aucctus ai | innov8rs | Disruptive Edge

2026

The Next Frontier in **Corporate Innovation**

AI is rewiring how organizations sense, test, decide, scale, and learn

Executive Summary

Three years after generative AI entered the workplace, its use across corporate innovation teams is nearly universal. Of the 119 professionals in our research, 97% report that their teams use AI. However, half report no measurable improvement in cycle time, and fewer than 1 in 10 use AI to inform the portfolio decisions that matter most.

The clearest pattern was that teams reporting stronger outcomes had built AI into shared workflows, decision points, measurement, and operating cadence rather than relying on individual prompts. Only 11% teams had reached the point where AI also monitored signals, identified risks or opportunities, and triggered work before a human asked. These teams reported faster cycles, greater use of AI in consequential decisions, and fewer data or access barriers.

This report shows where AI is creating value, where that value remains trapped, and what stronger-performing teams are doing differently. It then defines the system needed to make those gains repeatable and outlines how organizations can build toward it.

These findings capture a 2026 snapshot of a rapidly changing field.

5 key findings anchor our report:

01. AI use is nearly universal, but system-level integration remains rare.

AI has moved quickly into corporate innovation, with 97% of teams now using it. However, most integration stops at individual assistance or repeatable workflows. Only 11% use AI proactively to monitor signals, identify risks or opportunities, and trigger work before a human asks. None report systems that learn from outcomes and improve the innovation process itself, where gains begin to compound.

02. Teams with AI embedded beyond individual use make better decisions, not just faster ones.

Among teams where AI is built into shared workflows, decision points, metrics, and cadence, 69% use AI to inform kill, continue, or investment decisions, compared with 20% of teams using AI mainly as an individual assistant. The same teams are 6.2x more likely to report significantly faster innovation cycles. Cycle time is the leading indicator of a deeper operating-model change, not the endpoint.

03. AI stops where the money starts.

Even within teams that have adopted AI, its use declines as decisions become more consequential. AI use falls from 88% in research to 18% in scaling. Only 8% of teams use AI to directly inform kill, continue, or investment decisions, while 38% exclude it entirely. AI is concentrated where decisions are cheapest and least risky, while remaining largely absent where capital is committed. AI is evidently powerful in shaping ideas, but most teams have yet to realize its full potential in shaping the portfolio.

04. Structural change separates high performers.

Almost half of teams have made no changes to roles, cadence, stage gates, or KPIs while implementing AI. In contrast, teams that have changed at least 1 structural element in their new workflows are 4.5x more likely to report meaningful speed gains. Among the deepest AI adopters, 75% changed their operating model, 50% use AI in decisions, and 63% measure its impact formally.

05. Without visibility, measurement, and feedback, isolated gains cannot become organizational capability.

Most organizations do not have a reliable view of where AI is being used or what it improves. 53% of respondents use unsanctioned tools, leaving part of the work outside the systems leaders can see and support, while 55% of teams have no formal measure of AI's impact. Without stronger visibility and evidence, leaders struggle to identify which applications warrant further investment, build confidence in AI-supported decisions, or use outcomes to improve future work.

The next era belongs to organizations that build a capability that learns and compounds.

Every era of corporate innovation strengthened the discipline. The opportunity now is to make that progress cumulative.

At a recent roundtable of ten innovation leaders, we posed an uncomfortable question: are innovation teams temporary by design? The discussion surfaced what most in the room had lived firsthand, which is that innovation teams fail for many reasons. Shifting priorities, lost sponsors, pilots that never scaled, reorganizations that arrived before results did. But even the teams that succeeded shared a quieter limitation: their impact was episodic. Each launch stood on its own, the capability behind it lived in the people who built it, and when the team changed, the organization started over. The answer, we concluded, is that no one designs innovation teams to be temporary but almost no one designs them to last.

