Implementing Artificial Intelligence in Data-Driven Enterprises through a Ten-Phase Framework Based on Multiple Case Studies

Упровадження штучного інтелекту в орієнтованих на дані підприємствах на основі десятифазової моделі, розробленої за результатами кількох кейс-досліджень

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Purpose. To develop and empirically validate a ten-phase framework for the implementation of artificial intelligence (AI) in data-driven enterprises, conceptualizing AI adoption as a socio-technical transformation integrating strategic, technological, and human dimensions.

Method. Multiple case study design combined with Design Science Research. Data were collected from twelve enterprises across manufacturing, logistics, and healthcare sectors through interviews, workshops, process datasets, and surveys. Cross-case and within-case analyses were used to validate and refine the framework.

Findings. Organizations that completed all ten phases recorded measurable gains: +14% operational efficiency (OEE); –32% decision latency; +11% first-pass yield (FPY); >80% user adoption of AI-supported systems. Success depended less on algorithms and more on data integrity, strategic alignment, human participation, and embedded governance.

Theoretical implications: Integrates fragmented models (CRISP-DM, AI Maturity Models, TOE) into a unified, process-oriented framework; redefines AI maturity as a dynamic capability-building process; extends socio-technical systems theory by proving that human participation accelerates AI adoption.

Practical implications. Provides a replicable roadmap for scaling trustworthy and regulation-compliant AI aligned with the EU AI Act and ISO/IEC 42001. Demonstrates that data governance, competence development, and early compliance reduce failure risk and long-term cost.

Value. The first empirically validated end-to-end managerial framework linking strategy, data governance, human competence, and regulatory accountability into a single model for AI transformation. Bridges the gap between AI research and enterprise-level implementation.

Paper type. Empirical multiple-case study with a design-science contribution.

Мета дослідження. Розробити та емпірично підтвердити десятифазову модель упровадження штучного інтелекту (ШІ) у датаорієнтованих підприємствах, розглядаючи інтеграцію ШІ як соціально-технічну трансформацію, що поєднує стратегічні, технологічні та людські аспекти.

Метод дослідження. Методологія багаторазового кейс-дослідження у поєднанні з підходом Design Science Research. Дані зібрано в дванадцяти підприємствах промисловості, логістики й охорони здоров'я за допомогою інтерв'ю, робочих сесій, процесних масивів даних та опитувань. Перехресний та внутрішньокейсовий аналіз застосовано для перевірки й уточнення моделі.

Результати дослідження. Підприємства, що пройшли всі десять фаз, досягли підтверджених результатів: +14% зростання операційної ефективності (OEE); –32% скорочення часу ухвалення рішень; +11% підвищення частки першого придатного виробу (FPY); >80% рівень прийняття систем ШІ користувачами. Ключовими чинниками успіху виявилися не алгоритми, а цілісність даних, стратегічна узгодженість, залучення персоналу та вбудоване управління.

Теоретична цінність дослідження. Інтегрує розрізнені моделі (CRISP-DM, моделі зрілості ШІ, TOE) в єдину процесно орієнтовану систему; трактує зрілість ШІ як динамічне нарощування спроможностей; поглиблює соціально-технічну теорію, доводячи, що участь людей прискорює впровадження ШІ.

Практична цінність дослідження. Пропонує відтворювану дорожню карту для масштабування надійного та нормативно узгодженого ШІ відповідно до Європейського AI Act та ISO/IEC 42001. Доводить, що управління даними, розвиток компетентностей і раннє впровадження механізмів комплаєнсу мінімізують ризики та знижують витрати.

Цінність дослідження. Перша емпірично підтверджена наскрізна управлінська модель, що поєднує стратегію, управління даними, людські компетентності та регуляторну підзвітність у єдиній системі трансформації на основі ШІ. Усуває розрив між теорією ШІ та практикою підприємств.

Тип статті. Емпіричне багатокейсове дослідження з елементами Design Science.

Key words: artificial intelligence, digital transformation, socio-technical systems, data governance, trustworthy AI, organizational maturity.

Ключові слова: штучний інтелект, цифрова трансформація, соціотехнічні системи, управління даними, надійний ШІ, організаційна зрілість.

Introduction

Artificial intelligence (AI) has rapidly evolved from an experimental technology into a core enabler of digital transformation across industries. As enterprises increasingly rely on data to optimize operations, enhance decision-making, and drive innovation, AI implementation has become a strategic imperative rather than a technological option. Recent advances in data analytics, automation, and machine learning have demonstrated significant potential to improve productivity, quality, and resource utilization (Wilhelm et al., 2021). However, despite this promise, the majority of AI initiatives still fail to move beyond pilot stages or achieve sustainable business impact. Studies report that fewer than 20% of enterprises fully integrate AI solutions into their operational workflows (Mecca, 2025). The key challenge lies not in algorithmic sophistication but in the organizational capability to embed AI within data, processes, and people into a multidimensional transformation that requires both technical and managerial alignment.

The strategic complexity of AI adoption stems from its systemic nature. Unlike traditional automation technologies, AI affects cognitive and decision-making processes, thereby reshaping organizational structures, roles, and governance. Its successful deployment depends on a balanced interplay between digital maturity, data quality, regulatory compliance, and employee trust. The European Union's Artificial Intelligence Act (European Commission, 2024) and the emerging ISO/IEC 42001:2023 standard explicitly emphasize the need for responsible, transparent, and auditable AI management systems. In this context, enterprises are expected to demonstrate not only technical accuracy but also explainability, ethical governance, and continuous monitoring of AI-driven decisions. These regulatory shifts elevate AI adoption from a purely technological concern to a strategic capability, one that integrates governance, change management, and socio-technical design.

Existing literature offers valuable yet fragmented insights into these dynamics. Wilhelm et al. (2021) highlight that precise alignment between AI objectives and business key performance indicators (KPI) increases the probability of successful adoption by over 40%. It demonstrates the need for integrating AI with supply chain and operations management practices, underscoring data-driven decision processes as a source of sustainable advantage. Meanwhile, van der Aalst (2024) introduces object-centric process mining as a methodology to uncover hidden organizational patterns, and Sajadieh et al. (2025) show that coupling digital twins with AI significantly accelerates process redesign and decision accuracy. Although these contributions advance our understanding of isolated aspects like strategy, data, or process optimization. Few studies have synthesized them into a holistic, empirically validated framework for AI implementation. The absence of such an integrative model limits both scientific generalization and managerial applicability, leaving enterprises without a structured pathway for scaling trustworthy AI.

