

Charting the Strategic Path to AI Implementation: An Automation-Integration Framework for Enterprise AI Applications

Wullianallur Raghupathi, Aditya Saharia

Gabelli School of Business, Fordham University, New York, USA

Email: raghupathi@fordham.edu

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Abstract

Despite unprecedented investment in artificial intelligence, most organizations struggle to move beyond experimentation to achieve enterprise-wide value. Recent industry surveys indicate that while 88 percent of organizations now use AI in at least one business function, only 26 percent have developed the capabilities to generate measurable value at scale. This paper addresses this implementation gap by proposing a strategic framework for understanding and guiding AI application deployment. Drawing on recent enterprise AI research and established principles of technology integration in the IS literature, the framework conceptualizes AI implementations along two critical dimensions: the *degree of automation*—the extent to which AI systems operate autonomously in decision-making and execution—and the *degree of integration*—the connectivity of AI systems with enterprise platforms, data sources, and workflows. These dimensions define four distinct implementation configurations: isolated-supervised, isolated-autonomous, integrated-supervised, and integrated-autonomous. Drawing on diverse industry examples across healthcare, financial services, manufacturing, and retail, the analysis demonstrates how organizations can chart strategic paths toward more advanced configurations while balancing value creation, risk, and organizational readiness. The framework provides executives with a practical lens for evaluating AI opportunities, sequencing investments, and scaling enterprise value creation.

Keywords

Artificial Intelligence, AI Implementation, Enterprise AI, Automation, Integration, Digital Transformation, AI Strategy, Technology Adoption

1. Introduction

The deployment of artificial intelligence technologies across industries has reached an inflection point. Global enterprise spending on AI solutions reached \$37 billion in 2025, representing a 3.2x year-over-year increase from 2024 [1]. Organizations across sectors—from healthcare and financial services to manufacturing and retail—are investing heavily in AI capabilities, driven by the promise of operational efficiency, enhanced decision-making, and competitive advantage [2] [3]. Recent projections suggest that AI solutions could generate a cumulative economic impact of \$22.3 trillion by 2030 [4], underscoring the strategic importance of AI as a core component of digital strategy rather than a standalone technology investment [5].

Yet despite this enthusiasm and investment, a persistent gap separates AI experimentation from sustained enterprise value. The challenge of translating AI investments into meaningful business outcomes is well documented across industry studies [6]–[8]. McKinsey’s 2025 State of AI survey found that while 88 percent of organizations report regular AI use in at least one business function, the majority remain in experimenting or piloting stages at the enterprise level [9]. BCG’s complementary research reveals that only 26 percent of companies have developed the capabilities required to move beyond proofs of concept and generate tangible value [10]. Perhaps most strikingly, the MIT Media Lab’s State of AI in Business 2025 report finds that nearly 95 percent of organizations report little or no financial return from AI initiatives, while only approximately 5 percent capture substantial value—largely through highly integrated deployments that span multiple business functions.

These findings reveal a consistent pattern: widespread adoption alone is insufficient. Organizations that achieve meaningful AI impact share common characteristics, that is, they treat AI as a catalyst for transformation rather than an incremental efficiency tool, they invest heavily in integration infrastructure, and they focus resources on a limited number of high-impact initiatives rather than pursuing numerous disconnected pilots [10] [11]. The gap between experimentation and enterprise-level value creation reflects not primarily technical limitations but organizational challenges involving process redesign, cross-functional coordination, and strategic alignment [12] [13].

These challenges point to a critical gap in existing guidance: organizations lack a strategic framework for evaluating AI applications, sequencing implementation initiatives, and charting progression paths toward more advanced capabilities. While prior research has examined individual AI use cases, technical architectures, and organizational readiness factors, fewer studies provide an integrative perspective that helps executives understand how different AI configurations differ in their strategic implications and how organizations can deliberately evolve their AI capabilities over time.

In this paper, we address this gap by proposing a strategic framework for AI application implementation. Synthesizing insights from recent enterprise AI re-

search [9]–[11] and drawing on established principles of technology adoption [14] [15], organizational change [16], and IS governance [17], the framework conceptualizes AI applications along two critical dimensions: *degree of automation* and *degree of integration*. The degree of automation reflects the extent to which AI systems operate autonomously versus requiring human oversight—a dimension that has become central to discussions of agentic AI and human-AI collaboration [18]. The degree of integration captures how extensively AI systems connect with enterprise platforms, data sources, and workflows, a dimension that recurs across the reviewed sources as a frequently noted differentiator between organizations that capture value and those that do not [19] [20]. Together, these dimensions define a strategic space within which organizations can position existing AI applications, evaluate alternatives, and chart progressive implementation paths.

Two terms used throughout the paper warrant clarification at the outset. By *enterprise-wide value*, we mean performance gains that accrue across multiple business functions or processes through coordinated decision-making, shared data, and cross-functional workflow redesign, rather than localized improvements confined to a single task, team, or department. This stands in contrast to *local efficiency gains* (for example, faster document review within a single unit), which are real but bounded and additive; enterprise-level value arises when AI reshapes how work is coordinated across organizational boundaries, producing compounding rather than merely incremental benefits. The outcome logic of the framework is therefore directed at the latter: configurations are evaluated by their capacity to move organizations from isolated local gains toward enterprise-wide value. By *organizational readiness*, we mean the bundle of data, technical, and managerial capabilities including data quality and infrastructure, integration architecture, governance mechanisms, workforce skills, and change-management capacity that determines whether an organization can absorb a given AI configuration and translate it into sustained value.