The enduring teams we have worked with share four traits: a proven track record, an institutionalized way of working, credibility with executives, and, underneath all three, a process that demonstrably works. For those teams, our hypothesis is that the ceiling has lifted. They can now have compounded impact, institutionalizing both the best practices of the discipline and the accumulated evidence of what has actually worked inside their own company, at a scale and breadth that was not possible before. Rather than operating as a separate unit judged launch by launch, the innovation function becomes the arbiter of growth across the company and the owner of the system through which every business unit senses, tests, decides, and learns.

For teams still searching for what works, we would offer the opposite counsel: AI is not the fix. It multiplies the process it enters, which is a lesson that runs through this entire report. A struggling function that adds AI gets faster output from a process that was not producing results. The investment those teams need is in the fundamentals, and to get the system working first. The compounding comes after.

AI changes what can be retained, not just how fast the work moves. The evidence, decisions, and outcomes behind innovation work can now be captured once and carried across initiatives. Our hypothesis is that the next generation of innovation systems will be built with AI at their core, on the foundations the previous eras proved: the empathy of design thinking, the rigour of lean, the discipline of stage gates. These practices will not be replaced; they will be structured, improved, and institutionalized into core systems rather than carried in workshops and individual practitioners. This is the era of AI-Native Innovation, and the capability that defines it is the Innovation Intelligence System: a shared operating capability that improves with every cycle, even as teams, priorities, and structures change.

The rest of this report measures how far organizations have come toward building one, where the value is trapped along the way, and how the leading teams are closing the gap.

The Eras Of Innovation

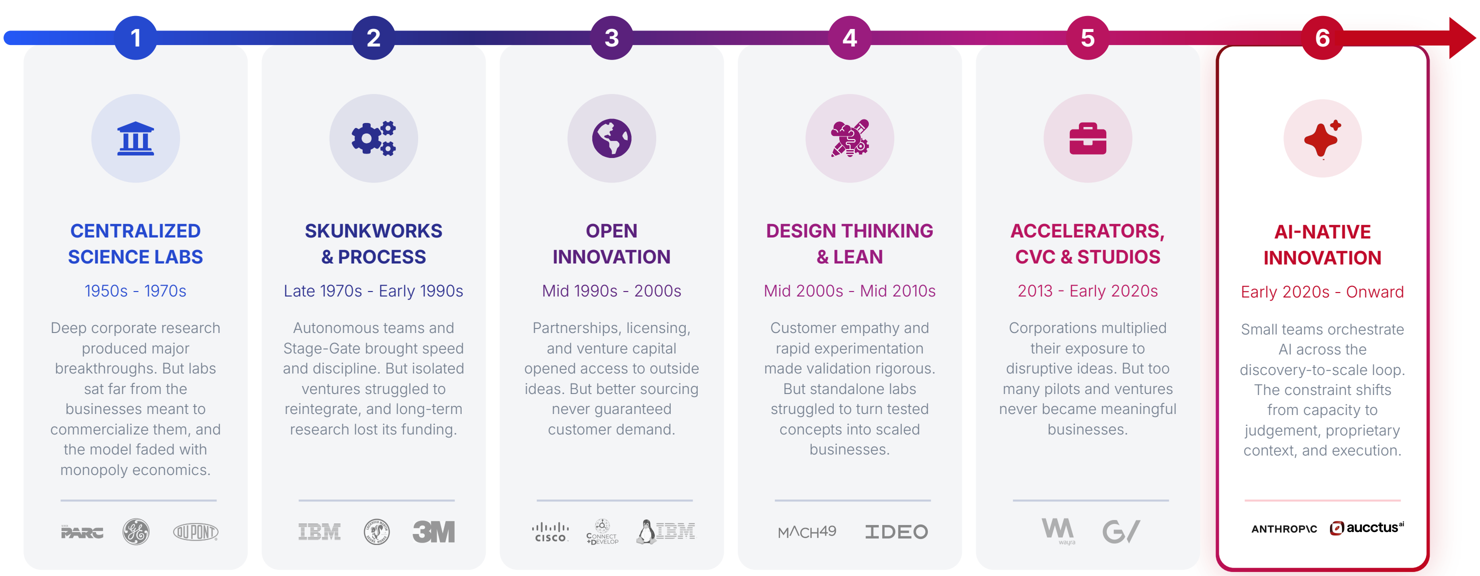


Fig 1. The evolution of corporate innovation models, and the core strengths and limitations associated with each.

