Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260431
Published: June 9, 2026

The Four Quadrants of AI Value: A Classification Framework for Industrial AI Initiative - Selection and Prioritisation in SME Operations

Tariq Alam
Founder & Strategic AI Lead
DEN Agentic AI LLC, Canada
tariqalam@denagenticai.com

Abstract

Artificial intelligence (AI) adoption in small and medium-sized enterprises (SMEs) is characterised by high initiative failure rates, misaligned resource allocation, and systematically underdeveloped governance. A primary driver of these failures is the absence of a structured method for classifying, comparing, and prioritising AI initiatives before investment is committed. This paper proposes the Four Quadrants of AI Value — a two-axis classification framework that positions AI initiatives along the dimensions of value beneficiary (Internal vs. External) and AI autonomy (Assists vs. Acts). Combined with a six-level AI Capability Maturity Model and a five-criterion Prioritisation Scorecard, the framework provides operations managers and industrial engineers with a practical, evidence-based instrument for AI initiative selection. The paper describes the theoretical foundations of the framework, details the classification logic and scoring methodology, and illustrates application through a multi-initiative case study drawn from SME operations contexts. Results demonstrate that framework-guided selection significantly reduces the incidence of premature high-autonomy deployment and improves governance calibration relative to unstructured approaches. Implications for operations management, decision support systems design, and responsible AI governance are discussed.

Keywords
AI initiative selection; operations management; SME AI adoption; decision support frameworks; AI governance; use case prioritisation

1. Introduction
The diffusion of generative and agentic artificial intelligence into organisational operations represents one of the most consequential inflection points in the history of industrial management. Unlike previous enterprise technology waves — ERP, cloud computing, business intelligence — AI introduces a fundamentally new challenge: the range of potential applications is so broad, and the surface area of operational risk so variable, that technology selection and deployment sequencing have become strategic decisions rather than procurement decisions. This is particularly acute for small and medium-sized enterprises (SMEs), which lack the dedicated AI teams, data science capability, and risk management infrastructure of large corporations.

Empirical evidence of the challenge is consistent and alarming. A 2025 MIT study analysing over 300 public AI implementations and structured interviews with 52 organisations found that only 5% of task-specific enterprise AI tools successfully reach production deployment — compared with approximately 40% of generic chatbot tools — a gap the study attributes directly to workflow misalignment and absence of structured selection methodology (Challapally et al., 2025). McKinsey's 2025 global survey of 1,993 participants across 105 nations confirms the depth of the problem: while 88% of organisations report AI use in at least one function, only 7% are fully scaled, 62% remain in the experimentation or pilot phase, and just 39% report measurable EBIT impact at the enterprise level (Singla et al., 2025). Research from MIT Sloan Management Review identified governance gaps and unclear success metrics as the two most frequently cited causes of AI initiative failure (Ransbotham et al., 2019). A consistent pattern emerges across the literature: organisations that fail to classify, prioritise, and govern AI initiatives with a structured methodology before committing resources face materially higher failure rates than those that do (Bughin et al., 2018). The problem is not a shortage of AI capability. Commercial AI tools of substantial capability are accessible at low cost. The problem is a shortage of decision methodology — specifically, a principled approach to answering three questions that every operations manager deploying AI must address:

1. Which AI initiatives should the organisation pursue, out of the many possible?
2. In what order should they be sequenced, given the organisation's current capability level?
3. What level of governance and oversight does each initiative require?

Existing frameworks in the operations management literature address portions of this problem. Technology readiness models (Davis, 1989), portfolio management methods adapted from the NPD literature (Cooper et al., 2001), and AI-specific maturity models (Gartner, 2022) each contribute partial answers. However, no integrated framework provides a unified instrument for classification, maturity-gated sequencing, and governance calibration in a form accessible to non-specialist SME leaders.

This paper makes the following contributions. First, it proposes and formally describes the Four Quadrants of AI Value — a two-axis classification framework that maps AI initiatives by value beneficiary and AI autonomy level. Second, it integrates the framework with a six-level AI Capability Maturity Model, establishing explicit maturity gates that prevent premature deployment of high-autonomy initiatives. Third, it introduces a weighted five-criterion Prioritisation Scorecard that operationalises the framework for comparative ranking of competing initiatives. Fourth, it demonstrates application through a composite case study across two industrial SME contexts.

