How to build a real AI strategy for your organization

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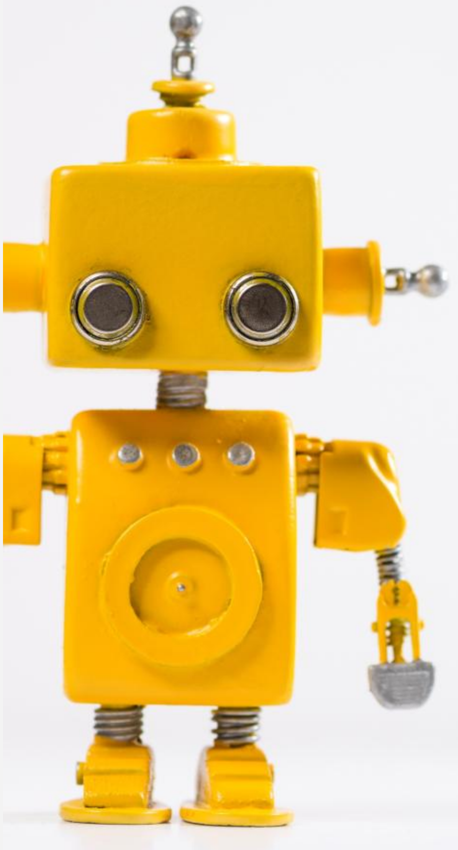
Introduction to AI Strategy

Artificial intelligence has moved from novelty to expectation, yet many organizations are still trapped in proof-of-concept mode. Tools proliferate, pilots multiply, and leaders struggle to explain how these efforts will shift the metrics that fund the business. It is telling that most companies have experimented with AI, but few can point to meaningful earnings impact. The gap is not ambition. It is strategy that is defined in business terms and executed with operational discipline.

How to Build a Real AI Strategy

An AI strategy starts by widening the lens. AI is not one headline tool or a single generative chatbot. It is a family of capabilities that help machines perceive, decide, and act, from predictive analytics and robotic automation to computer vision, natural language processing, and agentic systems that complete multi step work. When leaders define what AI means for their organization, they can move beyond vendor promises and toward a clear view of where AI can strengthen the value chain and create advantage. From there, the work becomes practical.



A real AI strategy is anchored to strategic outcomes such as productivity, margin, cost to serve, and customer experience, then translated into a focused set of use cases that balance impact with feasibility. It puts an operating model in place that prevents fragmentation, clarifies decision rights, and builds accountability through governance such as an AI council or a center of excellence. It also invests in the capabilities that make adoption durable: workforce fluency, fit for purpose technology architecture, and change leadership that redesigns workflows and equips managers to lead in an AI augmented environment.

This white paper offers a structured blueprint to help executives turn AI from scattered experimentation into a sustained driver of transformation that shows up in performance, process, and culture. It treats AI strategy as a continuous program that measures progress, learns quickly, and recalibrates as technology and business priorities shift.

If you are ready to elevate your workforce and harness the power of strategic planning and AI transformation, Talent Stratify can help you build an AI strategy that scales and delivers results

Establishing Strategic Anchors

Once the role of AI is clearly defined, the next step is to establish the strategic anchors that guide all AI initiatives. These anchors help answer the question of where AI will create differentiated value for the business. Rather than pursuing AI for novelty, leading companies connect each initiative to a core business outcome. These outcomes may include increased productivity, wider margins, reduced cost-to-serve, or improved customer experience. Every AI project should be explicitly tied to one or more of these value drivers.

Start by identifying the most urgent pain points or the most promising opportunities across these dimensions. If operational efficiency and cost control are priorities in your industry, AI might be applied to automate high-volume tasks or reduce error rates. Microsoft's early AI work illustrates this well. One of its most impactful use cases was improving developer productivity. Tools such as GitHub Copilot helped engineers write code more quickly and with fewer errors, allowing them to focus on higher-value tasks [10][11]. Cost-to-serve is another strategic anchor. In functions like customer service or claims processing, AI can lower service costs by automating routine interactions or triaging requests [12][13]. According to Microsoft's Tereza Nemessanyi, some of the most valuable AI applications are found in these high-cost domains, where automation reduces effort and complexity [12]. The key is to tie each AI investment to a meaningful business metric and apply AI where it can move those metrics most effectively.

Anchoring AI to business outcomes also requires setting clear targets and identifying specific use-case domains from the start. If the strategic goal is to improve customer experience, focus AI efforts on areas such as personalized recommendations, intelligent customer service agents, or predictive churn models. Track these use cases using metrics like Net Promoter Score or customer retention rates. If the priority is margin expansion, direct AI toward pricing optimization, supply chain forecasting, or process automation that reduces unit costs. Aligning AI initiatives to these kinds of outcomes ensures they deliver measurable business value.

A recent KPMG survey found that companies are increasingly focused on financial and operational metrics when evaluating AI. Fifty-one percent of firms identified revenue growth as the top return-on-investment metric, followed by profitability at 38 percent and productivity at 36 percent [14]. This trend shows a move away from abstract innovation efforts toward outcomes tied to business performance. AI strategic anchors should follow the same pattern. They must be defined in terms of real impact, such as faster time-to-market, lower operating costs, or improved customer satisfaction.

