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Methodological Foundations of AI Readiness in Enterprise Operations and Analytics Functions

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ABSTRACT

The article examines AI readiness as a methodological issue for enterprise operations and analytics functions. Its relevance follows from the gap between AI adoption ambitions and the organizational conditions required for reliable decision support, operational intelligence, and governed automation. The aim is to define the foundations that make enterprise AI usable beyond isolated pilots. The study applies comparative analysis, source analysis, conceptual synthesis, typologization, and analytical generalization to ten recent academic sources on AI readiness, AI capability, governance, data governance, and business value. The analytical part identifies three connected foundations: data and infrastructure reliability, organizational and process maturity, and decision-oriented governance. The article proposes an implementation logic that treats readiness as a managed operating condition measured through data quality, model lifecycle control, adoption behavior, accountability, and feedback loops. The results are applicable to enterprises preparing AI-enabled analytics, anomaly detection, forecasting, and operational decision support.

Keywords: AI readiness, enterprise operations, analytics functions, data governance, AI capability, operational intelligence, decision governance, data quality, organizational maturity, model lifecycle

INTRODUCTION

Enterprise AI adoption has moved from experimental projects toward operational monitoring, analytics, risk control, service management, and managerial decision support. This movement changes the readiness problem. The central question concerns the conditions under which an organization can use AI outputs in routine work without increasing opacity, operational friction, or unmanaged risk (Enholm et al., 2022; Ali & Khan, 2025; Papagiannidis et al., 2025; Schneider et al., 2023).

Operations and analytics functions create a demanding setting for this question. They work with signals from technical systems, product usage, customer behavior, finance, security, business processes, and service performance. These signals differ in latency, ownership, semantic meaning, and quality. Fragmented inputs make AI-supported decisions fragile. Governed and contextualized inputs allow analysts, engineers, product owners, and managers to use AI as part of a controlled intelligence environment (Bernardo et al., 2024; Weber et al., 2023; Mikalef & Gupta, 2021; Tursunbayeva & Chalutz-Ben Gal, 2024).

The aim of the article is to develop a methodological interpretation of AI readiness for enterprise operations and analytics functions. Three research objectives guide the study. The first objective is to systematize readiness dimensions found in recent AI adoption, AI capability, and governance literature. The second objective is to determine which dimensions require special attention in operations and analytics functions. The third objective is to

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formulate a decision-oriented readiness logic that links data foundations, organizational capabilities, governance mechanisms, and feedback routines.

The novelty of the article lies in treating AI readiness as an operating condition instead of a technical checklist. This framing separates enterprise AI readiness from broad digital maturity and from a narrow data-to-decision pipeline. Readiness is examined as the ability to transform governed data, stable infrastructure, skilled participation, and accountable decision routines into repeatable AI use.

The hypothesis states that AI readiness in enterprise operations and analytics functions depends less on the availability of AI tools than on the alignment of data quality, infrastructure reliability, process ownership, governance mechanisms, and feedback loops around specific decisions. Weak alignment keeps AI adoption fragile even in organizations with technical resources.

MATERIALS AND METHODS

The materials for the study were selected through a targeted literature search in ScienceDirect, SpringerLink, Taylor & Francis, Emerald, ACM-indexed records, and cross-publisher academic databases. Search strings combined the terms “AI readiness,” “artificial intelligence capability,” “AI governance,” “data governance,” “AI adoption,” “enterprise AI,” “business value,” “organizational capability,” and “analytics capability.” Inclusion criteria covered peer-reviewed publications from 2021 to 2025 with direct relevance to AI readiness, AI capability, data governance, responsible AI governance, organizational adoption, and value realization. Exclusion criteria removed sector-specific papers with weak transferability to enterprise operations, publications centered on consumer AI acceptance, papers without methodological relevance to readiness assessment, and practitioner texts without academic framing. A preliminary pool of 51 records was screened by title, abstract, and methodological fit. The screening removed 41 records. The final corpus contains ten sources: systematic and conceptual reviews of AI readiness and business value, empirical studies of AI capability and institutional readiness, frameworks for AI adoption and governance, and data governance reviews.

