Enterprise AI Adoption Decisioning

A practical executive guide to value, risk, and the AI ecosystem you must build first

"The bottleneck is never the bot. The AI agents are ready. Most organizations aren't."

Board / CEO Briefing

Tunde Kehinde

Managing Partner, 5054 Holdings

Cyril Simone

AI, Machine Learning & Quantum Computing

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Executive Summary

AI adoption is not a binary decision. It is a maturity ladder. The smart move is to incorporate AI in phases, starting with measurable, low-blast-radius use cases, then graduating to agents only after you have built the ecosystem that keeps them safe.

Self-learning and self-modifying agents are the top of the ladder, not the starting point. They can create step-change productivity, but they also create step-change risk. If your organization does not have strong data governance, auditability, tool controls, evaluation discipline, and incident response, agents will eventually do something expensive and embarrassing, at scale.

The most important thing to understand before reading further: AI is not a tooling purchase. It is an operating model change. Buying a copilot license and giving it to your team is not AI adoption. Adoption means redesigning workflows, redefining roles, building new evaluation, and monitoring disciplines, and committing to a sustained learning curve. Organizations that treat AI as a procurement decision rather than a transformation program consistently underperform, regardless of how much they spend.

Executives commonly fall into several traps when approaching AI. They assume that deploying a copilot will automatically produce ROI without integrating it into existing workflows and retraining teams to use it effectively. They ignore the need for evaluation and monitoring infrastructure until a high-profile failure forces a reaction. They underestimate the organizational politics: who owns AI, who funds it, who is accountable when it fails, and who has the authority to push adoption through resistant business units. And they skip the maturity ladder entirely, jumping to autonomous agents before the foundational capabilities are in place, which creates risk that is disproportionate to the value delivered.

This paper provides a structured decision framework, a maturity model for graduating through levels of AI autonomy, and the operational ecosystem you must build at each stage. It also addresses the questions that most commonly stall enterprise adoption: who owns AI inside the organization, what support they need from the top, what team is required, how to evaluate vendors without creating lock-in, and how to think about the cost model. Three anonymized case snapshots illustrate what these decisions look like in practice.

Evidence anchors (selected external findings used to ground this paper):

- Productivity gains are real but uneven: field experiments show ~14% average lift in customer support with larger gains for less-experienced workers (Brynjolfsson et al., NBER 2023).
- Controlled studies show ~40% faster completion on professional writing tasks with generative AI (Noy & Zhang, 2023) and faster completion on software tasks with coding copilots (Peng et al., 2023).
- Agentic systems amplify security risk: OWASP guidance elevates prompt injection and excessive agency/tool abuse; primary research demonstrates indirect prompt injection against real LLM-integrated applications (especially when RAG pulls untrusted content).

- Governance expectations are converging: NIST AI RMF + NIST GenAI Profile, ISO/IEC 42001, and the EU AI Act all emphasize lifecycle risk management, testing, logging, human oversight, and post-deployment monitoring.

The Executive Decision Framework: AI Adoption + Agent Autonomy

Decision you are making: Should we incorporate AI into the business? If yes, what level of autonomy and learning do we permit (copilots to agents to self-learning/self-modifying)?

Step	What You Decide	Key Takeaway
Step 1	Choose business outcomes (not AI projects)	If you cannot name measurable outcomes, you are not ready to adopt AI.
Step 2	Classify use cases by AI mode (Predict, Generate, Act)	Each mode has different risk and control requirements. Do not treat them the same.
Step 3	Select your maturity target (Level 0 through 5)	This is the real steering decision. Start low, graduate up only after building the ecosystem.
Step 4	Pass the ecosystem readiness gate	Each maturity level has minimum infrastructure you must have before moving up.
Step 5	Set autonomy and learning limits ("blast radius" contract)	Define what the AI can touch, how much it can do, and what is forbidden.
Step 6	Go/No-Go and funding rule	Fund in phases. Autonomy increases only after passing gates.

Step 1: Choose the Business Outcomes (not "AI projects")

Pick 2 to 4 outcomes you will measure quarterly:

- Cost-to-serve reduction (cycle time, staffing load)
- Revenue lift (conversion, retention, upsell)
- Quality/error reduction (rework, write-offs, leakage)
- Risk reduction (fraud, compliance, incidents)
- Speed (SLA, time-to-decision)

If you cannot name measurable outcomes, stop here. You are not ready.

