated models explicitly link AI adoption to economic investment logic or strategic utility (Agbaakin, 2025; Barjasic, 2025; Davenport & Ronanki, 2018; Gupta et al., 2024; Reim et al., 2020). A second area of consensus emerges around Structural Agility (KAD6). 93 percent of the models reject rigid, linear planning approaches in favor of agile, iterative, or cyclical procedures (Beck, 2025; Harlacher et al., 2023; Oluwamola et al., 2024; Tjondronegoro et al., 2022; Wildhirt et al., 2025). This widespread agreement reflects the probabilistic nature of machine learning systems, which require continuous data exploration, model refinement, and adaptive decision-making. Traditional waterfall methodologies are therefore viewed as structurally misaligned with the dynamics of AI development and deployment.

A third consensus establishes a data-as-infrastructure paradigm, recognizing that algorithmic sophistication is fundamentally constrained by data architecture. Specifically, 93 percent of the examined models integrate IT Infrastructure & Technical Interoperability (KAD3), and 91 percent mandate Data Availability & Quality (KAD1). Unlike traditional software deployments where data is merely an operational input, the literature conceptualizes data pipelines and scalable computing environments as the core enablers of AI capability (e.g., Agbaakin, 2025; Beck, 2025; Kutzias et al., 2023; Wendt, 2025). Consequently, the field uniformly rejects deploying AI atop legacy architectures, positioning data readiness as an indispensable prerequisite rather than a parallel IT workstream.

Finally, the models exhibit a strong conceptual consensus regarding the necessity of Workforce Adaptation and Algorithmic Trust, though they frequently lack actionable operationalization. The data reveals that 91 percent of the procedural frameworks acknowledge Workforce Competence (KAD7), and an equal 91 percent recognize Cultural Acceptance & Trust, frequently highlighting Explainable AI (KAD8). However, this high overall coverage primarily reflects theoretical problem awareness rather than prescriptive guidance. While the literature overwhelmingly agrees that human operators must be deliberately managed to mitigate deployment friction, only 33 to 38 percent of the models provide fully compliant and concrete steps to achieve this goal (e.g., Davenport & Ronanki, 2018; Kutzias et al., 2023; Wendt, 2025; Wildhirt et al., 2025). Thus, the scientific consensus firmly establishes workforce adaptation and trust-building as non-negotiable prerequisites for AI adoption, even as the field struggles to translate this awareness into structured, executable methods.

6.2 Identification of Research Biases

The visual analysis in **Error! Reference source not found.** reveals three structural biases that limit the effectiveness and completeness of current AI-adoption models. These gaps persist despite areas of conceptual consensus and explain why existing frameworks struggle to provide holistic, operational guidance:

- **Internal Focus Bias (Market Orientation Gap - KAD11):** Current research exhibits a pronounced internal focus, prioritizing technological feasibility over external strategic relevance. While an initial quantitative view suggests that a majority of frameworks (approx. 64 percent) acknowledge the relevance of market dynamics at a conceptual level, a detailed analysis of methodological depth reveals a notable limitation. Only a small subset, 20 percent of the artifacts, achieves "Full Compliance" by offering concrete, operationalized market scanning tools or competitive benchmarking mechanisms (specifically: De Silva & Alahakoon, 2022; Kohne, 2025; van der Vegt

et al., 2023; Voorde, 2024; Wendt, 2025). For the remaining 80 percent the market dimension is either addressed superficially or omitted entirely. More than 35 percent of the models do not include any actionable market-oriented steps (e.g., (Agbaakin, 2025; Davenport & Ronanki, 2018; Haefner et al., 2023; Hasterok & Stompe, 2022; Müller et al., 2021). This limited guidance may increase the risk of strategic drift, where organizations develop technically functional solutions that are developed in a vacuum and become strategically obsolete upon deployment (Amarilli et al., 2023). Addressing this vulnerability fundamentally requires the inclusion of Enterprise Architecture Management to enforce continuous Business-IT alignment and external responsiveness (Beese et al., 2023).

- **Technocratic Bias (Human-Centricity Gap - KAD9):** A pronounced deficit emerges in the domain of Human-Centric Design (KAD9), sharply contrasting with the literature's focus on post-hoc workforce adaptation. While existing frameworks extensively address user training and trust-building as deployment imperatives, procedural operationalization of user-centric design remains superficial. Only 33 percent of the models incorporate explicit UX design phases, participatory prototyping workshops, or continuous user feedback loops. The majority of frameworks exhibit a technocratic focus, prioritizing algorithmic performance over usability or ergonomic workforce integration (Chapman, 2000; Hasterok & Stompe, 2022; Kaur et al., 2025). Consequently, the literature implicitly treats users as passive recipients to be managed rather than active co-creators in the development loop. This imbalance contributes to well-documented deployment challenges, where technically robust systems suffer from poor algorithm-to-task fit or misaligned user interfaces, despite adequate change management.

Operationalization Gap (Data Governance - KAD2&4): Finally, a nuanced examination reveals a significant operationalization gap in both Data Governance (KAD 2) and Strategic Sponsorship (KAD 4), characterized by a discrepancy between problem awareness and solution operationalization. While approximately 85 percent of the models acknowledge these dimensions as requirements (e.g., Gupta et al., 2024; Saxena et al., 2024 regarding KAD2) (e.g., Agbaakin, 2025; Beck, 2025 regarding KAD 4), most remain at a high level of abstraction and are classified only as partially compliant. Only 18 to 24 percent of the models provide concrete and fully operationalized artifacts, such as compliance checklists, role descriptions, or budgeting templates, to bridge this gap (e.g., Peukert, 2025; Wendt, 2025 for KAD 2) (Harlacher et al., 2023; Kutzias et al., 2023 for KAD 4). This leaves organizations with a clear understanding of the risks but insufficient tools to mitigate them, creating a persistent implementation bottleneck.

In summary, the gap analysis provides a compelling rationale for the construction of a consolidated AI Adoption Model that integrates the strengths of existing approaches while addressing their structural limitations. While Wendt (2025) and Kutzias et al. (2023) provide the necessary structural coherence to serve as a foundation, the broader research landscape remains insufficient to address the holistic complexity of AI adoption due to the identified biases. Therefore, the subsequent model development systematically integrates these robust foundational structures with targeted high-performance method chunks from the wider corpus. This synthesis systematically resolves the identified deficits in market responsiveness, participatory human-centric design, and actionable data governance, effectively closing the gap between theoretical problem awareness and procedural execution.

7 Integrated Sociotechnical AI Reference model (ISAR-M)

Building directly upon the preceding gap analysis, this section presents the Integrated Sociotechnical AI Reference Model (ISAR-M) (see Figure 5). To address existing research fragmentation, the artifact is designed to operationalize the principle of joint optimization (Trist, 1981; Sarker et al., 2019). By enforcing a continuous parallel consideration of technological, organizational, environmental, and human-centric dimensions, the ISAR-M seeks to mitigate the risk of sociotechnical misalignment where technical maturity exceeds organizational maturity.

First, the model establishes a structural dual backbone derived from Wendt (2025) and Kutzias et al. (2023). These specific artifacts were selected as the primary foundation because they exhibited the highest degree of overall completeness relative to the identified Key Adoption Determinants. This comprehensive coverage ensures the foundational backbone captures the necessary breadth of factors required to manage complex sociotechnical transitions, mitigating the risk of structural inertia caused by overlooked variables (Hannan & Freeman, 1984).

Second, this foundation is augmented via a best-of-breed approach. For each of the eleven KADs, the backbone was systematically enriched using specific high-performance artifacts extracted from the pool of models that achieved a "Fully Compliant" rating for that specific determinant. This synthesis ensures that the resulting ISAR-M serves as an optimized procedural framework. It combines the holistic scope of the primary backbone with specialized procedural steps necessary to manage the reciprocal dependency between autonomous AI agents and human actors (Altepost et al., 2024).

The resulting process model structures the adoption lifecycle into four phases: Evaluate, Design, Realize, and Operate. To address the potential for sociotechnical misalignment, each phase enforces the parallel execution of organizational and technical workstreams, ensuring that technical maturity does not outpace social structures (Grisold et al., 2025; Sarker et al., 2019). This ensures the synchronized progression of human and technological readiness. The process flow is governed by a modified Stage-Gate Mechanism functioning as synchronization points to prevent temporal asynchrony (Sira, 2025). These nodes trigger immediate termination if technical capabilities outpace the requisite social structures (Leonard-Barton, 1988; Mikalef & Gupta, 2021). This mechanism protects organizations from premature scaling and misaligned deployments. In terms of granularity, the model functions as a comprehensive process framework supported by a detailed method specification that prescribes concrete role assignments, granular input/output artifacts, and granular procedural steps to ensure operational accountability and execution readiness. To address potential scalability challenges, the framework distinguishes between Core Activities (mandatory for structural integrity) and Conditional Activities (adaptable to specific risk contexts). This differentiation enables organizations to instantiate a roadmap tailored not only to organizational size, but also to regulatory environments, and domain-specific security requirements (e.g., critical infrastructure or healthcare). To ensure the proposed model functions as an actionable artifact rather than a purely conceptual framework, the following sections detail each phase through a standardized method description. This specification defines the activity, clarifies whether it is a mandatory core element or a risk-dependent conditional step, articulates the underlying goal and rationale, outlines the explicit process steps grounded in the literature, and identifies the responsible roles and required input and output artifacts. The corresponding specification tables are provided at the end of each phase description.