We center the framework on automation and integration because these two dimensions jointly determine where AI value is located in the reviewed sources: automation governs whether an AI system executes decisions or merely advises a human, while integration governs whether its effects remain local or propagate across the enterprise. Together they capture the two choices most consequential for whether AI moves beyond isolated experimentation. Other factors that clearly shape AI implementation, notably risk exposure, regulatory intensity, and task interdependence are treated as contextual moderators rather than additional axes. We do so because these factors do not define distinct system configurations; rather, they condition where along the automation and integration dimensions a given application can or should sit. Regulatory intensity, for instance, constrains feasible automation in a domain, and task interdependence raises the value of integration, but neither represents an independent design choice in the way that the level of automation and the degree of integration do.

The remainder of the paper is organized as follows. Section 2 examines the prin-

ciple of automation in AI applications, describing the continuum from supervised decision support to autonomous systems. Section 3 discusses AI integration, focusing on technical architectures, data interoperability, and the organizational value of connected AI systems. Section 4 develops the automation-integration framework and positions AI applications within its four quadrants. Section 5 presents industry examples and case studies illustrating each configuration. Section 6 discusses implications for IS research, practice, and policy, along with directions for future research. Section 7 outlines the scope and limitations. Section 8 concludes with strategic recommendations.

2. The Automation Dimension

AI applications differ significantly in the extent to which they operate independently of human intervention. The *degree of automation* refers to an AI system's capacity to make decisions and execute actions without human oversight [21]. This capability exists on a continuum, ranging from systems that primarily support human decision-making to those capable of autonomous operation across multiple organizational functions. Understanding this continuum is essential for evaluating the strategic role of AI applications and for positioning them within the automation-integration framework.

2.1. Evolution toward Autonomous Systems

AI systems have evolved substantially over time. Early expert systems relied on predefined rules and required extensive human configuration and supervision. Subsequent advances in machine learning enabled systems to learn patterns from data, improving performance in tasks such as prediction, classification, and optimization [22]. More recently, large language models and agentic AI systems have expanded capabilities beyond narrow tasks, enabling reasoning, multi-step planning, and adaptive execution across diverse domains [23]. McKinsey's 2025 survey found that 23 percent of organizations are now scaling agentic AI systems, with an additional 39 percent experimenting with AI agents capable of autonomous multi-step task execution [9].

As a result, modern AI systems increasingly combine multiple capabilities—perception, reasoning, decision-making, and execution—within integrated applications. This evolution supports gradual progression from supervised assistance toward conditional autonomy and, in selected domains, fully autonomous operation.

2.2. The Automation Continuum

AI automation is best understood as a spectrum of human-AI collaboration rather than a binary distinction [18] [21]. At lower levels, AI functions as a decision-support tool, providing insights while humans retain control over decisions and actions. As automation increases, AI systems augment human judgment by recommending actions, filtering options, or managing routine decisions within de-

defined boundaries. **Figure 1** illustrates the degree of automation across multiple dimensions of human-AI interaction.

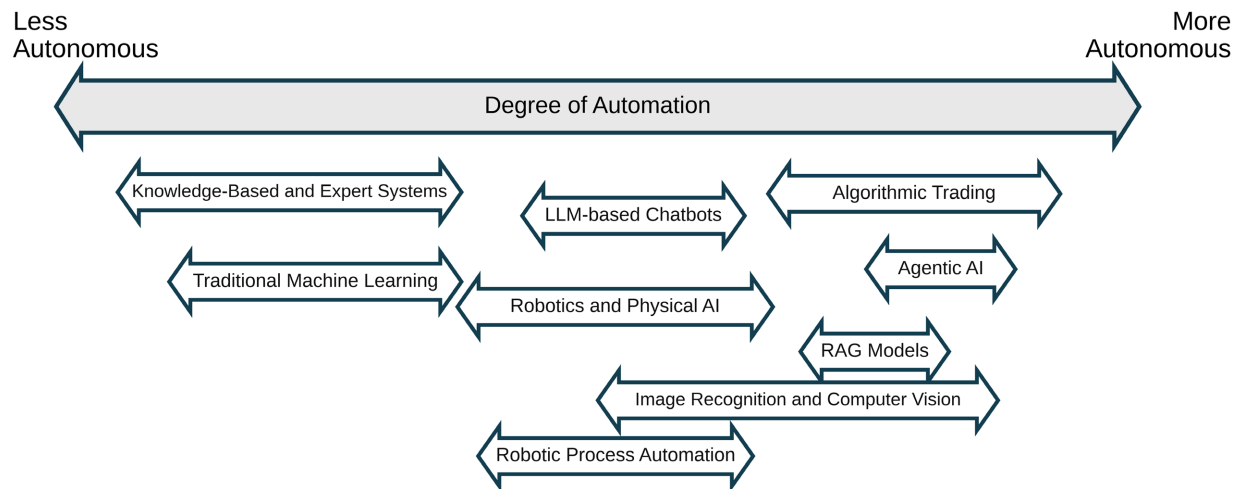


Figure 1. Degree of automation for AI systems.

At higher levels, AI systems operate autonomously under predefined parameters, escalating exceptions to humans only when necessary. Full autonomy represents the upper bound of the continuum, where AI systems independently manage end-to-end processes with minimal human intervention. Research on collaborative intelligence emphasizes that successful automation depends on aligning AI capabilities with human strengths and designing interaction models that support appropriate trust and accountability [21] [24].

2.3. From Analysis to Execution

Many early AI applications focused on analytics and reporting, where benefits such as improved insight generation are relatively easy to demonstrate [3]. While valuable, purely analytical systems offer limited transformational impact unless insights translate into action. Greater strategic potential arises when AI systems move from analysis to execution—automating decisions and operational processes in real time [25].

Achieving higher automation requires reliable system performance, transparency, and mechanisms for monitoring and intervention. Organizations must invest in data quality, continuous learning, and performance tracking to build confidence in automated decision-making. As AI systems demonstrate consistent behavior across diverse scenarios, organizations become more willing to delegate authority and expand the scope of autonomous operation [24].

