ChatGPT

CTO Action Plan 2026: Deploying Agentic AI with Governance and ROI

Executive Summary

In 2026, autonomous AI agents ("agentic AI") are moving from pilot projects to mainstream business operations [1]. These systems act as virtual teammates that can plan, execute tasks, and learn with minimal human input, promising dramatic efficiency gains. For example, organizations report **over 90% faster** data reconciliation with far fewer errors after introducing intelligent agents into workflows [2]. Such results translate to significant ROI by accelerating processes and freeing employees from drudgery to focus on higher-value work.

However, the **same AI autonomy that delivers speed can introduce new risks if unchecked** [3]. An unsupervised agent might propagate errors or bias at scale, undermining trust. **Robust governance and human oversight are therefore non-negotiable** in any agentic AI deployment. As Deloitte experts warn, truly autonomous agents "can potentially introduce more risk" than simpler AI applications unless the right controls are in place [4]. The imperative for CTOs is clear: harness the power of agentic AI *responsibly* – balancing innovation with safety, and ensuring every initiative yields measurable business value.

This action plan provides a strategic outline for cross-industry CTOs to deploy agentic AI with confidence and ROI. It covers:

- **Deployment Readiness:** Preparing data, infrastructure, and teams for autonomous AI – from unified data access to security and leadership buy-in.
- **Governance and Trust:** Establishing AI governance frameworks, policies, and oversight mechanisms to maintain compliance and stakeholder trust.
- **Executive Functions in System Design:** Applying cognitive principles (attention, planning, memory, metacognition) to AI architecture and workflows for more human-like intelligence and reliability.
- **MCP-Style Connector Architecture:** Designing a connector ecosystem (e.g. using the Model Context Protocol) that securely links AI agents to enterprise tools and data with standardized, auditable interfaces.
- **Compliance in Regulated Domains:** Adapting deployments for high-compliance sectors (healthcare, defense, supply chain, etc.), including stricter validation, ethical guardrails, and alignment with industry regulations.
- **Human–AI Orchestration:** Evolving organizational roles, skills, and culture to integrate AI "colleagues" – from upskilling talent and redefining roles to new collaboration workflows between humans and AI.
- **Measurement Frameworks:** Implementing metrics and feedback loops to track AI-driven outcomes (efficiency, quality, risk reduction) and ensure **ROI** is realized and demonstrated.

By following this plan, technical leaders can confidently scale autonomous AI agents from initial experiments to governed, enterprise-wide platforms. The end goal: capture the transformational upsides of agentic AI (speed, intelligence, cost savings) **while preserving control, compliance, and trust** at every step.

Deployment Readiness

Successful deployment of agentic AI starts with a solid **foundation**. Before giving AI agents free rein, a CTO must ensure the organization's data, technology, and people are prepared to support and supervise these powerful tools. Key readiness factors include:

- **Executive Vision and Buy-In:** Establish a clear vision for *why* and *where* to use AI agents, tied to strategic business goals (e.g. improving customer service or accelerating R&D) [5]. Make AI a boardroom topic, not just an IT experiment. Upskill the leadership team on agentic AI's potential *and* limitations so they can champion the effort with realistic expectations [5]. This top-down support ensures the initiative isn't a "random act of AI" but part of a multi-year strategy.

- **Data Foundation:** *"An agent is only as smart as the data and context you give it."* Ensure your data house is in order [6]. Audit and integrate relevant data sources – from internal databases to knowledge bases and documents – into a single accessible **knowledge layer**. Clean up silos and legacy data quality issues that could mislead an AI. Consider **context engineering**: identify what policies, historical records, or domain knowledge the agent will need, and make those available in its context window or memory store [6]. By shifting toward an authoritative "single source of truth" for key information, you prevent agents from working with outdated or inconsistent data.

- **Technology Infrastructure:** Modernize IT infrastructure to accommodate AI workloads and connectivity. This includes scalable cloud resources for AI model inference, data pipelines for real-time information flow, and integration middleware (connectors or APIs) for the agent to interface with enterprise systems. Verify that your tech stack (cloud platforms, dev tools, etc.) supports the latest AI agent frameworks and security controls – for example, ensuring your cloud or on-prem environment can host agent services and allow safe tool use via sandboxing or containerization.

- **Security, Identity, and Access Controls:** Treat AI agents as new digital "users" on your network. Assign **unique identities and credentials** to each significant agent, just as you would for a human employee [7]. This allows you to manage and monitor agent access to systems. Enforce **least-privilege access** for agents – limit what data and actions each agent can perform to only what is necessary for its role [7]. For example, if you're using Microsoft's ecosystem, tools like Entra ID can issue agent-specific IDs with defined permissions [7]. Early in any deployment, register your agents in a central directory or "agent registry" so IT knows what autonomous code is running where. This prevents a wild west of rogue bots and ensures security policies (encryption, data access rules, etc.) uniformly extend to AI agents.

- **Team Skills and Culture:** Prepare your **workforce** to work alongside AI. Inventory the skill gaps – not just among developers building the agents, but also among end-users who will use or supervise them. Provide training and change management so employees understand how to delegate tasks to AI, interpret AI outputs, and handle exceptions. Encourage a culture of *human-AI collaboration* by emphasizing that the goal is to **augment** human expertise, not replace it. When staff see agents as tools to offload grunt work (not threats to their jobs), adoption goes much smoother. (Notably, only 2% of large firms now remain uninterested in autonomous AI – the vast majority are engaged, so talent increasingly expects these tools at work [1] .)

- **Pilot Use-Case Selection:** Deployment readiness isn't just about tech—**choosing the right pilot projects** is part of preparation. Identify high-value, manageable workflows where an AI agent could make a clear impact within months [8] . Good candidates are often processes that are highly manual or data-intensive (e.g. coordinating compliance documents, triaging support tickets, consolidating reports) that frustrate teams today. Prioritize use cases that can demonstrate quick wins in efficiency or accuracy – this builds organizational confidence and measurable ROI. For instance, if loan processing in a bank or patient data entry in a hospital is a pain point, an agent that automates those steps could save hundreds of hours, yielding an early success story. **Start small, measure results, then iterate** – proving value on a pilot workflow paves the way for broader deployment.