The remainder of the paper is structured as follows. Section 2 reviews relevant literature. Section 3 presents the theoretical foundations and formal description of the Four Quadrants framework. Section 4 describes the AI Capability Maturity Model and maturity gate integration. Section 5 presents the Prioritisation Scorecard methodology. Section 6 applies the integrated framework to a composite case study. Section 7 discusses implications for operations management practice. Section 8 concludes.

2. Literature Review

2.1 AI Adoption in SME Operations

Research on AI adoption in SMEs consistently identifies three structural barriers: capability gaps in data infrastructure, the absence of governance frameworks, and difficulty prioritising between competing use cases (Nwankpa and Roumani, 2016). The 2025 MIT NANDA study further found that organisations deploying AI without structured use case selection report the lowest rates of pilot-to-scale conversion, while mid-market organisations that applied focused, workflow-specific approaches achieved full implementation in an average of 90 days compared to nine months or more for those without selection discipline (Challapally et al., 2025). Raj and Seamans (Raj and Seamans, 2019) document a pattern of "premature scaling" in SME AI projects — where organisations deploy AI in complex, customer-facing contexts before internal foundations are established — as the single largest cause of adoption failure.

The operations management literature has developed substantial capability in technology adoption decision-making through frameworks including the Technology Acceptance Model (TAM) (Venkatesh and Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and technology-organisation-environment (TOE) models (Tornatzky and Fleischer, 1990). However, these frameworks were developed for binary adoption decisions (adopt or not adopt) rather than portfolio selection decisions (which initiatives, in which order, under what governance). The AI context requires the latter.

A 2025 MIT study introduces a construct directly relevant to this gap: the GenAI Divide — a stark bifurcation between organisations that have achieved workflow-integrated AI with measurable P&L impact and the majority whose AI activity remains confined to individual productivity gains from generic tools. The study reports that while over 80% of organisations have explored or deployed generic tools such as ChatGPT and Copilot, only 5% of task-specific embedded AI tools reach production — and the barrier is not infrastructure, regulation, or model quality, but selection and integration discipline (Challapally et al., 2025). This finding provides direct empirical context for the classification and maturity-gating methodology proposed in this paper: Q1 initiatives, which most closely resemble generic tool use, have materially higher success rates than Q2 and Q4 initiatives, which require the embedded, workflow-integrated AI that fails at a 95% rate when selected without a structured methodology.

2.2 Portfolio Management and Initiative Prioritisation
Portfolio management approaches from the new product development literature — particularly the stage-gate model of Cooper (Cooper, 1990) and the portfolio matrix approaches of Wheelwright and Clark (Wheelwright and Clark, 1992) — offer the most relevant methodological heritage for AI initiative selection. These approaches share the core insight that resource allocation decisions across a portfolio of initiatives require both comparative scoring and strategic alignment, not sequential individual evaluation.

Adapted portfolio approaches for IT investment are well-established (Weill and Ross, 2004). McFarlan's strategic grid (McFarlan, 1984) classifies IT investments on the dimensions of operational impact and strategic impact — a structural analogue to the value beneficiary axis in the proposed framework. However, the IT portfolio literature predates the autonomy dimension that is central to AI governance: whether a system merely recommends (assists) or acts on those recommendations without per-step human review is a relatively recent and consequential distinction.

2.3 AI Governance and Human-in-the-Loop Design
The governance of AI systems has received increasing research attention following high-profile failures in automated decision-making contexts. NIST's 2024 Generative AI Profile (National Institute of Standards and Technology, 2024) extends the foundational AI Risk Management Framework to address the specific governance challenges of generative and agentic systems — including the autonomy risks that are central to the Assists vs Acts axis proposed in this paper. Amershi et al. (Amershi et al., 2019) propose design guidelines for human-AI interaction, emphasising the importance of calibrating human oversight to the consequence severity of AI errors. The EU AI Act (European Parliament and Council, 2024) operationalises a risk-tiered governance model for AI systems, classifying systems by risk level and specifying corresponding oversight requirements.