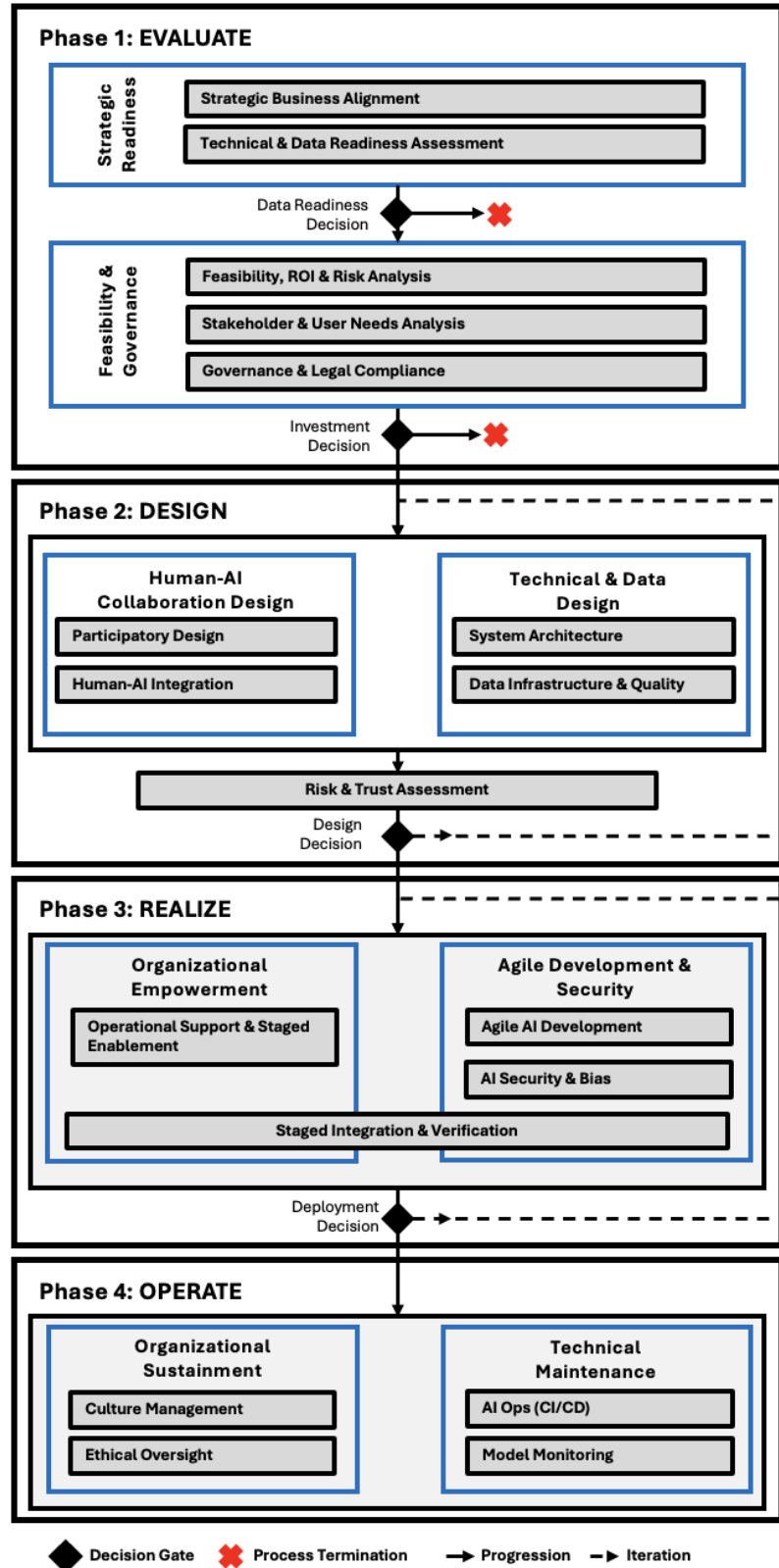


Fig. 5 The Integrated Sociotechnical AI Reference Model (ISAR-M)

7.1 Evaluate

The process (Figure 5) initiates with the Evaluate Phase, which serves to systematically de-risk the investment by diagnosing potential sociotechnical misalignment prior to financial or organizational commitment. To ensure the initiative responds effectively to external competitive pressures, the process begins within the Strategic Readiness block. Here, the organization executes Strategic Business Alignment. Unlike traditional models that focus solely on internal goals, this activity utilizes foresight techniques to identify emerging growth areas and conducts market scanning to ensure the solution aligns with external market velocity (KAD 11) rather than temporary technology hype (De Silva & Alahakoon, 2022; Wendt, 2025). By grounding the initiative in external relevance, the model mitigates the risk of developing technically sophisticated but strategically obsolete solutions.

Concurrently, the organization targets the foundational requirements through a Technical and Data Readiness Assessment. This step moves beyond conceptual architecture to an empirical infrastructure audit (KAD 3) and a dedicated feasibility study (Kutzias et al., 2023; Wendt, 2025). This parallel assessment is critical for identifying early signs of temporal asynchrony, where strategic ambition exceeds technical maturity. Consequently, the Data Readiness Decision Gate acts as the first formal termination point. If the assessment reveals insufficient data assets or inadequate data quality (KAD 1), the project is terminated to prevent structural inertia and avoid downstream rework.

Upon passing this filter, the process deepens into Feasibility and Governance. Here, the organization must quantify financial projections by incorporating preliminary make-or-buy cost estimates (KAD 4) and ranking opportunities using value-risk prioritization (KAD 5) (Wendt, 2025). In parallel, the organization must Analyze Stakeholders and User Needs. This involves not only identifying key players but actively creating persona profiles and user journey maps to visualize how the AI will impact daily work routines (Kutzias et al., 2023; Voorde, 2024). This ensures that human-centric considerations are embedded from the outset rather than retrofitted later. The phase concludes with the establishment of Governance and Legal Compliance (KAD 2) to operationalize data governance and regulatory requirements (Wendt, 2025). This holistic assessment culminates in the Investment Decision Gate, where the organization formally commits to the project only if the triad of strategic value, technical feasibility, and legal compliance is fully satisfied.

Table 2 ISAR-M Phase Evaluate

Activity & Nature	Goal (Rationale)	Process Steps & Literature Evidence	Roles & Key Artifacts
PHASE 1: EVALUATE			
<i>Sub-Group: Strategic Readiness</i>			
1.1 Strategic Business Alignment <i>Nature: Mandatory (Core)</i>	Ensure the AI initiative involves future market trends and supports high-level business objectives rather than being technology-led.	• Strategic Foresight: Utilize foresight tools to identify “potential growth areas” (Wendt, 2025) and conduct market scanning of deployed systems (De Silva & Alahakoon, 2022). • Define Value: Map proposed projects to measurable KPIs (e.g., revenue, cost, satisfaction) to secure executive legitimacy (Wendt, 2025). • Business Modeling: Utilize the Business Model Canvas to explicitly define value propositions and cost structures (Kutzas et al., 2023). • Technique (GenAI): Use a “Strategic Value Matrix” to classify the initiative (e.g., Growth Driver vs. Efficiency Booster) (Wildhirt et al., 2025).	Roles: Senior Leadership, CAIO. Artifacts: Strategic Alignment Map, Value Proposition Definition.
1.2 Technical & Data Readiness <i>Nature: Mandatory (Core)</i>	Verify that the existing IT and data landscape can actually support the proposed solution.	• Infrastructure Audit: Review hardware, software, and data pipelines to identify gaps (Wendt, 2025). • Data Feasibility Study: Execute a “strongly reduced project” focusing exclusively on data availability and quality (Kutzas et al., 2023).	Roles: Data Engineer, IT Architect. Artifacts: Readiness Assessment Report, Data Feasibility Study.
GATE 1A: DATA READINESS DECISION → <i>Outcome: Pass/Fail (Terminate if data quality insufficient).</i>			
<i>Sub-Group: Feasibility & Governance</i>			
1.3 Feasibility, ROI & Risk Analysis <i>Nature: Mandatory (Core)</i>	Quantify the financial viability and rank opportunities based on value vs. risk.	• Financial Projection: Project gains (Wendt, 2025), weighing setup costs against customization benefits (Hussain & Rizwan, 2024). • Opportunity Ranking: Use a “Prioritization Matrix” to rank ideas based on Value, Feasibility, and Strategic Alignment (Wendt, 2025). • Non-Monetary Goals (Conditional): Apply “Utility Analysis” when ROI is difficult to project (Kutzas et al., 2023).	Artifacts: Initial ROI & Risk Analysis, Utility Analysis.
1.4 Stakeholder & User Needs Analysis <i>Nature: Mandatory (Core)</i>	Identify user competence gaps and resistance points early to prevent adoption failure.	• Needs Assessment: List addressees and assess specific requirements (Kutzas et al., 2023). • User Profiling: Develop Persona Profiles to model needs and pain points (Kutzas et al., 2023). • Readiness Survey: Survey “Mental Readiness” (Fear vs. Curiosity) and Data Literacy (Schümann, 2024).	Artifacts: Stakeholder Requirement Matrix, User Journey Map, Cultural Readiness Scorecard.
1.5 Governance & Legal Compliance <i>Nature: Core / Conditional</i>	Create the decision-making structures and legal safeguards required for ethical operation.	• Policy Creation (Core): Develop AI Policy Handbook integrating legal (EU AI Act) and ethical standards (Wendt, 2025). • Purpose Definition (Core): Explicitly define “Intended Use” and exclusion criteria (Kim et al., 2023). • DPIA (Conditional): Execute Data Protection Impact Assessment for High Risk/EU (Kutzas et al., 2023).	Roles: Legal Counsel, Ethics Officer. Artifacts: AI Governance Framework, AI Policy Handbook, DPIA.
GATE 1B: INVESTMENT DECISION → <i>Outcome: Signed Investment Agreement (Go/No-Go based on Business Case & Risk).</i>			