It is important to support your strategic anchors with real examples that demonstrate measurable value. If the goal is to improve productivity, point to a company that has achieved it. Pfizer built an internal generative AI platform and deployed it across research, development, and business operations. The company expects to save one billion dollars annually through these use cases that are already in production [15]. Examples like this show that AI outcomes are not theoretical. In financial services, banks use AI for fraud detection and personalized wealth management, which has reduced risk exposure and increased cross-sell rates. In retail, companies such as Amazon apply AI to demand forecasting and supply chain analytics. These capabilities shorten delivery times and reduce inventory costs, improving both customer satisfaction and margin. These types of examples also help set priorities. They show stakeholders that the AI strategy is focused on business results, not experimentation. Strategic anchors help filter a long list of possible applications down to the few that matter most. Define what moving the needle means for your business. Whether the focus is on productivity, speed, quality, cost, or innovation, let those targets shape every AI decision.

Even with clear goals, many companies become overwhelmed by the sheer number of potential AI use cases. The solution is to prioritize opportunities using a structured approach that balances the expected value of each use case against the feasibility of implementation. One effective method is to use a two-by-two matrix that maps feasibility on one axis and value on the other. This tool helps identify which initiatives should be pursued immediately and which require longer-term planning [16].

High-value and high-feasibility projects are often your quick wins. These are initiatives that can deliver measurable impact with relatively low effort. High-value projects that are less feasible may represent long-term opportunities. These initiatives often depend on new capabilities, better data, or new infrastructure that must be developed over time [17]. Low-value use cases, even if technically easy, should generally be deprioritized or discarded [18]. Viewing your AI pipeline as a portfolio helps avoid two common failure modes. The first is chasing high-risk, impractical ideas. The second is focusing only on low-impact projects that do not advance your business goals.

To prioritize effectively, assess each use case against clear criteria across two dimensions: value and feasibility. On the value side, evaluate the potential business impact. Consider factors such as revenue growth, cost reduction, efficiency gains, customer experience improvements, or risk mitigation. Rate how closely the use case aligns with your strategic objectives. Ask whether it supports a core business priority or addresses a competitive gap [19].

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On the feasibility side, evaluate practical considerations. Determine whether the required data is available and of sufficient quality. Assess whether the current technology is capable of solving the problem, either with existing AI methods or those available through vendors [19]. Consider whether your organization has the talent and infrastructure to deliver the solution, or if substantial development is needed. Evaluate business readiness by asking if the initiative has sponsorship, process maturity, and a clear path to adoption, or if it is likely to face resistance [20]. Lastly, assess known risks. These could include regulatory constraints, ethical concerns, or the potential for bias, all of which may elevate the complexity of implementation [21].

Each factor can be scored on a standard scale to create an overall feasibility rating [19]. Use a structured scoring model to compare very different ideas, such as a supply chain forecasting tool versus a customer-facing chatbot, using a consistent evaluation framework.

What emerges from this analysis is a clear view of which initiatives can be pursued immediately and which should be staged for the longer term. Quick wins are high-value projects that are also feasible using existing data, technology, and capabilities. These efforts often solve well-defined problems and can be implemented without major delays. Delivering a few of these early creates proof points and builds momentum, which helps secure broader support.

At the same time, it is important to identify high-value projects that are less feasible today. These may require better data, updated processes, or more mature tools before they can be deployed effectively. While these initiatives may not produce results right away, they should still be part of the roadmap. Planning for them now allows you to build the foundation without slowing near-term progress. A strong AI roadmap balances short-term value with long-term innovation [22]. KPMG emphasizes that successful organizations must pursue both quick wins and transformational efforts that take more time to deliver [22].

Treat your AI pipeline like a portfolio. Double down on what moves the business.

USE CASE PRIORITIZATION FRAMEWORK

Focus where it counts

✓ High value, high feasibility? Execute now.

✓ High value, low feasibility? Stage for later.

✗ Low value? Skip it.

Consider Vodafone's approach to AI in customer service. The company faced a pressing challenge. Its call centers were overwhelmed, which led to poor service quality and high employee attrition [23]. Improving how customer inquiries were handled became a clear opportunity to impact both cost-to-serve and customer experience. Vodafone prioritized a use case in its support function by developing TOBi, a generative AI virtual agent designed to manage routine customer requests. This use case qualified as a quick win because the underlying technology—fine-tuned large language models—was already available, and the application itself was well understood [24].

The outcomes were immediate and measurable. TOBi now handles one million requests each month and resolves approximately 70 percent of them without human intervention [25]. For the remaining 30 percent, TOBi assists by summarizing the conversation and supporting an efficient handoff to human agents [25]. This allowed Vodafone to demonstrate value early by solving a real operational problem with a ready-to-deploy AI tool. The success of this initiative helped build internal momentum and secured stakeholder support for more complex AI efforts [26]. Starting with high-impact, feasible use cases helps establish credibility and encourages broader adoption.