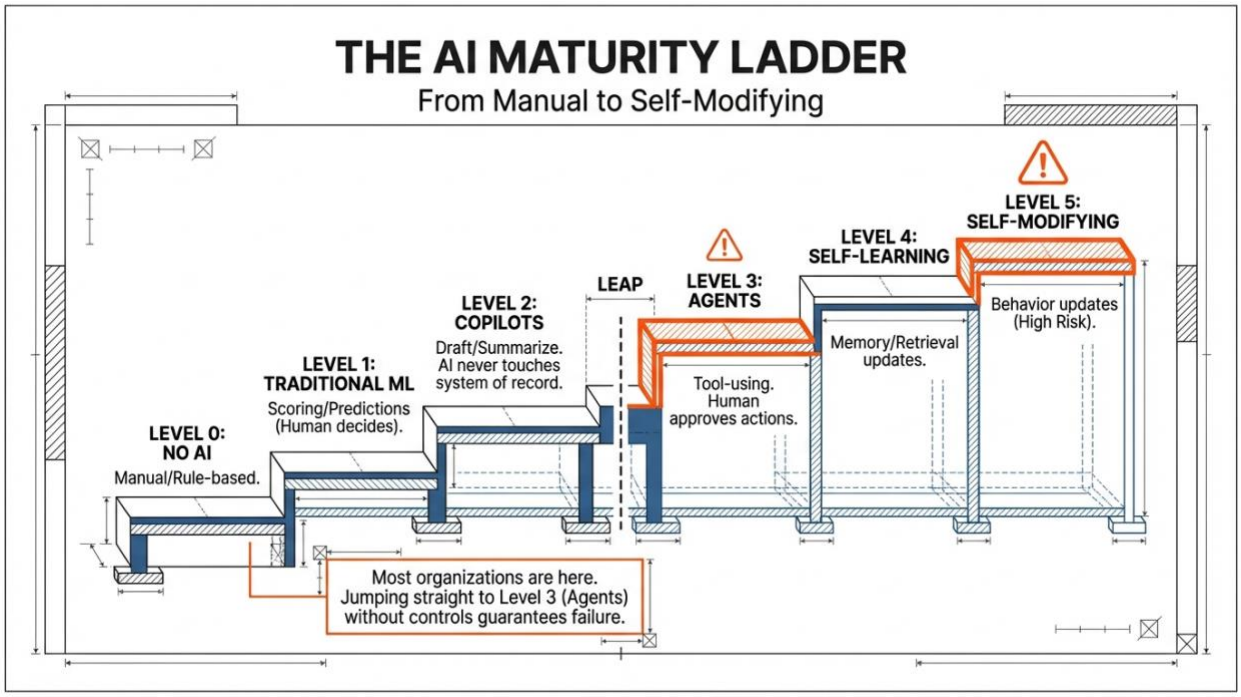
Step 2: Classify Candidate Use Cases by "AI Mode"

Put each use case into one of these buckets (because each has different risk and controls):

- M1: Predict/Score (ML) - forecasting, propensity, anomaly detection
- M2: Understand/Generate (LLMs) - summarization, drafting, Q&A, knowledge search
- M3: Act (Agents) - tool-using workflows that execute steps across systems

Step 3: Select the AI Maturity Target (12-18 months)

This is the real steering decision.



Level 0: No AI. Manual plus deterministic automation only.

This is where many organizations still are in production. All decisions and actions are performed by people or by traditional rule-based software (if X, then Y). There is no machine learning, no language models, and no intelligent automation. This is a perfectly valid starting point, and some processes should stay here permanently. Official business surveys that measure AI used in business functions (not just experimentation) show adoption is still a minority in several large economies—for example: ~20% of EU enterprises in 2025 (Eurostat), ~25% of UK businesses in late 2025 (ONS), and ~17% of US businesses as of Dec 2025 (US Census Bureau BTOS, cited by the Federal Reserve). Adoption is higher for large firms and definitions vary, so treat this as a baseline indicator, not a universal fact.

Level 1: Traditional ML at scale (M1). Scoring in batch/APIs; no autonomy.

At this level, the organization uses machine learning models to make predictions or flag patterns, but those predictions are delivered to humans who then decide what to do. For example, a model might score every customer by their likelihood to cancel their subscription, or flag transactions that look potentially fraudulent. The model generates a score or a recommendation; a person reviews it and acts. The AI has no ability to do anything on its own.

Level 2: LLM copilots (M2). Draft/summarize/retrieve with citations; no direct system writes.

Here, the organization introduces large language models that can read, write, and summarize text. A copilot might draft a response to a customer inquiry, summarize a 50-page contract, or search internal knowledge bases and return answers with citations. The critical constraint is that the copilot only

produces text for a human to review. It cannot send an email, update a database, approve a transaction, or take any action in any system. A person always sits between the AI and the outside world.

Level 3: Tool-using agents with approvals (M3-A3). Agents can execute actions only after explicit approval; strict tool allowlists.

This is the first level where AI can do things in your systems, not just read or write text. An agent at this level might assemble a dispute response, look up the relevant policy, draft the letter, and then queue it for a human to review and approve before it gets sent. The agent has access to specific tools (like your CRM, ticketing system, or email), but every action requires explicit human approval before it executes. Think of it as a highly capable assistant that prepares everything but always asks before pressing “send.”