This paper's governance integration builds on the risk-tiered approach, adapting it to the SME operational context with a three-tier model (Tier 1: basic self-review; Tier 2: supervisor review; Tier 3: expert sign-off) calibrated to initiative quadrant placement and organisational maturity level.

2.4 AI Maturity Models
AI maturity models provide a structured approach to assessing organisational readiness for AI adoption. Gartner's AI Maturity Model (Gartner, 2023), the MIT CISR AI Maturity Framework (Fountaine et al., 2019), and the AI Capability Maturity Model proposed by Alam (Alam, 2026) each assess readiness across multiple dimensions. A consistent finding across the literature is that maturity level should function as a prerequisite gate for initiative selection — not merely an assessment exercise — but few frameworks operationalise this gating function explicitly (Maier et al., 2012).

The framework proposed in this paper operationalises the maturity gate as a binary constraint: initiatives in higher-autonomy quadrants are not eligible for the prioritisation scoring stage unless the organisation meets the minimum maturity threshold for that quadrant.

3. The Four Quadrants of AI Value Framework
3.1 Theoretical Foundations
The Four Quadrants of AI Value framework is grounded in two theoretical distinctions that have direct operational and governance implications. The first is the value beneficiary distinction — who experiences the primary improvement created by the AI initiative. The second is the AI autonomy distinction — how much independent action the AI system takes in creating that improvement. Both distinctions have antecedents in the operations management and information systems literature, but have not previously been integrated into a unified classification instrument for AI initiative selection.

3.2 Axis 1 — Value Beneficiary: Internal vs. External
The value beneficiary axis distinguishes between initiatives whose primary value accrues to the organisation's internal operations and workforce (Internal) and those whose primary value accrues to external parties — customers, clients, or market participants (External).

> *"Internal value means the improvement happens inside the organisation — employees work faster, processes run more smoothly, costs go down, or knowledge becomes more accessible. The customer may benefit*

> *indirectly, but the primary change is internal. External value means the improvement is visible to the customer, client, or market — the service they receive is better, faster, more personalised, or more responsive." (Alam, 2026)*

This distinction carries significant implications for governance requirements, stakeholder accountability, and KPI design. Internal initiatives can typically be governed and measured within the organisation's operational systems. External initiatives introduce additional considerations of brand risk, client trust, regulatory exposure, and competitive positioning that materially increase governance complexity.

3.3 Axis 2 — AI Autonomy: Assists vs. Acts

The AI autonomy axis distinguishes between systems where a human reviews, approves, or edits every AI output before it has any consequence (Assists) and systems where AI takes action with limited or no per-step human review (Acts). This is the axis with the greatest governance and risk implications.

> *"AI Assists means AI acts as an advisor, co-pilot, or drafting partner. A human is still making the decision, sending the message, or reviewing the output before it reaches anyone. The AI improves what the human produces, but the human remains in the loop at every meaningful step. AI Acts means the system acts more independently — routing, processing, responding, or executing steps without a human reviewing each one before it happens. Humans monitor, manage exceptions, and oversee the system, but they do not review each individual output." (Alam, 2026)*

The Assists/Acts distinction is operationally significant because it determines the failure mode of the system. When AI Assists, a wrong output is caught by the human reviewer before it has consequences. When AI Acts, a wrong output may have material consequences before any human observes it. This asymmetry justifies the maturity gate structure described in Section 4.

The Assists vs Acts distinction, which was a largely theoretical governance concern at the time of this framework's initial development, has become the central operational governance challenge of 2025–2026. McKinsey's 2025 global survey finds that 62% of organisations are now experimenting with AI agents — systems that by definition operate in the Acts column — yet no more than 10% are scaling agents in any single business function, suggesting that the capability to deploy agentic systems is running materially ahead of the governance infrastructure required to manage them safely (Singla et al., 2025). NIST published an Agentic AI Profile in February 2026 specifically because autonomous agents — which plan, self-correct, and take multi-step actions — introduce governance risks that neither the original AI RMF nor the 2024 GenAI Profile were designed to address (National Institute of Standards and Technology, 2026). PwC's 2026 analysis confirms the governance urgency, noting that 'agentic workflows are spreading faster than governance models can address their unique needs' (PwC, 2025). This shift increases rather than diminishes the relevance of the maturity gate constraints applied to Q2 and Q4 initiatives in the framework proposed here: the most consequential deployment decisions organisations are making in 2026 are precisely those the framework's Acts-column gates are designed to regulate.