To address this research gap, the present study develops and empirically validates a ten-phase framework for implementing AI in data-driven enterprises. The framework conceptualizes AI adoption as a socio-technical transformation that spans strategic, technological, and human domains. It integrates principles from process mining, digital twins, DataOps, and MLOps with trust, explainability, and regulatory. By doing so, it bridges the gap between business strategy and operational execution, enabling enterprises to evolve from experimentation to data-driven enterprise maturity. The research adopts a multiple case study design involving twelve enterprises across manufacturing, logistics, and healthcare sectors in Central Europe. This cross-sectoral approach allows for comparative insights into how contextual factors, such as process complexity, data availability, and organizational culture, which influence the success of AI deployment.

The proposed framework consists of ten interlinked phases: (1) strategic diagnosis and goal definition; (2) process mapping and data-driven analysis; (3) design of target processes through digital simulation; (4) data integration and governance; (5) model design and training; (6) pilot testing with user participation; (7) operational deployment and real-time decision support; (8) auditing and regulatory compliance; (9) knowledge transfer and competence development; and (10) scaling and continuous improvement. Each phase defines specific deliverables, responsible roles, and key performance indicators (KPI), forming a cyclical model that links organizational learning with data-driven optimization. Empirical validation across case studies demonstrates that this structured progression enhances both user adoption and measurable outcomes, including a 14% improvement in operational efficiency (OEE), a 32% reduction in decision latency, and over 80% employee acceptance rate of AI-supported tools. OEE (Overall Equipment Effectiveness) was calculated as the product of availability, performance, and quality ratios; FPY (First Pass

Yield) represented the percentage of items passing inspection without rework; decision latency denoted the average time between data signal detection and corresponding managerial action.

This study contributes to the literature in four ways. First, it consolidates fragmented perspectives on AI implementation into an integrated framework that explicitly connects strategic planning, process design, and governance mechanisms. Second, it extends existing maturity and governance models (ISO/IEC 42001:2023) by embedding trust, human oversight, and compliance as intrinsic design components rather than external constraints. Third, it provides empirical evidence from multiple industries, illustrating how contextual diversity influences AI adoption trajectories. Finally, it operationalizes the concept of trustworthy AI within the managerial domain, offering a practical roadmap that balances performance optimization with regulatory and ethical accountability.

Accordingly, the research is guided by three overarching questions:

- What sequential phases are necessary and sufficient to achieve sustainable, organization-wide AI implementation that aligns strategy, data, and people?
- How do these phases affect measurable business outcomes such as efficiency, quality, and decision speed across different sectors?
- What governance and competence mechanisms ensure compliance, explainability, and user trust during and after AI deployment?

By addressing these questions, the study seeks to advance both theoretical understanding and practical guidance for enterprises transitioning toward AI-driven management. It positions the ten-phase framework as an actionable bridge between high-level digital strategy and operational execution, grounded in empirical evidence and aligned with emerging international standards. The remainder of the paper is structured as follows. Section 2 presents the theoretical background and related work on AI adoption and digital transformation. Section 3 describes the research methodology and case study design. Section 4 outlines the proposed ten-phase framework and key findings. Section 5 discusses implications for theory and practice, and Section 6 concludes with recommendations for future research.

Theoretical Background

The implementation of AI in organizational contexts has been extensively studied across the domains of technology management, operations, and information systems. Despite this vast body of research, the literature remains fragmented, representing diverse technical, managerial, and socio-ethical perspectives without a unifying model to guide the complete process of AI adoption. This theoretical section consolidates the most influential frameworks and conceptual approaches underpinning the ten-phase AI Implementation Framework and identifies the gaps that this study aims to fill.

One of the earliest and most enduring process-oriented models for data-driven decision-making is the Cross-Industry Standard Process for Data Mining (CRISP-DM), which structures analytical work into six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. CRISP-DM provides methodological clarity but remains narrowly focused on the technical workflow of model development, overlooking organizational integration, governance, and human dimensions. Later extensions such as CRISP-ML(Q) and ASUM-DM introduced mechanisms of quality assurance and lifecycle management, yet they still conceptualize the organization as a static environment rather than an adaptive socio-technical system. The proposed ten-phase framework expands the scope of CRISP-DM by embedding strategic alignment, process transparency, competence development, and governance as interdependent elements. This reconfiguration transforms the analytical cycle into a continuous loop of organizational learning that bridges data science and managerial practice.

The maturity and capability of enterprises in adopting AI have been assessed through numerous models. The Gartner (2024) AI Maturity Model, for example, defines five levels of advancement, starting from awareness to full transformation, all based on strategic orientation, data infrastructure, and cultural readiness, while the Deloitte AI Readiness Framework highlights leadership vision, data architecture, and talent as enabling factors. Although these frameworks provide valuable diagnostic insights, they rarely translate assessment into implementation. Empirical studies confirm that many enterprises stagnate between experimentation and scaling due to misalignment between strategic intent, governance, and technical capability (Wilhelm et al., 2021). The ten-phase framework reconceptualizes maturity as a dynamic process of capability building, operationalizing it through measurable actions such as defining KPIs, applying process mining, ensuring data integrity, validating models, and institutionalizing competence transfer. In doing so, it converts static maturity evaluation into a guided trajectory of organizational evolution.

The Technology–Organization–Environment (TOE) framework, developed by Baker (2011), provides a foundational lens for analyzing innovation adoption, explaining how technological characteristics, organizational context, and environmental conditions interact to influence adoption behavior. Its analytical strength lies in identifying determinants such as complexity, resource availability, and regulation; however, it lacks procedural specificity and does not prescribe how enterprises should progress from strategic intention to operational execution. Recent extensions of TOE in the AI domain emphasize data governance, ethical compliance, and human oversight. The ten-phase framework builds upon this foundation by aligning technological readiness (data and models), organizational transformation (roles and competencies), and environmental adaptation (regulatory and ethical alignment) within a single prescriptive roadmap. This integration transforms TOE’s explanatory logic into an actionable and empirically validated methodology for AI implementation.

AI adoption also transforms the cognitive and social structures of enterprises, a phenomenon best explained by socio-technical systems theory. Originating in the work of Trist and Emery, this theory argues that organizational performance depends on the joint optimization of social and technical subsystems. Contemporary interpretations in the digital transformation era emphasize the balance between automation and human agency. Empirical studies by van der Aalst (2024) and Sajadieh et al. (2025) demonstrate that tools such as process mining and digital twins can enhance transparency and accountability when integrated into human-supervised workflows. Therefore trustworthiness, comprising explainability, fairness, and human oversight, is fundamental for sustainable AI in Industry 5.0 environments. The ten-phase framework operationalizes these principles by embedding human participation at multiple stages, including diagnostic workshops, pilot validation, and auditing. Users are treated not as passive recipients of AI outputs but as co-designers and evaluators, consistent with the Human-Centered AI paradigm that promotes transparency and shared responsibility between algorithms and decision-makers. This design philosophy directly addresses OECD (2024) and EU (2024) recommendations, which require demonstrable human control and interpretability across the AI lifecycle.