7.2 Design

Following investment commitment, the Design Phase translates high-level requirements into concrete, operational specifications. This phase addresses the mutual interdependence between the technical artifact and the social system, recognizing that the tool shapes the user and the user behavior in turn shapes the tool (Altepost et al., 2024). To integrate the principles of human-centric design, the left-hand stream mandates a Human-AI Collaboration Design process involving Participatory Design. This engages end-users directly in the creation of interaction flows through mock-ups and early prototypes, ensuring that explainability requirements (KAD 9) are defined by those who will actually work with the system (Kim et al., 2023), rather than solely by engineers (Ruess et al., 2024). By grounding design decisions in lived work practices, the model reduces the risk of later resistance and enhances cognitive fit between human and machine.

In parallel, the Technical and Data Design stream focuses on defining a scalable system architecture. A pivotal component is the definitive Make-or-Buy Decision, which determines whether the organization will develop a proprietary model or configure a market-ready solution (Kutzas et al., 2023). The organization must then Design Operational Workflows by explicitly modeling the Human-Machine Interfaces (Kutzas et al., 2023). This step clarifies the division of labor, determining which tasks are suitable for automation and which require human judgment to establish structural agility (KAD 6) (Kutzas et al., 2023). These workflow models ensure that technical design choices remain aligned with organizational processes and competencies.

These parallel efforts merge into a dedicated Risk and Trust Assessment. In this activity, the conceptual model is assessed for privacy compliance, cybersecurity vulnerabilities (De Silva & Alahakoon, 2022), and

conviviality to ensure the system enhances rather than replaces human autonomy (Anagnostopoulou et al., 2024; Dusdal et al., 2023). The results feed into the Design Decision Gate. If the assessment reveals unmitigated ethical, security, or trust-related risks, the project is either terminated or returned for redesign. This gate thereby enforces the principle of joint optimization by ensuring that technical specifications remain consistent with the integrity of the social subsystem (Trist, 1981).

Table 3 ISAR-M Phase Design

Activity & Nature	Goal (Rationale)	Process Steps & Literature Evidence	Roles & Key Artifacts
PHASE 2: DESIGN			
<i>Sub-Group: Human-AI Collaboration Design</i>			
2.1 Participatory Design <i>Nature: Mandatory (Core)</i>	Involve end-users in the design of the interaction flow to ensure usability and explainability.	• Mock-up Workshops: Co-create interaction flows with end-users to test decision behavior (Ruess et al., 2024; Kim et al., 2023). • Explainability Requirements: Define XAI needs based on user trust requirements (Kutzius et al., 2023).	Roles: UX Researcher, End-Users, PO. Artifacts: User-Designed Interaction Flow, Usability & Explainability Specs.
2.2 Human-AI Integration <i>Nature: Mandatory (Core)</i>	Define how humans and machines interact in the new process to ensure structural agility.	• Human-Machine Interface (HMI): Explicitly model responsibility transfer between algorithm and human (Kutzius et al., 2023). • Task Allocation: Assess "Task Routinization" to determine automation vs. human judgment (Kutzius et al., 2023). • SOP Updates: Reconfigure Standard Operating Procedures for the new workflow (Wendt, 2025).	Artifacts: HMI Responsibility Matrix, Integrated Workflow Definition.
<i>Sub-Group: Technical & Data Design</i>			
2.3 System Architecture <i>Nature: Mandatory (Core)</i>	Define the technical skeleton and sourcing strategy to dictate the subsequent development path.	• Make-or-Buy Decision: Determine sourcing strategy based on expertise and costs (Kutzius et al., 2023). • Architecture Design: Define scalable architecture (e.g., Microservices) (De Silva & Alahakoon, 2022). • Vendor Validation (Conditional): Check compatibility, SLAs, and ethics for Buy-solutions (Beck, 2025).	Roles: AI Architect, Lead Developer. Artifacts: Make-or-Buy Decision Paper, System Architecture Diagram.
2.4 Data Infrastructure & Quality <i>Nature: Mandatory (Core)</i>	Construct a unified repository and rigorously verify data utility.	• Data Pipeline Design: Specify ETL processes and cleaning protocols (Wendt, 2025). • Quality Assurance: Acceptance testing for data completeness and correctness (Hasterok & Stompe, 2022). • Labeling Strategy: Define ground truth generation (In-house vs. Crowdsourcing) (Kutzius et al., 2023).	Artifacts: ETL Design Spec, Data Quality Report.
2.5 Risk & Trust Assessment <i>Nature: Mandatory (Core)</i>	Rigorous analysis of the conceptual model for ethical, privacy, and safety risks.	• Privacy & Security Audit: Assess design for compliance and adversarial vulnerabilities (De Silva & Alahakoon, 2022). • Conviviality Check: Ensure the system enhances rather than replaces human autonomy (Dusdal et al., 2023). • ALTAI Assessment (Conditional): Trustworthiness check for EU/High Standards (Anagnostopoulou et al., 2024).	Artifacts: Risk Assessment Report, ALTAI Compliance Report.
GATE 2: DESIGN DECISION → <i>Outcome: Approved Design Specification (Risk & Trust Cleared).</i>			

7.3 Realize

The Realize Phase manages the transition to implementation. This phase navigates the inherent tension where technical iteration velocity typically exceeds organizational absorption capacity. Instead of assuming that both trajectories naturally remain aligned, the model enforces the parallel advancement of technical construction and organizational adaptation to prevent a widening maturity gap.

On the technical track, the Agile Development and Security block executes Agile AI Development (Wildhirt et al., 2025). Whether through iterative coding sprints for proprietary models or through API integration for commercial solutions, the technical artifact evolves rapidly. To ensure robustness, this is paired with AI Security and Bias Protocols (KAD 10) to rigorously test for vulnerabilities, adversarial risks, and demographic fairness (Kim et al., 2023; Wendt, 2025).

To support parallel maturation, the Organizational Empowerment block runs concurrently. Drawing on the concept of Real-world Laboratories, the organization creates safe experimentation spaces (Stowasser & Suchy, 2020). These laboratories provide a mechanism for the workforce to test the system in a low-stakes environment. This approach of Staged Enablement prioritizes early familiarization over formal training to prevent cognitive overload and workforce fatigue (KAD 7). While technical development may still proceed faster, this approach aims to reduce the temporal lag of the social subsystem, thereby lowering the likelihood of the technology significantly outpacing human readiness.

Both streams converge in Staged Integration and Verification. This validation sequence integrates a mandatory Fidelity Check to verify the realized artifact against the design specifications defined in the Design Phase (Kutzias et al., 2023; Ruess et al., 2024) before employing silent studies to benchmark technical performance (van der Vegt et al., 2023). This ensures that the system matches user requirements without introducing operational risk. The phase concludes with the Deployment Decision Gate, which authorizes the transition to live operation only if the demonstrated value justifies the projected scaling costs (Porsch & Emler, 2025). This gate ensures that deployment is not driven by technical enthusiasm alone but by validated organizational benefit.