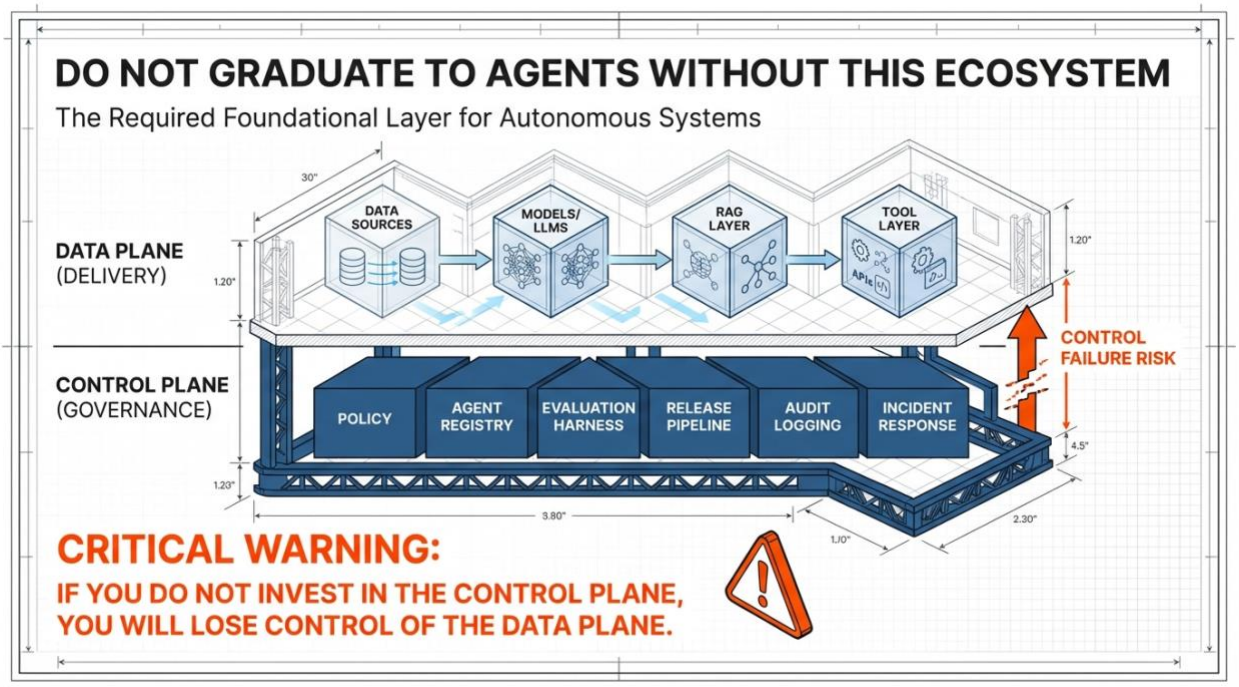
Level 4: Limited self-learning (Memory + Retrieval) (L1-L2). Agents can update scoped memory and retrieval indices; changes are reversible and audited.

At this level, the agent can learn from its interactions and improve over time within defined boundaries. For instance, it might update its own knowledge base when it encounters new information, refine how it searches for answers based on what worked before, or remember context from previous interactions with a specific customer. All these changes are logged, reversible, and scoped to specific areas. The agent is not rewriting its own instructions; it is updating the information it draws on.

Level 5: Controlled self-modification (Policies/Prompts) (L3). Agent behavior updates happen only through a gated release pipeline (tests, approvals, rollback). Weight updates and fine-tuning in production is usually a “no.”

This is the most advanced level, where the agent can modify how it behaves, not just what it knows. For example, it might update its own decision-making rules or adjust how it prioritizes tasks. This is powerful but carries the highest risk: an agent that can change its own behavior can drift in ways that are hard to detect. At this level, any change to agent behavior must go through the same kind of rigorous testing, approval, and rollback process that you would use for a production software release. No agent should be allowed to rewrite itself in real time without human oversight.

Step 4: AI Ecosystem Readiness Gate



Minimum ecosystem components you need before moving up:

For Level 1-2 (ML + Copilots):

- Data ownership and access controls
- Model/LLM usage policy and logging
- Basic evaluation and monitoring
- Security review for vendors/models

For Level 3 (Agents that act):

- Tool gateway, allowlisted actions, and schema validation
- Least privilege credentials and secrets management
- Audit logging (tamper-evident)
- Human approval workflow and separation of duties
- Circuit breakers / kill switch

For Level 4-5 (Learning/modifying):

- Versioned agent registry (charters, permissions, prompts/policies)
- Evaluation harness, regression, and adversarial testing
- Change control like software releases (two-person rule for high risk)
- Rollback and replay capability

- Incident response runbooks and on-call

Step 5: Set Autonomy and Learning Limits (the “blast radius” contract)

Autonomy: A0 read-only through A4 autonomous. Learning: L0 none through L4 model updates (offline only).

Why caps and approvals matter (risk math, not bureaucracy): if an agent has even a 0.01% per-action probability of a material policy breach or wrong write, then at 10,000 actions the chance of at least one incident is ~63% (1 - (1 - 0.0001)^10000). Action caps, approvals, and kill switches are the practical levers that keep N (actions) and p (per-action risk) bounded.

Define:

- Systems touched
- Action caps (per hour/day)
- Reversibility/rollback method
- Approval requirements
- Forbidden actions (hard deny)

Step 6: Go/No-Go and Funding Rule

- Go if: measurable ROI, controls in place, and operational ownership defined
- No-Go if: unmeasurable outcomes, missing telemetry, or you cannot bound blast radius
- Fund in phases. Autonomy increases only after passing gates.

The Business Case for “AI in General”

Where “AI in general” reliably pays off first

- Document and ticket summarization (support, ops, finance)
- Drafting and standard responses (customer comms, collections letters, internal updates)
- Knowledge retrieval with citations (policies, SOPs, product info)
- Prediction/scoring (churn risk, fraud signals, demand forecast)

Quantitative reality check: across multiple randomized and field experiments, copilots/LLM assistance can materially improve speed and quality, but results are heterogeneous. A widely cited field experiment in customer support found ~14% higher productivity on average, with larger gains among novice workers (Brynjolfsson et al., 2023). Controlled experiments on writing tasks report large time reductions (e.g., ~40% faster completion in one study), while other work shows a "jagged frontier"—performance improves on tasks within model strengths and can degrade outside them without training and scope boundaries. This is why the framework insists on wedge use cases, workflow integration, and an evaluation discipline before scaling autonomy.