Nearly every team has adopted AI, but only teams that have embedded it are seeing results.

The same underlying technology leads to very different outcomes when the surrounding system changes.

Since AI tools went mainstream in late 2022, the industry has focused heavily on adoption as the primary measure of progress. Licences purchased, seats activated, weekly active users, and prompts per employee all tell us whether people are actively using AI. They tell us much less about where AI is embedded in the work or whether it is improving outcomes. Our research found that 97% of innovation teams use AI. Based on adoption alone, most organizations would appear to be making meaningful progress.

The outcomes tell a different story. Half of those same teams report no measurable change in cycle time. 4 in 10 still make kill-or-continue decisions with no AI input whatsoever. If adoption were the variable that mattered, a 97% adoption rate could not coexist with a 50% no-improvement rate. Something else must explain who is getting results and who is not.

Integration depth was the factor most strongly associated with better outcomes. When we go beyond measuring usage alone and sort teams by how AI is integrated into the work, including whether it lives in individual prompt windows or in shared workflows, decision points, metrics, and operating cadence, the outcome data separates cleanly.

Teams whose AI use remains prompt-led and dependent on individual initiative achieve outcomes that are almost indistinguishable from those teams that barely use AI at all.

In contrast, teams who have integrated AI into how work is coordinated and advanced are operating in a different league: more likely to achieve faster cycles, face fewer data and access barriers, and use AI to confidently influence consequential decisions.

THE EMBEDDED ADVANTAGE

Toronto Transit Commission embedded AI into its innovation process, centralizing evidence, automating market research, testing assumptions rapidly with synthetic personas before resources are committed, and evaluating opportunities against its own unique strategy. Research that once took months is completed in days, and every concept now advances against the same evidence base, shifting the team's capacity toward judgement and delivery.

"What used to live on whiteboards and slide decks is now becoming an AI-enabled decision system for how we evaluate and advance innovation."
— Innovation Lead, Toronto Transit Commission

Most AI investment still aims to acquire greater capability through better tools, more licences, and broader training. However, AI usage itself is now table stakes, with the same models widely available to everyone. Stronger returns come from changing what happens around the tool, including where AI sits in the workflow, which decisions it informs, and how its contribution is measured; allowing teams to turn improvements from individual tasks into repeatable performance.

Fig 2. Share of n=119 respondents reporting key innovation outcomes by individual versus embedded AI use, 2026.

OUTCOME	INDIVIDUAL USE Prompt-led and dependent on individual users (stage 1).	EMBEDDED USE Built into workflows, decision points, metrics, and cadence (stage 3).	RELATIVE DIFFERENCE
Teams achieve 25%+ cycle-time gains	10% Of teams	62% Of teams	6.2x More likely
AI informs kill-or-continue decisions	20% Of teams	69% Of teams	3.5x More likely
Reported data quality or access barriers	22% Of teams	8% Of teams	2.8x Lower rate

The Innovation Intelligence Curve measures how deeply AI is embedded. It shows that 89% of teams remain in the first two stages.

While adoption is already easily tracked, teams rarely look at how the work is fundamentally changing.

The Innovation Intelligence Curve shows how deeply AI is embedded in their current innovation practice. Licences, usage, and activity remain useful measures of adoption, but they do not reveal whether AI has changed shared workflows, decisions, or the way learning carries forward.

Developed in 2023, the curve assesses an organization's innovation practice across four stages of AI integration:

- STAGE 1 — **Individual Assistant:** AI helps individuals complete tasks faster through prompt-based support.
- STAGE 2 — **Structured Workflows:** AI is built into repeatable workflows, with tools or agents orchestrated across multiple steps.
- STAGE 3 — **Proactive Intelligence:** AI monitors signals, identifies risks or opportunities, and triggers work before a human asks.
- STAGE 4 — **Self-learning Innovation:** AI learns from outcomes and recommends improvements to the innovation process itself.