In practice, prioritization is an ongoing discipline. As you deliver early use cases, you will gain a clearer understanding of what is truly feasible and where the challenges exist. These could include data quality issues, change management gaps, or technology limitations. The insights from early projects should inform future decisions. Some long-term opportunities may become more attainable once foundational work is complete. New high-value ideas may also surface from the business.

Treat the use case portfolio as dynamic. Update your feasibility and value assessments regularly to reflect changing business conditions and technical capabilities. At any given time, it should be clear which initiatives are ready to execute and which should be staged for later. This approach ensures resources are allocated effectively. Avoid chasing large, unrealistic concepts that will not scale. Also avoid spreading effort across low-impact projects that do not deliver business value. A healthy portfolio creates near-term wins while positioning a few longer-term opportunities to mature over time [16][17].

Designing the Operating Model

A strong AI strategy is not simply a collection of projects. It requires an operating model to support execution and oversight at scale. In many organizations, AI initiatives begin in disconnected pockets, often led by enthusiastic teams or isolated pilots. To advance beyond this stage, formal structures must be established. These include clear governance processes, defined roles and responsibilities, funding mechanisms, and decision rights to guide AI-related investments. An effective operating model ensures that AI is embedded into core business operations, rather than treated as a peripheral or exploratory effort.

One proven structure is to create a central AI governing body, such as an AI Council or Steering Committee. This group typically includes cross-functional leaders from areas such as IT, data science, business units, and risk [27][28]. Its mandate is to ensure alignment between AI initiatives and the broader business vision. The council sets policies, defines principles for responsible AI use, prioritizes major initiatives, and monitors performance and risk. It prevents AI from becoming siloed within technical teams and disconnected from strategic goals. In some companies, the council also operates at the board or executive level to anticipate developments in AI and adjust plans accordingly [27]. It brings together a diverse set of stakeholders, including legal, HR, and data governance, so that privacy, ethics, and workforce impact are addressed early in the design process [29][30].

Many organizations report that a formal AI council accelerates adoption. It provides a clear process for approving and scaling projects, avoiding the inefficiencies of decentralized experimentation. The council should also hold decision rights over key areas, such as which use cases receive funding, which governance standards must be met, and how to manage risk when balancing innovation with oversight.

Another structural component to consider is an AI Center of Excellence. This is a dedicated team that coordinates and supports AI initiatives across the organization [31]. While an AI council focuses on governance and strategic alignment, the Center of Excellence operates at a more tactical level. It centralizes core expertise, infrastructure, and best practices to help business units deploy AI effectively. The team may manage shared platforms such as data pipelines, development environments, and toolkits. It may also define coding standards, set governance policies, and offer advisory services to other teams.
The Center of Excellence addresses a common challenge. Many AI projects stall because individual teams lack a critical piece of the execution model. This could include missing data infrastructure, unavailable skillsets, or limited experience in deploying production-ready AI. By pooling expert resources, the Center of Excellence enables faster and more reliable delivery.

There are different ways to structure this function. Some organizations begin with a centralized model in which a single AI team drives all major initiatives. Others transition to a federated approach. In this model, the Center provides shared services and governance while business units maintain their own AI teams to develop domain-specific solutions [32]. This approach combines consistency with flexibility. It allows for reuse of tools and expertise, while ensuring that AI solutions remain relevant to the needs of each part of the business.

A scalable AI strategy depends on structured governance, this means defining clear ownership, enabling shared delivery, and choosing an operating model that fits how your business runs

Operating Model Considerations

Governance that drives scale	✓ Create a central AI council to align strategy, policy, and oversight ✓ Stand up a Center of Excellence to deliver tools, platforms, and support ✓ Use centralized or federated models depending on how your business runs

There is no universal model for how to structure an AI operating model, but clarity is essential. Decide early how governance will work and who is accountable for specific decisions. One of the most important choices is how funding will be managed. Some organizations use a centralized approach, where a single AI innovation budget is controlled by the council or Center of Excellence. This model ensures that high-priority, cross-functional projects have access to resources. Others use a decentralized model, where business units fund their own AI initiatives but submit proposals for review and approval through a central governance body.

Whichever model is used, the funding process must be transparent. Executives should understand how to get an AI proposal resourced and what criteria must be met. These criteria might include a compelling business case, alignment with strategic anchors, and compliance with technical or governance standards. Also define decision rights clearly. The AI council might be responsible for approving high-cost or high-risk projects, while smaller efforts can be approved within business units as long as they follow established guardrails. The Center of Excellence may also take ownership of technical standards, such as selecting cloud platforms or setting approved AI frameworks to maintain enterprise-wide consistency.

Without clearly defined responsibilities, decision-making can stall. Some teams may avoid action due to lack of clarity, while others may move forward without coordination, leading to fragmented solutions. A clear operating model avoids both extremes and creates the structure needed for scale.

When designing the AI operating model, include human governance as a core component. Identify who will be responsible for ensuring that AI models behave as intended and do not drift into unethical or ineffective outcomes. Many organizations expand their data governance frameworks to include AI-specific oversight. One approach is to establish an AI ethics board or risk committee that evaluates sensitive use cases such as hiring decisions or customer eligibility for fairness and compliance [33]. This body can operate as a sub-group within the AI council or as an independent committee that collaborates with it.