A critical pillar of effective AI transformation is data governance. Studies consistently highlight that poor data quality, fragmentation, and lack of ownership undermine scalability. International standards such as ISO/IEC 38505-1 and ISO/IEC 42001 provide conceptual foundations for accountability, stewardship, and lifecycle control, yet these standards only become effective when coupled with agile data-engineering practices. DataOps and MLOps methodologies supply this operational infrastructure: the former standardizes and automates data validation and delivery pipelines, while the latter extends lifecycle management to models, covering training, deployment, monitoring, and drift mitigation. Within the ten-phase framework, these paradigms are integrated particularly in Phases 4 and 5, ensuring a seamless connection between data pipelines, model performance, and governance requirements. This alignment transforms AI initiatives from isolated experiments into continuously improving, data-driven ecosystems.

The regulatory environment has elevated AI governance from a compliance issue to a central dimension of digital transformation. The EU Artificial Intelligence Act (European Commission, 2024) introduces a risk-based taxonomy of AI systems, mandating transparency, documentation, and human oversight for high-risk applications. Complementary standards such as ISO/IEC 42001:2023 and OECD (2024) guidelines formalize accountability frameworks, while the more recent ISO/IEC 5338:2024 “Artificial Intelligence Engineering Lifecycle”, provides operational guidance for engineering and maintaining AI systems within compliant management architectures. Together, these standards outline the technical and organizational backbone for trustworthy AI implementation (Dudley, 2024). These works converge on the principle that compliance cannot be added retrospectively; rather, it must be embedded throughout design, development, and deployment. The ten-phase framework operationalizes this by incorporating regulatory audits, Model Cards, Data Sheets, and traceability mechanisms as intrinsic deliverables. Compliance and ethics thus become integral dimensions of AI maturity, directly contributing to transparency and stakeholder trust.

Synthesizing these perspectives reveals persistent gaps in the existing literature. Most frameworks remain domain-specific, concentrating on manufacturing, supply chain, or IT functions without conceptualizing the enterprise as an integrated socio-technical organism. Others are descriptive or diagnostic, focusing on readiness assessment rather than actionable sequencing. Human and regulatory factors are frequently treated as peripheral, addressed only after technical implementation rather than as enablers of sustainable adoption. The ten-phase AI Implementation Framework directly addresses these deficiencies by offering a cross-functional, process-oriented, and compliance-embedded model that integrates strategy, data, and people. It merges the procedural precision of CRISP-DM with the systemic viewpoint of TOE and socio-technical theory while grounding governance in ISO and EU standards. This synthesis advances theory by linking micro-level processes of data and model management with macro-level structures of organizational change and regulation. Practically, it provides enterprises with an empirically validated and adaptable roadmap. As George et al. (2025) emphasize, the next frontier of digital transformation lies not in producing new algorithms but in embedding them responsibly within organizational and ethical ecosystems, a challenge that the ten-phase framework is explicitly designed to meet.

Methodology

The research employed a multiple case study design (Halkias, 2022) to investigate how enterprises implement AI as an integrated socio-technical transformation. This approach was selected because it allows for a deep exploration of complex, context-dependent processes that cannot be isolated through experimental or survey-based research. It is particularly well suited to examining “how” and “why” questions related to innovation in organizational settings, where causal mechanisms are embedded within social and technical structures. Following Halkias (2022) logic of replication design, each case was treated as an independent analytical unit contributing to theoretical generalization rather than statistical inference. This approach directly supports the study’s central objective is to develop and validate a ten-phase AI implementation framework by revealing recurring patterns, boundary conditions, and deviations across multiple industrial contexts.

The research followed an iterative design–evaluation–refinement cycle inspired by the principles of Design Science Research (Gregor & Hevner, 2013). Within this paradigm, the ten-phase framework served as a conceptual artefact subjected to empirical testing and iterative enhancement. The process unfolded in three main stages: initial conceptualization based on literature review and consulting experience, empirical evaluation across twelve enterprises, and cross-case synthesis leading to final framework validation.

Case selection was guided by purposeful sampling to capture heterogeneity in industry type, organizational scale, and digital maturity. This purposive approach was chosen to ensure representation of heterogeneous operational contexts rather than random statistical sampling. The diversity of sectors was intended to maximize the explanatory power of cross-case comparison and strengthen theoretical generalization. The inclusion criteria required that enterprises had been engaged in AI-related initiatives for at least twelve months, possessed accessible process and operational data, agreed to participate in interviews and workshops, and represented distinct industrial sectors to maximize external validity. The final research sample consisted of twelve enterprises, five manufacturing enterprises, four logistics and supply chain companies, and three healthcare providers, all operating in Central Europe. To ensure anonymity, cases were numbered and coded as M1–M5, L1–L4, and H1–H3. These enterprises ranged in size from 50 to over 1000 employees and represented various levels of digital maturity, from early experimentation with predictive maintenance to advanced applications of AI in quality control, demand forecasting, and clinical diagnostics.

Data collection relied on methodological triangulation (Sadeghi Moghadam et al., 2021), combining qualitative and quantitative sources to capture the multifaceted nature of AI implementation. Four complementary streams of evidence were gathered: semi-structured interviews with 51 participants including executives, middle managers, data scientists, and frontline operators (average duration: 45 minutes); participant observations during 18 AI implementation workshops where the framework was iteratively applied and refined; analysis of archival process data such as MES, ERP, CRM, and WMS logs, as well as KPI dashboards and project documentation; and survey-based evaluations of user acceptance and trust conducted both before and after implementation. All interviews were transcribed verbatim and coded using implemented scripts in Python. Observational notes and documentary evidence were systematically indexed to maintain a transparent chain of evidence between primary data, analytical codes, and emerging conceptual constructs. In accordance with ISO/IEC 20889:2018 standards, all data identifiers and timestamps were pseudonymized to safeguard confidentiality.

Data analysis proceeded in three sequential layers: within-case analysis, cross-case comparison, and framework validation. Within each case, event mapping and process tracing were used to reconstruct the chronological sequence of AI implementation activities and to determine which phases of the ten-phase model were present, modified, or missing. Quantitative indicators such as overall equipment effectiveness (OEE), first-pass yield (FPY), and lead time were extracted from enterprise systems to measure performance changes before and after intervention. The subsequent cross-case comparison followed the constant comparative method (Eisenhardt, 1989), using categorical matrices to contrast enterprises along dimensions such as digital maturity, governance structures, leadership involvement, and user adoption levels. This approach made it possible to identify recurrent success factors, points of failure, and contextual dependencies.