In this research, each of the 119 teams was placed on the curve based on the behaviours they reported.

The first finding that stands out is movement. When we designed the curve in 2023, nearly every organization we assessed sat at the base. Today, 47% have crossed into our second stage, structured workflows. This is the first genuine migration of the AI era, and proof that the climb is happening, not hypothetical. The current distribution is concentrated in the first half of the curve. 42% of teams remain at Stage 1, 47% have reached Stage 2, and 11% have progressed to Stage 3. None have reached Stage 4.

The current results suggest that structured workflows are becoming more common, although 89% of teams have yet to reach Proactive Intelligence.

AI AS STANDARD PRACTICE — MARS

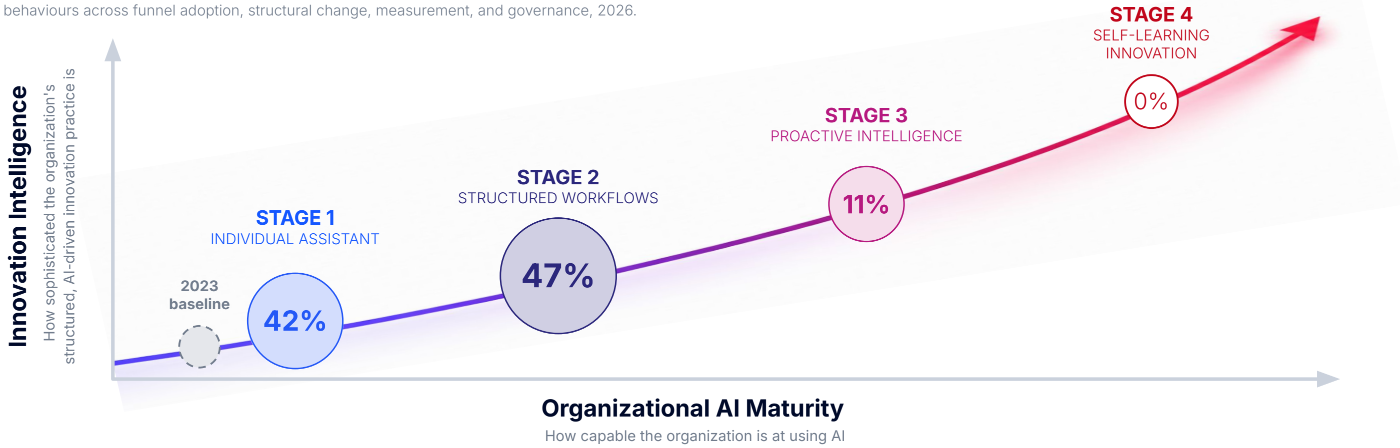
Mars, a global family-owned business, exemplifies the move to Stage 2. AI is embedded across its core innovation workflows, from brand intelligence to commercial assessment, and leaders treat its use as an expectation rather than an option. When a use case proves out, Mars redesigns the workflow around it, turning individual experiments into repeatable, organization-wide capability.

"Unless you change the way people work, the tool is sitting there and nobody will actually use it. It's not the tool itself, but it's how do we actually change the workflow."
— Head of Growth Strategy, Portfolio and Innovation, MARS

The concentration in Stages 1 and 2 helps explain why adoption has outpaced performance. Stage 2 is a meaningful step because AI begins to shape repeatable work rather than remaining dependent on individual prompting. Progressing further requires the organization to monitor signals continuously, trust AI in more consequential decisions, and use outcomes to improve future work. Few teams have established those conditions.