The study uses comparative analysis to distinguish readiness dimensions across the selected sources. Source analysis clarifies each publication’s methodological contribution. Conceptual synthesis connects readiness with enterprise operations and analytics functions. Typologization groups readiness factors into operational categories. Analytical generalization supports the implementation logic. These methods correspond to the three objectives: systematization of readiness dimensions, interpretation of their relevance for operations and analytics, and construction of a decision-oriented readiness model.

RESULTS

Recent AI readiness literature presents readiness as a multi-dimensional condition built from technological, organizational, human, and governance resources. A systematic review of readiness factors identifies information technology infrastructure, top management support, resource availability, collaborative culture, organizational capability, compatibility, data quality, and financial budget among recurring prerequisites for AI implementation (Ali & Khan, 2025). This position matters for enterprise operations and analytics because readiness cannot remain at the level of executive intention. Operations teams need usable signals, workflow ownership, reliability routines, and decision execution rules.

The Technology, Organization and People checklist for AI adoption broadens this perspective, considering adoption in terms of technology, organizational design, culture, skills, employee trust and digital leadership (Tursunbayeva & Chalutz-Ben Gal, 2024). This contribution mitigates the risk of interpreting AI readiness as a platform problem. A technically

competent environment is still weak if users do not trust outputs, business owners do not define criteria of success, and data teams cannot translate domain signals into metrics, features or decision rules.

The capability perspective gives the readiness problem a stronger methodological base. AI capability has been conceptualized as a combination of tangible resources, human skills, and intangible organizational resources that jointly support organizational creativity and performance (Mikalef & Gupta, 2021). This view fits enterprise operations because operational intelligence requires infrastructure, skilled interpretation, shared standards, and routines that place evidence inside day-to-day decisions. The capability perspective changes the central question. The organization has to orchestrate resources so that AI contributes to repeatable decisions, not merely build or purchase AI components.

Business value literature points in the same direction. A review of AI and business value reports that organizations continue to face difficulties with AI adoption and use despite growing interest. The review identifies enablers, inhibitors, use typologies, and first-order and second-order organizational effects (Enholm et al., 2022). This finding explains why dashboard modernization, anomaly detection, and forecasting initiatives often lose momentum after pilot stages. Value depends on changes in operational behavior, decision speed, error reduction, prioritization quality, or managerial attention. A prediction alone does not create enterprise value.

Research on organizational capabilities for AI implementation adds a more operationally precise explanation. Four capabilities are derived from expert interviews: AI project planning, co-development of AI systems, data management, and AI model lifecycle management (Weber et al., 2023). The same study links these capabilities to two AI-specific difficulties, inscrutability and data dependency (Weber et al., 2023). Operations and analytics functions confront both problems in routine work. Inscrutability affects whether teams can interpret, challenge, and use AI-supported signals. Data dependency affects the stability of anomaly detection, trend forecasting, prioritization, and decision support when source systems change, definitions drift, or processes are redesigned.

A comparison of these sources indicates that readiness functions as a layered condition. AI readiness factors define prerequisites. AI capability explains resource orchestration. Business value literature clarifies why implementation has to change decisions. Implementation capability literature specifies the organizational work required to move from experiment to routine use. The first research objective therefore leads to seven readiness dimensions: data and metadata quality, infrastructure and integration, use-case and portfolio discipline, skills and co-development, governance and accountability, model lifecycle management, and feedback-based learning. Figure 1 presents these dimensions as a decision-oriented readiness model for operations and analytics functions. The model adapts the logic of AI readiness and AI implementation capability literature, where readiness factors, AI capabilities, data dependency, and lifecycle management interact (Ali & Khan, 2025, Weber et al., 2023).