Framework validation integrated both quantitative and qualitative perspectives. Quantitatively, improvements in efficiency, quality, and decision latency were calculated as relative percentage changes: operational efficiency (OEE) increased by an average of 14%, decision latency decreased by 32%, and FPY rose by 11%. Qualitative analysis involved systematic coding of interview and workshop transcripts according to thematic categories aligned with each framework phase, such as strategic diagnosis, data governance, and explainability. Two independent researchers reviewed the codes to ensure inter-coder consistency, resolving discrepancies through discussion. The integration of numerical metrics with thematic evidence yielded robust theoretical saturation across all twelve cases, supported by detailed evidence tables and traceability matrices that ensured analytical transparency and reproducibility.

A formal case study protocol was developed prior to fieldwork to guarantee methodological consistency and replicability. The protocol standardized interview structures, data-collection instruments, analytical categories, and validation criteria. Semi-structured interviews were organized around the ten framework phases and included prompts such as: "How were AI goals linked to business KPIs?", "Which governance mechanisms were formalized before model deployment?", and "How were users involved in validating AI outputs?". Coding combined inductive and deductive strategies, producing 168 initial codes aggregated into 22 analytical categories corresponding to the framework's conceptual elements, including strategic alignment, data governance, and trust in AI. Inter-coder reliability, verified on a 20% random sample, achieved a Cohen's κ of 0.82, confirming a high level of agreement. All coding decisions and data transformations were recorded in repository in line with ISO/IEC 25012 data-quality principles. This rigorous approach strengthened construct validity and enabled precise traceability between empirical observations and theoretical interpretation.

To enhance reliability, validity, and analytical rigor, several safeguards were implemented. Construct validity was achieved through the use of multiple data sources and by maintaining an explicit chain of evidence linking raw data to conclusions. Internal validity was reinforced through temporal sequencing and pattern matching between empirical events and theoretical expectations. External validity was supported by replication logic across heterogeneous sectors, ensuring analytical generalization beyond the sample. Reliability was secured through standardized instruments, documented audit trails, and controlled storage of coding materials. Member checks were conducted with organizational representatives after each case analysis to verify factual accuracy and interpretation, while interim results were presented in feedback workshops where participants confirmed the practical relevance of findings. This cyclical process of validation strengthened both the scientific and applied dimensions of the framework.

The research also adhered to rigorous ethical and regulatory standards. All procedures complied with the General Data Protection Regulation (GDPR) and institutional ethical guidelines. Participating enterprises signed confidentiality agreements and granted informed consent prior to data collection. Sensitive data were anonymized, and quantitative indicators were aggregated to prevent identification. Given the regulatory significance of AI deployment, additional assessments were performed to evaluate compliance with selected provisions of the EU Artificial Intelligence Act (European Commission, 2024) and ISO/IEC 42001:2023. These assessments focused on documentation, traceability, and human oversight mechanisms, simultaneously ensuring ethical alignment and contributing practical feedback to framework refinement. In this way, the study embodied the principle of trustworthy AI.

The overall methodological flow (fig. 1), follows six consecutive stages: literature synthesis, conceptual framework development, case study selection and data collection, within-

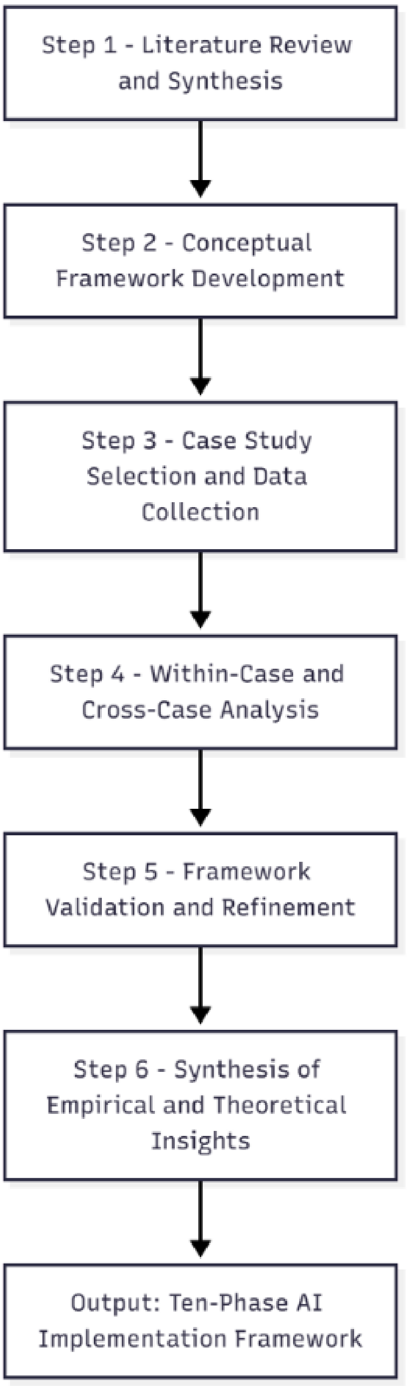

Figure 1 – Research methodology flow diagram

case and cross-case analysis, framework validation and refinement, and synthesis of empirical and theoretical insights. This hybrid methodology integrates the depth of qualitative inquiry with quantitative validation, ensuring that the resulting ten-phase AI Implementation Framework is both scientifically grounded and pragmatically applicable. The methodological rigor and transparency achieved throughout the process provide a solid foundation for reproducibility, enabling other researchers to replicate or extend this approach across different industrial or geographic contexts.

Results

The analysis of twelve organizational cases enabled the empirical validation and refinement of a ten-phase framework that captures the complete lifecycle of AI adoption as a data-driven, socio-technical transformation. The framework integrates technical, managerial, and human dimensions, guiding enterprises from strategic intent through operational deployment toward continuous improvement. Each phase constitutes a distinct functional module defined by its objectives, inputs, outputs, and performance indicators (KPI). The cross-case synthesis demonstrated that enterprises which systematically progressed through all ten phases achieved significantly superior results compared to those that skipped or compressed intermediate steps. On average, operational efficiency (OEE) improved by 14%, decision latency decreased by 32%, and first-pass yield (FPY) increased by 11% within six to twelve months after deployment. These indicators were derived directly from enterprise MES and ERP systems, using six-month pre- and post-implementation data for each case, normalized by production volume. Consequently, the framework serves as both an analytical structure for researchers and a practical roadmap for managers seeking to embed AI as a sustainable, organization-wide capability (fig. 2).