The operating model should embed these oversight functions directly into the development lifecycle. For example, any AI system that materially affects people should require an ethical impact assessment before deployment. Beyond governance, plan for the organizational change needed to support AI adoption. This includes creating roles such as AI product managers, model validators, or change leaders within business units. Many organizations also appoint AI ambassadors or translators in each department. These individuals serve as bridges between technical teams and business teams to improve understanding and accelerate adoption of AI use cases.

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The AI operating model should be designed to make AI a long-term capability, not a temporary initiative. This requires building forums, processes, and structures that endure over time. Some organizations establish an AI Council that meets regularly to review progress, resolve challenges, and update the AI roadmap based on evolving priorities [34]. The Center of Excellence may take responsibility for setting technical standards, offering training, and supporting the broader organization as AI capabilities mature.

Formalizing these roles and routines shifts AI from ad hoc experimentation to disciplined, strategic execution. According to experts at Collibra, the specific structure may vary. Some companies use an AI council, others a Center of Excellence, and others rely on cross-functional task forces. Some use a combination of these approaches [35]. The goal is not the format itself, but ensuring that someone has clear responsibility for coordinating AI efforts across silos. Without this structure, even strong strategies can falter due to fragmentation or lack of oversight. A well-designed operating model provides the foundation to scale AI reliably and integrate it into the business over time.

Building your AI Strategy for Scale

One of the most common pitfalls in corporate AI programs is what many refer to as pilot purgatory. This is the situation where companies launch numerous proof-of-concept projects that never scale to production and therefore deliver limited business impact. Avoiding this outcome requires a deliberate focus on scalability from the beginning. AI should not be treated as a perpetual research experiment.

Two common challenges often block progress. The first is fragmentation, where isolated projects are not coordinated and fail to generate cumulative value. The second is duplication, where multiple teams attempt to solve the same problem or independently purchase similar AI tools without alignment. Both problems waste resources and slow down organizational learning. Gartner estimates that up to 25 percent of enterprise AI spending is duplicative, often the result of uncoordinated efforts across teams [36]. A study by Accenture found that 75 percent of executives struggle to move AI initiatives beyond the pilot phase due to poor integration and weak process discipline [37]. These findings make one point clear. Scaling does not happen automatically. It must be planned, governed, and executed with intention.

The first step toward scaling AI is gaining visibility into where it currently exists and how it is being used. With the rise of easy-to-deploy AI tools, many departments may be embedding AI features independently. This often results in a fragmented landscape with limited coordination. For example, the Sales team might implement an AI assistant inside its CRM. Customer Service may adopt a separate chatbot. Finance could purchase a standalone forecasting tool. These tools may not communicate with each other or follow shared policies. This siloed approach leads to redundant spending and inconsistent results [38][39].

Inconsistent use of AI systems across applications can erode user trust and slow adoption. Risk management also becomes more complex when tools handle data and privacy differently [40][41]. To address this, conduct a comprehensive audit of AI initiatives across the organization. Document which tools are in use, who owns them, and what purposes they serve. This inventory helps identify areas of overlap and reveals opportunities to consolidate.

The objective is to move from a fragmented, tool-centric approach to one that is centered on platforms and integration. Instead of asking how many AI tools are deployed, ask whether those systems work together and share insights across teams [42]. Where possible, standardize core platforms that can be reused across functions, rather than allowing each team to procure its own isolated solution.

Integration is essential for scaling AI impact. AI cannot remain an isolated or peripheral capability. To generate real business value, it must be embedded directly into core systems and operational workflows. McKinsey research describes this challenge as the generative AI paradox. Many organizations adopted chatbots and virtual assistants quickly, but these tools often failed to deliver measurable outcomes because they were not fully integrated into end-to-end processes [43][44].

To build for scale, AI capabilities must connect to the systems that power the business. This includes enterprise resource planning platforms, supply chain systems, and customer engagement workflows. Integration often requires middleware or enterprise AI platforms that link machine learning models to existing systems. For example, a demand forecast generated by an AI model should flow directly into the production planning tool. Similarly, a customer service model should deliver outputs into the live agent desktop to support real-time assistance. This level of interoperability turns disconnected tools into intelligent workflows [42]. It also enables AI systems to share context. A marketing insight can inform a sales recommendation, creating cumulative value rather than siloed insight [45][46].

Another essential part of scaling is establishing a shared AI foundation and infrastructure. In the pilot stage, teams often assemble whatever tools are available to prove a concept. While this may work temporarily, moving to production requires stability, security, and consistency. IBM's AI leadership in manufacturing found that scaling beyond isolated pilots depends on investing in a common infrastructure that supports reuse, governance, and integration across teams [47].

This foundation can include containerized AI runtime environments or centralized MLOps pipelines that all teams use for deploying and monitoring models. Standardizing this layer avoids the need for each team to build its own system. Data pipelines and governance frameworks should also be established early so that models have reliable access to high-quality data once they are in production. Automating the full AI lifecycle, including data preparation, model training, deployment, and monitoring, is essential to manage solutions at scale. Without this automation, each new model becomes a manual effort, which slows down delivery.