Table 4 ISAR-M Phase Realize

Activity & Nature	Goal (Rationale)	Process Steps & Literature Evidence	Roles & Key Artifacts
PHASE 3: REALIZE			
<i>Sub-Group: Organizational Empowerment</i>			
3.1 Operational Support & Staged Enablement <i>Nature: Mandatory (Core)</i>	Synchronize upskilling with technical maturity by delaying formal qualification until the software is operationally stable.	• Protected Experimentation: Create “Real-world Labs” for testing and qualification needs (Stowasser & Suchy, 2020). • Skills Gap Analysis: Launch data literacy programs for critical reflection (Schümann, 2024; Wendt, 2025). • Role Adaptation: Adapt job descriptions for AI-augmented responsibilities (Kutzias et al., 2023).	Roles: HR, L&D Specialist. Artifacts: Training Curriculum, Skill Gap Analysis, Adapted Job Profiles.
<i>Sub-Group: Agile Development & Security</i>			
3.2 Agile AI Development <i>Nature: Path-Dependent</i>	Build or configure the solution iteratively.	Branching Logic: → Path A (Make): Iterative coding sprints to train stochastic models (Wendt, 2025). → Path B (Buy): Configuration of vendor parameters and API integration (Wildhart et al., 2025). Core (Both): Implement “Rapid Prototyping Sprints” focused on tangible outputs (Wildhart et al., 2025).	Artifacts: Model Codebase OR Config Files, GenKI-Backlog.
3.3 AI Security & Bias <i>Nature: Mandatory (Core)</i>	Protect the system from manipulation and ensure ethical fairness.	• Adversarial Testing: Test vulnerabilities and robustness against noisy input (Wendt, 2025). • Bias Detection: Ensure fairness across demographic subgroups (Kim et al., 2023). • AISeOps: Implement input sanitization to filter harmful prompts/data (Wendt, 2025).	Artifacts: Adversarial Test Report, Bias Audit Certificate.
3.4 Staged Integration & Verification <i>Nature: Mandatory (Core)</i>	Validate the technical artifact against design specifications and test its interaction in a risk-free environment.	• Fidelity Check (Verification): Conduct a mandatory audit comparing the realized system against Phase 2 interaction designs to detect design drift and trigger iterative realignment (Ruess et al., 2024; Kutzias et al., 2023; Expert E2). • Silent Studies/Shadow Mode: Test system without risk to live operations (van der Vegt et al., 2023). • Workflow Testing: Test tool-workflow interaction as a distinct component (van der Vegt et al., 2023). • Value Check: Compare PoC added value against scaling costs (Porsch & Emler, 2025).	Artifacts: Shadow Mode Performance Report, Integration Test Logs.
GATE 3: DEPLOYMENT DECISION → Outcome: Authorization to Deploy (Proof-of-Concept Value Confirmed).			

7.4 Operate

The final Operate Phase is designed to deliver sustained value by countering the natural tendency toward disorder, in both data models and organizational engagement. It consists of three tightly interlinked components: technical maintenance, organizational sustainment, and ethical oversight. The Technical Maintenance block establishes Automated Operations, implementing CI/CD pipelines for automated deployment (Wendt, 2025). A central element is Model Monitoring, which tracks performance indicators to detect data drift, the gradual shift in input distributions that erodes model accuracy. Once drift is identified, automated retraining routines are triggered to restore model performance and ensure the system remains adaptive and reliable over time (Wendt, 2025).

Concurrently, the Organizational Sustainment block executes a Cultural Management program to maintain long-term engagement and prevent erosion of trust (KAD 8). This includes targeted communication strategies, such as myth-busting town halls, to reduce irrational fears and mitigate resistance (Peukert, 2025; Wendt, 2025). Furthermore, the organization actively monitors the psychological impact through Stress Profiles and job satisfaction evaluations to prevent alarm fatigue, ensuring the social subsystem remains resilient (Kim et al., 2023; Stowasser & Suchy, 2020).

To safeguard long-term integrity, the process requires Ethical Oversight via governance bodies such as a Resonance Body (Plafky & Badertscher, 2025). This continuous feedback mechanism protects professional autonomy from algorithmic overreach, ensuring that the sociotechnical system remains balanced, transparent, and adaptable as it evolves.

Table 5 ISAR-M Phase Operate

Activity & Nature	Goal (Rationale)	Process Steps & Literature Evidence	Roles & Key Artifacts
PHASE 4: OPERATE			
<i>Sub-Group: Organizational Sustainment</i>			
4.1 Culture Management <i>Nature: Mandatory (Core)</i>	Secure long-term adoption and foster a positive culture.	• Myth-Busting & Comm: Town halls to explain strategy and reduce fears (Peukert, 2025). • Stress Profiling: Monitor psychological impact and job satisfaction (Stowasser & Suchy, 2020). • Peer Support: Implement "Tandem-Learning" and "AI Ambassador" network (Ruess et al., 2024; Schümann, 2024). • Knowledge Sharing: Maintain central "AI Knowledge Wiki" (Ruess et al., 2024).	Artifacts: Communication Plan, AI Ambassador Network, Stress Reports.
4.2 Ethical Oversight <i>Nature: Conditional</i>	Ensure continuous ethical reflection and protect professional judgment.	• Resonance Body: Maintain body to reflect on ethical cases (Plafky & Badertscher, 2025). • Case Reflection: Discuss issues where AI output conflicted with professional autonomy (Plafky & Badertscher, 2025).	Artifacts: Ethics Audit Report, Incident Register.
<i>Sub-Group: Technical Maintenance</i>			
4.3 AI Ops (CI/CD) <i>Nature: Mandatory (Core)</i>	Ensure robust, automated deployment and monitoring.	• Automated Operations: Implement CI/CD pipelines for deployment and rollback (Wendt, 2025). • Infrastructure Monitoring: Monitor IT metrics (CPU, Memory) alongside model performance (Wendt, 2025).	Artifacts: CI/CD Pipeline Configuration, Rollback Protocol.
4.4 Model Monitoring <i>Nature: Mandatory (Core)</i>	Prevent model decay and ensure technical responsiveness.	• Drift Detection: Monitor for "Data Drift" and trigger immediate re-training (Wendt, 2025). • Retraining Policy: Trigger adjustments immediately when deviations occur (Wendt, 2025).	Artifacts: Drift Monitoring Dashboard, Maintenance Log.

8 Evaluation

This study adopts the Framework for Evaluation in Design Science (FEDS) (Venable et al., 2016), utilizing the Human Risk & Effectiveness strategy. Because AI adoption involves substantial sociotechnical risk, immediate naturalistic deployment would introduce operational vulnerabilities. Therefore, the evaluation prioritizes ex-ante rigor, progressing from an analytical Informed Argument for structural consistency to scenario-based testing of mechanical logic, concluding with a preliminary applicability check through expert interviews.

8.1 Structural Consistency and Requirement Mapping

This part of the evaluation assesses the artifact against the structural quality criteria of completeness and consistency (Prat et al., 2015) to analytically verify that the ISAR-M satisfies the design requirements derived in the analysis phase.

As a structural backbone Wendt (2025) and Kutzias et al. (2023) were selected based on their empirical coverage of the identified Key Adoption Determinants. Their synthesis addresses distinct but complementary operational scopes: Wendt (2025) provides enterprise-level governance architecture, while Kutzias et al. (2023) contributes agile, human-centric adaptability. Their synthesis yields a scalable framework that avoids the limitations inherent in using either model alone, thereby supporting structural completeness across diverse organizational contexts.

While the backbones define the necessary phases, the ISAR-M adds the necessary procedural depth. By integrating specialized method chunks, such as participatory protocols, the model ensures every requirement (KADs) is paired with an executable procedure. This operationalization transforms static phases into a dynamic control loop. The decision gates create internal consistency by requiring dual inputs, structurally preventing technocratic progression without social validation and enforcing joint optimization.

8.2 Scenario-Based Demonstration

To verify the goal efficacy of the proposed artifact, this section employs a descriptive evaluation via illustrative scenarios (Hevner et al., 2004). Following the FEDS strategy of "Human Risk & Effectiveness," this analytical method tests the internal logic of the artifact. To ensure representative validity, the scenarios were explicitly selected to mirror the two primary structural asymmetries identified in the problem analysis: the Internal Focus Bias

and the Technocratic Bias. Consequently, the demonstration focuses on negative path scenarios to verify that the ISAR-M mechanically arrests sociotechnical misalignment before resources are irreversibly committed.

Scenario A: Resource Protection (The Data Readiness Gate):

- Context: An organization initiates a Generative AI project driven by high strategic pressure (*Strategy* = 1), such as an automated customer support bot. However, the underlying data foundation consists of unstructured, consent-ambiguous legacy data.
- Mechanism: Under a traditional Internal Focus model (as identified in the gap analysis), executive sponsorship would typically override technical concerns, authorizing a pilot phase and accruing sunk costs. The ISAR-M, however, imposes the Data Readiness Gate (Phase 1) as a hard constraint. The gate logic necessitates the explicit input of a validated Purpose Binding Report. Since the data lacks cleared consent for this specific purpose, the governance condition (*Governance* = 0) mathematically overrides the strategic fit.
- Outcome: The gate triggers an immediate Stop decision. This demonstrates the model's ability to protect resources by preventing investment in initiatives that are strategically attractive but technically non-viable. The scenario confirms that the ISAR-M systematically blocks premature progression when foundational compliance conditions are unmet.

Scenario B: Sociotechnical Synchronization (The Deployment Gate):

- Context: A predictive maintenance model iterates rapidly within the Real-world Laboratory (Design Phase), achieving high technical accuracy. However, due to time pressure, the team skips the Participatory Co-Design workshops required by the organizational stream, resulting in low organizational readiness.
- Mechanism: A framework affected by from Technocratic Bias would validate the model based solely on its high F1-score and authorize deployment. In the ISAR-M, the Deployment Gate functions as a mandatory synchronization point requiring dual validation inputs. The gate detects the absence of the Workforce Impact Analysis, violating the principle of Joint Optimization.
- Outcome: Despite technical validity, the gate remains closed, triggering a mandatory iteration loop. This prevents Temporal Asynchrony, ensuring that technically valid but socially incompatible solutions cannot proceed until the organizational subsystem reaches the required readiness level.