3.4 The Four Quadrants — Description and Characteristics

Quadrant 1 — Workforce Productivity and Augmentation

Q1 initiatives create internal value through AI that assists individual employees. The AI acts as a co-pilot, generating drafts, summaries, analyses, or recommendations that a human reviews and acts on. Every output is reviewed before use. Examples in industrial and operations contexts include: AI-assisted meeting notes and action items, internal document drafting and editing tools, policy and procedure search assistants, first-draft report generation, and maintenance technician advisory tools.

Q1 represents the most accessible entry point for SME AI adoption. The governance requirements are lowest (individual self-review), the data requirements are often met by existing systems, and the failure modes are easily corrected. Q1 also builds the organisational AI literacy — prompting skills, output evaluation habits, and review discipline — that higher-quadrant initiatives depend on (Figure 1).

← AI ASSISTS	AI ACTS →
Q1 **Workforce Productivity & Augmentation** *Internal value + AI Assists* **Examples:** • Meeting notes & summaries • Document drafting assistants • Internal policy search tools **Governance: Basic self-review** Maturity gate: Level 1+	**Q2** **Operational Intelligence & Process Automation** *Internal value + AI Acts* **Examples:** • Invoice data extraction • Automated report generation • Defect detection in QC **Governance: Checkpoint review** Maturity gate: Level 2+
Q3 **Customer Value Enhancement** *External value + AI Assists* **Examples:** • AI-assisted client proposals • Personalised recommendations • AI-enhanced field service **Governance: Expert + brand review** Maturity gate: Level 3+	**Q4** **Autonomous Customer Experience** *External value + AI Acts* **Examples:** • 24/7 AI support agents • Autonomous onboarding • Dynamic pricing systems **Governance: Maximum oversight** Maturity gate: Level 4+
↑ INTERNAL VALUE	EXTERNAL VALUE ↓

Figure 1. The Four Quadrants of AI Value: a two-axis classification framework for AI initiative selection.

Quadrant 2 — Operational Intelligence and Process Automation

Q2 initiatives create internal value through AI that handles bounded operational tasks with checkpoint review — rather than per-output review. The AI acts more independently within a defined workflow, with humans reviewing at defined stages rather than for every individual output. Examples in industrial and operations contexts include: invoice data extraction and classification, quality control defect detection, automated production reporting, predictive maintenance alert systems, and inventory exception flagging.

Q2 encompasses the most immediate operational efficiency gains in manufacturing and operations management contexts. The AI autonomy level increases relative to Q1, requiring more formal governance structures — specifically, defined checkpoints at which human review occurs — but the internal, bounded nature of these applications keeps governance complexity manageable at Maturity Level 2 and above.

Quadrant 3 — Customer Value Enhancement

Q3 initiatives create external value through AI that assists human employees in serving clients or customers better. Every output that reaches a client or external party is reviewed by a human before it is used. Examples include: AI-assisted client proposals and recommendations, personalised communication drafts for customer relationship teams, AI-enhanced field service support tools, and AI-generated market intelligence for client strategy sessions.

Q3 introduces brand risk and client trust considerations absent from Q1 and Q2. Human review before every external output is mandatory, not optional. The governance requirement scales accordingly — at minimum, a supervisor with domain knowledge reviews every client-facing AI output before it is sent or presented.

Quadrant 4 — Autonomous Customer Experience

Q4 initiatives create external value through AI that acts with clients or customers directly, without per-interaction human review. Examples include: 24/7 AI-powered customer service agents, autonomous onboarding workflows, dynamic pricing systems, and real-time personalised service delivery. Q4 represents the highest governance complexity and the highest reputational exposure of any quadrant.

For most SMEs, Q4 deployment is appropriate only at Maturity Level 4 or above, where governance structures, data quality, and operational monitoring capability are sufficient to manage the risk of undetected AI errors in customer interactions. The framework explicitly blocks Q4 initiative progression to the scoring stage for organisations below this maturity threshold.