By building this infrastructure early, organizations avoid the common problem of pilots stalling due to technical limitations. AI must be treated as an enterprise capability, not as a series of disconnected experiments. This may involve dedicated cloud environments, standardized development tools, and collaboration between IT and data engineering from the start. Companies with strong digital cores, such as unified data platforms and modern cloud infrastructure, are better equipped to scale AI efficiently and consistently [48].

Preventing duplication and fragmentation requires strong governance embedded in the AI operating model. When an AI council or Center of Excellence is in place, establish clear processes such as technology review boards. Before any team acquires a new AI tool, they should consult with the central group to determine whether an existing solution already meets their needs. In some cases, the request may reveal an opportunity to develop a broader, shared platform. This process not only saves money but also ensures consistent governance. For example, it helps confirm that any system handling customer data complies with company standards for privacy and security.

Gartner reports that enterprises often overspend on AI due to overlapping functionality across departments. They recommend rationalizing the portfolio to eliminate duplicate investments and improve system oversight [49][50]. Achieving scale does not always mean launching more projects. In many cases, it means consolidating around a few high-value platforms and investing in better integration. Fewer, more connected tools often create more impact than many disjointed efforts.

It is important to integrate AI into daily business operations and culture. Scaling AI is not only a technical challenge. It is also an organizational shift. AI capabilities should become part of the standard decision-making and execution process. This includes training end users and updating workflows to ensure that AI outputs are actually used. For example, supply chain planners should reference AI-generated demand forecasts in their planning sessions. Call center workflows should incorporate suggestions from AI agents in a structured and repeatable way.

It also requires changes to how performance is managed. Include AI metrics, such as model accuracy or the percentage of decisions influenced by AI, in regular business reviews. When these indicators are tracked alongside other core KPIs, it signals that AI has become a true part of the business. Some organizations formalize this by adding AI adoption goals into managerial objectives. Others create cross-functional product teams focused on embedding AI into operational workflows continuously, rather than treating AI as a project with a fixed end point.

McKinsey recommends shifting from disconnected pilots to sustained delivery through structured programs. This includes moving from isolated AI teams to cross-functional transformation squads and from experimentation to scaled execution [51]. In practice, this could mean creating a transformation roadmap for each major business process. That roadmap would outline how AI contributes and assign shared ownership to IT, AI, and business leaders responsible for implementation.
In summary, to succeed with AI, start by designing for scale. Build the technical foundation early. This includes data infrastructure, integration layers, and governance frameworks that reduce fragmentation and support cross-functional alignment. AI should be embedded into business operations from the beginning, not treated as a demonstration tool on the sidelines. When AI is fully integrated into the work itself, organizations move beyond isolated pilots and begin unlocking value across the enterprise.

One of the clearest signs of impact is when AI outcomes begin appearing in financial results. Research shows that while nearly 80 percent of companies have experimented with AI, a similar percentage report no meaningful impact on earnings [52][53]. What separates leaders from laggards is not interest in AI, but the ability to scale. There is a meaningful difference between a few prototypes and fully deployed systems that improve cost structures, decision accuracy, or service levels. Scaled outcomes come from consistent architecture, governance, and integration. That discipline is what turns innovation into long-term advantage.

Capability Roadmap: Talent, Tech and Change

Executing an AI strategy requires more than implementing technology. It involves building the organizational capabilities that allow AI to be adopted, scaled, and sustained. Becoming an AI-enabled enterprise means investing in people, platforms, and change leadership. This section introduces a capability roadmap that spans three domains: talent, technology, and organizational change. The goal is to ensure the workforce is prepared, the technology stack is stable, and the organization can adapt at pace.

AI is ultimately powered by people. These are not just data scientists, but every employee who will interact with AI tools or interpret AI-generated insights. Building capability starts with talent development and education. This happens on two levels: deep technical roles and broad organizational fluency. On the specialist side, organizations may need to hire or upskill roles such as machine learning engineers, data engineers, MLOps experts, and AI product managers. Many companies underestimate the importance of these adjacent roles beyond traditional data science [54]. Scaling AI requires full delivery teams that can deploy, monitor, and maintain models in production environments.

Equally important is the fluency of leadership and frontline teams. AI fluency means understanding what AI can and cannot do, how to interpret its outputs, and how to collaborate with systems in real-time [55]. The objective is not to teach everyone how to build models, but to instill a mindset grounded in experimentation, data use, and outcome orientation. Executives in particular should develop a working knowledge of AI concepts to make better decisions and avoid hype-driven adoption [56]. Many organizations are addressing this through formal learning programs. These include AI ethics briefings for senior leaders, hands-on training for managers, and tailored onboarding for frontline teams. For example, a customer service agent might be trained to work more effectively alongside an AI assistant. Change leadership begins with knowledge, so early investment in education is critical.

Workforce planning for AI remains a major gap in many organizations. Few companies have a clear understanding of what skills will be required in the next few years or a roadmap for building them. Only 26 percent of executives report having a complete view of their future workforce needs, and just 25 percent have a plan to close those gaps [57][58]. For those who take this seriously, the opportunity is clear. They will be ready with the necessary talent while others are still reacting.