3. The Integration Dimension

Integration refers to the ability of AI systems to connect and exchange data with other organizational systems, external platforms, and data sources in order to support coordinated, intelligent operations. Across the reviewed industry and aca-

demographic sources, integration capability recurs as one of the factors most often associated with the difference between organizations that capture AI value and those that do not [20] [26]. In contrast to isolated AI applications that operate on static or manually prepared data, integrated AI systems draw on real-time information across organizational boundaries and can trigger actions within connected workflows. As such, integration shapes whether AI capabilities remain localized or become embedded in enterprise-wide decision-making processes.

3.1. The Strategic Value of Integration

The degree of integration fundamentally shapes the organizational impact of AI. When AI systems operate in isolation, they may generate accurate predictions or insights within specific functions, but their influence is limited. Insights must be manually interpreted, transferred, and acted upon, increasing delays and inconsistency [27]. Isolated systems often reinforce data silos and constrain AI's ability to support cross-functional optimization.

Higher levels of integration enable AI systems to access comprehensive organizational data, coordinate decisions across multiple functions, and initiate actions directly within operational systems. Integration transforms AI from an analytical add-on into a mechanism for organizational coordination. Prior research on information exchange and interoperability demonstrates that substantial organizational value arises when systems can share data and coordinate processes across functional and organizational boundaries [28]—a principle that extends directly to integrated AI systems.

3.2. Technical Dimensions of Integration

AI integration typically occurs across three interrelated layers. At the *data layer*, integration involves connecting AI systems to diverse data sources such as transactional systems, data warehouses, and real-time streams. This requires reliable data pipelines that ensure data quality, consistency, and timeliness [29]. Organizations increasingly adopt architectural approaches such as data fabrics or data meshes to provide unified access to distributed data while preserving governance [30].

At the *application layer*, integration enables AI systems to interact with business applications through APIs, messaging systems, and event-driven architectures. These mechanisms allow AI outputs to trigger downstream actions and participate in end-to-end workflows. Microservices-based architectures support this form of integration by enabling modular, loosely coupled components to evolve independently while remaining interoperable.

At the *user experience layer*, integration embeds AI capabilities directly into the tools employees use in their daily work. Rather than requiring users to consult separate analytics platforms, integrated AI appears within operational interfaces, supporting decisions in context. This form of integration increases adoption and effectiveness by aligning AI outputs with existing workflows [24].

3.3. Challenges to Integration

Despite its strategic value, integration presents significant challenges. Integration costs are typically front-loaded, while benefits are distributed across stakeholders. Organizations must invest in data standardization, interface development, and system interoperability before realizing visible gains. Legacy technology environments complicate integration efforts, as many organizations operate heterogeneous systems developed over decades, with incompatible data models and limited interoperability. The Deloitte 2024 survey [11] found that resistance to adopting AI solutions often stems from unfamiliarity with technologies or from skill and technical gaps rather than fundamental technology limitations.

4. The Automation-Integration Framework

To provide a strategic perspective on AI implementation, we synthesize insights from recent enterprise AI research into a two-dimensional framework. The automation-integration framing emerges from consistent patterns in how organizations create and capture AI value. Industry research consistently shows that organizations achieving significant impact combine two characteristics: they deploy AI systems capable of autonomous operation within defined domains, and they integrate those systems extensively with enterprise data and workflows [9] [10] [26]. These observations align with established IS principles regarding technology-enabled process transformation and system interoperability. The resulting framework conceptualizes AI implementations along the dimensions of *degree of automation* and *degree of integration*, reflecting AI systems' capacity for autonomous decision-making and their dependence on comprehensive data connectivity.

A brief note on method clarifies how the framework was developed. This is a conceptual paper, and the framework was derived through a structured narrative synthesis rather than a systematic empirical study. We assembled source material in two streams. First, for the conceptual foundations, we drew on established information systems scholarship on technology adoption, organizational change, and IS governance, together with recent peer-reviewed work on AI in organizations, selecting sources that directly addressed how automation and connectivity shape technology value. Second, for evidence on enterprise AI value patterns, we reviewed recent industry and practitioner research from established firms and research centers (for example, McKinsey, BCG, Deloitte, MIT CISR, and MIT Media Lab), prioritizing reports that presented data on adoption, integration, and value capture. From these sources we identified recurring themes—most consistently, the joint importance of autonomous operation and enterprise integration—which we abstracted into the two framework dimensions. The industry examples in Section 5 were then selected purposively to illustrate the four resulting configurations: for each quadrant we sought publicly documented implementations across diverse sectors (healthcare, financial services, manufacturing, retail, and others) for which the level of automation and the degree of integration could be reasona-

bly inferred from public reporting. The examples are intended to demonstrate the framework’s descriptive range rather than to constitute a representative or exhaustive sample.

4.1. Framework Structure

Together, these dimensions define a strategic space within which organizations can position existing AI applications and plan future investments. **Figure 2** illustrates the resulting automation-integration matrix, which delineates four distinct AI implementation configurations: isolated-supervised, isolated-autonomous, integrated-supervised, and integrated-autonomous. Each quadrant represents a characteristic combination of human involvement, system connectivity, and organizational coordination. The framework does not assume a single optimal configuration; rather, it highlights trade-offs and progression paths that organizations can navigate based on context, strategic objectives, and risk tolerance.