Common executive traps

- Treating AI as a tooling purchase rather than an operating model change
- Assuming copilots automatically produce ROI without workflow integration
- Ignoring evaluation/monitoring until after a high-profile failure

What to approve first

Approve 1 to 2 “wedges” that:

- Reduce cycle time or cost-to-serve
- Fit existing workflows
- Have clean metrics
- Do not require high autonomy

Organizational Ownership and Accountability

The most common reason enterprise AI adoption stalls is not technical. It is organizational. In most companies, three or four executives each believe AI falls under their remit, and none of them want to be accountable if it goes sideways. The result is committee paralysis: endless pilot discussions, no production deployments, and a growing gap between the organization and its competitors.

Before selecting a single use case, leadership must answer a structural question: who owns AI in this organization? There are three viable models, and the right one depends on the company's size, culture, and operating model.

Model A: Centralized AI Office

A dedicated AI or Data Science team reports to a Chief AI Officer, Chief Data Officer, or CTO. This team owns the platform, sets standards, and partners with business units to deliver use cases. This model works well for organizations that need strong governance and are in regulated industries. The risk is that it becomes a bottleneck and disconnects from business priorities.

Model B: Federated with Central Standards

Each business unit has embedded AI capability (whether internal hires or vendor-supported), but a central team sets the architecture, security, and evaluation standards. The central team provides shared infrastructure (model hosting, tool gateways, evaluation harnesses) and reviews agents before production. This model works for larger organizations with diverse business lines. The risk is inconsistency and duplicated effort.

Model C: Business-Led with Technical Guardrails

A business leader (typically the COO or a P&L owner) owns AI outcomes, and technology provides the platform and guardrails. This model works when AI is being used primarily to optimize existing operations rather than build new products. The risk is that the business leader underestimates technical complexity.

Regardless of the model chosen, three accountability principles apply:

- A single executive must be named as the accountable owner for AI outcomes and risk. Shared ownership is no ownership.
- The accountable owner must have both budget authority and the ability to make production deployment decisions.
- Separation of duties must exist between those who build/configure agents and those who approve their deployment, particularly at Maturity Levels 3 and above.

Executive Support: The Air Cover That Makes or Breaks AI Programs

Budget, resources, and support are the three prerequisites for any enterprise initiative to succeed. Most organizations get the first two partially right and the third one completely wrong. Budget gets allocated. Headcount gets approved. But the AI initiative owner is then left to navigate organizational resistance, skepticism, and the inevitable early failures alone. When the first pilot underperforms, when a model hallucinates something embarrassing, or when a business unit leader publicly questions the investment, the AI owner needs someone above them who will hold the line. Without that, the program dies not from technical failure but from political exhaustion.

Why Support Matters More Than Budget

AI adoption is not a linear process. Unlike a software implementation where you can project milestones with reasonable confidence, AI programs involve experimentation, iteration, and failure. The first model will not be good enough. The first agent will make mistakes. The first set of metrics will show ambiguous results. This is normal. It is how the technology works. But most organizations are not structured to tolerate this kind of ambiguity, especially when the investment is visible and the expectations are high.

The AI initiative owner needs the CEO, the board, or both to understand and communicate three things to the rest of the organization:

- AI success is non-linear. There will be a period of investment before returns materialize, and early results will be uneven. This is expected, not a sign of failure.
- The AI owner has the authority to make decisions, reallocate resources, and push back on business units that resist integration. This authority must be visible and reinforced, not just stated once in a memo.
- The organization will be measured on its willingness to adopt, not just the AI team's ability to deliver. If business units refuse to integrate AI tools into their workflows, that is a leadership problem, not a technology problem.

What CEO and Board Support Looks Like in Practice

Support is not a speech at a town hall. It is a set of repeated, concrete actions:

- Regular check-ins between the CEO and the AI owner (monthly at minimum) where progress is reviewed against the non-linear reality of the work, not against a waterfall timeline that was never realistic.
- Public reinforcement when setbacks occur. When a pilot underperforms, the CEO should frame it as a learning investment, not a failure. This sets the tone for the entire organization.
- Willingness to remove blockers. If a business unit leader is passively resisting adoption, the CEO must intervene directly. The AI owner should not have to fight political battles that only the CEO can win.

- Board-level reporting that includes AI progress as a standing agenda item, not a one-time update. This signals to the entire C-suite that AI is a strategic priority, not a side experiment.
- Protection of the learning period. For the first 6 to 12 months, the AI program should be evaluated on capability-building milestones (models deployed, workflows integrated, evaluation infrastructure built) rather than hard ROI targets. Premature ROI pressure kills AI programs before they have a chance to compound.

The Consequences of Absent Support

When the AI owner lacks genuine executive support, a predictable pattern emerges. Early wins are achieved through sheer effort, but they are fragile. The first visible failure triggers skepticism. Budget gets quietly redirected. The best technical talent leaves because they can see the program is not backed. Within 12 to 18 months, the organization declares that “AI did not work for us” when what happened is that leadership did not create the conditions for it to work.