Every AI strategy should include a workforce assessment and development plan. Identify which roles in your organization will be most affected by AI. This includes both roles that need to be upskilled to use AI effectively and roles that may be augmented or partially automated. For instance, if finance analysts will soon use automated reporting, train them to shift their time toward deeper analysis rather than manual tasks. Incorporate AI competencies into leadership development and technical learning programs. Some organizations establish internal academies or offer credentials that certify employees at different levels of AI proficiency.

Talent acquisition also plays a role. Hiring key experts such as a chief AI officer or head of MLOps can accelerate capability building. These leaders will be more effective if the organization around them is prepared to adopt and apply AI tools. This reinforces the need for widespread fluency, not just isolated expertise. The goal is to build a workforce that sees AI as a tool to enhance their impact. When employees apply their domain knowledge to guide AI use and make smarter decisions, AI becomes a capability multiplier. Organizations that invest in this human capital dimension tend to deliver more successful AI initiatives. They have the right mix of skills, culture, and ownership to turn plans into outcomes.

On the technology side, a practical AI strategy requires deciding which capabilities to build internally and which to source externally. This is the classic build versus buy decision. Given the growing availability of AI solutions in the market, it often makes sense to avoid custom development for every use case. One industry leader recommends buying approximately 80 percent of needed AI capabilities and reserving custom development for the 20 percent that create unique business value [59].

A strong AI roadmap requires investment in people, not just platforms. Organizations need to develop talent, support leadership fluency, and make early decisions about what to build and what to buy

Capability Building Priorities

Build for adoption, not just deployment	✓ Upskill both specialists and business leaders to use and interpret AI ✓ Make talent fluency and change leadership core to your roadmap ✓ Decide early which AI capabilities to build versus buy

Many enterprise platforms such as ERP and CRM systems now include embedded AI functionality. Analysts expect this trend to accelerate, with Gartner forecasting that more than 80 percent of software vendors will embed generative AI into their products by 2026 [60]. This means companies can often access strong AI functionality by upgrading or optimizing their current tools. These solutions are typically easier to deploy, integrate better with core systems, and require less time to maintain.

Vendor tools should be used wherever they meet the business need. For example, if a forecasting module in your ERP system is sufficient, prioritize that option rather than building a custom model. Reserve internal development efforts for AI solutions that differentiate your business. This might include models trained on proprietary data that deliver insights no competitor can replicate. A balanced approach to build versus buy enables speed and scalability. By minimizing custom development for routine tasks, your teams can focus on strategic capabilities while reducing long-term technical overhead.

Maintaining a flexible architecture is essential to support both purchased and internally developed AI components. One option is to adopt an API-based structure or a modular AI mesh, where various services—whether internal or vendor-supplied—can be orchestrated together [61]. This reduces the risk of vendor lock-in and allows components to be swapped as technology evolves. For example, an organization might begin with an external natural language processing API to support a chatbot. Later, it may develop a proprietary NLP model trained on internal data to improve accuracy. A flexible architecture should support this transition without requiring a complete rebuild.

IT and data platforms must also be ready to support enterprise-grade AI deployment. Verify that your cloud infrastructure is capable of hosting and scaling models. Assess whether your data engineering pipelines are equipped to deliver high-quality data consistently into production environments. Invest in foundational elements such as data lakes, feature stores, and monitoring systems. These components may not be high profile, but they are essential for running AI at scale with reliability and consistency.

Another area of focus is selecting the right tools and frameworks to support efficient development. Standardize on a core toolset approved by the Center of Excellence or IT organization. This might include a preferred machine learning library, an AutoML platform, a common model serving solution, and a shared development and testing environment. Standardization reduces infrastructure complexity and prevents teams from solving the same technical problems multiple times.

While staying current on emerging tools is important, new technologies should only be adopted when they serve a clear business need. Some organizations assign their AI council or CoE a technology scouting role to assess innovation pipelines. Strategic partnerships can also accelerate maturity. Cloud vendors often provide accelerators or embedded experts who can work alongside internal teams to design effective solutions and build staff capability.

Over time, focus on developing internal intellectual property that differentiates your business. This may include proprietary datasets, custom AI models, or integrated workflows that reflect your domain expertise. When evaluating whether to build or buy, ask whether the solution provides strategic value or if an external option can meet the need faster. This mindset keeps your technology investments focused on outcomes and avoids unnecessary complexity.

One of the most underestimated aspects of AI capability building is managing organizational change. Deploying AI alters how people work, which can create confusion, hesitation, or resistance if not addressed early and deliberately. A practical AI strategy treats change management as a core component from the outset, not as an afterthought. This means planning from day one how to engage stakeholders, communicate clearly, and adapt business processes and policies to accommodate new tools and workflows.

Booz Allen emphasizes that the benefits of AI will not be realized unless the implementation is paired with a thoughtful change strategy. This includes open communication, support for those affected, and equipping teams to use new capabilities effectively [62]. Change management starts by involving end users early in the process. When employees have input into the design of AI tools that will impact their jobs, adoption improves. Leaders must also be transparent about the purpose of the initiative, how it connects to broader strategic goals, and how it will benefit both the company and its people. A realistic explanation of how roles may shift is essential to building trust and readiness.