Low embeddedness is not necessarily an innovation failure. In safety-critical or heavily regulated environments, remaining at Stage 1 or Stage 2 may be deliberate. The curve measures depth of integration, not quality of innovation. The question is not "why aren't we higher?" but "is our position deliberate, and are we excellent at the level we have chosen?" For most teams, our evidence suggests it is not deliberate. The next section examines why.

Fig 3. Share of n=119 teams at each stage of the Innovation Intelligence Curve, assigned from reported behaviours across funnel adoption, structural change, measurement, and governance, 2026.



AI adoption collapses as innovation moves closer to impact.

Today, the front of the funnel is accelerating, while the processes that make the decisions continue to stay the same.

The Innovation Intelligence Curve measures how deeply AI is embedded in the work. The next question is where that integration sits across the innovation lifecycle. This distribution matters because the cost of a poor decision rises as an initiative moves closer to market. Weak market research may lead to a week of rework. A weak business case can waste months of effort and damage the team's credibility. A poor scaling decision puts capital, market position, and sometimes the mandate of the innovation function at risk.

Our data shows that AI is used most heavily where the consequences of being wrong are lowest. 88% of teams apply it in research, sensing, and discovery, where much of the work can be completed by individuals and corrected quickly. Use falls to 44% in experimentation and testing, where more functions become involved, and to 18% in scale-up and go-to-market. From the first signal to the point where an initiative enters the market, AI use drops by 70 percentage points.

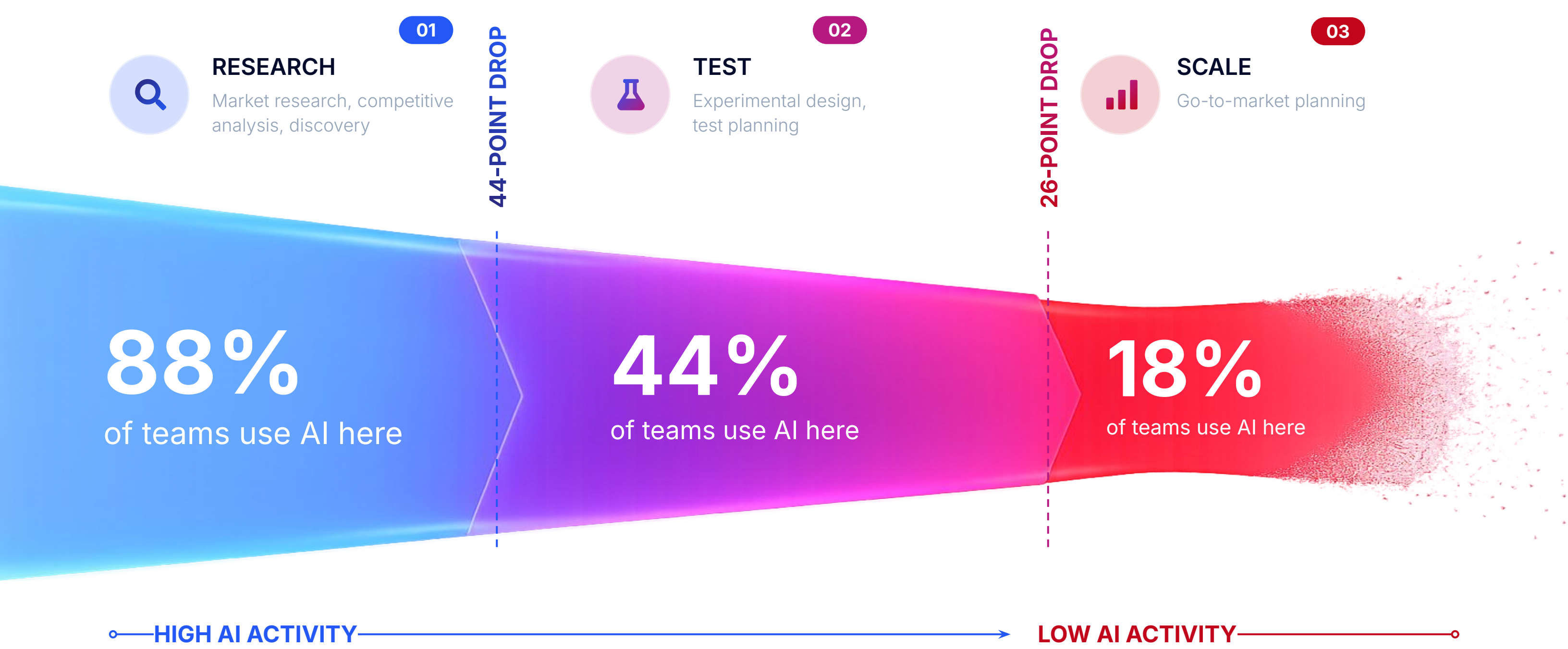
The decline reflects how the work changes across the funnel. Early-stage activities are relatively low-risk, require limited coordination, and fit naturally with individual, prompt-based use. Later stages depend on shared evidence, cross-functional alignment, clear governance, and confidence in decisions that commit resources. Most organizations have given employees access to AI without making the changes needed to use it in these more consequential parts of the work.