The enterprises that succeed with AI are not the ones with the biggest budgets or the most advanced technology. They are the ones where the person running the AI program has a CEO who says, publicly and repeatedly, “This is a priority, this person has my backing, and we are going to stay the course even when it gets uncomfortable.” That is what support means.

Talent and Operating Model

The team required to run AI well changes significantly as you move up the maturity ladder. Most enterprises underestimate this. They fund the technology but not the people who keep it working. Below is a practical guide to the roles required at each level.

Levels 1-2 (ML and Copilots)

At this stage, you need data engineers who can build and maintain clean data pipelines, a machine learning engineer or applied scientist who can evaluate and fine-tune models, a product or program manager who can translate business outcomes into use case specifications, and a security/compliance reviewer who can assess vendor data handling. Many organizations can start here with 3 to 5 people plus vendor support.

Level 3 (Agents That Act)

Agents require a meaningful step up in operational capability. In addition to the Level 1-2 team, you need platform/infrastructure engineers who can build and maintain tool gateways, approval workflows, and audit logging. You need an evaluation specialist who can design test harnesses and adversarial scenarios. You also need an on-call rotation with incident response capability, because agents can fail at any hour.

Levels 4-5 (Learning and Self-Modification)

At this level, the team resembles a software release engineering function. You need release engineers who manage the gated deployment pipeline for agent behavior changes. You need adversarial testers who probe for prompt injection, tool abuse, and drift. And you need a governance lead who maintains the agent registry, reviews charters, and owns the audit trail.

Build vs. Buy vs. Partner

Most enterprises at Levels 1-3 will rely heavily on vendor platforms and system integrators. The critical question is not “build or buy” but “what must we own internally.” At a minimum, you must own the evaluation and monitoring capability. If you outsource the ability to know whether your AI is working correctly, you have outsourced the ability to manage risk.

When (and Why) to Move from Copilots to Agents

What changes when you introduce agents

Agents do not just generate text. They trigger actions across systems. That requires:

- Access control
- Approval gates
- Audit logs
- Kill switches
- Deterministic tool interfaces

Good first agent targets (bounded, reversible)

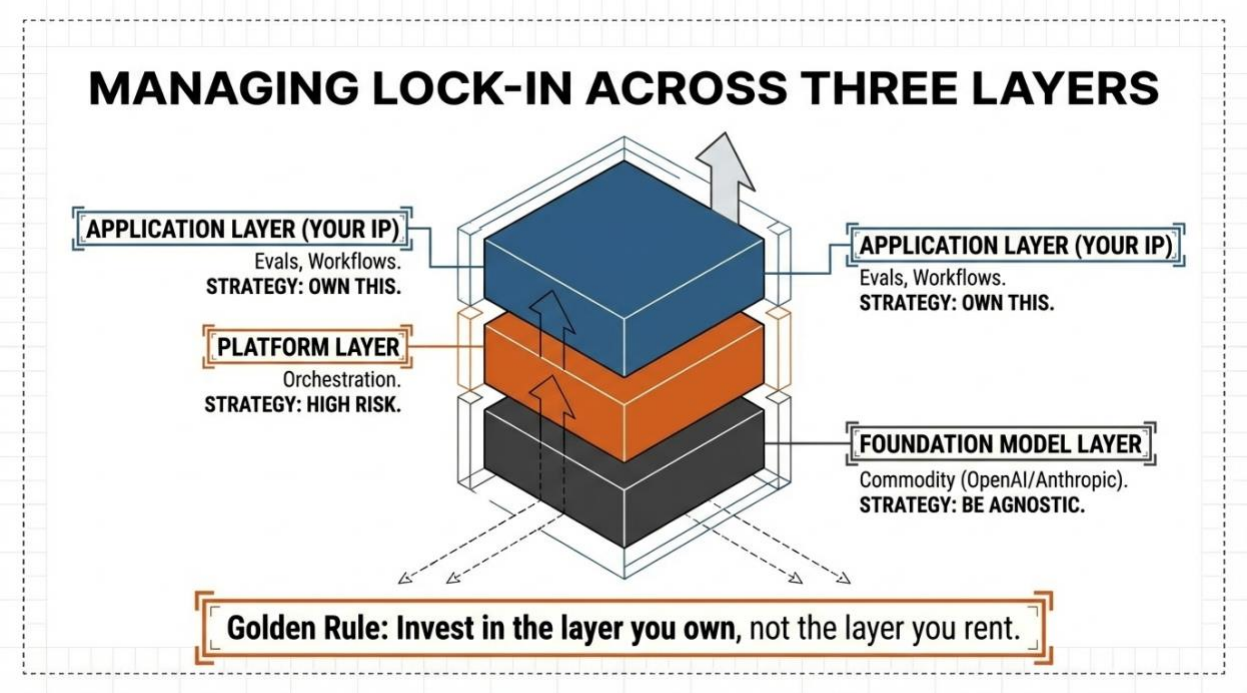
- Service desk runbook execution (approval required)
- Disputes/collections case assembly (agent drafts, human approves sends/updates)
- Procurement intake (agent classifies, drafts comparisons, routes approvals)
- Data operations (agent proposes fixes, generates scripts, but cannot deploy)

Where you should not start

- Autonomous customer communications without review
- Anything that can move money, change pricing, approve credit, or alter financial postings without multi-step approvals.