By fortifying data, infrastructure, security, and skills upfront, you create a **safe sandbox** for agentic AI to succeed. As one CTO aptly said, *"Speed without control is chaos."* Laying these groundwork elements ensures that when you turn on your first agents, you have the **controls** in place to channel their speed productively [9] . In short, get your house in order before inviting in the AI. This foundation phase might feel time-consuming, but it separates those organizations that scale AI effectively from those that stumble with early failures.

Governance and Trust

Deploying autonomous AI at scale **demands a "Governance First" approach**. When software is making decisions on your behalf, trust is paramount – among executives, employees, customers, and regulators alike. A 2025 survey of federal agencies put it well: *accountable autonomy* is the model to strive for, where *"agents move quickly, but humans define the mission, approve exceptions, and own the outcomes."* [10] In practice, this means instituting strong oversight and risk management from day one, not as an afterthought. The U.S. Department of Health & Human Services' new AI strategy, for example, makes its first pillar "ensure governance and risk management for public trust," highlighting ethics, transparency, and **clear rules so AI is trustworthy and accountable** [11] .

To build similar trust in your organization, implement a formal **AI Governance Framework** with appropriate policies, structures, and processes. The following are key pillars of governance and risk control for agentic AI (adapted from industry best practices and frameworks [12] [13]):

- **Governance Structure & Policies:** Establish an internal **AI governance board or council** to oversee all autonomous AI initiatives [14] [15] . This should be cross-functional (IT, security, legal, compliance, business unit heads) to cover all angles. Define clear **AI use policies**: What decisions or actions are AI agents allowed to make independently? What requires human approval? Set boundaries on high-risk activities. Align these policies with recognized external frameworks like the NIST AI Risk Management Framework for trustworthy AI [12] (and any sector-specific standards). The aim is to bake ethics, accountability, and risk limits into the project from the outset.

- **Data and Model Governance:** Treat AI models and knowledge sources as critical assets under governance. Ensure **data quality and privacy controls** are in place for any data your agents use [13] . Maintain an inventory or *system of record* of all AI models and agents deployed – documenting their intended use, training data, assumptions, and limitations [16]. This cataloging makes audits and updates manageable. Validate models before deployment (through rigorous testing and perhaps formal validation for regulated cases) and *version-control* any changes. Always know what logic or data an agent is acting on – surprises here can be costly. If your agent uses external foundation models (like an LLM API), track the version and have a process to evaluate updates from the vendor. Strong model governance prevents “black box” issues and builds accountability for outcomes.

- **Audit Trails and Traceability: Log everything** an agent does [17]. Every action, recommendation, or decision an AI agent makes should produce an auditable record – think of it as a detailed event log or even journal of its “thought process”. This provides ground truth for troubleshooting and is essential for compliance in regulated industries. For example, if an AI medical assistant suggests a treatment change, you need a record of why (inputs, rule applied, etc.). Many AI platforms now support capturing model inputs/outputs and even chain-of-thought traces [17]. Ensure these logs are securely stored and indexed. Audit trails enable **after-the-fact analysis** (e.g. showing a regulator how an AI arrived at a lending decision) and are invaluable for internal review or incident investigation. A Deloitte study emphasizes that agentic AI *must* have built-in audit logging and **human override** mechanisms to mitigate the risks of high autonomy [17]. In short – trust, but verify, *and record*.

- **Human-in-the-Loop Oversight:** No matter how advanced your AI, keep humans in the loop **for high-stakes decisions or novel situations** [18]. Design workflows where an AI agent’s output is routed to a human decision-maker whenever certain criteria are met – e.g. low confidence scores, abnormal recommendations, or ethically sensitive matters. For instance, an AI triaging insurance claims might auto-approve straightforward cases, but flag complex or borderline ones for human review. A trading agent might need a human sign-off for any transaction above a risk threshold. **Human override pathways** act as a safety net and help cultivate trust: your staff and customers know the AI isn’t operating in a vacuum without oversight [19]. Plan training for these human overseers as a new responsibility: they will need to understand enough of the AI’s logic to catch mistakes and provide meaningful feedback. Over time, as the AI proves its accuracy, you might dial up its autonomy *in some areas* – but keeping a human fail-safe is an enduring best practice, especially in regulated sectors.

- **Clear Goal Alignment & Guardrails:** Define what the AI *can do* – and **explicitly what it** cannot*. ***In other words, build*** ***guardrails** into the agent’s operating parameters [20]. These can be business rules, ethical constraints, and hard limits coded right into the system. For example, an agent managing supply chain orders might be forbidden from spending above a set dollar limit or from altering any customer data. A marketing AI might be allowed to draft content but *not send it* to customers without approval. Wherever possible, enforce such rules in code or configuration (not just in policy documents) – this is **architecture-enforced governance** that turns paper policies into active constraints [21]. The AI’s actions stay within your organization’s risk appetite and compliance bounds by design. Modern agent frameworks often provide policy config files or “guardrail scripts” for this purpose. Use them liberally. If a rule gets violated (say an AI tries to access a restricted database), have it trigger an automated denial or alert. These measures ensure your agent remains a responsible digital citizen of your enterprise.

- **Bias Mitigation and Fairness:** Be proactive in preventing and monitoring **bias** in AI decisions [22]. Autonomous agents can magnify unfair biases present in data or logic, which is unacceptable in domains like lending, hiring, healthcare, etc. Implement bias testing as part of model development – e.g. test a loan approval agent for disparate impact on different demographic groups, and retrain or adjust thresholds if bias is detected [22]. Set **fairness metrics** (such as error rates by group) to track in production. Many organizations embed bias checks into the pipeline, for instance using bias detection modules or running periodic fairness audits on outcomes. The goal is to ensure AI decisions are **explainable and equitable** to stakeholders. In regulated domains, this is more than ethical – it ties directly to compliance with anti-discrimination laws (fair lending laws, EEOC rules for hiring, etc.) [22]. Make fairness a first-class success criterion for your AI, not an afterthought.

- **Continuous Monitoring and Auditing:** Plan for **ongoing oversight** of your AI in production – *"don't set and forget"* [23]. Just as you monitor networks for intrusions or uptime, monitor your AI's behavior and performance. Establish automated alerts for anomalies: e.g., if an agent's decisions suddenly drift from expected patterns or if its error rates spike. This can catch issues like model drift, data pipeline failures, or even malicious interference. Some teams schedule periodic "AI audits" or stress tests, where they intentionally throw edge-case scenarios at the agent to see how it handles them [23]. Consider adopting a practice from finance: **regulatory sandboxes** – a controlled environment to trial major AI changes or new agents before full rollout [24]. Simulate worst-case scenarios (security breaches, bad data inputs, etc.) and verify the agent fails safely (or can be shut down quickly). Continuous monitoring ensures that as conditions change – markets fluctuate, regulations update, data drifts – you catch any misalignment early and keep the AI operating within safe bounds.