8.3 Applicability Check

To complement the analytical validation, we conducted a naturalistic applicability check following Rosemann and Vessey (2008). The objective of this evaluation was to assess the utility of the ISAR-M and to identify operational boundary conditions to refine the final artifact design. Data collection relied on semi-structured interviews with the three domain experts detailed in Table 1 to ensure a purposive sampling strategy for a triangulation of sociotechnical perspectives. The Data analysis followed a pattern-matching approach based on condensed interview protocols (Miles & Huberman, 1994). Key concepts were aggregated into a construct matrix (see Table 10) to ensure cross-case comparability. The Aggregation can be seen in Table 11.

Despite their diverse backgrounds, the panel validated the fundamental architectural logic of the artifact. All experts confirmed that the explicit visual separation of the Organizational Stream and Technical Stream is necessary. E1 noted that visualizing the social stream as an equal parallel to engineering legitimizes invisible work, such as culture management, that is frequently cut from project budgets. Furthermore, the experts validated the model as a necessary normative guidance. Regarding Phase 1, E1 and E2 admitted that the strict *Data Readiness Gate* is often porous in current practice where projects proceed under risk. However, E2 explicitly validated the necessity of this strictness to prevent sunk costs, stating that vague requirements in this phase are a primary cause of later project failure.

Operational Frictions and Contextual Divergence:

The evaluation revealed distinct tensions between the prescriptive logic of the draft model and operational constraints which necessitated specific refinements.

- Linearity vs. Iteration: A structural tension emerged regarding the transition from Realize to Operate. E2 (Startup Context) criticized the linear visualization and noted that in agile practice, the completion of a Proof of Concept rarely leads immediately to operations but requires a feedback loop back to the Design phase. This suggests that the model, in its current form, may underrepresent the circular dynamics required in high-velocity development settings.
- Synchronization of Upskilling: Operational critique was directed at the synchronization of Phase 3. E3 warned that upskilling timed too early, specifically before the software is operationally difficult, as training

requires a finished product. This indicates that successful instantiation of the model requires a staggered approach where organizational measures are triggered by technical maturity rather than running strictly simultaneously.

- **Governance Scale:** Contextual divergence appeared regarding governance scope. While E1 validated the utility of strict gates to save effort on unviable projects, E2 highlighted that the single-project focus of the model misses critical Internal Dependencies (e.g., lessons from prior initiatives). E2 suggested that without visualizing these cross-functional dependencies, the model risks creating organizational silos, particularly in dynamic startup environments.

Based on these findings, the final version of the ISAR-M presented in this paper underwent a specific iteration cycle to address the identified frictions.

1. **Recursive Feedback Pathway:** To resolve the linearity critique (E2), we placed the linear connector with a recursive feedback pathway in Staged Integration & Verification. This refinement institutionalizes the agile loop, ensuring the model supports iterative prototyping rather than forcing a premature rollout.
2. **Staggered Enablement Logic:** To mitigate the risk of training fatigue (E3), we refined the upskilling activity in the Design Phase. We split the generic requirement into Exploratory Prototyping (low-stakes familiarization) and Formal Role Training (high-stakes qualification). This ensures that social readiness matches the maturity of the technical stream.
3. **Core vs. Conditional Classification:** To resolve the governance tension (E1 vs. E2), we introduced a meta-data distinction in the activity descriptions. Activities are classified as Core Activities (mandatory for structural integrity) or Conditional Activities (scalable based on risk). This refinement allows the framework to accommodate varying organizational sizes without compromising the rigor of the decision gates.

9 Discussion

9.1 Theoretical Contribution

Addressing the fragmentation of the AI adoption research landscape, this study consolidates isolated perspectives into a unified prescriptive model. By synthesizing these fragmented adoption models into the prescriptive ISAR-M, this study contributes an instantiation of a theory for design and action (Gregor, 2006). Consistent with this theoretical class, the ISAR-M moves beyond description to offer explicit principles of form and function. This synthesis contributes to the knowledge base primarily by structuring the problem domain and advancing sociotechnical methodology. Specifically, the artifact posits a testable prescriptive principle: by structurally enforcing dual-stream validation (social and technical) at mandatory decision gates, organizations can actively arrest temporal asynchrony and prevent sociotechnical misalignment.

Regarding the structural organization of the heterogeneous domain, this research derives eleven Key Adoption Determinants (KADs) to provide a validated evaluative lens. This taxonomy allows researchers to diagnose structural deficiencies in existing artifacts, specifically identifying the prevalence of Internal Focus and Technocratic biases. This establishes a baseline for understanding why traditional methodologies may inadvertently foster sociotechnical misalignment, providing a diagnostic tool rather than just a descriptive list.

Complementing this diagnostic framework, the study maps the fragmented AI adoption landscape by categorizing existing approaches into five distinct clusters. By categorizing the landscape into Strategic, Engineering, Sociotechnical, SME-specific, and Domain-specific streams, this study highlights the highly specialized nature of current research. Beyond classification, this analysis reveals critical evolutionary trends: notably, the regional divergence between international technical acceleration and the DACH region's emphasis on collaborative design, as well as the shift from *building* algorithms to *integrating* services and the democratization of AI for SMEs. This mapping clarifies that the current lack of a unified standard is a result of fragmented specialization. Drawing on these insights, the subsequent ISAR-M is introduced to propose a synthesis of these divergent perspectives.

In terms of methodological advancement, the ISAR-M operationalizes the methodology of Joint Optimization. While the model's structural foundation ensures empirical coverage, the primary theoretical contribution is the methodological synthesis and temporal synchronization of these components. By integrating distinct engineering and human-centric streams into a unified workflow, the model enforces a specific temporal pacing. Integrating specialized high-performance artifacts into this backbone operationalizes the principle of joint optimization (Trist, 1981). This architectural logic aligns the velocity of the technical stream with the organizational stream, mitigating the risk of temporal asynchrony where technical maturity outpaces the capacity of the social subsystem to adapt.

Concurrently, the artifact advances the operationalization of Embedded Governance. Addressing the identified Operationalization Gap, the ISAR-M translates abstract ethical principles into concrete boundary objects anchored at mandatory Decision Gates. This transforms governance from a passive external oversight function into an active internal design constraint. This ensures that the social subsystem maintains necessary oversight capabilities throughout the technical lifecycle, reducing the likelihood of ethical decoupling.

Consequently, the ISAR-M extends beyond the capabilities of the current state-of-the-art through three specific methodological distinctions:

- From Descriptive Taxonomy to Prescriptive Theory: While comprehensive strategic frameworks (e.g., Wendt, 2025) define vital governance requirements, they often remain at an abstract, descriptive level. The ISAR-M translates these taxonomies into executable design theory by embedding validated, specialized method chunks directly into a cohesive governance structure.
- Architecturally Enforced Synchronization: Prior models typically arrange technical and organizational steps sequentially or rely on consensus-based phase transitions (e.g., Kutzias et al., 2023). The ISAR-M mitigates temporal asynchrony by instituting hard decision gates that mandate dual inputs from both social and technical streams before progression is permitted.
- Continuous Sociotechnical Sustainment: Foundational human-centric models frequently conclude their prescriptive guidance upon deployment. Recognizing the probabilistic nature of machine learning, the ISAR-M introduces a formalized sustainment phase that structurally couples automated technical maintenance with active cultural management to manage long-term sociotechnical co-evolution.

9.2 Managerial Implications

This study responds to the execution gap in AI adoption by offering practitioners a structured mechanism to navigate sociotechnical complexity.

A primary managerial implication is the support for strategic de-risking via empirical gatekeeping. To counter the Internal Focus Bias, managers should apply the Data Readiness Gate to filter projects based on feasibility rather than intent. Consequently, the framework does not necessitate a pre-existing threshold of organizational maturity for deployment. However, its effective application presupposes a baseline of operational capability, comprising domain expertise and technical infrastructure, to enable the organization to initiate, execute, and sustain the proposed ISAR-M process. This mitigates the Strategic Drift by forcing an early termination of initiatives lacking foundational assets, preventing resource misallocation driven by sunk costs.

Regarding process dynamics, the framework provides a mechanism to manage the sociotechnical maturity gap. Recognizing that technical engineering iterates faster than organizational empowerment, the model compels managers to modulate project velocity. By synchronizing technical scaling with the capacity of Real-world Laboratories, practitioners can better navigate the tension between agile development and organizational inertia, thereby reducing the risk of workforce rejection.

From a compliance perspective, the framework facilitates the transition from abstract compliance to auditable trust. By embedding specific artifacts as mandatory input/output objects, the model creates necessary audit points for regulated environments. This proactive identification of governance risks secures the organization's license to operate by addressing ethical liabilities prior to deployment.