The Vendor Decision

For most enterprises at Maturity Levels 1 through 3, the AI adoption decision is, in practice, a vendor selection decision. You are not building foundation models. You are choosing which ecosystem to commit to, how much lock-in you are willing to accept, and where you draw the line between platform dependency and internal capability.



The Three Layers of Vendor Dependency

Think about vendor relationships across three layers:

Foundation model layer. This is where you choose between providers like OpenAI, Anthropic, Google, Meta (open-source), or others. The key risk is that model capabilities, pricing, and data handling policies change frequently. The mitigation is to design your application layer to be model-agnostic where possible, so you can swap providers without rebuilding workflows.

Platform/orchestration layer. This includes the tools that manage prompts, retrieval, agent orchestration, and tool connectivity. Vendor options range from cloud-native solutions (Azure AI, AWS Bedrock, Google Vertex) to independent platforms. Lock-in risk is highest here because switching platforms means re-engineering workflows.

Application layer. This is where AI meets your specific business processes. It includes the integrations with your systems of record, the approval workflows, the evaluation harnesses, and the monitoring dashboards. This layer should be owned internally whenever possible, even if you use vendor components underneath.

Non-Negotiable Vendor Evaluation Criteria

- Data usage and retention: Will the vendor train on your data? Can you opt out? What is the retention policy?
- Audit export: Can you export complete logs of all model interactions, tool calls, and agent actions?
- Evaluation tooling: Does the vendor support systematic evaluation, or are you limited to manual spot-checking?
- Cost transparency: Is pricing predictable? Are there usage-based spikes that could surprise finance?
- Exit strategy: What does migration look like if you need to switch providers?

The Required AI Ecosystem (What You Must Build)

Think of the ecosystem as two planes:

1) Data-plane (delivery)

- Data sources, ingestion, and access controls
- Models/LLMs and prompt/policy layer
- Retrieval layer (RAG)
- Agent/tool layer (for agents)
- Monitoring and telemetry

2) Control-plane (governance)

- AI policy and risk management
- Model/agent registry (versions, permissions, charters)
- Evaluation harness (golden tests and adversarial tests)
- Release pipeline and rollback
- Incident response and audit exports

If you do not invest in the control-plane, you will eventually lose control of the data-plane.

Risk, Compliance, and Non-Negotiable Controls

AI risks (general)

- Data leakage, IP exposure, privacy violations
- Hallucinations and incorrect recommendations
- Biased or inconsistent outcomes
- Vendor lock-in and uncontrolled cost

Agent risks (additional)

- Prompt injection through docs/tickets
- Tool abuse via over-permissioned tokens
- Silent drift (learning makes it worse over time)
- Reputational damage at scale

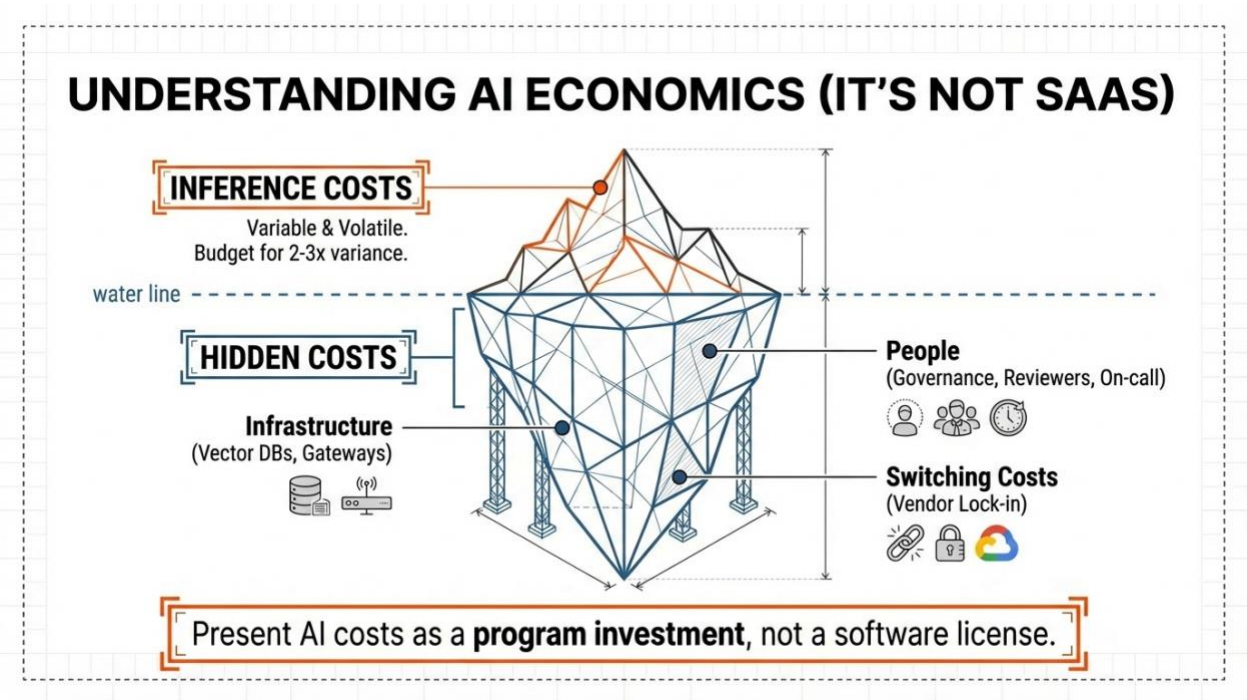
Note: these are not theoretical risks. OWASP's guidance for LLM applications and AI agents explicitly flags prompt injection, insecure output handling, and excessive agency/tool access as top failure modes. Separately, primary research has demonstrated indirect prompt injection: malicious instructions embedded in documents/web pages can be retrieved into an agent's context and executed as if they were trusted instructions. If you plan to index tickets, emails, or documents for RAG, you must treat that content as untrusted input and test accordingly.