- **Security & Resilience:** Because agents often have broad access to systems and data, securing them is paramount. Work with your cybersecurity team to apply best practices: compliance with standards like SOC 2 or ISO 27001 for data handling, up-to-date encryption, robust authentication for any AI APIs used, and so on [25]. Use **network segmentation** or other controls so that if an AI agent is compromised or malfunctions, it can't wreak havoc beyond its domain. Additionally, design agents to be **resilient** to errors – for example, have fail-safe triggers. If an agent encounters data or scenarios outside its training (a likely cause of AI "hallucinations"), it should default to a safe action (like deferring to a human or pausing) rather than producing a dangerous output [25]. Building in such resilience (think of it as an AI "circuit breaker") will prevent one-off glitches from cascading into serious incidents.

Finally, governance is not a static checklist – it's an **ongoing commitment**. Consider publishing an **AI use report** internally (or even publicly) each year to document how you're using AI and managing its risks, as HHS now plans to do [26]. This transparency can boost public trust and internal accountability. And remember, **culture** is part of governance: encourage employees to speak up about AI-related concerns, create channels for feedback on agent decisions, and celebrate teams that improve processes safely with AI. By fostering a culture of responsible innovation, you reinforce that *everyone* has a role in governing AI, not just the compliance folks. In summary, robust governance and trust mechanisms will let you **scale agentic AI confidently**, knowing that guardrails are in place to prevent surprises. Trust – among users, customers, and regulators – is the currency that will ultimately determine your AI program's longevity and success.

Executive Functions in System Design

One of the most intriguing ways to design effective AI systems is to take inspiration from **human cognition** – specifically, the brain's *executive functions*. Executive functions (EFs) are the higher-order cognitive skills humans use to manage complex tasks: things like **attention**, **working memory**, **planning**, **self-monitoring (metacognition)**, **impulse control**, and **cognitive flexibility**. Framing your AI system architecture around these functions can ensure that your agents have a more **robust and human-like problem-solving approach**, rather than being narrowly task-specific. Nick Baguley, an AI thought leader, calls executive functions "the brain's hidden infrastructure beneath leadership, judgment, and persistence," noting that they are the leverage point for effective action [27]. By translating these into our AI designs, we create agents that don't just perform single tasks, but can **orchestrate themselves intelligently** in dynamic situations.

Let's consider how key executive functions map to AI system components and what best practices emerged by 2026 to emulate these capabilities:

- **Sustained Attention:** Humans excel (to a point) at focusing on goals despite distractions. AI has an advantage here – it **never tires or gets distracted**, processing whatever data it's given relentlessly. In fact, an AI agent can monitor thousands of information streams in parallel without fatigue [28]. The challenge is *focusing it on the right signals*. Design your agent with context filters or relevance algorithms so it attends to what matters. For example, if an AI assistant is managing a project, it should watch for key deadline changes or blockers in project data, not every minor status update. Use event triggers or anomaly detectors to direct the AI's attention. This ensures the agent's "vigilance" is high where it counts, mimicking how a good manager keeps their eye on critical metrics.

- **Working Memory & Context Management:** Working memory is our brain's scratchpad – holding information temporarily to work through a problem. Today's AI agents **need extended context** to function effectively (beyond the fixed window of an LLM). Incorporate a **knowledge repository** or memory module for your agents. This could be a vector database or knowledge graph that the agent can query for facts, recent interactions, and domain knowledge. By 2025, AI systems began to use enterprise knowledge graphs to give agents a form of long-term memory [29]. However, unlike humans, AI doesn't natively know what to "forget" [30]. Without limits, an agent might fixate on irrelevant details or overload its prompt context with noise. Implement strategies for memory management: e.g., time-based forgetting (older data gets lower priority), or logic to prune facts that are irrelevant to current goals. Ensuring the agent has the **right information at hand (and extraneous info filtered out)** is crucial for complex reasoning.

- **Planning and Goal-Directed Behavior:** Planning is a quintessential executive function – formulating a goal, devising steps, anticipating needs and pitfalls [31]. Infusing this into AI means enabling agents to **break tasks into subtasks, sequence actions, and handle dependencies**. In practice, this might involve a *planning algorithm or module* (some teams use AI planners or specialized models like GPT-4 with chain-of-thought prompting to let the agent outline multi-step solutions). By 2026, advanced agent frameworks support multi-step workflows natively – for example, Microsoft's Azure Agent Foundry introduced tools for multi-agent process orchestration, where one agent can hand off to another in a defined sequence [32]. Ensure your AI has a notion of "done" versus "not done" states, and can prioritize tasks (possibly through a scoring function or instruction tuning for prioritization).

The agent should also be able to adjust its plan if conditions change – akin to **cognitive flexibility** (another EF). Some approaches include having a monitoring loop where the agent checks if its actions are moving toward the goal, and if not, re-plans. In sum, bake a **planning capability** into the system so the agent isn't just reactive but can proactively chart a course to an objective.

- **Cognitive Flexibility:** This is the ability to switch strategy or perspective when faced with new information or setbacks [33]. Rigid AI systems fail when something unexpected happens outside their training. To achieve flexibility, give your agents access to multiple tools or modes of reasoning. For example, if one approach fails, allow the agent to try a different method (perhaps even by calling a different model better suited to the task). Some enterprises use an ensemble of models: one fast but shallow model and one slower but more thorough model, and let the agent choose or consult both depending on the scenario – a rough analog of switching thinking modes. Also encourage a design where agents can escalate to a human or an analytic module if they are unsure, rather than blindly proceeding. This adaptability ensures the agent can handle novel situations more gracefully. Internally, techniques like reinforcement learning with human feedback (RLHF) have been used to train agents to adjust behavior based on context changes, which effectively imparts some flexibility in decision-making.