Despite this rigor, the framework calls for contextual instantiation rather than rigid adherence. Practitioners are advised to treat the ISAR-M as a configurable reference repository rather than a static checklist. By leveraging the distinction between core activities (essential for structural integrity) and conditional activities (risk-dependent), managers can tailor the governance overhead to the specific project scope. This ensures that procedural rigor remains a supportive guardrail rather than becoming a bureaucratic impediment to agility. To further support this modularity, practitioners might consider mapping the ISAR-M's decision gates and workflows into existing software tools. Digitizing the process could help formalize the necessary documentation and risk assessments without adding excessive manual overhead to agile teams. Integrating these mechanisms directly into established project management environments minimizes disruptive system and media breaks, enabling the seamless generation of audit protocols and the automated documentation of critical decisions.

9.3 Limitations

While this study adheres to Design Science Research guidelines, distinct limitations concerning artifact construction, evaluation, and scope remain.

Regarding artifact construction, the reliance on Assembly-Based Method Engineering introduces a dependency on the selected structural backbones. Consequently, the artifact inherently inherits potential blind spots

from these source models, if foundational models fail to capture latent variables like emerging generative AI risks, this artifact likely shares those limitations. Although this dependency is partially mitigated by the independent derivation of Key Adoption Determinants (KADs), the synthesis of method chunks from heterogeneous sources may still introduce contextual friction. Therefore, the artifact must be understood as a prescriptive Meta-Model requiring careful instantiation rather than a rigid prescription. Additionally, since the problem identification rests on a systematic literature review, the artifact's structure remains sensitive to the specific selection criteria and theoretical lens applied during the initial analysis. Because papers failing to meet these strict structural criteria were completely excluded, the study may have inadvertently missed valuable insights embedded within those discarded works meaning total exhaustiveness cannot be fully guaranteed. Furthermore, the derived list of Key Adoption Determinants is inherently unable to be completely exhaustive due to organizational complexity and should therefore be viewed as a synthesized consensus rather than a definitive taxonomy of all potential adoption variables.

Methodological constraints also extend to the evaluation strategy and scope. Adhering to the FEDS framework, validation remains predominantly *ex ante*, combining analytical scenario-based assessments with semi-structured expert interviews. While demonstrating structural consistency and perceived utility, the study lacks longitudinal summative data confirming that organizations adhering to the ISAR-M outperform others over a full lifecycle. Most critically, because the current evaluation relies primarily on *ex-ante* analytical methods and expert applicability checks, the model has yet to be actively applied and tested end-to-end within a live organizational setting. Moreover, the artifact exhibits a situational boundary: the explicit inclusion of high-governance elements, such as a Works Council or Data Protection Impact Assessments, reflects a distinct orientation towards European regulatory frameworks, potentially constraining applicability in non-European or unregulated contexts.

Finally, the pursuit of joint optimization necessitates a complexity trade-off. The embedding of high-governance artifacts and parallel workstreams demands significant organizational resources to satisfy the identified operationalization gap. Without context-specific tailoring, this granularity risks over-engineering for low-risk use cases or resource-constrained environments. Specifically, the mandatory data artifacts may exceed the operational capacity of smaller organizations, inadvertently inducing the very structural inertia the model aims to mitigate.

9.4 Future Research

While the ISAR-M seeks to address operational gaps, the analysis indicates structural characteristics in the current discourse that frame the trajectory for future inquiry regarding the long-term dynamics and contextual application of such frameworks. Addressing the operational gaps of AI adoption requires the scientific discourse to move from fragmentation toward convergence. We therefore suggest that future research priorities shift toward validating and extending synthesized models such as the ISAR-M. Instead of developing separate novel frameworks for every emerging contextual challenge the discipline would benefit significantly from converging on a shared baseline and systematically iterating upon its design.

Regarding the temporal dimension of sociotechnical alignment, a critical avenue for inquiry emerges from the tendency in existing literature to concentrate on early-stage adoption. This focus suggests a potential oversight regarding the theoretical concept of misalignment over time. As both technical systems and organizational routines are prone to gradual degradation, future research could fruitfully extend the focus from the initial adoption event to AI Sustainment. Longitudinal studies would be valuable to investigate how organizations manage the dual challenge of data drift and cultural fatigue post-deployment, assessing whether the governance structures proposed in this study are sufficient to mitigate this decay over time.

Beyond temporal dynamics, the interface between human expertise and algorithmic learning warrants deeper investigation through Participatory Engineering. The emphasis on technical construction observed in the review suggests that current frameworks frequently limit human involvement to design or validation, treating the training phase as a closed loop. Future inquiry might investigate mechanisms through which non-technical domain experts can remain actively involved during this phase, exploring how they might influence the learning logic of the system to foster a co-evolution of human expertise and machine capability.

In terms of procedural formalization, research should address the operationalization gap by increasing the model's granularity. While the current framework provides a processual structure, future work must define specific execution techniques for individual phases and develop a comprehensive Data Model to formalize the input-output artifacts governing stage transitions. This operationalization could ultimately be supported by the development of a dedicated software tool designed to guide practitioners through the necessary gates, ensuring that the theoretical guardrails are easily executable in daily practice.

Finally, the classification of ISAR-M as a Meta-Model necessitates a rigorous examination of contingency and instantiation. Given the potential cost of alignment inherent in such comprehensive frameworks, future research

should apply Contingency Theory to define their boundary conditions. Empirical studies are recommended to identify the specific threshold where governance overhead might exceed its risk-mitigation value, potentially deriving instantiation rules to assist practitioners in tailoring the model's complexity to varying organizational sizes, risk profiles and regulatory context. Ultimately, validating these dynamics requires a transition to naturalistic inquiry, accompanying a full-scale deployment of the framework within a corporate environment to empirically benchmark its utility.

10 Conclusion

This research investigated the methodological fragmentation within the AI adoption literature to derive a unified prescriptive framework. Addressing the research question, the study first executed a systematic comparative analysis of 45 existing procedural models based on uniform, empirically validated criteria. This evaluation revealed that current approaches are frequently characterized by structural biases, specifically the separation of engineering workflows from strategic management. To address this misalignment, the Integrated Sociotechnical AI Reference Model (ISAR-M) was developed using an assembly-based method engineering approach. By synthesizing disparate method chunks into a holistic process model, the artifact provides the structural guidance necessary to assist organizations in navigating the execution gap between strategic intent and operational reality. Initial expert applicability checks suggest that this structure offers valuable preliminary guidance for practitioners, though future naturalistic deployment remains necessary to fully confirm its practical efficacy.

The findings suggest that scalable AI adoption depends less on isolated technical capabilities than on the rigor of the adoption process itself. Two central insights emerge. First, the model proposes sociotechnical parallelism, characterized by the simultaneous advancement of technical maturity and organizational empowerment, as a critical mechanism to mitigate technocratic bias. Second, the study suggests that abstract governance principles are most effective when operationalized through mandatory decision gates. In this sense, the ISAR-M functions as a synchronization mechanism that stabilizes the design phase by aligning technical feasibility with organizational readiness and ethical compliance across the lifecycle.

As the technical barriers to entry for General Purpose AI continue to lower, the primary challenge for organizations appears to shift toward the sociotechnical dimension. Frameworks like the ISAR-M point towards a future where success is defined not solely by model accuracy, but by organizational compatibility. Thus, the management of AI may increasingly resemble rigorous change management, where the synchronized evolution of workforce capabilities, governance structures, and ethical standards becomes a defining metric for sustainable digital transformation.

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Use of Artificial Intelligence

The authors utilized AI-assisted writing tools during the preparation of this manuscript to support language refinement and text drafting. All AI-generated or AI-assisted content was critically reviewed, revised, and validated by the authors. The authors take full responsibility for the integrity and accuracy of all content presented. No AI tools were used to generate, fabricate, or manipulate research data or figures.

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Appendix – Process models / KADs