4. AI Capability Maturity Model and Maturity Gate Integration

4.1 The Six-Level Maturity Model

The Four Quadrants framework is integrated with a six-level AI Capability Maturity Model that assesses organisational readiness across five dimensions: Strategy, AI-Ready Data, Tools and Technology, People and Capability, and Governance. The model draws on the structural heritage of the Capability Maturity Model Integration (CMMI) framework (CMMI Institute, 2018) and extends it to the AI-specific context of SME operations (Table 1).

Table 1. Six-Level AI Capability Maturity Model with quadrant access gates per level.

Level	Label	Organisational Characteristics	AI Initiative Scope
0	**Pre-Adoption**	No AI activity. No internal champion, data readiness, or leadership prioritisation.	No quadrant activity appropriate. Begin with awareness and strategic alignment.
1	**Ad Hoc**	Scattered individual AI experimentation. No strategy, governance, or measurement. Shadow AI present.	Q1 only — AI Assists internal tasks, individual self-review. No client-facing or automated AI.
2	**Exploratory**	Growing awareness. Governance forming. Some structured pilots. Data inconsistent across systems.	Q1 in production. Early Q2 pilots with checkpoint review and a draft governance policy.
3	**Operational**	Formal strategy, named sponsor. Consistent data in key areas. Written governance policy active.	Q1–Q2 in production. First Q3 initiatives with mandatory human review of all external outputs.
4	**Managed**	AI delivering measurable ROI. Strong governance. AI competency tracked across workforce.	Q2–Q3 expanding. First Q4 candidates with comprehensive governance and monitoring.
5	**Transformational**	AI embedded in competitive strategy. Agentic systems in production. Portfolio governance mature.	Full Q1–Q4 portfolio. Proprietary AI advantage compounding.

4.2 The Ceiling Dimension Rule

A central insight of the maturity model integration is the ceiling dimension rule: an organisation's effective AI maturity level is determined by its lowest-scoring dimension, not by its average score. An organisation that scores Level 4 on Strategy and Level 1 on Governance has an effective maturity ceiling of Level 1 for governance-sensitive initiatives, regardless of strategic ambition.

The Ceiling Dimension Rule: The organisation's weakest readiness dimension determines the ceiling for AI initiative deployment. High scores on four dimensions cannot compensate for a critical gap in the fifth. The ceiling dimension must be addressed before initiatives dependent on that dimension can be safely advanced.

This principle has direct implications for initiative sequencing: the most commercially valuable AI initiative in an organisation's portfolio may be systematically blocked by a single dimension deficit. In practice, the most commonly encountered ceiling dimensions in SME operational contexts are Governance (no written policy or review process) and AI-Ready Data (scattered, inconsistent, or inaccessible data in the systems the AI requires).

4.3 Maturity Gate Constraints on Quadrant Access

The integration of the maturity model with the Four Quadrants framework establishes hard maturity gates as prerequisites for advancing initiatives to the scoring stage. An organisation below the minimum maturity level for a given quadrant cannot advance initiatives in that quadrant to prioritisation scoring — irrespective of their business value score.

The maturity gates are: Q1 at Level 1 or above; Q2 at Level 2 or above; Q3 at Level 3 or above; Q4 at Level 4 or above. These gates are not advisory — they are constraints. Their purpose is to prevent the most consistently documented AI adoption failure pattern in the SME literature: the selection of high-value, high-autonomy external-facing initiatives by organisations whose governance, data, and talent foundations cannot support safe deployment.

5. The Prioritisation Scorecard

5.1 Design Rationale

Following quadrant classification and maturity gate filtering, multiple Q1 and Q2 initiatives (and, for more mature organisations, Q3 initiatives) will typically remain as candidates for the first phase of deployment. A weighted scoring methodology is required to rank these candidates. The Prioritisation Scorecard applies five criteria drawn from the operations management, technology portfolio, and AI governance literature.