- **Inhibitory Control (Impulse Control):** In humans, this prevents rash actions – *thinking before acting*. For AI, **guardrails and approval steps** are the mechanisms of impulse control. We already covered guardrails in the Governance section; from a system design view, you might implement a check where the agent's plan or action is evaluated against a set of rules or an "ethical AI" module before execution. For instance, if an agent generated an email response to a client, an impulse-control layer might scan it for sensitive content or compliance issues (like no privacy breach) before it goes out. Large language models often have built-in content filters – leveraging those or adding custom filters is crucial [34]. The latest generation of AI agents in enterprise come with policy engines that will intercept any disallowed actions (e.g., attempting to access a file it shouldn't). Use these features. In short, design the system such that the agent *cannot* easily do something outside its allowed scope, no matter what. This mimics the human executive function of holding back inappropriate actions.

- **Metacognition (Self-Monitoring):** Metacognition is "thinking about thinking" – the ability to observe and evaluate one's own performance [35]. For AI, early versions lacked this; they would plow ahead without self-checking. But new approaches are giving agents a form of self-reflection. One pattern is the use of a *"judge" or "critic" model* that evaluates the primary agent's output (like having a second AI agent that says "I will double-check the work") [36]. Another pattern is prompting the agent to reason step-by-step and then review its steps for mistakes before finalizing an answer (a technique shown to reduce reasoning errors). In system design, you can instantiate a **supervisory agent** whose role is to oversee others – this meta-agent can catch inconsistencies or decide when to involve a human [36]. For example, in a complex multi-agent workflow handling a loan origination, you might have one agent as a coordinator that monitors all the other agents' outputs for compliance and coherence – essentially an AI project manager with an executive oversight function [36]. The coordinator agent can query others, verify results, and flag anything that doesn't look right. By designing such meta-level monitoring (either via a dedicated agent or as a built-in audit function), you imbue the system with a **feedback loop for continuous improvement** – much like humans reflecting and learning from their work.

> **“Context is the hidden thread that ties executive functions together, providing clarity, relevance, and direction to decision-making.”** [37] This quote underscores that no matter how many cognitive functions we emulate, they must operate on the **right context**. Always consider how your agent obtains context about the user, task, and environment. Techniques like session memory, user profiles, or real-time data retrieval help provide the rich context that humans intuitively carry into decisions. Without it, an AI’s “executive” abilities will be working in the dark.

In summary, bringing executive function concepts into AI architecture leads to more **adaptive, reliable agents**. Instead of a brittle bot that does only A then B, you get a quasi-“autonomous executive” that can focus attention, remember and use knowledge, plan multi-step solutions, self-correct, and stay within bounds. This doesn’t require sci-fi general intelligence – it’s achieved through thoughtful system engineering and use of emerging AI techniques. The payoff is agents that behave less like narrow tools and more like competent team members, able to handle real-world complexity. As you design your platforms, **ask of every AI agent**: How will it know what to focus on? How will it remember context? Can it plan and adjust? What stops it from going off the rails? Does it know when it needs help? These questions lead directly to the executive function-oriented design choices that separate an *average* AI assistant from a truly *agentic*, resilient one.

MCP-Style Connector Architecture

Early adopters of agentic AI learned that integrating AI agents into real business processes is often less about the AI model itself and more about **connecting the AI to the right tools and data**. Traditionally, hooking an AI system to a company’s internal applications or databases meant a lot of custom integration work – essentially building one-off bridges for each new tool. This approach doesn’t scale; it’s like giving your AI dozens of proprietary cables when what it needs is a universal port. Enter the **Model Context Protocol (MCP)**: an open standard (introduced in late 2024 by Anthropic and embraced industry-wide by 2025) that provides a *universal connector* for AI agents [38] [39]. Think of MCP as the *“USB-C of AI integration”* [40] – a standard way for an AI agent (client) to plug into various systems (through MCP servers) and interact with them securely.

With an **MCP-style connector architecture**, you design your AI platform around *standard connectors* rather than bespoke integrations. Major AI providers like Anthropic, OpenAI, and Microsoft have built support for MCP or similar protocols into their agent frameworks [41] [42]. What this means practically is that instead of your AI needing to know the specifics of each system’s API, it speaks a common MCP language to any system that has an MCP adapter. For example, you could have an MCP server for your CRM, one for your database, one for your ERP. Your AI agent can query “customer order status” and, via MCP, the request routes to the CRM connector seamlessly. This **simplifies development and maintenance drastically** [39] [43]. As new tools come along, you just add an MCP connector for them, rather than altering the agent’s core logic.

Key benefits of adopting a connector architecture with MCP (or an equivalent standard) include:

- **Interoperability and Flexibility:** MCP creates an **interoperable ecosystem**. Any AI agent can connect to any tool for which an MCP server exists, without custom coding [44] [43]. This makes your AI stack more modular. You can swap out backend systems or add new data sources without retraining or recoding the agent; just plug in the new connector. It future-proofs your architecture –

an important consideration given how fast enterprise tech stacks evolve. As UiPath noted, before MCP each integration was a brittle one-off, but with MCP the agent's intelligence is no longer "trapped in silos" of specific integrations [45] [46].

- **Rich Context via Real-Time Data:** The very name "Model **Context** Protocol" highlights context-sharing. Connectors allow AI agents to pull in **real-time, contextually relevant data** on demand, rather than being limited to their training data [47]. For instance, an agent might use MCP to retrieve the latest sales figures from a database or fetch an email from a client communications log when formulating a response. This leads to far more accurate and useful outputs [47]. In effect, MCP breaks the barrier between the AI and live data. By 2026, this on-demand context is essential for enterprise AI – static models alone can become stale or misinformed.

- **Security and Governance Built-In:** A standardized connector approach also aids security and governance. MCP connectors act as controlled gateways. Each connector can enforce **permissions and logging** for the tool it represents [48]. For example, your document repository connector might only allow the agent to read from a certain folder and will log every file accessed. This aligns with the "least privilege" principle on a technical level [48]. You configure the connector once with appropriate access rules, and you know any compliant AI agent will adhere to those rules when interfacing with that system. Furthermore, because all interactions funnel through a handful of MCP servers, it's easier to monitor and audit agent behavior across systems, rather than chasing down dozens of API calls. In short, **connectors simplify oversight** – you have a choke point to observe and control what the AI is doing in external applications.