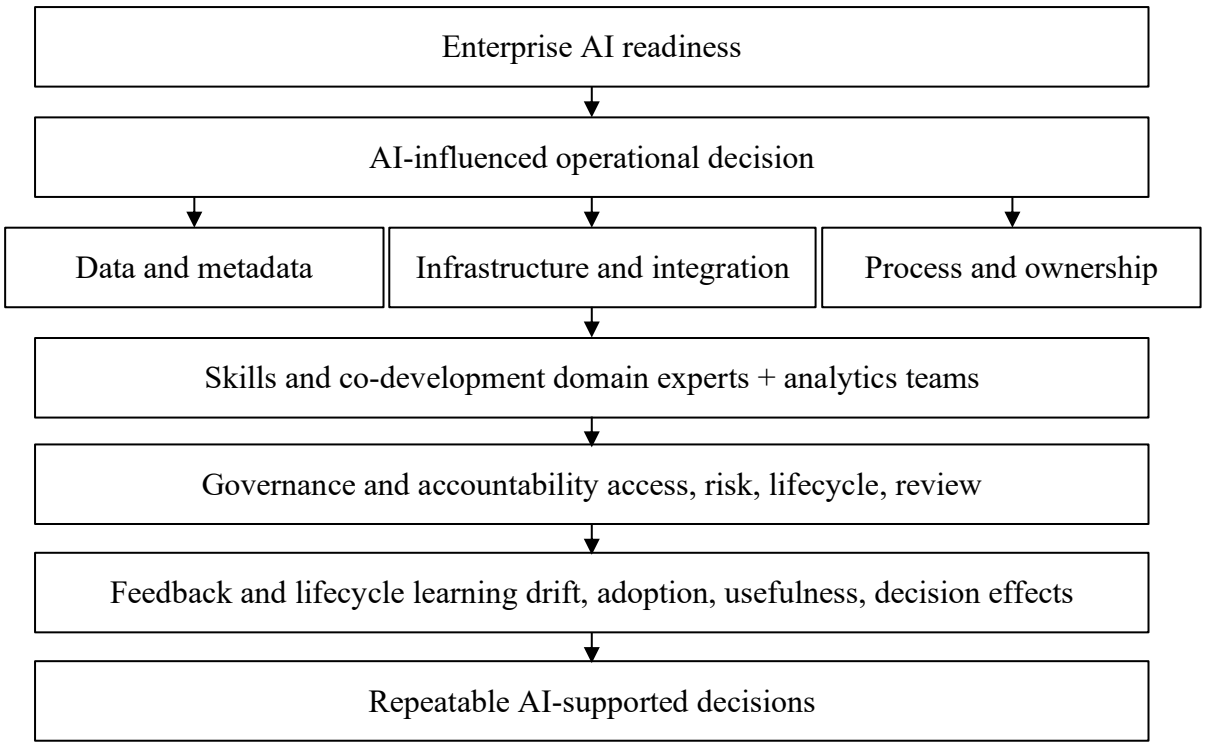


Figure 1. Decision-oriented AI readiness model for enterprise operations and analytics functions (author's synthesis based on Ali and Khan, 2025, and Weber et al., 2023)

The figure places readiness across several organizational groups. Data teams shape data and metadata foundations. Platform teams maintain infrastructure and integration. Product and operations leaders define process ownership. Analytics specialists and domain experts carry co-development. Governance bodies set control logic. Feedback loops connect production behavior with model and process revision. This distribution has direct relevance because operations and analytics functions sit between technical systems and managerial action.

Data governance literature reinforces the first layer of the model. A systematic review of data governance and quality management presents governance through frameworks, maturity assessment, assurance, quality, and practical application of governance initiatives (Bernardo et al., 2024). In enterprise AI readiness, data governance serves more than a compliance function. It determines whether operational signals can be discovered, interpreted, reused, and trusted. A metric without lineage, ownership, or quality thresholds transfers uncertainty into AI-supported analytics. Model teams cannot repair that uncertainty after the fact.

Literature on responsible AI governance adds another requirement. A review of responsible AI governance separates principles from the practices that translate responsible AI into structural, relational, and procedural mechanisms (Papagiannidis et al., 2025). This distinction is important because operations and analytics functions often require fast responses. Speed without governance creates exposure to erroneous escalation, biased prioritization, uncontrolled automation, and unclear accountability. AI readiness thus requires governance built into data access, model evaluation, monitoring, exception handling, and human review.