Non-negotiables to require before "agents that act"

- Least privilege
- Tool allowlists and strict schemas
- Audit logs with tamper evidence
- Human approvals for high-impact actions
- Circuit breakers and kill switch
- Release discipline (no ad hoc "agent changes")

Understanding the AI Cost Model

AI costs do not behave like traditional enterprise software licensing, and this catches many executives off guard. A SaaS platform has a predictable per-seat or per-module cost. AI costs are usage-driven, variable, and often opaque until you are already committed.



The Four Cost Categories

1. Inference costs. Every time a model processes a request, you pay for tokens (the unit of text processed). Costs vary dramatically by model: a simple summarization call on a smaller model may cost fractions of a cent, while a complex multi-step agent workflow using a frontier model can cost dollars per execution. At enterprise scale, these costs compound quickly. Budget for usage-based pricing with a meaningful variance range (often 2-3x your initial estimate during ramp-up). Public cloud pricing pages (e.g., AWS Bedrock) make this explicit: pricing is typically per-token/per-request and can change as models and tiers evolve.

2. Infrastructure and platform costs. These include the hosting environment for your retrieval layer (vector databases, search indices), the tool gateway and orchestration layer, logging and monitoring infrastructure, and evaluation/testing environments. These costs are more predictable but are frequently underestimated because they are treated as "technical overhead" rather than core program costs.

3. People costs. The talent required to run AI well is the largest ongoing cost at Maturity Levels 3 and above. This includes not just the build team but the operational team: evaluation specialists, on-call

engineers, governance leads, and the business analysts who define and measure outcomes. Most failed AI programs are underfunded on people, not technology.

4. Opportunity and switching costs. Choosing a vendor ecosystem creates dependency. Switching costs are real and include re-engineering integrations, retraining staff, re-validating outputs, and potential data migration. Factor these into your total cost of ownership from the start, not as an afterthought.

CFO-Ready Guidance

When building the business case, present AI costs as a program investment (analogous to a digital transformation initiative), not a line-item software purchase. Include a 6-month ramp-up period where costs will be higher relative to output as the team builds capability. Set quarterly cost review gates tied to the same KPIs used to measure business outcomes. If the cost-to-value ratio is not improving quarter over quarter, that is an early warning signal that the program needs course correction.

Roadmap and Funding Logic (12-18 months)

Phase 0 (2-4 weeks): Decide and set guardrails

- Pick outcomes and KPIs
- Choose 1-2 wedges (M1 or M2)
- Stand up AI governance and logging
- Define autonomy/learning limits (future-proof)

Phase 1 (4-10 weeks): Deliver measurable wins (copilots/ML)

- Deploy copilots in workflows (draft and retrieve with citations)
- Establish baseline vs. post metrics
- Build evaluation harness

Phase 2 (8-16 weeks): Introduce bounded agents (A3)

- Tool gateway, approvals, audit, and kill switch
- Start with reversible actions and strict caps

Phase 3 (ongoing): Enable limited learning (L1-L2)

- Memory and retrieval updates only
- Full provenance, TTL, and rollback

Phase 4 (rare): Controlled self-modification (L3)

- Gated prompt/policy updates only through CI/testing and approvals
- No “live self-rewrite” in production.

The Transformation Gap: What Enterprises Actually Face

Enterprises are not two years away from being AI-native. When the full transformation sequence is mapped honestly, most large organizations are four to six years away. The gap between those two estimates is almost entirely organizational, not technical. Understanding why requires mapping the actual sequence of work, not the marketing sequence. Insight: The delay is not caused by new technology; it is caused by the pace at which organizations can absorb new decision-making technology.

Start with the infrastructure problem. As of mid-2024, roughly 63% of SAP ECC customers globally had still not migrated to S/4HANA Cloud, which is the platform that is a prerequisite for the AI capabilities SAP now markets. You cannot apply an AI layer to a system you have not migrated. The migration itself is a two-to-four-year program costing tens of millions of dollars before a single AI feature is configured or tested. SAP reached what it described as a “significant maturity milestone” only in May 2025, with the unveiling of its AI Foundation, the unified development layer across its suite. That foundation only just arrived. Customer build begins after that. (Sources: Gartner as reported by CIO.com; Gartner data reported by The Register; SAP News Center for Joule/AI Foundation statements.)

The headline numbers compound the confusion. SAP reports that its generative AI copilot, Joule, is embedded in over 80% of its most-used tasks across the portfolio. But “embedded” means available in the product, not deployed, configured, tested, validated against a specific enterprise's data architecture and compliance requirements, and actually adopted by a workforce whose incentive structures and decision-making habits were built for a pre-AI world. Available and adopted are separated by the entirety of the hard work.