- **Faster Deployment and Ecosystem Leverage:** The rise of MCP has brought with it an ecosystem of **pre-built connectors**. Developers have created open-source MCP servers for common apps (Google Drive, Slack, GitHub, databases, etc.) [49]. Companies like Cloudflare and UiPath integrated MCP to allow their automation bots and AI services to tap into many systems out-of-the-box [50] [51]. By adopting this architecture, a CTO can accelerate agent deployment – instead of spending months integrating an AI with your SAP system, you might use a pre-made SAP MCP connector and get started in days. This also encourages experimentation: business analysts or "citizen developers" can mix and match connectors to prototype new agent uses without hardcore coding, since the heavy lifting of integration is handled by the standard. The net effect is faster time-to-value for AI projects and broader utilization of AI across the enterprise.

As you design your agentic platform, consider making MCP (or a similar open connector standard) a cornerstone of your architecture. Encourage your software vendors to provide MCP endpoints for their products – many forward-thinking tech providers are doing so as it gains traction [52]. It's not often we see an industry consensus around a standard so quickly, but MCP addresses a pain point everyone faced: connecting AI to the "world outside the model."

> **"Open technologies like the Model Context Protocol are the bridges that connect AI to real-world applications, ensuring innovation is accessible, transparent, and rooted in collaboration."** – *Dhanji R. Prasanna, CTO at Block (Square)* [53]

This quote exemplifies the sentiment that a **universal connector** is not just a technical nicety, but the key to making AI a practical, integrated part of business innovation. By deploying a connector-based architecture, you enable your AI agents to truly act as **digital workers** that can use the same apps and data your human workers do – but with the speed and diligence of a machine.

Finally, note that alongside connectors, you'll want an **agent orchestration layer** (sometimes called an *AI control plane*). This is like a command center to register connectors, manage agent instances, and monitor their activity. Microsoft's "Agent 365" and similar tools were introduced to serve this purpose – giving enterprises a central place to apply security and compliance rules to all their agents and connectors [54]. Whether you use a commercial solution or build your own, plan for this management layer. It will handle discovery of connectors, routing requests, scaling agents up/down, and aggregating logs for oversight. In short, connectors plus a control plane equal a powerful, governable AI fabric across your organization.

Compliance in Regulated Domains

All industries adopting AI must mind governance, but **regulated sectors** (like healthcare, financial services, defense, energy, and critical infrastructure) have a uniquely high bar for compliance. In these domains, errors or unchecked autonomy can not only cost money – they can harm lives or breach laws. CTOs in such sectors need to deploy agentic AI with an extra layer of caution and rigor, meeting both internal risk standards and external regulatory requirements. The good news: as of 2026, regulators themselves are embracing AI (the FDA, for instance, launched an agency-wide agentic AI platform for its staff with proper oversight [55]), so there is growing guidance on how to do this responsibly.

If you operate in a high-compliance industry, consider the following strategies as you implement AI agents:

- **Embed Industry Compliance from Design:** Align your AI development with relevant regulations and guidelines *from the start*. For healthcare, that means HIPAA for patient data privacy; for finance, it's rules like AML/KYC and model risk management SR 11-7; for defense, it could be Department of Defense AI Ethical Principles or ITAR export controls on data, etc. Map out which laws or standards apply to your AI use case. For example, the FDA's AI initiatives must ensure 21 CFR Part 11 compliance (for software used in regulatory processes) – your AI platform should be designed to log and audit changes in ways that satisfy those rules. Use established frameworks: the **NIST AI Risk Management Framework** is a popular baseline for trustworthy AI across sectors [12]. It provides a taxonomy for securing and auditing AI which you can adapt to specific compliance regimes.

- **Intensified Governance and Oversight:** On top of the general governance discussed earlier, regulated domains often require formal **oversight structures** and documentation. Form an **AI Governance Board** or steering committee if you haven't already (many banks and government agencies have done this) [15]. This board should perhaps include a Chief Risk Officer or General Counsel alongside IT and business execs, to ensure compliance perspectives are central. Hold regular reviews of AI performance and any incidents. Additionally, involve your *Audit* and *Risk* teams early – ask them to develop an **AI controls audit plan**. This might include verifying that every model is documented, every decision traceable, and that contingency plans exist for AI failures. Some regulated orgs have even created an "AI Ombudsman" role – an internal watchdog to field concerns or conduct independent assessments of AI fairness and safety. While that may not be required, it's indicative of the thorough oversight culture to foster.

- **Comprehensive Audit Trails and Reporting:** In regulated settings, assume that one day you'll need to show an auditor (or a court) exactly what your AI did and why. We already emphasized audit logging; here, ensure those logs are **comprehensive and immutable**. Use append-only logs and back them up to a secure, tamper-evident storage. Implement regular *reporting* as well: for instance, a monthly compliance report on AI decisions. The HHS, as noted, plans annual public reports on AI use in healthcare [26] – you might produce internal reports that detail things like the number of AI-triggered transactions, overrides by humans, any deviations or errors caught, etc. This not only prepares you for external scrutiny but forces discipline internally. Moreover, be ready to provide **explanations** for AI outputs. Techniques for explainable AI (XAI) can help translate a model's decision into human-readable rationale. Regulators increasingly expect this, especially if AI is involved in decisions like loan approvals, medical diagnoses, or security clearances. Investing in XAI tools or using inherently interpretable models in critical areas can pay off when you need to justify an outcome.

- **Human Accountability and Optionality:** A pattern emerging in government AI adoption is to **keep AI assistance optional for humans** and *clarify accountability*. For example, the FDA's internal AI platform allows employees to use AI agents for tasks but doesn't force them – and it emphasizes that humans remain responsible for final decisions [55]. You may consider a similar stance: AI provides recommendations or draft outputs, but a human must actively decide to accept or implement them. This approach can satisfy regulators that you haven't ceded control to an algorithm. Clearly document roles in your procedures: who is accountable if the AI makes a mistake? (The answer should never be "no one" – it might be the manager overseeing the process or an AI product owner.) By having a named responsible party and an option for human intervention at any point, you align with the principle that AI augments rather than replaces professional judgment in regulated activities.

- **Validation, Testing, and Sandboxing:** Before deployment in a live regulated environment, subject your AI agents to **rigorous validation tests**. This could include compliance scenario testing, where you run the agent through past cases and ensure it would have complied with all rules. Many financial firms now require AI models to go through a model validation team similar to how they validate quantitative models – checking for conceptual soundness, bias, overfitting, etc., and signing off on usage scope. Additionally, **pilot in a sandbox** if possible: for instance, run the agent in parallel to human workers for a period, comparing results, before allowing the agent to operate on its own. Regulators often are comforted by phased rollouts. In fintech, "regulatory sandboxes" supervised by regulators allow testing a new AI service on a small scale – engaging with regulators proactively via such mechanisms can be wise. Even internally, a sandbox environment that mirrors production but doesn't impact real customers (or patients, etc.) is a safe space to iron out kinks. Only once the agent consistently behaves within compliance expectations in the sandbox do you let it into real operations [24].