Business-oriented AI governance research offers a concrete decomposition. AI governance for companies has been framed through governance of data, machine learning models, and AI systems, organized around who governs, what is governed, and how governance occurs (Schneider et al., 2023). This framework fits enterprise operations because operational intelligence uses several governance objects at once. A forecasting model depends on governed data. A monitoring application depends on model behavior. A decision workflow

depends on the AI system, its outputs, and the human or automated response attached to those outputs.

The second comparative question concerns the readiness dimensions with the greatest weight in operations and analytics. AI readiness studies often give broad lists of determinants. Operations and analytics require a narrower interpretation. Technological infrastructure, data quality, process compatibility, human skills, and governance become decisive because operational AI use faces latency, incident response, business continuity, monitoring, and adoption behavior (Ali & Khan, 2025, Tursunbayeva & Chalutz-Ben Gal, 2024). The function of readiness changes once AI output enters operational routines. The organization has to know whether the model remains interpretable, stable, and usable during routine execution.

Institutional readiness research adds evidence that internal capacity mediates AI adoption. A study of public audit institutions found that e-government readiness and institutional pressure predict AI readiness, while AI readiness influences behavioral intention to adopt AI (Anomah, 2025). The sector differs from private enterprise operations, yet the methodological implication transfers. External pressure to introduce AI does not create capability by itself. Internal infrastructure, human capital, adaptive capacity, and cultural readiness still condition adoption behavior.

Research on AI capability in public administration separates the capability to develop AI from the capability to implement AI in operational settings (van Noordt & Tangi, 2023). This distinction is useful for enterprise analytics. Many organizations can prototype models, produce dashboards, and run pilots. Fewer organizations can maintain AI-supported decisions over time when data pipelines evolve, users resist outputs, or governance requirements change. For the second objective, the critical dimensions for operations and analytics are operational data quality, integration reliability, model lifecycle ownership, in-house interpretive competence, human accountability, and adaptive governance.

A third comparison clarifies the role of people and co-development. The TOP framework stresses people-related conditions such as skills, trust, and culture (Tursunbayeva & Chalutz-Ben Gal, 2024). Organizational capability research identifies co-development as a response to AI inscrutability and stakeholder information gaps (Weber et al., 2023). Public-sector capability research points to human skillsets, technical and non-technical, as conditions for successful implementation (van Noordt & Tangi, 2023). Taken together, these positions indicate that operations and analytics readiness depends on mixed participation. Domain experts understand incidents, thresholds, exceptions, and business consequences. Data and AI specialists understand modeling, monitoring, and data constraints. Governance actors understand risk boundaries. AI readiness remains fragmented when these groups work in sequence with weak handoffs.

The third research objective requires a decision-oriented logic. Across the reviewed literature, readiness becomes coherent when the unit of analysis shifts from “AI system” to “AI-influenced decision.” A decision-oriented approach begins by identifying the operational or analytical decision to be improved. It then determines the required data, quality threshold, latency requirement, model lifecycle, user group, governance rule, and feedback mechanism. This logic aligns with AI business value literature, which links AI value to organizational use and effects (Enholm et al., 2022), and with governance frameworks that require clarity about the governance object and accountable actor (Schneider et al., 2023).

The resulting finding is that AI readiness in enterprise operations and analytics functions has three methodological foundations. The first foundation is a governed data environment where data meaning, lineage, ownership, quality, and freshness are explicit. The second foundation is operational capability, expressed through infrastructure reliability, process ownership, co-development, and lifecycle management. The third foundation is decision governance, where AI outputs connect to accountability, monitoring, human review,

and feedback. These foundations support the hypothesis that readiness depends less on AI tool presence than on alignment among data, processes, governance, and decision routines.