Leaders should directly address employee concerns about job relevance. Many workers may fear that AI will displace them or reduce their value. The communication strategy should focus on augmentation and elevation. AI should be framed as a tool that removes repetitive tasks and allows people to focus on more strategic, creative, or judgment-based work. Share real examples from within or outside the company where employees have used AI to improve performance. For example, a salesperson using an AI-powered recommendation engine to better serve clients and improve sales results. Turn these early adopters into peer mentors and visible champions of the change.

In addition to messaging, performance management systems must evolve. When AI assumes part of a role, redefine success for that role. Ensure that employees are incentivized to use AI rather than avoid it. Change management also involves addressing shifts in workflows. AI may disrupt long-standing processes or require entirely new ones. Invest in process redesign and documentation to ensure these changes are fully understood and can be sustained at scale.

Leadership enablement is also essential. Senior leaders, from the executive team to frontline managers, must demonstrate active support for the AI transformation. The CEO and other senior executives should clearly communicate how AI fits into the broader strategic vision. This sets the tone for the entire organization. Middle managers must be trained to lead hybrid teams that work with AI systems. For example, a customer service leader should know how to interpret chatbot metrics and coach their team to integrate AI into their workflows.

If managers do not understand or trust the AI systems in use, they can become a barrier to adoption. On the other hand, when leaders promote experimentation and encourage learning, they help create a culture that embraces innovation. Some companies formalize this commitment by including AI-related goals in management performance plans. Others form cross-functional AI squads led by business leaders to drive adoption across business units. IBM observed that top manufacturers created AI squads with process engineers, data scientists, compliance officers, and change leaders. These teams not only build the solutions but also develop the frameworks and playbooks needed for adoption at scale [63].

When planning your capability roadmap, set clear milestones across talent, technology, and change. For example, by the second quarter of next year, launch an AI literacy program that 100 managers complete as a talent objective. Establish a new data platform that supports model deployment as a technology milestone. Identify change champions in five business units as part of the change leadership strategy. These actions should be treated with the same urgency and rigor as delivering a new AI use case.

Track progress consistently. Monitor whether employees are completing the training. Assess whether adoption of the data platform is increasing. Evaluate whether change champions are actively engaging their teams and gathering feedback. A disciplined, execution-focused approach ensures that capability building moves in step with AI deployment.

Organizational culture will determine whether the AI strategy produces real outcomes. Skills, mindset, and governance practices matter just as much as technical readiness. Building a strong foundation of talent, sound technology infrastructure, and effective change leadership creates an environment where AI can succeed. When these elements are in place, your workforce is empowered to use AI, not displaced by it.

Measurement and Recalibration

No AI strategy is complete without a feedback loop. In a rapidly changing environment, measurement is essential to track progress and ensure continued relevance. Metrics allow you to evaluate whether the strategy is delivering results and help identify where to make adjustments. Without this, the strategy risks becoming static and disconnected from business impact.

Begin by defining metrics that correspond to each phase of your AI transformation. During the pilot phase, focus on foundational indicators. These may include the number of use cases tested, the percentage of employees trained in AI fundamentals, model accuracy during testing, or reductions in cycle time within specific processes. As the organization moves into scale, shift toward outcome-based metrics. Track revenue growth attributed to AI, such as improvements driven by AI-powered product recommendations. Measure cost reductions resulting from automation, customer satisfaction improvements tied to AI-assisted service, and reductions in errors or compliance incidents.

It is also important to track adoption. In many organizations, AI tools are deployed but not consistently used. Monitor usage data such as the number of active users, how often AI recommendations influence decisions, or how frequently features are accessed. IBM experts recommend evaluating adoption, efficiency, and business value at every phase—from initial pilots through full enterprise rollout [64]. This ensures that you are not just deploying technology but are actually realizing benefits aligned with strategic goals.

Many organizations still struggle to measure the return on investment from AI. Only 15 percent of business leaders have put formal metrics in place to track AI outcomes [65]. This gap undermines the ability to scale AI and justify further investment. Establishing a measurement framework early in the process improves transparency, supports business case development, and builds internal credibility.

Capturing AI's value may require nontraditional approaches. Many of AI's benefits are indirect or intangible. These include better decision-making, faster innovation cycles, or improved employee morale due to reduced manual work. Relying solely on standard financial metrics may understate the total impact. KPMG recommends that organizations track both tangible and intangible outcomes to gain a full picture of value creation [22].

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Examples of relevant metrics include improvements in operational efficiency, such as reduced processing time, or the launch of new AI-enabled services. Competitive advantage can be tracked through changes in win rates or market share that are supported by AI. Risk reduction may show up through fewer compliance issues or audit flags due to AI monitoring. When direct attribution is difficult, use proxy metrics. For example, if the goal is improved quality, track defect or rework rates. If the goal is productivity, measure output per employee or task duration. Edvantis recommends measuring how many previously manual processes have been automated and whether those changes reduced error rates [66]. You can also estimate cost savings in areas such as energy consumption or maintenance if those were targeted [67].

The objective is to connect AI investments to observable business results. Perfect attribution may not be possible in every case. Still, measurable trends in the right direction after implementation provide strong signals of impact.