- **Incident Response and Fail-safes:** Despite best efforts, things can go wrong. Have a clear **AI incident response plan**. For example, if an autonomous agent in a power grid control system starts behaving oddly, who gets alerted and how do they shut it down? You should be able to **disable or quarantine an AI agent immediately** if it's malfunctioning – build a "big red button" into the system. Conduct drills or tabletop exercises on AI failure scenarios (much as cyber teams do drills for breaches). Also plan for regulatory notifications: certain sectors require you to report significant system failures or breaches within tight timeframes. Decide in advance what constitutes a reportable AI incident (e.g., an agent making an unauthorized transaction or exposing sensitive data). It's better to self-report under control than have an issue discovered externally. Showing that you can detect and respond to AI issues quickly will further bolster trust with regulators.

In highly regulated domains, compliance is not a one-off task but a continuous posture. The strategies above echo a common theme: *be proactive, be thorough, and document everything*. Many of these practices (audit trails, human oversight, bias checks) we've already discussed as general governance – in regulated sectors they just need to be turned up to 11. Additionally, keep an eye on emerging regulations: governments worldwide are formulating AI-specific laws (e.g., the EU AI Act). Ensure your governance team monitors these and that your AI systems are **flexible enough to adapt** to new compliance requirements (for instance, if a law mandates additional record-keeping or transparency features, you should be able to update your system to accommodate that).

Done right, a strong compliance approach doesn't stifle innovation – it **enables it** by creating the conditions for safe experimentation. When executives, regulators, and customers trust your AI, you'll have more freedom to expand its use cases. Thus, for CTOs in regulated industries, investing in compliance is investing in the *sustainable growth* of AI capabilities.

Human–AI Orchestration

One of the most profound shifts agentic AI brings is in the **workforce and organizational dynamics**. AI agents aren't just new software to install – they function as **virtual team members**. This means companies must thoughtfully orchestrate how humans and AI agents work together, capitalizing on each other's strengths. The mantra is *"augmentation over replacement."* Rather than viewing AI as a threat to jobs, forward-looking organizations treat AI agents as a new class of employee – tireless collaborators that handle the grind, while humans focus on what humans do best (judgment, creativity, empathy). Achieving this vision requires **redefining roles, retraining staff, and evolving processes**. In 2025, only 2% of large enterprises said they were not interested in autonomous AI, yet less than half of workers had received relevant upskilling [1] [56]. Bridging this gap is a leadership challenge as much as a technical one.

Here's how CTOs and other executives can foster effective human–AI orchestration:

- **Reimagine Roles and Responsibilities:** As AI agents take on routine and data-heavy tasks, **human roles will be redefined, not eliminated** [57]. Identify which job tasks can be offloaded to AI and which new tasks emerge for humans. For example, a financial analyst might spend less time compiling reports (AI can do that) and more time interpreting results and strategy. New roles are already appearing, such as **"AI Agent Supervisor"** – an employee who oversees and quality-checks the work of AI agents (analogous to a manager for digital workers) [58]. Another is **"Context Engineer"** – someone who curates the data, prompts, and knowledge context that an AI agent uses, ensuring it remains effective [59]. Even line managers will evolve: as McKinsey noted, tomorrow's managers will **coach and develop AI agents** on their team, not just human employees [59]. Start updating job descriptions and org charts to account for these shifts. Employees should see a path for themselves in an AI-enabled organization – whether it's becoming super-users of AI or stepping into entirely new positions that didn't exist before.

- **Upskilling and Continuous Learning:** A robust **AI training program** for staff is vital. It's not a one-and-done workshop, but an ongoing effort to raise *AI literacy* and confidence at all levels [60]. Key areas include: understanding how AI agents work (at a conceptual level), knowing the capabilities and limits of the specific tools in use, learning to interpret AI outputs (e.g., spotting when an AI answer might be wrong or biased), and basic skills like prompt engineering for those interacting with LLM-based agents. Emphasize practical, job-specific training: for instance, train customer support reps on using an AI assistant to draft responses, or train doctors on an AI that summarizes patient charts. According to a McKinsey study, 75% of workers expect AI to change their jobs in the next five years, but less than half have been upskilled so far [56] – leaders must urgently close this gap. Encourage a growth mindset: position AI training as a career growth opportunity ("learn to leverage AI and increase your impact") rather than a threat. This will help turn any fear into excitement about mastering new tools [61].

- **"Citizen Developer" Enablement:** One powerful approach to human-AI collaboration is to enable **domain experts to create their own AI solutions** with minimal coding. Modern AI platforms offer low-code or no-code environments where non-programmers can configure workflows or even custom agents [62]. For example, Microsoft's Copilot Studio allows business users to assemble AI components visually. By training and encouraging your staff to be *"citizen developers,"* you tap into frontline innovation. The people who best understand a process (be it a sales pipeline or a lab procedure) can design an AI assist for it, rather than waiting on IT. Some companies have set up *AI Sandboxes* or **Innovation Labs** for employees to experiment safely with AI on real problems [63]. With guardrails in place (e.g. data anonymization, approval before deployment), this democratization can greatly accelerate AI adoption and morale. It signals trust in your employees to shape the future of work and turns them into active participants rather than passive recipients of AI changes.

- **Cross-Functional Implementation Teams:** Adopting agentic AI at scale **is not solely an IT project** – it cuts across technology, operations, risk, HR, and more. Break down silos by forming **cross-functional AI teams or task forces** [64]. For instance, if deploying an AI in hospital administration, include clinicians, data scientists, IT integrators, and compliance officers in the project team. This ensures the solution is grounded in real-world context and constraints. Nick Baguley notes that successful deployments often pair domain experts with AI engineers "to co-develop an agent," each bringing unique insights [65]. A financial services firm did this by pairing traders and loan officers with AI developers to automate parts of trade settlement and loan processing [65]; in a healthcare analogy, you might pair nurses with AI specialists to build an agent that automates initial patient triage notes. These cross-functional teams also model the new collaboration culture that AI workflows require – they break the mentality of "this is an IT initiative" and make it a joint business-technology effort.