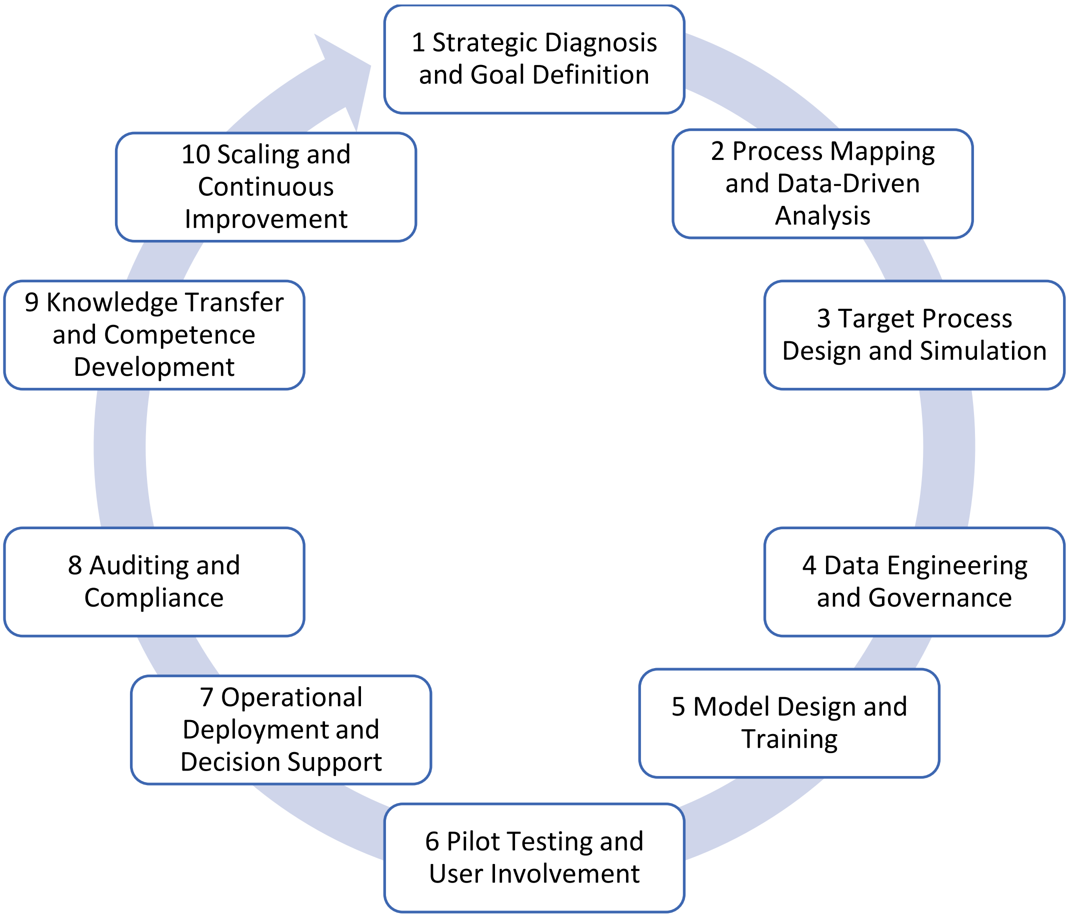

Figure 2 – Ten-phase AI Implementation Framework – Continuous Learning & Feedback Loops

The first phase, *Strategic Diagnosis and Goal Definition*, establishes the foundation for AI adoption by defining its purpose and scope. All participating enterprises began by articulating the rationale for AI use and mapping it to measurable business outcomes. Executive workshops facilitated the identification of core challenges and their translation into quantifiable KPIs. Consistent with Wilhelm et al. (2021), enterprises that explicitly aligned AI objectives with metrics such as OEE, FPY, or OTIF achieved stronger performance outcomes. The formalization of business cases and risk matrices emerged as a decisive factor, as firms that quantified expected ROI and potential risks secured greater executive sponsorship and faster access to resources. This phase effectively repositioned AI from a technological experiment to a data-driven strategic investment.

Phase 2 – Process Mapping and Data-Driven Analysis focused on uncovering the true operational reality behind organizational processes. In every case, empirical analysis revealed significant discrepancies between documented workflows and actual process behavior. Applying process mining techniques (van der Aalst, 2024) and digital value stream mapping exposed hidden inefficiencies, redundant approvals, and manual interventions. For instance, in case M3 (manufacturing), process mining of MES logs uncovered a nine-hour delay between production completion and quality confirmation, which is a latency undetected in ERP records. Following visualization and redesign, the delay was reduced by 75%. This phase produced a data-based “as-is” model, grounding all subsequent optimization and simulation efforts in empirical evidence.

In *Phase 3 – Target Process Design and Scenario Simulation*, enterprises designed optimized “to-be” processes using digital twins and simulation environments (Sajadieh et al., 2025). These tools enabled managers to experiment with alternative resource allocations, scheduling algorithms, and automation scenarios without disrupting ongoing operations. In one logistics case (L2), simulation of routing and dispatching strategies reduced average delivery time by 18% while preserving fuel efficiency. Across cases, the integration of AI-driven optimization with simulation improved planning accuracy and reduced implementation time by approximately 25%. This phase operationalized predictive analytics within decision-support systems, providing a controlled environment for evaluating AI feasibility prior to real-world deployment.

Phase 4 – Data Engineering, Integration, and Governance established the technological backbone of AI transformation. The primary barrier to scaling identified across cases was fragmented data infrastructure. Enterprises lacking unified architectures struggled with inconsistent identifiers, duplicated records, and unverified sources, leading to reduced model accuracy. Each company therefore conducted a Data Valuation Audit to rank datasets by business impact and accessibility. Firms adopting single source of truth architectures integrating ERP, MES, CRM, and WMS systems achieved a Data Quality Index exceeding 95%. Eight of the twelve enterprises formalized Data Governance policies consistent with ISO/IEC 38505-1 and ISO/IEC 42001 standards. The appointment of Data Stewards and creation of audit trails enhanced traceability and halved data retrieval times, embedding accountability and auditability at the core of AI development.