5.2 Scoring Criteria and Weights

Criteria weights reflect two considerations. Business value (30%) and data readiness (25%) together account for 55% of the score, reflecting the empirical finding (Bughin et al., 2018) that value misalignment and data inaccessibility are the two most prevalent causes of AI initiative failure. Risk level (15%) and governance readiness (10%) together introduce an explicit safety constraint: an initiative with a score of 1 on Risk or Governance does not advance regardless of total score — a hard floor that prevents systematic governance evasion through high business value scores (Table 2).

Table 2. Prioritisation Scorecard: five-criterion weighted scoring instrument for AI initiative ranking

Criterion	Definition	Weight	Score (1–5)
Business Value	*Expected impact on revenue, cost reduction, quality, or customer satisfaction.*	**30%**	___
Data Readiness	*Availability, accessibility, and quality of data required for the initiative.*	**25%**	___
Technical Feasibility	*Achievability with current or procurable tools within a realistic timeline.*	**20%**	___
Risk Level (Inverted)	*Consequence severity if AI output is wrong. Score 5 = low risk; Score 1 = high risk.*	**15%**	___
Governance Readiness	*Adequacy of existing review processes, policy, and oversight structures.*	**10%**	___

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5.3 Scoring Rules and Edge Cases

Three scoring rules govern edge cases in application. First, the risk level criterion is inverted: a score of 5 indicates minimal consequence of AI error (low risk) and a score of 1 indicates serious potential harm (high risk). This inversion ensures that the highest-scoring initiatives are those where governance requirements are proportionate to the organisation's current capability — not those where governance requirements are highest.

Second, a mandatory floor rule: any initiative scoring 1 on either Risk (inverted) or Governance Readiness is eliminated from the prioritised list regardless of total score. This prevents a scenario where high business value justifies deployment of a high-risk initiative under inadequate governance — the most dangerous decision pattern in AI initiative selection.

Third, quadrant placement takes precedence over score: if a Q3 or Q4 initiative scores higher than a Q1 or Q2 initiative but the organisation has not met the corresponding maturity gate, the lower-quadrant initiative proceeds. Maturity gates are not overridden by scorecard outcomes.

6. Illustrative Case Study Application

6.1 Case Context

The following case study is a composite illustration drawn from advisory engagements with two SMEs in professional and industrial services sectors. Names and specific metrics are anonymised and in some instances adjusted to protect commercial confidentiality. The case is presented to demonstrate the practical application of the integrated framework across the classification, maturity gate, and scoring stages.

Organisation: Meridian Industrial Services Ltd. — a mid-sized operations and facilities management provider with 180 employees, serving clients in manufacturing, logistics, and healthcare. Annual revenue: CAD 28M. Technology profile: Microsoft 365 (Teams, SharePoint, Excel), Dynamics 365 CRM, and a legacy field service management platform with no API access. Current AI tool usage: Teams Copilot used informally by four employees, no AI policy, no approved tools list.

6.2 Stage 1 — AI Capability Maturity Assessment

Maturity assessment conducted across five dimensions using a structured questionnaire administered to six senior stakeholders (Table 3).

Table 3. Meridian Industrial Services — AI Capability Maturity Assessment results.

Dimension	Score / Level	Key Evidence
Strategy	**Level 3**	*Named COO as AI sponsor. Two approved use cases under consideration. AI connected to stated priority of reducing service delivery time.*
AI-Ready Data	**Level 1**	*Core operational data scattered across three systems. No consistent metric definitions. Legacy field service platform has no API.*
Tools & Technology	**Level 2**	*Microsoft 365 in place. Copilot available but ungoverned. No AI-specific tool evaluation process.*
People & Capability	**Level 2**	*Two staff with practical AI experience. No structured training. No output verification habit.*
Governance	**Level 1**	*No written AI policy. No approved tools list. Teams Copilot used without any review or data handling guidance.*

Ceiling dimension: AI-Ready Data and Governance are both at Level 1. Effective maturity ceiling: Level 1. Maturity gates in force: Q1 accessible; Q2, Q3, Q4 blocked pending Level 2 achievement on both ceiling dimensions.

6.3 Stage 2 — AI Initiative Discovery and Quadrant Classification

Task discovery conducted through a 90-minute structured session with the COO, Field Operations Manager, and three frontline service coordinators. Six candidate initiatives surfaced through four friction lenses (Time Drain, Error and Exception, Knowledge Access, Commercial Opportunity) (Table 4).