- **Change Management and Communication:** Introducing AI agents can be jarring if not managed well. Develop a **change management plan** that communicates the *why*, *how*, and *what* of the AI rollout to all stakeholders. Be transparent about which tasks will change and which won't. Solicit input and address concerns – e.g., some employees might worry about job security or feel uneasy about trusting an AI's work. Craft messaging that the AI is there to **assist** and elevate their work (provide concrete examples relevant to each department). Highlight success stories internally: for instance, if an operations team saved 30% of their time using an agent, share that story and how those team members then used that time for more valuable work. Also, provide channels (like an AI helpdesk or champion network) where employees can ask questions or report issues with the AI. The goal is to build trust in the AI over time. Many companies find that starting with volunteer early adopters, then gradually expanding, creates a group of internal champions who help peers get comfortable. Pulse surveys can gauge sentiment and adoption – if employees feel the AI makes their job harder, that's a red flag to address through either tool improvement or training.

- **Foster a Collaborative Culture:** Ultimately, you want a culture where **human–AI collaboration is second nature**. Encourage teams to think of workflows in terms of "who (or what) is the best entity to do this task – a person or an AI or both together?" For example, a human might draft a strategy, then an AI agent refines the details and does the number crunching, then the human reviews and finalizes. Make such *hybrid workflows* commonplace. Some organizations formalize this by updating standard operating procedures to explicitly include AI steps. Also, redefine performance metrics if needed: if an AI does 50% of a task and a human does 50%, ensure your evaluation of the human's performance accounts for how effectively they leveraged the AI, not just the output itself. In other words, **reward effective use of AI**. This sends the message that working smart with AI is valued. Studies show that companies leading in AI have employees who act more as **"orchestrators of value"** rather than just task executors [66]. They set goals, manage workflows and combine AI + human efforts to achieve results – much like a conductor with sections of an orchestra. Strive to develop your people into these orchestrators. As Sia Partners observed, this cultural leap is as significant as the technology leap [66]. It requires leadership at all levels to model collaborative behavior (for instance, an executive openly using an AI assistant for meeting prep, demonstrating it's not beneath them to use the tool).

> **"The workforce moves from being task executors to orchestrators of value, a cultural leap as significant as the technology itself."** [66] *– Insight from Sia Partners on the future of work in the AI era.*

This quote encapsulates the endgame: employees empowered by AI to deliver greater value, rather than replaced by AI. To get there, **human resources strategy must evolve in tandem with technology strategy**. Hire for adaptability and digital aptitude. Update training continuously. And crucially, involve your people in shaping how AI is used – co-create solutions with them so they have ownership. When employees see AI agents as *partners* that make their jobs better and more engaging, the organization unlocks the full potential of hybrid human-AI teams.

In summary, human-AI orchestration is about **integrating AI into the fabric of your operations and culture**. It touches job design, skills, team structure, and change management. A calm, positive, and inclusive approach will ease the transition. Companies that master this orchestration will not only gain efficiency but also have more satisfied employees (freed from drudge work) and more agile teams. In a world where every competitor might have access to similar AI technology, the differentiation will be *how well your people embrace and excel with that technology*. Those who do will create a symbiosis between human creativity and machine intelligence that propels them far ahead.

Measurement Frameworks

To ensure that agentic AI deployments actually deliver on their promises, CTOs must establish clear **measurement frameworks**. This means defining what success looks like in quantitative and qualitative terms, tracking progress rigorously, and feeding those insights back into strategy. AI projects can sometimes ride on hype; a measurement discipline cuts through by continually asking: *Are we getting ROI? Are we managing risks?* Without these feedback loops, you might scale an AI program that automates a lot but accomplishes little. Conversely, good metrics can demonstrate wins (building further buy-in) and catch issues early so you can course-correct. Here’s how to approach measuring agentic AI initiatives:

- **Define Key Performance Indicators (KPIs) Up Front:** Before deploying an AI agent, decide on the **specific metrics** that constitute success for that use case [67] . Tie these to business outcomes, not just technical metrics. For example, if rolling out an AI claims processing agent, KPIs might include: average processing time per claim (target: reduce from 5 days to 1 day), human labor hours saved per week, accuracy or error rates (target: <1% error rate, matching or improving on human benchmark), and customer satisfaction scores post-claim (looking for an uptick due to faster responses). If the agent is internal (say triaging IT tickets), measure employee satisfaction or turnaround time on those requests. **Set baseline measurements** before AI introduction so you know the starting point. Whenever possible, also establish a financial proxy for metrics – e.g. hours saved can be translated into dollars saved, error rate reduction can be tied to cost of rework avoided, etc.

- **Instrument and Collect Data Continuously:** Implement the tools and processes to **gather metric data automatically** from the AI systems [68] . This might involve dashboards that log every transaction the agent handles along with timestamps, outcomes, and any human interventions. Many AI platforms now have telemetry features; for instance, Microsoft introduced an “Agent Factory” tool that meters workflow outcomes to help calculate ROI [67] . If not, you might use general analytics: log files plus scripts to calculate metrics over time. The key is to make measurement low-effort – it should be baked into the system. For qualitative measures like customer satisfaction, incorporate survey triggers or feedback requests in the AI-driven process (“How was our service?” after an AI-assisted call, for instance). Also track usage metrics: how often are people actually using the AI agent? Low utilization could indicate a problem with trust or usefulness.

- **Focus on Efficiency, Quality, and Value Metrics:** Most AI ROI will come from **efficiency gains** (speed, volume) and **quality improvements** (accuracy, consistency). Ensure your framework covers both. Common metrics include: **time saved** (per task or in aggregate), **throughput** (how many tasks can be handled in a given time, perhaps 24/7 now), **error or rework rates**, **decision latency** (e.g., time to detect a risk and respond), and **cost per transaction** (which ideally drops as AI takes on work) [67] [69] . There may also be **outcome metrics** specific to the function, like fraud loss reduction, or procurement savings found, or fewer customer churns thanks to proactive AI outreach. Don’t neglect **human-centric metrics**: for example, measure employee engagement or satisfaction after AI adoption. Are employees less bogged down in tedious tasks? This could be surveyed or inferred via something like Net Promoter Score internally. One might even track the **reallocation of time** – e.g., “Agents saved 1000 hours this quarter, and we reinvested 600 of those hours into customer advisory roles.” Such metrics show how AI is augmenting human work.