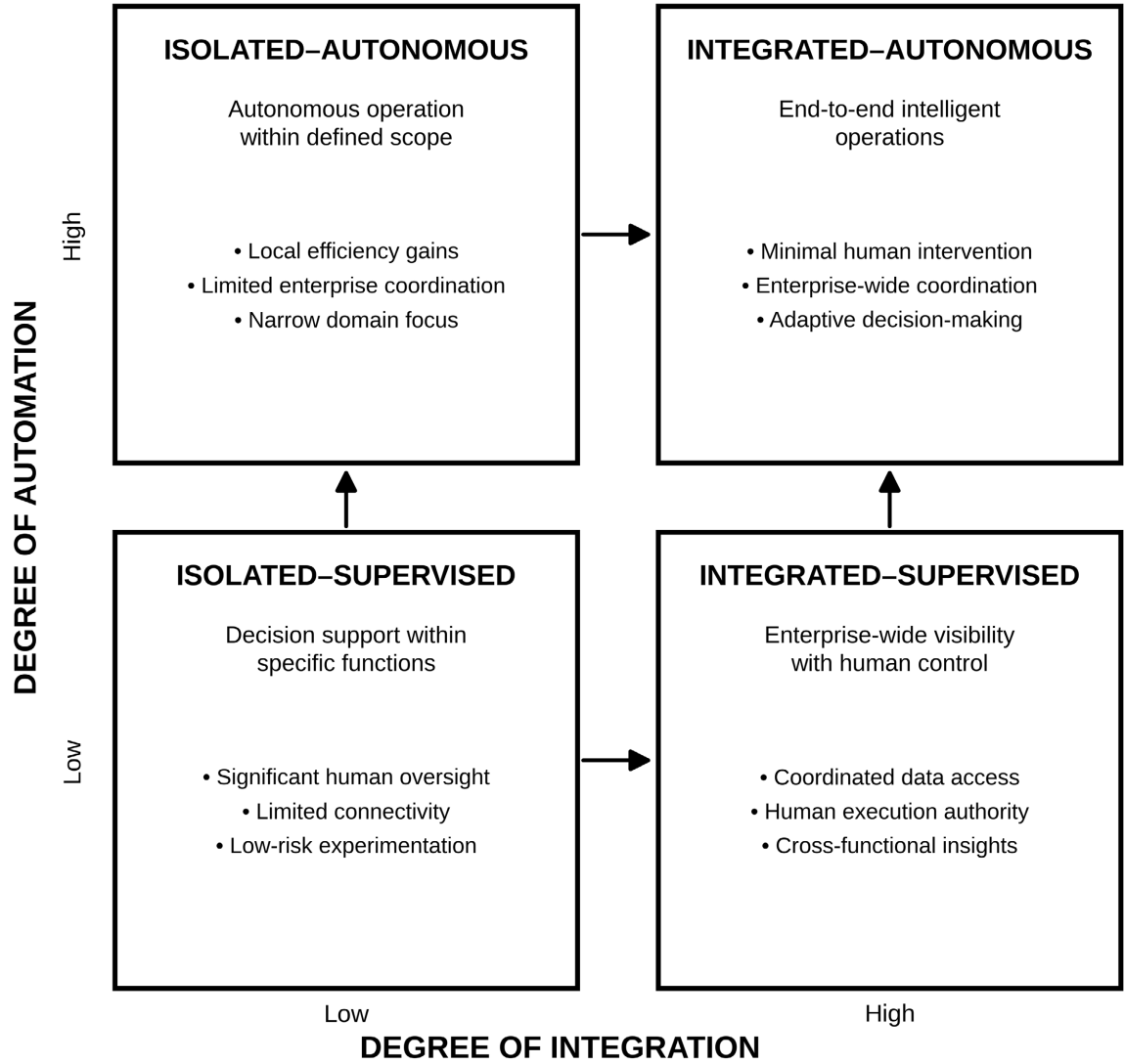


Figure 2. Automation-integration matrix.

4.2. Quadrant Descriptions

1) *Low Automation/Low Integration (Isolated-Supervised)*

This quadrant represents early-stage AI implementations characterized by limited autonomy and minimal connectivity. AI systems function as decision-support tools within specific departments, with significant human oversight and manual data transfer. These applications are typically used for experimentation, capability building, and low-risk value demonstration. Organizations in this configuration can build familiarity with AI while containing risk, but value creation remains localized and difficult to scale.

2) *High Automation/Low Integration (Isolated-Autonomous)*

In this quadrant, AI systems operate autonomously within well-defined scopes but remain functionally isolated from broader enterprise systems. These systems can execute decisions at scale and speed, delivering substantial local efficiency gains—such as automated quality inspection or algorithmic trading within a single asset class. However, limited integration constrains their contribution to broader organizational coordination. Value is captured within functional silos rather than across the enterprise.

3) *Low Automation/High Integration (Integrated-Supervised)*

Integrated-supervised systems combine extensive data connectivity with continued human involvement in decision-making. AI systems provide enterprise-wide visibility and insights while humans retain control over execution. This configuration is common in regulated or high-stakes environments where accountability and contextual judgment are critical. AI enhances human decision-making by synthesizing information across functions, but the pace of action depends on human capacity. Importantly, this configuration should not be read as a transitional stage on the way to full autonomy. In a range of settings it represents a deliberate and stable end state. Where decisions carry irreversible safety consequences (for example, clinical treatment or critical-infrastructure control), where accountability is legally assigned to a human actor (as in credit adjudication, medical diagnosis, or judicial and regulatory contexts), or where outcomes hinge on contextual and ethical judgment that resists codification, retaining human authority over execution is the appropriate target configuration rather than a temporary limitation. In such domains, the value of integration lies in giving human decision-makers comprehensive, real-time intelligence, while the supervisory boundary is preserved by design. The boundary conditions for remaining in this quadrant are therefore the inverse of those that favor progression: high regulatory intensity, high error cost, and high reliance on tacit judgment all weigh toward integrated-supervised as the preferred end state.

4) *High Automation/High Integration (Integrated-Autonomous)*

This quadrant represents the most advanced AI implementations, where autonomous systems operate across integrated enterprise architectures. AI systems coordinate end-to-end processes, dynamically allocate resources, and adapt to changing conditions with minimal human intervention. While strategically pow-

erful, these configurations require sophisticated governance, robust data infrastructure, and organizational readiness. Organizations achieving this configuration report the highest value capture but represent a small minority of AI deployments [19].