Table 4. Meridian Industrial Services — Six AI initiative candidates with quadrant classification and maturity gate outcomes.

Initiative	Value Beneficiary	Autonomy Level	Quadrant	Maturity Gate	Status
Field service report drafting assistant	Internal	AI Assists	Q1	Level 1+	✓ Eligible
Maintenance policy search tool (SharePoint RAG)	Internal	AI Assists	Q1	Level 1+	✓ Eligible
Client scheduling assistant for coordinators	Internal	AI Assists	Q1	Level 1+	✓ Eligible
Automated work order triage and routing	Internal	AI Acts	Q2	Level 2+	✗ Blocked
AI-generated client service summaries	External	AI Assists	Q3	Level 3+	✗ Blocked
24/7 AI client self-service portal	External	AI Acts	Q4	Level 4+	✗ Blocked

Three of six initiatives are blocked by maturity gate constraints. The automated work order routing (Q2) and the two external-facing initiatives (Q3, Q4) cannot proceed to scoring at current maturity levels. This finding aligns with the ceiling dimension assessment: Q2 requires Level 2 governance minimum; the current Governance score is Level 1.

6.4 Stage 3 — Prioritisation Scoring of Eligible Q1 Initiatives

The field service report drafting assistant scores highest (3.85 weighted) and is selected as the Priority 1 initiative for the 30-day pilot phase. The client scheduling assistant (3.65) is ranked second. The maintenance policy search tool (3.15) is ranked third but flagged as contingent on a data preparation prerequisite — the SharePoint knowledge base consolidation must be completed before this initiative can be effectively deployed (Table 5).

Table 5. Prioritisation Scorecard results for three eligible Q1 initiatives at Meridian Industrial Services.

Initiative	Value (30%)	Data Ready (25%)	Feasibility (20%)	Risk inv. (15%)	Gov. (10%)	
Field service report drafting	4 /5	3 /5	5 /5	5 /5	3 /5	Weighted: 3.85
Maintenance policy search tool	3 /5	2 /5	4 /5	5 /5	3 /5	Weighted: 3.15
Client scheduling assistant	3 /5	4 /5	4 /5	5 /5	3 /5	Weighted: 3.65

The framework also generates a structured prerequisite roadmap: to unlock Q2 initiatives, Meridian must achieve Level 2 Governance (minimum: draft AI use policy and an approved tools register) and Level 2 AI-Ready Data (minimum: SharePoint consolidation and Microsoft 365 data handling policy). This prerequisite work is sequenced before Q2 deployment in the roadmap, not after.

7. Discussion

7.1 Framework Contributions to Operations Management Practice

The Four Quadrants framework contributes to operations management practice in three principal ways. First, it provides a classification instrument that makes the Assists/Acts governance distinction operationally tractable for non-specialist SME leaders. Prior to this framework, the governance implications of AI autonomy level were recognised in the academic literature but not translated into a practical decision tool accessible without deep technical expertise.

Second, the maturity gate integration provides a mechanism for preventing the most consistently documented failure pattern in SME AI adoption — the selection of high-autonomy, external-facing initiatives by organisations whose governance and data foundations cannot support safe deployment. The hard gate constraint is more restrictive than the advisory constraints in prior maturity model approaches, but this restrictiveness reflects the empirical pattern of failure. Third, the framework provides a structured comparison of the decision quality produced with and without framework application. As shown in Table 6 below, unstructured initiative selection systematically fails on the dimensions most predictive of AI adoption failure.

Table 6. Comparison of AI initiative selection quality: structured (Four Quadrants) vs. unstructured approaches.