This leaves teams able to generate research, ideas, and early validation faster than their organizations can evaluate, fund, and advance them. The front of the funnel accelerates, while the middle and end continue to operate through the same decision processes and bottlenecks. AI can therefore worsen a long-standing problem in corporate innovation by increasing the volume of opportunities without improving the organization's ability to move the right ones forward.

70 -point drop From early identification to go-to-market planning.

Capturing more value means extending AI beyond the lower-risk work at the front of the funnel and into the decisions that determine what gets funded, scaled, and brought to market. Teams need visibility into where AI is being used, evidence of where it improves performance, confidence to apply it to consequential decisions, and a way for the outcomes of one initiative to inform the next. The following section examines the hurdles that prevent most teams from building those conditions.

Fig 4. The AI adoption funnel across n=119 teams, showing the share using AI at each innovation phase based on reported use by activity, 2026.



AI value compounds only when teams clear the hurdles between experimentation and scale.

These barriers are organizational, not technical, which is why no amount of tools can remove them.

Teams in the upper stages of the Innovation Intelligence Curve are 6x more likely to report meaningful cycle-time gains, yet 89% remain in the first two stages. The gap is not explained by access to better models, since teams across the curve use largely the same underlying technology. Leadership resistance is also not the main constraint. Only 4% of respondents cited executive scepticism as a barrier. The more persistent barriers sit in how the organization manages the work around AI.

Four hurdles recur as teams move up the curve. At each one, AI is already creating value, but that value has not yet become visible, measurable, trusted, or reusable across the organization. Work that remains outside sanctioned systems cannot be properly supported or repeated. Without measurement, leaders cannot compare results or determine where further investment is justified. Without evidence, AI rarely earns a role in decisions that commit capital. And without a learning loop, the outcomes from one initiative do not improve the workflows, decisions, or resource allocation that follow.

GUARDRAILS THAT ENABLE

EllisDon

EllisDon, a $10B+ Canadian construction services firm, treated employee experimentation with AI as demand to be channelled rather than risk to be banned. The company bought enterprise licences, built sandboxed environments walled off from live project data, and published a governance framework, giving employees a sanctioned place to build what they were already building on their own. Individual initiative became a governed, shared capability, and tasks that once took four hours now take 30 minutes.

"People are going to experiment anyway, so give them an environment where the SVP of Cybersecurity can sleep at night. Get that right, and your people will hand you the innovation."
— Chief Information Officer, EllisDon

AI amplifies the system around it. Where these conditions are missing, faster output can add noise, increase bottlenecks, and create more work for the same decision process. Where they are connected, gains at one stage improve the next. Better research strengthens the evidence available to decision-makers, stronger evidence builds trust, and better decisions increase the chances that the right opportunities reach the market.

Removing these hurdles requires changes to how work is structured, how impact is measured, and how decisions are made. Given that those capabilities are built within the organization, they remain valuable even as the underlying models and tools become widely available. The next section sets out where organizations can act and invest to make progress.