Table 6 Process Model Overview

Author (Year)	Title	Type	Sector	Sequence	Methodology
Agbaakin (2025)	Leveraging AI as a Strategic Growth Catalyst...	Preprint	SMEs	4 Phases	Quantitative (Market Data)
Anagnostopoulou et al. (2024)	Trustworthy AI in education: A Roadmap...	Conf. Paper	Education	4 Phases	Conceptual (ALTAI Criteria)
Barjasic (2025)	Praxisorientierter Leitfadens zur Implementierung	Book Chapter	Service Mgmt.	5 Phasen	Action Research (Pilot)
Beck (2025)	KI-Projekte gestalten: Der große Entwurf	Book Chapter	Sales	4 Steps	Strategic Mgmt. Framework
Chapman (2000)	CRISP-DM 1.0	Standard	Data Mining	6 Phases	Framework Definition
Davenport & Ronanki (2018)	Artificial Intelligence for the Real World	Journal	Enterprises	4 Steps	Qualitative (Case Studies)
De Silva & Alahakoon (2022)	An artificial intelligence life cycle...	Journal	General	4 Phases	Taxonomy Development
Didas & Mutajwaa (2025)	Roadmap to Systematic Understanding of AI...	Journal	IT / Dev	4 Steps	Narrative Review
Dukino & Hölzle (2024)	Ein Vorgehensmodell zum systematischen Planen...	Book	Data Science	6 Steps	Framework Definition
Dusdal et al. (2023)	Konviviale Künstliche Intelligenz	Journal	Socio-technical	4 Phases	Conceptual Development
Eberlein et al. (2025)	Schritt für Schritt zur eigenen KI-Lösung	Whitepaper	SMEs	3 Phases	Workshop Method
Gupta et al. (2024)	Strategic Framework for Implementing AI...	Conf. Paper	Organizations	3 Steps	Conceptual Modeling
Haefner et al. (2023)	Implementing and scaling artificial intelligence	Journal	Innovation	3 Steps	Systematic Review
Harlacher et al. (2023)	Roadmap für den Weg zur eigenen KI-Lösung	Book Chapter	Work / Social	5 Steps	Synopsis of Tech Models
Hasterok & Stompe (2022)	PAISE@ – process model for AI systems eng.	Journal	Engineering	7 Phases	Systems Engineering
Hussain & Rizwan (2024)	Strategic AI adoption in SMEs	Preprint	SMEs	5 Stages	Conceptual Framework
Kaur et al. (2025)	Adoption of AI in Cybersecurity...	Journal	Cybersecurity	3 Steps (TOE)	Literature Analysis
Kim et al. (2023)	Organizational Governance of Emerging Tech.	Conf. Paper	Healthcare	8 Points	Grounded Theory
Kohne (2025)	Erfolgreiche Einführung von Künstlicher Intelligenz	Book Chapter	SMEs	4 Steps	Practice-oriented
Kutzas et al. (2023)	Leitfaden zur Durchführung von KI-Projekten	Book	Work Env.	5 Phases	Laboratory Evaluation
Lamba & Kaur (2024)	AI Application Framework For Syst. Onboarding	Journal	Organization	4 Steps	Needs Assessment
Merhi (2021)	A Process Model of AI Implementation...	Conf. Paper	Management	3 Stages	CSF Identification
Mishra & Pani (2020)	Business value appropriation roadmap for AI	Journal	KM	3 Steps	Innovation Strategy
Müller et al. (2021)	Künstliche Intelligenz: Roadmap zur Aufdeckung...	Book Chapter	Digitalization	3 Steps	Case Study Analysis
Nair et al. (2025)	Critical activities for successful implementation...	Journal	Healthcare	3 Steps	QIF Mapping
Oluwamola et al. (2024)	Business Transformation through AI Adoption...	Journal	Agile Ent.	7 Phases	Architecture Analysis
Peukert (2025)	Praktische Lösungsansätze für die Integration...	Book Chapter	Organization	3 Steps	Interactive Training
Plafky & Badertscher (2025)	Strategien für die KI-Implementierung	Book Chapter	Social Work	3 Steps	Neo-institutionalist
Porsch & Emler (2025)	KI- & Daten-Betriebsmodell	Book Chapter	Performance	3 Steps	TOM Approach
Reim et al. (2020)	Implementation of Artificial Intelligence (AI)	Journal	Business	4 Steps	Literature Review
Ruess et al. (2024)	Künstliche Intelligenz in betrieblichen Prozessen	Journal	Ops Processes	4 Steps	Interview Study
Sánchez et al. (2025)	Artificial Intelligence Adoption in SMEs	Journal	SMEs	6 Phases	Survey (TOE-DOI)
Saxena et al. (2024)	Roadmap for AI Implementation in BFSI	Book Chapter	Finance	3 Phases	Case Use Analysis
Schümann (2024)	KI-Readiness – verstehen, akzeptieren, einführen	Book Chapter	General	5 Steps	Practice Roadmap
Shailendra et al. (2024)	Framework for Adoption of GenAI in Education	Preprint	Education	4 Steps	Gap Analysis
Smit et al. (2024)	Towards Human-AI Symbiosis	Journal	Auto / IT	4 Steps	Design Science Research
Stowasser & Suchy (2020)	Einführung von KI-Systemen in Unternehmen	Whitepaper	Enterprises	4 Phases	Expert Whitepaper
Tjondronegoro et al. (2023)	Responsible AI Implementation	Journal	Innovation	4 Steps	Human-centered Design
van der Vegt et al. (2023)	Implementation frameworks for clinical AI	Journal	Clinical	5 Phases	Scoping Review
Voorde (2024)	Navigating towards AI success	Journal	Pharma	5 Steps	Compliance (GMP)
Walter et al. (2021)	A Strategic AI Procedure Model	Conf. Paper	Energy	3 Phases	Top-down Research
Weinberg (2025)	Framework for Adoption of GenAI	Preprint	SMEs	4 Phases	Theoretical Synthesis
Wendt (2025)	AI Adoption & Management Framework	Whitepaper	IT Gov.	6 Steps	Lifecycle Governance
Werner & Schmalenbach (2024)	Navigating AI Adoption	Conf. Paper	SMEs	2 Steps	DSR
Wildhirt et al. (2025)	Generative KI erfolgreich implementieren	Book Chapter	Enterprises	4 Steps	Best Practice

Table 7 Process Model Completeness

Reference	Total Score	Max Score	Completeness (%)
Wendt 2025	22	22	100.00
Kutzias et al. 2023	21	22	95.45
Harlacher et al. 2023	19	22	86.36
van der Vegt et al. 2023	19	22	86.36
De Silva & Alahakoon 2022	19	22	86.36
Wildhirt et al. 2025	18	22	81.81
Beck 2025	18	22	81.81
Plafky & Badertscher 2025	18	22	81.81
Kim et al. 2023	17	22	77.27
Smit et al. 2024	17	22	77.27
Porsch & Emler 2025	17	22	77.27
Stowasser & Suchy et al. 2020	16	22	72.72
Shailendra et al. 2024	15	22	68.18
Nair et al. 2025	15	22	68.18
Saxena et al. 2024	14	22	63.63
Schümann 2024	14	22	63.63
Peukert 2025	14	22	63.63
Voorde 2024	14	22	63.63
Müller et al. 2021	14	22	63.63
Riedel et al. 2024	13	22	59.09
Werner & Schmalenbach 2024	13	22	59.09
Oluwamola et al., 2024	13	22	59.09
Reim et al. 2020	12	22	54.54
Anagnostopoulou et al. 2024	12	22	54.54
Walter et al. 2021	11	22	50.00
Weinberg 2025	11	22	50.00
Barjasic 2025	11	22	50.00
Tjondronegoro et al. 2022	11	22	50.00
Hasterok & Stompe 2022	11	22	50.00
Hussain & Rizwan 2024	11	22	50.00
Kohne 2025	11	22	50.00
Chapman 2000	10	22	45.45
Merhi 2021	10	22	45.45
Kaur et al. 2025	10	22	45.45
Eberlein et al. 2025	10	22	45.45
Dusdal et al. 2023	10	22	45.45
Ruess et al. 2024	9	22	40.90
Haefner et al., 2023	9	22	40.90
Lamba & Kaur 2024	8	22	36.36
Gupta et al., 2024	8	22	36.36
Davenport & Ronanki 2018	7	22	31.81
Sánchez et al. 2025	7	22	31.81
Agbaakin 2025	7	22	31.81
Mishra & Pani 2020	6	22	27.27
Didas & Mutajwaa 2025	2	22	9.09

Table 8 Heatmap Coverage of KADs in Process Models

Dimensions	Key Adoption Drivers (KADs)	Ratio of Models			Total	Coverage % (by Compliance)			Cov. % Any [*]
		Not	Partial	Full		Not	Partial	Full	
I: Technology & Data	1. Data Availability & Quality	4	27	14	45	9	60	31	91
	2. Data Governance, Security & Privacy	7	27	11	45	16	60	24	84
	3. IT Infrastructure & Interoperability	3	34	8	45	7	76	18	93
II: Organization & Strategy	4. Strategic Sponsorship & Fin. Viab.	7	30	8	45	16	67	18	84
	5. Perceived Relative Advantage	0	24	21	45	0	53	47	100
	6. Structural Agility & Processes	3	26	16	45	7	58	36	93
III: Human-Centricity	7. Workforce Competence	4	26	15	45	9	58	33	91
	8. Cultural Acceptance & Trust (XAI)	4	24	17	45	9	53	38	91
	9. Human-Centric Design (UX)	16	14	15	45	36	31	33	64
IV: Environment	10. Responsible AI & Regulatory	6	24	15	45	13	53	33	87
	11. Market Responsiveness	16	20	9	45	36	44	20	64

^{*} Note: The 'Coverage % Any' metric aggregates models classified as either partially or fully compliant.