4.3. Strategic Progression across Quadrants

The framework highlights potential progression paths from isolated, supervised implementations toward integrated, autonomous systems. This progression is neither automatic nor uniform across organizations. Research indicates that organizations successfully scaling AI concentrate resources on a limited number of high-impact initiatives rather than pursuing numerous disconnected pilots [10]. Leaders focus on the most promising opportunities and expect more than twice the ROI that other organizations do.

Rather than prescribing a single end state, the framework provides a lens for evaluating trade-offs, sequencing investments, and aligning AI initiatives with organizational capabilities. Many organizations deliberately maintain different configurations across functions, balancing value potential, risk exposure, and implementation complexity. Movement toward higher levels of automation and integration should be understood as contingent on strategic context rather than universally optimal.

4.4. Propositions and Decision Rules

To make the framework more testable for researchers and more actionable for managers, we distill the preceding analysis into four propositions. These are offered as conjectures consistent with patterns in the reviewed sources, to be examined empirically rather than as established findings.

Proposition 1 (Integration and enterprise value). Holding automation constant, higher integration is associated with a greater share of value realized at the enterprise level rather than confined to local efficiency gains.

Proposition 2 (Automation without integration). Increasing automation without corresponding integration tends to amplify localized efficiency while leaving enterprise-level value largely unchanged, because gains remain trapped within functional silos.

Proposition 3 (Readiness as a constraint). The feasibility of progression toward integrated-autonomous configurations is bounded by organizational readiness; organizations that advance automation or integration beyond their data, governance, and change-management capacity realize lower value and higher risk than those that sequence the two dimensions in step with readiness.

Proposition 4 (Context-dependent end state). In regulated, safety-critical, or judgment-intensive domains, integrated-supervised configurations represent a preferred and stable end state rather than an intermediate stage, and attempts to maximize automation in these settings reduce rather than increase net value once accountability and error costs are considered.

As a corresponding decision rule, managers can position each AI application on the two dimensions, then progress along the integration dimension before the automation dimension where readiness permits, and treat high regulatory intensity, high error cost, or high reliance on tacit judgment as signals to hold a supervised boundary regardless of available automation capability.

5. Industry Examples and Case Studies

To illustrate the strategic framework, this section presents examples of AI implementations across the four quadrants. Classifications are based on qualitative assessment of publicly reported implementations. To reduce ambiguity and improve replicability, two simple criteria guided placement. An implementation was coded as *high automation* when the AI system executes decisions or actions within its scope without requiring human approval for each instance (escalating only exceptions), and as *low automation* when a human reviews and authorizes the system's outputs before action is taken. An implementation was coded as *high integration* when it draws on real-time data from, and can trigger actions within, multiple enterprise systems or functions, and as *low integration* when it operates on static or manually transferred data within a single function and does not initiate downstream actions. Borderline cases were assigned to the quadrant reflecting the system's dominant mode of operation; because these assignments rest on public information, alternative classifications remain possible where internal detail would refine the judgment. The purpose of these examples is not exhaustive coverage but demonstration of how organizations position AI applications within the framework and how these positions reflect differing strategic choices and industry contexts.

5.1. Isolated-Supervised Implementations

Organizations in this quadrant typically deploy AI as decision-support tools within specific functions, with substantial human oversight and limited system connectivity. These applications build analytical capability and demonstrate value in low-risk settings. **Table 1** summarizes representative isolated-supervised implementations across industries.

1) *Financial Services: Credit Risk Assessment*

JPMorgan Chase employs machine learning models to score credit applications and flag potential risks based on historical data [3]. Loan officers retain full decision authority, reviewing AI recommendations alongside contextual and regulatory considerations. The system operates as a standalone analytical tool that enhances consistency and efficiency while remaining human-controlled. Similar implementations are widespread across banking, where AI-generated risk scores inform but do not replace human judgment on loan approvals.

2) *Healthcare: Clinical Decision Support*

Healthcare organizations increasingly deploy AI-powered clinical decision support systems that analyze patient data and suggest potential diagnoses or treat-

ment options. These systems alert physicians to potential drug interactions, flag abnormal test results, and recommend evidence-based care protocols [31]. However, clinicians retain full authority over treatment decisions. The AI operates within electronic health record systems but does not autonomously order tests or prescribe medications. This supervised configuration reflects both regulatory requirements and the importance of clinical judgment in patient care.

3) *Retail: Demand Forecasting*

Retailers deploy predictive analytics tools to forecast demand across product categories and store locations. These systems analyze historical sales data, seasonal patterns, and promotional calendars to project future demand [32]. Merchandising teams review forecasts and make final decisions about inventory levels and replenishment orders. While the AI provides valuable analytical support, human planners retain control over execution and can override algorithmic recommendations based on market knowledge or strategic considerations.

Table 1. Examples: isolated-supervised configuration.

Industry	Application	Organization/System	Key Characteristics
Financial Services	Credit risk scoring	JPMorgan Chase ML models	AI flags risk factors from historical data; loan officers retain full decision authority over approvals
Healthcare	Clinical decision support	Epic CDS, Cerner alerts	AI analyzes patient data, suggests diagnoses; physicians retain full authority over treatment decisions
Retail	Demand forecasting	Blue Yonder, Oracle	Predictive models analyze sales patterns; merchandising teams review and decide inventory levels
Legal	Contract review	Kira Systems, Luminance	AI extracts clauses, identifies risks; attorneys review findings and provide client advice
HR	Resume screening	HireVue, Pymetrics	AI ranks candidates by fit scores; recruiters make all hiring decisions

5.2. Isolated-Autonomous Implementations

In this configuration, AI systems operate independently within narrowly defined domains, delivering significant local efficiency gains while remaining disconnected from broader enterprise coordination. **Table 2** summarizes representative isolated-autonomous implementations across industries.