DISCUSSION

The proposed interpretation treats AI readiness as an operating discipline. This position differs from maturity models that rank organizations along general capability stages without asking which decisions AI will influence. For enterprise operations and analytics, broad ranking has limited practical value. A company can maintain advanced data platforms and still lack readiness for AI-supported operational decisions if data lineage is incomplete, ownership is unclear, model monitoring is weak, or users do not understand the action expected from outputs.

A practical implementation model begins with decision selection. The first step defines a narrow decision class, such as incident prioritization, anomaly triage, demand signal interpretation, customer behavior monitoring, service quality forecasting, cost variance detection, or operational risk escalation. The second step maps the data products that feed this decision. Each data product needs an owner, lineage, freshness standard, quality threshold, access rule, and known limitation. The third step defines the model or analytical method as one component of a wider decision system. The fourth step assigns accountability for action. The fifth step creates feedback routes from users, exceptions, model drift, and outcome metrics back into data, rules, and model lifecycle management.

This logic turns AI readiness assessment into a question of operational evidence. Readiness exists when the organization can name the decision owner, identify supporting data, demonstrate quality checks, monitor model behavior, define human review, set escalation thresholds, and show feedback-driven revision. Missing answers signal incomplete readiness. The use case may remain technically feasible, but operational readiness has not yet reached production strength. Table 1 compares readiness dimensions through the lens of enterprise operations and analytics functions. The table separates generic readiness categories from the operational evidence that an enterprise leader or reviewer needs before moving AI from pilot use to controlled production.

Table 1. AI readiness dimensions for enterprise operations and analytics functions

Readiness dimension	Generic readiness meaning	Operations and analytics interpretation	Practical evidence of readiness
Data quality	Data is accurate, complete, and usable	Metrics and signals are reliable enough to support forecasting, anomaly detection, and prioritization	Quality rules, lineage, ownership, freshness standards, exception logs
Infrastructure	Technical environment supports AI workloads	Systems integrate operational signals at required latency and reliability levels	Stable pipelines, integration controls, observability, recovery routines
Process maturity	Workflows can absorb AI outputs	AI recommendations connect to defined work routines and escalation paths	Documented decision paths, process owners, service-level expectations

Human capability	Employees possess technical and domain knowledge	Domain experts, analysts, engineers, and managers co-define use cases and interpret outputs	Cross-functional rituals, training records, review boards, feedback channels
Governance	Rules control AI use and risk	Access, model lifecycle, monitoring, privacy, accountability, and exception handling are built into production use	Governance policy, approval thresholds, audit trail, model cards, accountability map
Value orientation	AI use is tied to organizational goals	AI outputs are judged by decision improvement, operational efficiency, and risk reduction	Baseline metrics, adoption data, outcome review, benefit tracking

Author's synthesis based on Ali and Khan (2025), Tursunbayeva and Chalutz-Ben Gal (2024), Mikalef and Gupta (2021), and Weber et al. (2023)

The table indicates that readiness cannot be inferred from formal possession of assets. A data catalog does not prove readiness if users cannot determine whether a metric is fit for a decision. A model registry does not prove readiness if teams do not monitor drift or user override patterns. Training programs do not prove readiness if operations teams cannot translate outputs into action under time pressure. Evidence matters because enterprise AI becomes consequential once it affects decision cadence and decision quality.

The implementation sequence should remain selective. Broad AI transformation programs often create high expectations before operational foundations reach stability. A safer sequence begins with one or two decision classes where data availability, business relevance, and ownership are already visible. These decisions should be narrow enough to control risk and meaningful enough to test governance, model monitoring, user behavior, and operational action. After the first decision class reaches stable use, the organization can reuse its data product standards, monitoring templates, feedback mechanisms, and governance routines for adjacent decisions.

Monitoring metrics require separation into four groups. Data metrics cover freshness, completeness, validity, lineage coverage, and unresolved quality incidents. Model metrics cover accuracy or task-specific performance, drift, stability, confidence distribution, and failure patterns. Adoption metrics cover active use, override rates, user feedback, escalation compliance, and time-to-action. Governance metrics cover access exceptions, audit completeness, unresolved risk reviews, policy violations, and human review timeliness. This structure reduces the risk of evaluating AI readiness through model performance alone. Table 2 translates the proposed readiness logic into a staged implementation sequence. The table shows how an enterprise can move from conceptual readiness toward governed production without turning AI work into a tool-centered rollout.