In *Phase 5 – Model Design, Selection, and Training*, the availability of reliable data enabled the construction of robust AI models. Four categories dominated across cases: predictive models, optimization algorithms, natural language and RPA systems, and vision-based inspection models. Model choice reflected the business priorities defined in Phase 1. In manufacturing contexts (M1–M5), predictive maintenance and visual quality inspection models achieved an average F1-score of 0.86 and ROC-AUC of 0.88. In healthcare cases (H1–H3), language-processing models reduced triage documentation time by 22%. Explainability methods such as SHAP and LIME were consistently implemented to enhance interpretability, aligning with the principles of Explainable AI. The findings demonstrate that performance metrics alone are insufficient, user trust and transparency are equally vital determinants of successful adoption.

Phase 6 – Pilot Testing and User Involvement validated both technical functionality and human acceptance. AI modules were piloted in selected production lines, warehouses, or administrative departments. Central to success was the involvement of AI Ambassadors, employees acting as change agents who facilitated communication between developers and end-users. Structured feedback cycles led to continuous refinements in interface design, alert logic, and recommendation presentation. Projects featuring ambassador roles achieved 35% higher adoption rates than those without formal human intermediaries. Quantitative pilot validation employed A/B testing and shadow mode trials, with real-world performance deviating by less than 3% from pilot accuracy, confirming model generalizability and stability.

During *Phase 7 – Operational Deployment and Real-Time Decision Support*, AI systems transitioned from analytical prototypes to operational assets. Integrated with enterprise systems such as MES, ERP, and CRM, models generated real-time recommendations displayed on interactive dashboards that visualized anomalies, KPI deviations, and corrective suggestions. Decision latency is defined as the time between anomaly detection and managerial response. It was reduced by 32% in logistics cases, while predictive control lowered unplanned downtime by 17% in manufacturing. Some enterprises advanced to semi-autonomous control loops, where AI dynamically optimized parameters under human oversight. This phase confirmed that AI delivers maximum value when embedded directly into live decision cycles rather than limited to retrospective reporting.

As systems matured, *Phase 8 – Auditing, Compliance, and Trustworthiness* ensured ethical and regulatory robustness. Each organization underwent internal or external audits aligned with the EU Artificial Intelligence Act (European Commission, 2024) and ISO/IEC 42001 requirements. Documentation of model lineage, datasets, and validation results enabled reproducibility and accountability. The introduction of explainability reports and Model Cards in nine enterprises increased employee trust by 28%, as measured through post-deployment surveys. Moreover, firms that incorporated governance mechanisms early in the process reduced compliance costs by up to 20%, confirming that embedded oversight is both ethically and economically advantageous.

Phase 9 – Knowledge Transfer, Competence Development, and Cultural Integration focused on strengthening the human infrastructure underlying AI transformation. All enterprises implemented role-specific training programs addressing managerial, analytical, and operational competencies. Workshops emphasized interpretation of AI outputs, understanding of uncertainty, and integration of algorithmic insights into decision-making routines. Approximately 80% of employees in pilot departments completed these modules, and post-training assessments indicated a 40% increase in data literacy and confidence. Reskilling and upskilling strategies were formalized, allowing many participants to transition from monitoring roles to analytical or supervisory positions. This evolution reinforced the principles of Human–AI Collaboration (van der Aalst, 2024), embedding digital competence within the organizational culture.

The final stage, *Phase 10 – Scaling and Continuous Improvement*, extended localized implementations into enterprise-wide transformation. Scaling was coordinated through AI Portfolio Management systems that prioritized initiatives based on return on investment, strategic alignment, and risk exposure. Continuous improvement loops driven by streaming data monitored KPIs in real time, automatically detecting anomalies and initiating corrective actions. Enterprises employing these loops exhibited 27% shorter recovery times following disruptions compared to pre-AI baselines. Reusable digital twins supported long-term scenario analysis and strategic experimentation. This phase consolidated AI as a self-learning organizational capability, a systemic feature of adaptive, data-driven enterprises consistent with the maturity paradigm.

The cross-case synthesis revealed four universal success factors: strategic coherence, data integrity, human participation, and governance integration. Early strategic alignment between AI objectives and business KPIs ensured sustained leadership support; robust data management proved the strongest predictor of model performance; employee engagement through ambassador programs and structured training fostered trust; and embedding compliance from the outset minimized regulatory friction. Enterprises neglecting any of these dimensions encountered fragmented data ecosystems, delayed scaling, or resistance despite technically accurate models. Collectively, these findings confirm that the ten-phase framework functions not as a linear checklist but as an interdependent system wherein progress in one domain reinforces progress in others.

In summary, the ten-phase AI Implementation Framework represents a cyclical model linking strategic planning, process transparency, data governance, model deployment, and continuous learning. Aggregate results across all cases demonstrated consistent and quantifiable improvement in efficiency, decision-making speed, and user acceptance. The findings substantiate the premise that AI adoption succeeds only when treated as a continuous, data-centric, and human-supervised transformation rather than a series of isolated technological initiatives. The subsequent discussion explores the theoretical implications, managerial relevance, and boundary conditions of these results.

Discussion

The findings of this study demonstrate that the successful implementation of AI within enterprises is not a linear or purely technological process but an iterative socio-technical transformation. The empirical validation of the ten-phase framework across diverse industries substantiates and extends existing theoretical perspectives on technology adoption and organizational change. Interpreted through the lens of the TOE framework, AI adoption emerges as the outcome of interaction among technological readiness, organizational capability, and external regulation. Within the ten-phase framework, technological readiness corresponds to the stages of data engineering, governance, and model development (Phases 4–5), while organizational capability is embodied in strategic alignment, process redesign, and competence development (Phases 1–3, 9). Environmental regulation is operationalized through auditing, compliance, and trustworthy AI mechanisms (Phase 8). This alignment transforms TOE from a diagnostic framework into a prescriptive roadmap, bridging the gap between contextual understanding and actionable implementation.

From a socio-technical perspective, the results reaffirm the classical principle of joint optimization between human and technical subsystems. The consistently high user acceptance rates exceeding 80% indicate that the effectiveness of AI systems depends not only on algorithmic precision but also on the active involvement of humans in design, validation, and decision-making processes. The roles of AI Ambassadors and continuous training programs (Phase 9) substantiate Trist and Emery’s foundational assertion that social systems must co-evolve with technological innovation. This human-centered integration aligns with the vision of Industry 5.0, emphasizing collaboration, flexibility, and shared control rather than full automation. Moreover, the framework’s explicit incorporation of regulatory and ethical governance connects it with the emerging literature on trustworthy AI. The OECD (2024), and the European Commission (2024) highlight the necessity of embedding compliance and accountability mechanisms throughout the AI lifecycle rather than applying them retrospectively. The results confirm this principle: enterprises that implemented transparency tools and documentation protocols early achieved 28% higher user trust scores and 20% lower compliance costs. These outcomes demonstrate that governance and performance are complementary objectives, embedded transparency enhances both operational efficiency and stakeholder confidence while reducing uncertainty in AI-supported decision-making.