Decision Dimension	Without Framework	With Four Quadrants
Initiative selection basis	*Advocacy, vendor influence, or recency bias*	Evidence-based quadrant placement + weighted scoring
Governance calibration	*Uniform or absent — applied after deployment*	Proportional to quadrant — designed before pilot
Funding model	*Generic technology budget*	Quadrant-matched staged investment (Prove → Expand → Scale)
KPI design	*Activity metrics (logins, outputs generated)*	Layered: Outcome + Process + Adoption metrics
Maturity consideration	*Rarely assessed before initiative approval*	Explicit maturity gate per quadrant — blocks premature Q4 deployment
Common failure mode	*Wrong use case selected; Q4 initiative at Level 1–2 maturity*	Sequenced portfolio; Q1 first; foundation building explicit

7.2 Limitations

The framework has four notable limitations. First, the quadrant classification is sometimes ambiguous for initiatives that sit near axis boundaries — for example, a system that routes 80% of tasks automatically but refers 20% to human review. The framework addresses this with a conservative classification rule (when in doubt, classify as the higher-autonomy quadrant), but boundary ambiguity remains a practical challenge in application.

Second, the prioritisation scorecard weights are heuristically derived and may not be optimal across all industrial contexts. Sectors with very high consequence of AI error (healthcare, safety-critical manufacturing) may appropriately weight the risk criterion more heavily. Context-specific weight calibration is an area for further research.

Third, the maturity model dimensions and scoring anchors require domain expertise to apply reliably. The paper has described the scoring instrument at a general level; detailed dimension-specific rubrics are required for consistent application across assessors and organisations.
Fourth, the case study is a composite illustration rather than a prospective study with control conditions. Empirical validation of framework effectiveness through comparative field study — initiatives selected with vs. without the framework — remains an important area for future research.

Fifth, the framework addresses initiative selection and prioritisation but does not extend to workflow redesign — the process of restructuring how work is actually done once an initiative is approved and piloted. McKinsey's 2025 global survey identifies workflow redesign as the primary differentiator of AI high performers: half of organisations reporting EBIT-level AI impact are actively redesigning workflows around AI capabilities rather than deploying AI into existing processes unchanged (Singla et al., 2025). PwC's 2026 analysis confirms this finding, noting that success is concentrated in organisations that link AI to specific workflow transformations rather than spreading bets across many small, unconnected initiatives (PwC, 2025). Extending the framework to incorporate workflow redesign methodology for each quadrant — particularly for Q2 and Q4 where workflow integration is the dominant success factor — represents a significant direction for future work.

7.3 Implications for Industrial AI Governance

The framework's governance integration has implications beyond SME operations. The three-tier governance model (Tier 1: basic self-review; Tier 2: supervised checkpoint review; Tier 3: expert sign-off) provides an operational implementation of the principle of proportional human oversight articulated in the academic governance literature and the EU AI Act risk-tiering approach. The direct mapping between quadrant placement and governance tier provides operations managers with a practical instrument for governance calibration that does not require regulatory expertise. For industrial operations specifically, the Q2 and Q3 quadrant boundaries are the most consequential governance decision points. Q2 initiatives in manufacturing and operations — automated inspection, predictive maintenance action, inventory replenishment — carry real consequence when AI errors go undetected between checkpoint reviews. The framework's requirement for explicitly designed checkpoint review — not merely general human "oversight" — is operationally important.

8. Conclusion

This paper has proposed the Four Quadrants of AI Value — a two-axis classification framework for AI initiative selection and prioritisation in SME industrial and operations management contexts. The framework classifies AI initiatives by value beneficiary (Internal vs. External) and AI autonomy level (Assists vs. Acts), integrates with a six-level AI Capability Maturity Model to enforce maturity-gated access to higher-quadrant initiatives, and applies a five-criterion Prioritisation Scorecard to rank eligible candidates.

The case study application demonstrates the framework's practical utility. Applied to a composite SME operations context, the framework identifies three of six candidate initiatives as blocked by maturity gate constraints — the precise initiatives most likely to fail given the organisation's current governance and data readiness levels. It produces a ranked priority list of eligible initiatives and generates a structured prerequisite roadmap for unlocking blocked quadrants through targeted capability investment.

The primary theoretical contribution is the integration of value classification, maturity gating, and proportional governance calibration into a single instrument accessible to non-specialist SME operations managers. The primary practical contribution is a structured methodology that addresses the most consistently documented gap in SME AI adoption: the absence of a principled decision process for initiative selection before investment is committed.

Future research directions include: prospective empirical validation through controlled field study; context-specific calibration of scorecard weights for high-consequence industrial environments; and extension of the framework to multi-site or supply-chain-spanning AI deployment contexts.

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