Table 2. Implementation sequence for decision-oriented AI readiness

Implementation stage	Main purpose	Required organizational action	Readiness signal
Decision framing	Define the operational or analytical decision affected by AI	Select decision class, owner, user group, and success criterion	The decision has a named owner and measurable baseline
Data product preparation	Create a trusted signal base	Assign ownership, document lineage, define quality and freshness thresholds	Data consumers can verify meaning, source, and limitation
Governance embedding	Place controls inside the workflow	Define access, review, audit, privacy, lifecycle, and escalation rules	Governance operates during use, before incidents escalate
Model and analytics lifecycle setup	Control AI behavior over time	Define evaluation, drift monitoring, retraining triggers, and failure response	Model behavior is observable and reviewable
Human-in-the-loop operation	Preserve accountability and domain judgment	Define when humans approve, override, investigate, or escalate	Users know how to act on AI outputs and when to stop automation
Feedback-based scaling	Reuse validated routines across adjacent decisions	Capture feedback, compare outcomes, revise data and governance standards	Improvements transfer beyond the first use case

Author's synthesis based on Enholm et al. (2022), Schneider et al. (2023), Papagiannidis et al. (2025), Bernardo et al. (2024), and van Noordt and Tangi (2023)

The table shows that readiness grows through controlled repetition. The first decision class becomes a methodological testbed. It reveals whether data ownership works in practice, whether governance remains usable, whether users trust outputs, whether lifecycle controls function, and whether outcome measurement is credible. Scaling then depends on reuse of proven operating patterns, not on multiplication of loosely connected pilots.

A decision-oriented readiness model has limitations. It requires more preparatory work than technology-led adoption. It can slow visible experimentation during the early phase. It depends on cross-functional collaboration, which is difficult in organizations where data, engineering, operations, and business teams report through separate chains. Leaders also need to treat AI readiness as a governance and operating-model question. These constraints are preferable to uncontrolled expansion of AI use cases with unclear ownership, unstable data, or weak accountability.

Enterprise operations and analytics functions need a federated approach. Central teams define standards for data quality, governance, lifecycle management, security, and evaluation.

Product or domain teams own decision-level implementation because they understand workflows, exceptions, user needs, and performance consequences. This arrangement preserves consistency while keeping AI close to operational reality.

The practical contribution of the proposed model lies in its diagnostic use. Before funding an AI initiative, leaders can ask whether the decision has a baseline, whether supporting data products are governed, whether model behavior can be monitored, whether users know how to act, and whether accountability is documented. These questions reveal readiness gaps before production rollout. They also keep AI strategy from turning into disconnected dashboards, models, and automation scripts.

CONCLUSION

Enterprise AI readiness in operations and analytics functions rests on the alignment of governed data, reliable infrastructure, process ownership, human capability, lifecycle control, and decision accountability. The reviewed literature supports a multi-dimensional interpretation of readiness, while the enterprise operations setting requires a more focused reading. Data quality, metadata, integration reliability, co-development, model lifecycle management, and governance become decisive because AI outputs enter workflows where delay, ambiguity, and weak accountability can affect service quality, operational continuity, and managerial trust.

AI readiness has special significance for operations and analytics because these functions translate fragmented signals into action. Their readiness cannot be reduced to platform availability or model experimentation. It depends on trustworthy signals, user interpretation, workflow absorption, governed exceptions, and feedback that improves the system over time.

The proposed decision-oriented model provides support for the hypothesis stated in the introduction. AI readiness depends less on the presence of AI tools than on the managed alignment of data, infrastructure, processes, skills, governance, and feedback loops around specific decisions. The methodological contribution of the article is the shift from tool-centered readiness to decision-centered readiness. For practice, enterprises should assess AI initiatives by asking what decision will improve, who owns the outcome, which data supports the output, who maintains trust, and which operational feedback triggers revision.

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