1) *Manufacturing: Automated Quality Inspection*

Manufacturers such as Foxconn and BMW deploy computer vision systems that autonomously inspect products and reject defects in real time [32] [33]. These systems analyze images of components or finished products, identify defects with precision exceeding human inspectors, and automatically route defective items for rework or disposal. The AI operates at high speed with minimal human intervention during production. However, these systems often remain isolated from upstream planning or downstream logistics systems, limiting their contribution to enterprise-wide optimization.

2) *Financial Services: Algorithmic Trading*

Quantitative trading firms deploy algorithms that autonomously execute trades based on predefined strategies and real-time market data. These systems can analyze market conditions, identify opportunities, and execute thousands of transactions per second without human approval for individual trades. Risk parameters and trading limits are established in advance, but execution is fully automated within those boundaries. While highly autonomous, many trading systems operate within specific asset classes or strategies and may not be fully integrated with firm-wide risk management platforms.

3) *Customer Service: Automated Response Systems*

Organizations deploy conversational AI systems that autonomously handle routine customer inquiries without human intervention. These chatbots and virtual assistants can answer frequently asked questions, process simple transactions, and troubleshoot common problems. Gartner [34] estimates that AI-powered customer service solutions will handle a significant share of customer interactions by 2027. While autonomous within their defined scope, many such systems operate as standalone tools rather than integrated components of comprehensive customer relationship management platforms.

Table 2. Examples: isolated-autonomous configuration.

Industry	Application	Organization/System	Key Characteristics
Manufacturing	Quality inspection	Foxconn, BMW, Cognex	Computer vision detects defects in real-time; auto-rejects flawed units; isolated from planning systems
Financial Services	Algorithmic trading	Two Sigma, Citadel	Executes thousands of trades/second within preset risk limits; often siloed by asset class
Customer Service	Virtual assistants	Zendesk AI, Intercom	Handles routine inquiries autonomously; escalates complex issues; limited CRM integration
Agriculture	Autonomous equipment	John Deere, Blue River	AI-guided tractors/harvesters operate independently; limited farm management integration
Security	Threat detection	CrowdStrike, Darktrace	Autonomous monitoring, anomaly detection, alerting; may operate separately from SIEM

5.3. Integrated-Supervised Implementations

This configuration combines extensive data connectivity with continued human decision authority. AI systems provide enterprise-wide visibility while humans retain control over execution. **Table 3** summarizes representative integrated-supervised implementations across industries.

1) *Sales and Marketing: AI-Enhanced CRM*

Salesforce Einstein exemplifies integrated-supervised AI by connecting customer data across sales, marketing, and service functions to generate predictions and recommendations [35]. The system analyzes customer interactions, purchase history, and behavioral patterns to identify sales opportunities, predict churn risk,

and recommend next-best actions. Human sales representatives and marketers determine how and when to act on these insights, preserving contextual judgment while benefiting from enterprise-wide intelligence. This configuration is common where relationship management and human judgment remain critical to outcomes.

2) *Healthcare: Integrated Clinical Analytics*

Health systems deploy enterprise analytics platforms that integrate data from electronic health records, laboratory systems, imaging archives, and claims databases to provide comprehensive patient views and population health insights. AI algorithms identify patients at risk for adverse events, predict readmissions, and recommend preventive interventions. Care teams review these recommendations and make decisions about patient outreach and care coordination. The integrated data enables insights not possible from isolated systems, while human oversight ensures appropriate clinical judgment [31].

3) *Supply Chain: Visibility Platforms*

Global enterprises deploy supply chain visibility platforms that integrate data from suppliers, logistics providers, and internal systems to provide real-time tracking and predictive analytics. AI algorithms analyze patterns to predict disruptions, recommend alternative suppliers, and optimize inventory placement. Supply chain managers review recommendations and make decisions about supplier selection, inventory rebalancing, and logistics routing. Integration enables coordination across complex global networks while human judgment addresses exceptions and strategic trade-offs.

Table 3. Examples: integrated-supervised configuration.

Industry	Application	Organization/System	Key Characteristics
Sales/Marketing	AI-enhanced CRM	Salesforce Einstein	Integrates customer data across functions; provides predictions; humans decide actions
Healthcare	Population health	Epic Healthy Planet	Integrates EHR, claims, social data; identifies at-risk patients; care teams decide interventions
Supply Chain	Visibility platforms	SAP IBP, Kinaxis	Real-time tracking across suppliers; predicts disruptions; planners make sourcing decisions
Financial Services	Enterprise risk	Moody's Analytics, SAS	Aggregates risk across portfolios; models scenarios; risk committees make decisions
Manufacturing	Digital twins	Siemens MindSphere	Integrates sensor data for simulation; predicts performance; engineers decide optimizations

5.4. Integrated-Autonomous Implementations

This configuration represents the most advanced implementations, where autonomous systems coordinate decision-making and execution across multiple functions with minimal human intervention. **Table 4** summarizes representative integrated-autonomous implementations across industries.

1) *E-commerce: Intelligent Fulfillment Operations*

Amazon's fulfillment operations exemplify integrated-autonomous AI, coordinating demand forecasting, inventory placement, robotic picking, packing optimization, and logistics routing across a global network [36]. AI systems operate continuously and adaptively, making millions of decisions daily about which products to stock in which warehouses, how to route orders through fulfillment centers, and which delivery options to offer customers. Human involvement focuses on strategic oversight and exception management rather than routine decisions. This configuration enables the speed, scale, and efficiency that define modern e-commerce logistics.