- **Calculate Return on Investment (ROI):** Ultimately, you’ll want to boil improvements down into a financial ROI for the AI project (especially to justify scaling or additional investment). This can be straightforward for efficiency gains – e.g., hours saved * average fully-loaded cost of those employees, gives a labor cost savings value [68] . Or, if AI allowed you to avoid hiring additional staff to handle growth, calculate the avoided headcount cost. Quality improvements might be quantified by cost of errors (say an error costs $X on average to fix, and you reduced errors by Y, so X*Y saved), or by risk reduction (fewer compliance fines or losses). Some benefits are harder to monetize (like faster cycle time leading to more customer satisfaction), but you can make reasonable estimates (customer sat can be* _linked to retention rates and thus revenue, etc.). Document your assumptions and have a range (e.g., conservative, likely, optimistic ROI scenarios). Regularly update this ROI as data comes in. In practice, it often helps to show a running total of value delivered_* by the AI initiative – e.g., “six months in, $500K in operational savings and $200K in additional revenue opportunities identified.” This keeps the board and stakeholders bought in.

- **Iterate and Improve Based on Measurements:** Metrics are not just to pat yourself on the back; they should drive **continuous improvement**. Set up a cadence (monthly or quarterly) where the AI project team reviews the data and asks: Are we hitting targets? If not, why? For instance, if the AI isn’t saving as much time as expected, is it because employees aren’t using it fully (adoption issue), or because it’s having errors requiring rework (quality issue)? Identify the bottlenecks or issues and address them – maybe more training is needed, or the model needs a tweak, or a workflow adjustment. Conversely, if an AI agent is exceeding goals easily, that might signal an opportunity to expand its scope or take it to more departments. Be willing to **pivot or pull back** based on evidence [70]. It’s better to refine or even cancel an underperforming pilot than to double down due to sunk-cost fallacy. The measurement framework gives you the factual basis to make those calls dispassionately. Many successful AI adopters follow a “start small, measure, and scale what works” philosophy – treat initial deployments as experiments and be ready to iterate.

- **Monitor Risk and Trust Metrics:** Beyond business KPIs, track metrics that indicate the health of **governance and trust** in the AI system. For example, how many times did human overrides occur? Are they decreasing over time (as the AI improves) or increasing (possible red flag)? How many bias or ethics exceptions have been flagged (hopefully zero)? If using an AI in customer-facing scenarios, what is the customer sentiment specifically on AI interactions (e.g., do customers complain about the AI or praise the faster service)? Regulators or risk officers might want a **risk dashboard** showing things like model drift indicators, compliance checks passed, etc. If you’ve set thresholds (e.g., “AI can only handle transactions up to $10k”), measure how often it bumps against those thresholds or tries to exceed them. Essentially, ensure your metrics also capture that the **guardrails are working** and the AI remains under control. These measurements will feed back into your risk management process – e.g., if override frequency is high, maybe the agent’s autonomy was dialed up too fast and you need to tighten criteria.

- **Communicate Value to Stakeholders:** Develop a habit of reporting AI performance and value to stakeholders in **simple terms**. Dashboards or scorecards can be helpful. For instance, a quarterly AI Value Report to your executive team could highlight key wins (with data) like “Customer Service AI handled 5,000 chats this quarter with a 92% resolution rate, saving an estimated 2,000 agent hours and improving average response time from 5 minutes to 1 minute. [67] ” and “AI-driven quality control reduced product defect rate from 1.5% to 1.0%, preventing an estimated $100K in rework costs.” Including a few testimonial snippets (e.g., a manager describing how their work improved) can add color. The goal is to make sure everyone sees *tangible results*, keeping enthusiasm high and alignment tight. This also prepares you with evidence when requesting budget for further AI investments.

By establishing a strong measurement framework, you essentially create the *nervous system* for your AI program – sensing performance and guiding actions. It transforms the conversation from “we believe AI is helping” to “we know AI achieved X and we learned Y.” Especially for multi-year strategies, this data-driven approach is crucial for maintaining momentum and making informed decisions on where to focus next. In sum: **measure what matters**, and use those insights to continuously **maximize ROI and minimize risk** in your agentic AI journey.

Strategic Next Steps

Agentic AI promises transformative benefits, but realizing them requires deliberate action. As a CTO or technology leader, you've seen in this outline that success comes from both **technical excellence and governance excellence**. The next step is to translate these principles into a concrete roadmap for your organization. To kickstart that process, we invite you to consider two focused initiatives:

- **Governance Sprint:** A short, intensive engagement (e.g. 1–2 weeks) where our experts work with your key stakeholders to assess your current AI governance readiness and craft a tailored action plan. In a Governance Sprint, we dive into your specific context – identifying gaps in policy, data management, security, or compliance that need addressing before scaling AI. The outcome is a clear governance framework (roles, processes, and controls) and a prioritized checklist to implement it. This gives you a running start on establishing the "trust layer" for agentic AI in your enterprise.

- **Executive AI Briefing:** A high-level, executive-friendly session to align your leadership team on agentic AI strategy and opportunities. This can be a half-day workshop or executive offsite presentation where we illustrate the 2026 state-of-the-art (with examples relevant to your industry), discuss the competitive landscape, and address questions or concerns your board/C-suite may have. The goal is to ensure top-level buy-in and understanding, so that the push for AI adoption is truly organization-wide and driven from the top. We often find that an Executive Briefing energizes leadership by painting the art of the possible while also reinforcing the importance of governance and ROI – it sets the tone *"let's innovate, but responsibly."*

Taking either of these steps will help convert the insights from this whitepaper into an actionable game plan. **In summary, the time to act is now**. Agentic AI is no longer a speculative concept – it's here, and competitors across sectors are already deploying it to gain an edge. Those who move from cautious experimentation to scaled implementation (with the proper safeguards) will lead their industries in efficiency, responsiveness, and innovation capacity.

CTO Action Plan 2026 is about balancing bold moves with wise governance. By preparing thoroughly, governing diligently, designing intelligently, and measuring relentlessly, you can deploy autonomous AI agents that drive outstanding ROI and stakeholder trust. We encourage you to **reach out for a Governance Sprint or Executive Briefing** to accelerate your journey. With the right strategy and support, your organization can confidently embrace agentic AI as a core pillar of its multi-year roadmap – delivering value safely and sustainably.

Let's turn this plan into reality, and position your enterprise to thrive in the era of intelligent agents. The opportunity is immense, and with a solid action plan, so are the rewards.

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