The actual sequence a large enterprise faces is rarely articulated plainly, but it runs as follows. First, the enterprise must be on a platform version that supports the intended AI capabilities. Most are not. Second, they must complete platform migration, typically two to four years depending on system complexity and technical debt. Third, they must configure AI features for their specific workflows, data architecture, and regulatory environment. Fourth, they must train the workforce, not just on the tool but on new ways of working. Fifth, and this is where most roadmaps simply stop, they must actually change how decisions get made. That last step is not a technology project. It is a leadership project, and it takes longer than any software upgrade.

Enterprises that attempt to skip from foundational automation directly to agentic or self-modifying systems, without first proving reliability, auditability, and organizational trust at lower capability levels, tend to roll back the entire program. The sequencing is not a theoretical construct. It is a practical constraint imposed by the pace at which organizations can absorb and govern new decision-making infrastructure. Any honest autonomy and displacement strategy must force leadership to make explicit choices about how much autonomy the organization is ready to control, not how much the technology could theoretically support.

A company can have AI embedded in its ERP environment, hold licenses for every major AI tool across its software stack, and still not be AI-native, because its processes, incentive structures, and governance culture were designed for a world in which humans made every consequential decision and software

simply recorded the outcomes. Redesigning that operating model is not a function of software procurement. It is a function of organizational transformation at the executive level, which proceeds at a fundamentally different pace than technology deployment.

The enterprises most likely to close the gap are those whose leadership teams understand this distinction early, build the organizational infrastructure before scaling autonomy, and resist the pressure to conflate tool availability with operational readiness. The ones most likely to lose years are those whose AI strategy is owned by IT rather than by the executive accountable for the business outcome it is meant to change.

Executive Appendix: Toolkit

The following templates are designed to accelerate your AI adoption program. Each one has been refined through real enterprise engagements and maps directly to the decision framework outlined in this paper.

- AI Strategy One-Pager: outcomes, KPIs, wedge use cases, maturity target, budget bands
- Use Case Scorecard: value, feasibility, control feasibility, observability, time-to-impact, risk tier
- AI Ecosystem Readiness Checklist: data governance, logging, evals, monitoring, IAM, vendor posture
- Copilot Deployment Checklist: grounding rules, citations, redaction, user training, human QA loop
- Agent Charter Template: purpose, autonomy tier, learning level, allowed tools/actions, forbidden actions, approvals, caps, rollback
- Action Allowlist/Denylist Template: tool endpoints, objects, fields, rate limits, approval requirement
- Risk Register Template: top 10 risks with detection and response
- Pilot Exit Criteria: KPI thresholds, safety thresholds, and operational readiness
- Vendor Evaluation Checklist: data usage/retention, training on your data, audit export, controls, eval tooling, cost transparency
- Organizational Ownership Matrix: RACI chart for AI decisions across CTO, COO, business unit leads, and compliance
- AI Cost Model Template: inference, infrastructure, people, and switching cost projections by maturity level
- Talent Requirements by Maturity Level: role descriptions, headcount ranges, and build-vs-buy guidance

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To receive the complete toolkit with ready-to-use templates, or to discuss how this framework applies to your organization, contact us at tk@5054holdings.com or Cyril.simone@dimensioneleven.com. We work with enterprises at every stage of the AI maturity ladder, from first-use-case selection through full agent deployment.

About the Authors

Tunde Kehinde is the Managing Partner of 5054 Holdings, where he invests in and builds businesses across technology and infrastructure. He co-founded Jumia, helping scale the business through its formative growth years and contributing to over $1 billion in enterprise value by designing go-to-market strategy, operating cadence, and trust mechanisms in complex, low-trust markets prior to its public listing on the NYSE. He subsequently led growth and investment strategy at Lidya, a cross-border fintech lender, where he originated and deployed over $150 million in private credit across the U.S., Europe, and Africa, achieving a 99% repayment rate through rigorous underwriting, dynamic pricing, and disciplined borrower acquisition. Across his career, Tunde has led over 1,500 direct and indirect reports across multiple continents, installing the operating rhythm, ownership structures, and performance standards required to sustain growth at scale. He is a Guest Lecturer at Howard University School of Business and serves as an advisor to enterprises navigating AI adoption, operating model transformation, and capital allocation strategy. Tunde completed his MBA at Harvard Business School.

Cyril Simone is a technology executive and researcher with over 20 years of experience at the intersection of AI, machine learning, and enterprise transformation. He served as VP of Global Technology at News Corp, where he led large-scale technology strategy across the company's media and publishing portfolio. Prior to that, he was Head of Northeast Professional Services at Sun Microsystems and served as Chief Architect for a multi-year transformative education product for the K-12 space in the United States, a joint venture with Office Depot and IBM Watson. As Senior Manager of Data Science at Capgemini, Cyril was Sector Lead for media and entertainment clients including Comcast/NBCUniversal, Disney, Sony, CBS, and Viacom. He has managed global teams of over 500 people. Cyril currently leads research in non-linear and quantum computing solutions for AI performance optimization, and is the founder of iLiner Studios, which creates immersive digital music experiences using advanced AI, and Mercado AI, an AI-driven marketplace that optimizes the agricultural supply chain from farm to market.

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