It is equally important to establish a regular cadence to review and recalibrate your AI strategy. Technology and market conditions shift quickly. What was considered advanced two years ago may now be commonplace. New opportunities or risks can also surface without warning. A well-managed AI strategy must remain dynamic and responsive.

Schedule quarterly or semi-annual reviews to evaluate whether your current direction is still valid. This can be led by the AI council or a dedicated strategy group. Use these sessions to revisit assumptions, assess whether milestones and KPIs have been met, and identify any newly available AI capabilities or regulatory changes that require attention.

For example, if a competitor launches an AI product in a space you intended to pursue later, you may decide to accelerate your development to maintain competitive positioning. Alternatively, if pilot results reveal poor data quality in a specific domain, it may make sense to postpone the associated use case. You could instead invest in improving the data or shift focus to a different, more viable area.

Being willing to adjust course is a sign of disciplined leadership. It shows that decisions are based on evidence, not inertia.

Recalibration is most effective when it remains aligned to your original strategic anchors and informed by what you have learned.

One practical method for recalibrating your AI strategy is to borrow from agile software development. Use retrospectives and iterative planning to refine your approach. After each major AI project or implementation phase, conduct a structured review. Capture what worked, what failed, and what should be adjusted. These insights should directly inform your next planning cycle.

For example, you may realize that your change management effort fell short during deployment. In the next phase, you would allocate more resources to training, communication, and stakeholder engagement. You might also discover a new high-value use case while working with a specific business unit. If that use case is more strategic than one already on your roadmap, make the switch and drop the lower-value initiative.

Experts emphasize the importance of combining a clear strategy with tight feedback loops. When this structure is in place, organizations can shift from experimentation to impact by using lessons learned to guide refinements [68]. In practice, disciplined governance may include monitoring model performance through a dashboard maintained by the Center of Excellence, conducting regular audits of outcome metrics, and establishing feedback channels. These mechanisms allow employees and customers to report on where AI is helping and where it may need adjustment.

When adjusting your AI strategy, stay aligned with your broader business goals. Recalibration is not about random changes. It is about making informed decisions based on evolving conditions while staying true to your strategic anchors. For example, if your focus is on improving customer experience and you observe a shift in the market toward AI-driven personalization, it may make sense to invest in those capabilities. If productivity is a key anchor and a new AI tool shows strong potential for efficiency gains, you may decide to accelerate adoption.

Not every initiative will succeed. If a particular AI use case fails to deliver the expected outcome, it may need to be scaled down or discontinued. The key is to treat that outcome as a learning opportunity rather than a failure. This mindset—built around testing, learning, and adjusting—is increasingly recognized as essential to AI adoption. Wharton research notes that success with AI often depends on short development cycles, iteration, and the willingness to pivot based on what the organization learns [69]. Companies that view AI implementation as a continuous journey tend to achieve greater returns than those that stick to rigid plans regardless of changing circumstances.

As part of this recalibration, monitor not only performance metrics but also risk and ethical indicators. Track the number of AI-related incidents, such as model errors that affected business operations. Evaluate how often your systems pass bias audits or meet compliance requirements. If risk indicators start to trend in the wrong direction, take action. You may need to pause deployment, retrain models, or introduce more human oversight. For example, if an AI system used in HR decisions shows evidence of biased outcomes, temporarily remove it from use until the issue is corrected. Responsible recalibration ensures that your strategy adapts not only for business results but also for ethical and safe deployment.

Celebrate success and share results widely across the organization. Measurement should uncover areas of positive impact. When it does, make those gains visible. Highlight successful AI projects and quantify their value. For example, you might report that an AI-enabled scheduling system saved five million dollars this year and improved on-time delivery by 15 percent [67]. Publicizing these outcomes helps build internal momentum and strengthens the business case for continued investment.

When making changes to your roadmap, frame them as opportunities. For instance, communicate that a lesson from one use case has led you to pivot toward a more promising area. Stakeholders are more likely to support a change in direction when they understand that it is grounded in evidence and linked to a clear strategic vision. Transparency in recalibration builds trust. It signals that leadership is actively steering the AI transformation with discipline and focus, not reacting impulsively.

Your AI strategy should remain dynamic. Establish clear metrics, review progress regularly, and create the mechanisms to act on what the data reveals. Be prepared to scale what works, course-correct when necessary, and adjust to external shifts in technology or market dynamics. A culture of continuous improvement ensures the AI journey remains valuable over time. As AI capabilities evolve, such as the emergence of agentic AI systems, your strategy should be ready to incorporate them without disruption. A strategy that is continually measured and refined becomes a long-term enabler of transformation, not a temporary experiment.

By following this battle-tested blueprint – defining AI in business terms, anchoring it to value, rigorously prioritizing, setting up the right operating model, focusing on scale, building capabilities in people and tech, and constantly measuring and adjusting , you can move beyond innovation theater to genuine competitive advantage. The companies that succeed with AI will be those that marry bold vision with disciplined execution. They will elevate their workforce with new skills and smarter tools, integrate AI into the core of how they operate, and continuously align AI initiatives with strategic outcomes.

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