2) *Ride-Sharing: Dynamic Platform Operations*

Uber's platform demonstrates integrated-autonomous AI in a service context, coordinating dynamic pricing, driver dispatch, route optimization, and demand prediction in real time across millions of rides daily. AI algorithms continuously balance supply and demand, adjusting prices to attract drivers to high-demand areas while optimizing routes to minimize passenger wait times. The system integrates payment processing, safety monitoring, and customer feedback into a comprehensive operational platform. Human intervention focuses on policy decisions and exception handling rather than individual ride coordination.

3) *Energy: Autonomous Grid Management*

Electric utilities deploy AI systems that autonomously manage power grid operations, balancing supply and demand in real time across thousands of generation sources and millions of consumption points. These systems integrate data from smart meters, weather forecasts, renewable generation facilities, and industrial consumers to predict demand, optimize generation scheduling, and manage grid stability. AI can autonomously dispatch resources, adjust voltage levels, and reroute power flows to prevent outages. Human operators monitor overall system performance and handle strategic decisions, but routine operations are fully automated.

Table 4. Examples: integrated-autonomous configuration.

Industry	Application	Organization/System	Key Characteristics
E-commerce	Fulfillment operations	Amazon FBA, Ocado	Coordinates forecasting, inventory, picking, packing, routing; millions of autonomous decisions daily
Transportation	Ride-sharing platforms	Uber, Lyft, Grab	Real-time dynamic pricing, driver dispatch, route optimization; autonomous platform operations
Energy	Grid management	ERCOT, National Grid	Autonomous load balancing, generation dispatch, outage prevention across millions of endpoints
Finance	Integrated trading	Jane Street, Virtu	Cross-asset market-making with real-time risk integration; autonomous execution across markets
Retail	Autonomous stores	Amazon Go, Zippin	Cashierless checkout, real-time inventory tracking, integrated replenishment systems

5.5. Patterns across Industries

Across industries, these examples illustrate that organizations rarely adopt AI uniformly across all processes. Instead, they deploy different configurations depending on risk tolerance, value potential, regulatory constraints, and organizational readiness. Digital-native organizations often progress more rapidly toward integrated-autonomous configurations due to stronger data foundations and architectural flexibility, while legacy organizations must modernize existing systems while maintaining operational continuity.

The framework clarifies these strategic choices by highlighting how automation and integration jointly shape AI's organizational impact. Movement toward more advanced configurations requires not only technical capability but also organizational change management, process redesign, and governance structures appropriate to increased autonomy.

6. Discussion and Implications

The automation-integration framework provides a strategic lens for understanding AI implementation choices and their organizational implications. This section discusses implications for information systems research, managerial practice, and public policy, along with directions for future research.

6.1. Implications for IS Research

The framework contributes to IS research on technology adoption and digital transformation in several ways. First, it synthesizes recent enterprise AI research into a coherent strategic lens that captures how AI differs from earlier generations of enterprise technology. The automation dimension reflects the fundamental shift in human-technology relationships that distinguishes AI—where systems actively participate in decision-making rather than merely supporting human activities [13] [25] [37].

Second, the framework highlights integration as a recurring factor associated with the transformation of AI from localized analytical capability into enterprise-wide intelligence. This finding resonates with longstanding IS research on the value of interoperability and information exchange, while extending these insights to contexts where integrated systems can autonomously coordinate actions across organizational boundaries. The MIT CISR Enterprise AI Maturity Model similarly emphasizes that organizations in advanced stages of AI maturity build 'modular, interoperable platforms and data ecosystems to enable enterprise-wide intelligence' [26] [38]. Future research should examine the specific integration mechanisms—technical, organizational, and governance-related—that enable progression toward more advanced configurations.

Third, by positioning AI implementations within a two-dimensional strategic space, the framework enables comparative analysis across industries, organizational contexts, and time periods. Researchers can examine which configurations are associated with different outcomes, how organizations move across quadrants

over time, and what factors enable or constrain progression. This approach complements case-based research on individual AI implementations by providing a common vocabulary for cross-case comparison.

The framework also raises questions for future IS research. How do organizational factors such as data maturity, technical capability, and change management capacity influence optimal configuration choices? What governance mechanisms are most effective at different points in the automation-integration space? How do industry-specific regulatory environments shape feasible progression paths? These questions connect AI implementation research to broader IS traditions in technology adoption, organizational change, and IT governance.

6.2. Implications for Practice

For executives and managers, the framework provides practical guidance for AI implementation strategy. Several implications emerge from the analysis.

Assess current positioning. Organizations should evaluate where their existing AI applications fall within the framework. Many organizations maintain a portfolio of applications across multiple quadrants, reflecting different maturity levels and strategic priorities. Understanding this portfolio provides a foundation for identifying gaps, redundancies, and opportunities for progression.

Prioritize integration infrastructure. The evidence reviewed here recurrently points to integration as an important enabler of AI value creation. Organizations that invest in data infrastructure, API architectures, and interoperability standards create foundations for scaling AI impact across functions. Conversely, organizations with fragmented data environments and disconnected systems will struggle to progress beyond isolated implementations, regardless of the sophistication of individual AI tools.

Concentrate resources on high-impact initiatives. Research indicates that organizations achieving meaningful AI value focus on a limited number of high-impact use cases rather than pursuing numerous disconnected pilots [10]. The framework helps identify which applications have the greatest potential for progression and enterprise-wide impact, enabling more disciplined investment prioritization.

Match configuration to context. The framework does not prescribe universal progression toward integrated-autonomous systems. In highly regulated industries, contexts requiring significant human judgment, or applications involving substantial risk, integrated-supervised configurations may represent appropriate end states. Organizations should match AI configurations to the specific requirements of each domain rather than pursuing maximum automation or integration for its own sake.

Develop governance that scales with autonomy. As organizations move toward more autonomous and integrated configurations, governance requirements intensify. Organizations should develop governance structures and risk management mechanisms appropriate to their current and target configurations, recog-

nizing that approaches suitable for isolated-supervised applications will be insufficient for integrated-autonomous systems.