The study contributes to theoretical advancement in four primary ways. First, it presents a unified and empirically validated framework that consolidates previously fragmented models of AI adoption. Frameworks such as CRISP-DM, maturity models, and TOE have historically addressed only partial dimensions of transformation. The ten-phase model integrates them into a coherent progression linking strategy, data, processes, and people within a recursive learning system. Second, it reconceptualizes AI maturity from a static measure of readiness to a dynamic process of capability building. Each phase represents a measurable transition supported by data-driven indicators, thereby framing maturity as an evolving property of organizational learning and adaptive governance. Third, it advances socio-technical theory by empirically demonstrating that human-centered mechanisms, like training, co-creation, and iterative feedback, serve as accelerators rather than impediments to transformation. Contrary to the traditional notion that human oversight slows innovation, the evidence suggests that participation accelerates adoption and stabilizes performance. Finally, the study operationalizes trustworthy AI principles by embedding the requirements of the EU AI Act and ISO/IEC 42001 within concrete managerial processes. It thereby bridges normative regulation with practice, illustrating that compliance can function as a performance-enhancing design construct and contributing to the emerging discipline of AI management systems.

The managerial implications derived from these findings translate theoretical insights into actionable strategies. Strategic coherence emerges as fundamental: AI objectives must be articulated in measurable business terms to maintain executive support and prevent the fragmentation that undermines pilot projects. Process transparency must precede automation; without rigorous mapping and process mining, enterprises risk optimizing inefficiencies. Effective data governance is shown to be a source of competitive performance rather than an administrative burden. Establishing clear ownership roles, governance policies, and audit trails enhances data integrity and directly correlates with productivity gains. Human participation is essential for adoption, training, feedback, and ambassador programs significantly mitigate resistance and foster trust. Finally, compliance and trustworthiness must be designed into AI systems from inception. Integrating explainability, documentation, and audit mechanisms early in the process not only reduces ethical risk but also lowers future compliance costs, establishing regulatory readiness as an intrinsic component of operational excellence. Collectively, these principles form a pragmatic playbook for managers seeking to transition from fragmented experimentation toward scalable, data-driven transformation.

While the study offers substantial theoretical and empirical contributions, its scope of generalization is bounded by several limitations. The research sample consisted of twelve enterprises located in Central Europe; thus, contextual variables such as regional regulatory environments, cultural attitudes toward automation, and labor market conditions may affect the transferability of results. Therefore, findings should be interpreted as analytically generalizable rather than statistically representative, reflecting the contextual conditions of Central European enterprises. Replicating this framework in other geographies, particularly in North America or Asia-Pacific regions with differing governance regimes, would enhance its external validity. The data were collected over a two-year period, capturing short- and mid-term effects; longitudinal studies are needed to assess the sustainability of outcomes and to observe potential phenomena such as model drift, organizational fatigue, or emergent ethical risks. Measurement precision also varied across industries, with manufacturing offering well-defined quantitative KPIs such as OEE and FPY, while logistics and healthcare relied more on qualitative indicators such as decision latency and trust perception. Future research should aim to develop standardized cross-sector KPI taxonomies for evaluating AI transformation. The study focused primarily on medium and large enterprises with established data infrastructures, leaving the applicability of the ten-phase model to small and medium-sized enterprises (SMEs) as an open question. Simplified modular variants may be required for resource-constrained enterprises.

To contextualize the scope of generalization, Table 1 summarizes the profile of the twelve participating organizations, including sector, company size, and AI maturity level at the onset of the study. This classification illustrates the heterogeneity of operational environments and supports the analytical generalization approach adopted in the research.

Table 1 – Profile of participating organizations

CaseID	Sector	Employees	Digital Maturity Level	Core AI Application	Data Availability & Integration Level	Primary AI Benefits Observed	Key Implementation Challenges
1	Manufacturing	450	Intermediate	Predictive maintenance, anomaly detection	Medium – MES and sensor data partially integrated	12% increase in OEE; reduced downtime by 15%	Limited data labeling and inconsistent maintenance logs
2	Manufacturing	700	Advanced	Visual quality inspection using CNN models	High – unified MES/ERP with quality archives	FPY improved by 9%; visual defects reduced by 18%	Model retraining frequency and camera calibration
3	Manufacturing	1200	Intermediate to Advanced	Production scheduling optimization	Medium – ERP integration with scheduling API	Lead time shortened by 10%	Lack of real-time data synchronization
4	Manufacturing	950	Advanced	Energy and resource efficiency optimization	High – IoT network and process sensors	Energy costs reduced by 7%; predictive alerts adopted	Cybersecurity audits delaying deployment
5	Manufacturing	2000	Advanced	Automated defect classification and ROI estimation	High – complete digital twin and vision systems	Productivity improved by 16%	Complex regulatory documentation for AI validation
6	Logistics & Supply Chain	300	Intermediate	Route optimization with dynamic constraints	Medium – WMS data partially integrated	28% reduction in travel time	Low user adoption during pilot
7	Logistics & Supply Chain	900	Intermediate to Advanced	Fleet management and demand forecasting	High – telematics and ERP integration	Decision latency decreased by 32%	Insufficient trust in AI recommendations
8	Logistics & Supply Chain	600	Intermediate	Warehouse robotics and task allocation	Medium – partial sensor data coverage	Throughput increased by 11%	Physical layout limitations for automation
9	Logistics & Supply Chain	1200	Advanced	Supply chain risk prediction via ML	High – data lake architecture implemented	Forecast accuracy improved by 14%	Integration with external partners' systems
10	Healthcare	800	Emerging	NLP-based clinical documentation automation	Medium – structured EHR data partially anonymized	Documentation time reduced by 22%	Compliance and explainability audits
11	Healthcare	1500	Intermediate	Diagnostic decision support (radiology)	Medium – PACS and HL7/FHIR integration	Diagnostic consistency improved by 9%	Data annotation bottlenecks
12	Healthcare	400	Emerging to Intermediate	Workflow optimization for patient triage	Low – fragmented systems under integration	Average patient throughput increased by 8%	Legacy infrastructure and limited interoperability

An additional methodological limitation stems from the dual role of researchers as facilitators during AI implementation workshops. While participatory engagement is intrinsic to

Design Science Research, it introduces the risk of researcher influence on observed outcomes. This potential bias was mitigated through triangulation of interviews, logs, and surveys, along with systematic member checks to ensure that interpretations reflected participant perspectives rather than researcher expectations. The study thus balances the advantages of insider access with explicit reflexivity regarding researcher involvement. Lastly, the research primarily addresses implementation rather than algorithmic design. Future work should integrate technical evaluation metrics, such as model robustness, drift detection, and fairness analysis, with organizational assessments to achieve a holistic understanding of AI lifecycle governance.