Table 9 Thematic Clustering of Process Models (Total N=45)

Cluster Name	Focus	Included Papers (Authors)	Count
Cluster 1: The Strategic Perspective (<i>Management & Governance</i>)	Strategic alignment, governance structures, business models, and organizational anchoring.	- Davenport & Ronanki (2018) - Porsch & Emler (2025) - Plafky & Badertscher (2025) - Wendt (2025) - Wildhirt et al. (2025) - Peukert (2025) - Oluwamola et al. (2024) - Gupta et al. (2024) - Lamba & Kaur (2024) - Schümann (2024) - Haefner et al. (2023) - Merhi (2021) - Mishra & Pani (2020) - Walter et al. (2021) - Reim et al. (2020)	15
Cluster 2: The Engineering Perspective (<i>Technical Lifecycle</i>)	Technical lifecycle, Data Science processes, Systems Engineering, and development methodology.	- Didas & Mutajwaa (2025) - De Silva & Alahakoon (2022) - Hasterok & Stompe (2022) - Müller et al. (2021) - Chapman (2000)	5
Cluster 3: The Sociotechnical Perspective (<i>Human-Centric</i>)	Human-machine interaction, Change Management, participation, ethics, and culture.	- Smit et al. (2024) - Ruess et al. (2024) - Harlacher et al. (2023) - Dusdal et al. (2023) - Kutzias et al. (2023) - Tjondronegoro et al. (2023) - Stowasser & Suchy (2020)	7
Cluster 4: SME-Specific Adoption	Models explicitly developed for Small and Medium-sized Enterprises (SME) or the mid-market.	- Agbaakin (2025) - Sánchez et al. (2025) - Weinberg (2025) - Kohne (2025) - Eberlein et al. (2025) - Dukino & Hölzle (2024) - Werner & Schmalenbach (2024) - Hussain & Rizwan (2024)	8
Cluster 5: Domain-Specific Implementation	Adaptation of AI models for specific industries such as healthcare, education, finance, or sales.	- Beck (2025) - Barjasic (2025) - Nair et al. (2025) - Kaur et al. (2025) - Shailendra et al. (2024) - Saxena et al. (2024) - Anagnostopoulou et al. (2024) - Voorde (2024) - van der Vegt et al. (2023) - Kim et al. (2023)	10

Appendix – Expert Applicability Check

Table 10 Interview Guideline Structure

ID	Topic	Question / Prompt
Part 1: Background & Context (<i>Purpose: Establish profile, bias, and maturity</i>)		
Q1	Demographics & Maturity	Could you briefly describe your current role and your specific touchpoints with AI projects? How would you rate your organization's AI maturity on a scale from 1 (Experimental) to 5 (Highly Industrialized)?
Q2	Phase Focus	Looking at the four phases of the model (Evaluate, Design, Realize, Operate), where does your personal professional focus typically lie?
Part 2: Structural Validity (<i>Purpose: Assess logical flow and cognitive grasp</i>)		
Q3	Intuitive Flow	Please scan the entire model visually. Does the graphical representation guide you intuitively through the process, or are there areas where your gaze "gets stuck" or the sequence appears unclear?
Q4	Reality Check	Compared to the reality in your organization: Does this linear flow (including the feedback loops) reflect the actual dynamics of your AI projects, or do your structural processes deviate significantly from this?
Part 3: Detailed Phase Evaluation (<i>Purpose: Validate specific constructs and gates</i>)		
<i>Phase 1: Evaluate</i>		
Q5	Data Readiness Gate	Reflecting on the "Data Readiness Decision" (depicted as a strict stop/go gate): How does your organization proceed if technical/data readiness is deemed insufficient? Are projects actually stopped, or often continued under caveats?
Q6	Feasibility Scope	Looking at the "Feasibility & Governance" block: From your perspective, is there a critical aspect missing that is mandatory for a sound "Investment Decision"?
<i>Phase 2: Design</i>		
Q7	Socio-Technical Balance	The model visually places "Human-AI Collaboration Design" on equal footing with "Technical & Data Design." Is this weighting a reflection of your lived practice, or is it an aspirational goal?
Q8	Risk Assessment Timing	We have placed the "Risk & Trust Assessment" as a design decision gate at the end of this phase. Based on your experience, is this the correct timing, or should this validation happen earlier/differently?
<i>Phase 3: Realize</i>		
Q9	Parallelism (Tech vs. Org)	The model suggests that "Organizational Empowerment" (e.g., Upskilling, Support) runs parallel to technical "Agile Development." How practicable and resource-feasible is this parallelism in your daily operations?
Q10	Staged Integration	We highlight "Staged Integration" as a separate entity. What specific challenges do you see in the transition from agile development to integration that justify (or refute) this emphasis?
<i>Phase 4: Operate</i>		
Q11	Organizational Sustainment	This phase includes "Culture Management" and "Ethical Oversight." How do you operationalize such "soft" factors in continuous operations? Are these continuous processes or punctual audits?
Q12	Success Metrics	Beyond technical "Model Monitoring": What other success metrics (e.g., Business Value, ROI, User Adoption) must be anchored here to justify long-term operations to management?
Part 4: Utility & Impact (<i>Purpose: Evaluate pragmatic value</i>)		
Q13	Problem Solving	Which common problem or misunderstanding in AI projects could be avoided by the consistent application of this model?
Q14	Applicability	Could you imagine using this model as a "High-Level Roadmap" or checklist in your next project kickoff? (Why / Why not?)
Q15	The "Magic Wand"	If you could change, delete, or add one box, arrow, or decision in this model to make it fit your ideal way of working perfectly—what would it be?
Part 5: Conclusion		
Q16	Omissions	Is there a significant aspect (e.g., Compliance, External Partners, Budgeting) that we have completely overlooked in this process flow?

Table 11 Evidence Matrix and Concept Aggregation

Construct / Topic	Aggregated Findings (2nd Order)	Representative Evidence (Translated Data Extracts)
Structural Validity (Q3: Visual Flow, Q4: Reality Check)	Non-Linear Reality: The linear flow is generally accepted, but experts emphasize the cyclical nature of AI (loops) and the need for context-specific jumps (e.g., MVP logic, Privacy checks).	• E1: "More of a cycle than a linear process due to optimization loops." / Flow fits reality. • E2: Missing return loop from Realize to Design (MVP logic). Phase 2 is shorter for startups. • E3: Generally logical. Needs jumps to earlier phases for specific blockers (e.g., Data Privacy).
The "Blind Start" Phenomenon (Q5: Data Readiness)	Business Priority over Technical Readiness: Contrary to the model's strict "stop" gate, organizations often proceed without full data readiness due to ROI pressure or lack of information.	• E1: Business Case often precedes readiness check; projects start to see "if effort is worth it." • E2: Lack of readiness does not stop process; "Service on top" used to fix data later. • E3: Critical info (e.g., data quality) often missing at this stage; projects continue "blindly."
Investment Decision Factors (Q6: Feasibility)	Stakeholder & Trust Gaps: The model focuses on hard factors; experts highlight soft hurdles (trust, capacity) as critical for investment decisions.	• E1: No additions. • E2: Missing: Stakeholder capacity, skepticism/trust evaluation, and alignment on results. • E3: Current model coverage is sufficient.
Socio-Technical Gap (Q7: Balance)	Aspiration vs. Reality: High agreement on the necessity of "Human-AI" design, but admission that it is systematically neglected in practice.	• E1: "Wishful thinking rather than reality"; human aspect gets less attention. • E2: Tech is weighted higher; logic breaks in Operate phase causing disappointment. • E3: Both equally essential; collaboration is key to success.
Risk Gating (Q8: Assessment Timing)	Timing Validation: Unanimous agreement on the placement of the risk gate.	• All Experts: Confirmed the position of the Risk & Trust Assessment as correct/sensible.
Realization Dynamics (Q9: Parallelism, Q10: Staged Integration)	Contextual Friction: Parallel execution (Tech + Org) works for agile startups but faces resource/logic hurdles in corporates. Security is a major constraint for integration.	• E1: Parallelism unpractical (resource constraints). Integration only for "Ambassadors," not general users. • E2: Parallelism very feasible (Delivery Meetings). Distinction between Dev/Staging/Prod essential. • E3: Parallelism difficult (Training requires finished product). Security rules prevent "unfinished" integration.
Sustainment & Operations (Q11: Culture/Ethics)	Process vs. Audit: Culture is seen as a long-term continuous struggle; Ethics requires formalization (audits) which is currently often lacking.	• E1: Culture often neglected. Ethics requires concrete checks/audits. • E2: Continuous improvement with spot audits. • E3: Culture takes years to change. Ethical oversight must be embedded in safety culture + audits.
Success Measurement (Q12: Monitoring)	Beyond Model Accuracy: Need to expand metrics to include ROI, Capacity, and Speed.	• E1: Impact on different groups (Internal vs. Customer). • E2: ROI vs. Cost (FTE), freed-up capacity, speed, subjective result quality. • E3: Use-case specific metrics.
Utility & Applicability (Q13: Problem Solving, Q14: Roadmap Use)	Guidance & De-Risking: The model is validated as a tool to prevent "scope creep" and "late blockers" (legal/privacy), serving as a high-level roadmap.	• E1: Saves effort on unviable projects; clarifies complexity. Too high-level for immediate use without examples. • E2: Prevents missing milestones; ensures early user involvement. • E3: Clears blockers (Legal/Finance) early; acts as a preparation checkpoint.
Model Refinement (Q15: Magic Wand, Q16: Missing Aspects)	Feedback Loops & Externalities: Requests to visualize the iterative loops (MVP) and external dependencies (Sales/Vendor selection) more clearly.	• E1: Simplify complexity. Add Ethical Oversight to Realize phase. • E2: Add feedback loop from Realize → Design (Iterative MVP). Add "Sales Perspective" and "Internal Dependencies." • E3: Stronger focus on Process/Domain knowledge in Design.

Note: Derived from Interview Questions 3-16

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [AllTables.docx](#)