6.3. Implications for Policy

The framework also has implications for policymakers concerned with AI governance, workforce development, and economic competitiveness.

Regulatory frameworks should accommodate configuration diversity. AI applications in different quadrants present different risk profiles and governance requirements [39] [40]. Regulatory approaches that treat all AI applications uniformly may impose unnecessary burdens on low-risk implementations while providing insufficient oversight for high-autonomy, high-integration systems. Configuration-aware regulatory frameworks could provide more proportionate oversight aligned with actual risk levels.

Workforce development should address human-AI collaboration. As organizations progress across the framework, the nature of human work shifts from direct task execution toward supervision, exception handling, and strategic oversight. Workforce development programs should prepare workers not only for displacement but also for new roles in human-AI collaborative systems. This includes technical skills for working with AI tools and judgment skills for effective oversight of autonomous systems.

Support for integration infrastructure. The evidence reviewed here suggests that integration capability is among the important factors shaping AI value creation. Policies that support development of shared data infrastructure, interoperability standards, and integration platforms—particularly for small and medium enterprises that may lack resources for independent development—could accelerate AI adoption and value creation across the economy [41].

6.4. Future Research Directions

Several promising directions for future research emerge from this framework.

Longitudinal analysis of progression paths. Empirical research could examine how organizations move across framework quadrants over time, identifying common progression paths, barriers to advancement, and factors that accelerate or impede movement. Such research could test whether particular sequences of implementation are associated with superior outcomes.

Configuration-performance relationships. Future studies could examine whether specific configurations are associated with different performance outcomes, and how these relationships vary by industry, organizational size, and strategic context. This research would help refine understanding of when different configurations are appropriate.

Governance mechanisms across configurations. Research could investigate how governance structures, risk management practices, and accountability mechanisms should differ across framework quadrants. This includes examination of technical controls, organizational processes, and human oversight approaches ap-

appropriate to different levels of automation and integration.

Human-AI collaboration dynamics. As organizations implement AI across the framework, the nature of human-AI interaction changes substantially. Research could examine how work roles, skill requirements, and organizational structures evolve as AI systems become more autonomous and integrated, building on emerging research on collaborative intelligence [18] [21].

Cross-industry comparative analysis. Comparative research across industries could identify sector-specific patterns in AI implementation, including how regulatory environments, competitive dynamics, and industry structure shape configuration choices and progression opportunities.

7. Scope and Limitations

This study is subject to several limitations that should be considered when interpreting its contributions. As a conceptual and illustrative analysis, the paper does not empirically test hypotheses or establish causal relationships between AI implementation configurations and organizational performance outcomes. Instead, the primary objective is to develop a strategic framework that clarifies how AI applications differ along the dimensions of automation and integration and how these differences shape organizational impact.

First, the study relies on qualitative assessment of publicly reported AI implementations drawn from industry reports, academic literature, and practitioner sources. These secondary sources vary in depth, transparency, and methodological rigor. The classification of specific implementations into framework quadrants is necessarily interpretive, and alternative classifications may be appropriate with access to proprietary data or direct organizational observation.

Second, the framework abstracts from industry-specific regulatory, technological, and institutional constraints. Although the automation-integration dimensions are broadly applicable across sectors, the feasibility and desirability of movement toward higher levels of automation and integration vary considerably by context. The framework is intended as a strategic lens rather than a prescriptive roadmap applicable uniformly across all settings.

Third, the framework presents automation and integration as relatively stable dimensions, whereas in practice, AI implementations evolve dynamically over time. Organizations may occupy multiple quadrants simultaneously across different functions, or deliberately maintain lower configurations for certain processes due to risk considerations or strategic choice. Progression through the framework should be understood as contingent rather than inevitable.

Despite these limitations, the framework provides a useful strategic perspective for understanding AI implementation choices. By clarifying trade-offs associated with different configurations and highlighting integration as an important enabler of value creation, the study contributes to ongoing discussions about how organizations can move beyond isolated experimentation toward sustained enterprise-level AI impact.

8. Conclusions

Artificial intelligence continues to attract unprecedented organizational investment, yet the gap between experimentation and sustained value creation remains substantial. This paper addresses that gap by offering a strategic framework that clarifies how AI applications differ along two critical dimensions—degree of automation and degree of integration—and how these differences shape organizational impact.

The automation-integration framework synthesizes diverse AI applications within a unified strategic lens that accommodates both human-centered decision support and autonomous execution. By positioning applications across four configurations—isolated-supervised, isolated-autonomous, integrated-supervised, and integrated-autonomous—the framework provides a vocabulary for assessing current positions, comparing alternatives, and planning progression paths. The industry examples demonstrate that organizations rarely pursue uniform approaches to AI; instead, they maintain portfolios of applications across configurations, balancing value potential, risk, and organizational readiness.

The framework highlights integration as a recurring factor associated with the transformation of AI from localized capability into enterprise-wide intelligence. Organizations that invest in data infrastructure, interoperability, and cross-functional coordination create foundations for scaling AI impact. Conversely, organizations with fragmented data environments will struggle to progress beyond isolated implementations regardless of the sophistication of individual AI tools.

For executives, the framework provides practical guidance for evaluating AI opportunities, sequencing investments, and aligning AI initiatives with organizational capabilities. Rather than prescribing universal progression toward maximum automation and integration, the framework emphasizes strategic fit between AI configurations and organizational context. The strategic objective is not automation for its own sake, but deliberate movement toward configurations that align with business strategy, risk tolerance, and capability readiness.

As AI technologies continue to evolve—with agentic systems, multimodal capabilities, and advanced reasoning expanding the frontier of what AI can accomplish—the fundamental challenges of coordinating intelligent systems and managing autonomous decision-making will persist. The automation-integration framework provides a durable foundation for navigating these challenges and for charting strategic paths toward more effective and responsible AI implementation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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