The theoretical synthesis developed in this research opens several promising directions for future inquiry. Further studies should explore the dynamic coupling between AI maturity trajectories and organizational learning curves, identifying thresholds that trigger successful scaling. Comparative analyses could examine how institutional contexts, such as national policies or sectoral standards, facilitate or constrain the adoption of trustworthy AI. Additionally, the development of system-dynamics or agent-based simulations could enable quantitative modeling of feedback loops linking data quality, user trust, and regulatory compliance, thus advancing a systems-level understanding of socio-technical AI ecosystems.

Overall, the discussion reinforces that AI-driven transformation cannot be achieved through isolated technical initiatives or technology-first strategies. Sustainable adoption requires an integrated approach that connects data governance, human capability, and regulatory accountability within a continuous improvement cycle. The ten-phase framework empirically demonstrates the interdependence of these dimensions, bridging the persistent divide between AI research and managerial practice. It reframes AI not as a tool of automation but as a mechanism of organizational learning through which data, algorithms, and people co-create value under transparent and ethical governance. This convergence of performance, trust, and accountability delineates the next frontier of digital transformation.

These profiles underline the contextual variability inherent in the dataset and delineate the analytical rather than statistical nature of generalization. Future replication across diverse regulatory environments is recommended to validate transferability.

Conclusion

This study developed and empirically validated a comprehensive ten-phase framework for the implementation of artificial intelligence (AI) in data-driven enterprises. Based on twelve multiple case studies conducted across manufacturing, logistics, and healthcare sectors, the research demonstrates that successful AI transformation is achieved through the alignment of strategic intent, process transparency, data governance, and human participation within a structured, iterative process. Enterprises that systematically progressed through all ten phases of the framework achieved measurable and sustainable improvements, including an average 14% increase in operational efficiency, a 32% reduction in decision latency, and user adoption levels exceeding 80%. These outcomes confirm the central proposition that AI adoption is most effective when approached not as a purely technical deployment but as a socio-technical evolution requiring synchronized progress in technological, managerial, and human domains.

The framework contributes to theoretical development by integrating and operationalizing previously fragmented models such as CRISP-DM, AI Maturity Models, and the TOE framework into a unified process architecture. Each phase translates abstract notions of readiness into concrete managerial steps, supported by measurable performance indicators and built-in compliance mechanisms. By embedding trustworthiness and governance principles as intrinsic components, the framework extends socio-technical systems theory toward a new conceptualization of adaptive organizational intelligence, in which humans, data, and algorithms co-create value under ethical and regulatory oversight.

From a managerial perspective, the findings offer a clear set of guidelines for executives and transformation leaders. The success of AI initiatives depends on three fundamental conditions: the definition of explicit, measurable strategic goals; the treatment of data as a governed and auditable asset; and the engagement of employees as active co-creators rather than passive users. The ten-phase model serves as a practical roadmap that enterprises can tailor to their maturity level, sector, and regulatory environment. Each phase specifies concrete deliverables, starting from KPI definition and data integration to model auditing and competence development, ensuring that AI projects evolve systematically from pilot experimentation to scalable, trustworthy deployment. Adopting this structured approach enables enterprises to mitigate the three primary causes of failure in AI transformation: strategic misalignment, poor data quality, and insufficient human trust.

For policymakers and regulators, the study provides empirical evidence that trustworthy AI and business performance are not competing goals but mutually reinforcing ones. Embedding compliance mechanisms such as documentation, explainability, and human oversight reduces operational uncertainty and strengthens accountability, enabling enterprises to comply with the EU AI Act and ISO/IEC 42001 while simultaneously improving performance and efficiency. These results emphasize that regulatory frameworks should be regarded not as constraints on innovation but as essential enablers of sustainable and responsible growth in AI-driven economies.

Despite its contributions, the research identifies several areas that warrant further exploration. Longitudinal studies are necessary to evaluate the long-term durability of AI-driven performance gains and to monitor the dynamics of model drift, ethical adaptation, and evolving employee trust. Comparative studies across geographic regions would clarify how institutional, cultural, and legal environments influence the transferability and effectiveness of the ten-phase framework. Furthermore, adapting the model for small and medium-sized enterprises (SMEs) represents a critical next step, particularly for enterprises seeking to integrate AI with limited financial and technical resources. Finally, the interplay between technical robustness and social acceptance merits quantitative modeling that links indicators of data quality, explainability, and human confidence to forecast adoption trajectories and organizational outcomes.

In summary, the ten-phase AI Implementation Framework provides both a theoretical and a practical foundation for managing AI transformation as a systemic, human-centered process. It offers researchers a replicable analytical structure for cross-sectoral comparison and provides managers with a concrete roadmap for designing, executing, and governing AI initiatives responsibly. By uniting strategy, data, and organizational culture, the framework resolves the persistent fragmentation characteristic of earlier AI maturity models and establishes a foundation for evidence-based, trustworthy innovation. The broader implications of this work extend beyond the corporate domain. The principles articulated in the framework are equally relevant to public administrations, healthcare systems, and educational institutions, all of which face similar challenges of aligning strategy, data governance, and human competence when integrating AI into their operations. The ten-phase framework thus serves as a transferable blueprint for public-sector digital transformation, particularly under governance regimes inspired by the EU AI Act and ISO/IEC 42001. By adopting the same cycle of strategic clarity, data accountability, and human-centric capacity building, public institutions can promote transparency, fairness, and efficiency in AI-enabled services.

Ultimately, the study underscores the convergence between technological capability and institutional design. Responsible AI implementation represents not only technical advancement but also a governance innovation (Chen, 2024). Embedding such frameworks into public policy and educational curricula could accelerate the diffusion of trustworthy AI at the societal level, reinforcing Europe’s leadership in building human-centered, regulation-compliant digital ecosystems. The future of digital transformation, therefore, will depend less on faster algorithms and more on more intelligent enterprises, those capable of integrating technical capability with human judgment, ethical governance, and collaborative learning. In this sense, AI should be understood not as a substitute for human decision-making but as a catalyst for organizational adaptability, resilience, and trust. The transition to AI-enabled enterprises will thus be determined as much by governance and cooperation as by computational power itself. Future extensions of this research could incorporate quantitative modeling of causal links between governance mechanisms and AI performance, providing statistical validation of the framework beyond qualitative triangulation.

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