Consistent barriers to integration

STAGE 1

Shadow Use

AI is creating value in individual work, but it happens outside the systems the organization can see, guide, or repeat.

53%

53% of teams already use AI tools their employer hasn't sanctioned

STAGE 2

Measurement Gap

AI is improving how work gets done, but leaders cannot tell what is working, compare it across teams, or improve the system.

55%

55% of teams have no formal measurement of AI's impact, or anecdotes only

STAGE 3

Decision Trust Threshold

AI can generate stronger signals, but its value stays limited until leaders trust it enough to shape real decisions.

<10%

Fewer than 1 in 10 say AI directly informs kill, continue, or investment decisions

STAGE 4

Scaling Cliff

AI can help the system learn from what works, but most teams are not yet using that learning to improve how innovation happens.

~0%

Almost no team has AI embedded in how it scales what it launches

Fig 5. Barriers to AI integration by stage, with share of teams affected, n=119, 2026.

The strongest teams fund what works today while protecting the small bet that compounds.

The barriers outlined in the previous section cannot be addressed through a single category of investment.

Organizations need to capture value from the applications that already work, test AI in more consequential parts of the innovation process, and begin building the capabilities required for deeper integration. Overinvesting in the frontier can put money behind systems the organization is not ready to govern or trust. Staying only with research assistants, drafting tools, and sensing may produce near-term gains, but leaves AI concentrated in the same lower-risk work.

A 70/20/10 allocation provides a practical starting point. Around 70% of investment should support AI workflows that are already proving useful, including market sensing, competitive intelligence, insight synthesis, business-case development, assumption mapping, and test design. The focus should be on making the strongest uses repeatable, measuring the improvement they create, and extending them across the team where the evidence supports it.

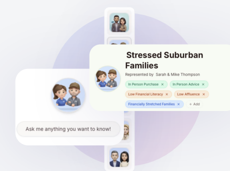
The next 20% should fund pilots in areas where the organization still needs evidence and experience. Experiment execution, learning synthesis, decision-gate support, and synthetic research all bring AI closer to shared workflows and portfolio choices. These pilots should show whether the application improves the work and identify what needs to change around it, including the data available, the controls in place, the roles involved, and the way decisions are reviewed.

The remaining 10% should be protected for capabilities that will take longer to develop. Dynamic portfolio allocation, AI-supported commercialization, and a self-learning innovation system depend on connecting work that is often fragmented across teams and stages. These investments may not produce an immediate return, but they begin creating the shared infrastructure and feedback loops that allow learning from one initiative to improve the next.

EVIDENCE BEFORE SCALE

Beem CREDIT UNION

Beem Credit Union trained synthetic personas on its customer data to validate and prioritize its product roadmap. By comparing AI-generated insights with product managers and real customer feedback, the team built confidence in using synthetic research to accelerate product validation and launches.



The percentages are a guide rather than a fixed formula. The discipline comes from keeping all three horizons active and connected. Proven applications provide evidence that can support pilots in more demanding areas. Those pilots reveal where trust breaks down and where the operating model needs to change. Longer-term investments give the organization a way to retain and reuse what it learns. Without that final horizon, teams may become faster at individual activities while the broader innovation capability remains largely unchanged.

1

SCALE NOW

Proven use cases delivering reliable, recurring value

- Market & trend sensing
- Competitive intelligence
- Customer insight synthesis
- Business-case modelling
- Assumption mapping & test design

2

PILOT NEXT

Emerging plays with high learning potential

- AI-assisted experiment execution
- Learning & feedback synthesis
- AI-enabled decision gates
- Synthetic customer research

3

BUILD TOWARD

Frontier investments with long-term leverage

- Dynamic portfolio and resource allocation
- AI-orchestrated commercialization
- The self-learning innovation system

Fig. 6. A 70/20/10 investment model for balancing proven AI applications, emerging pilots, and longer-term system capabilities.

The lasting advantage lies in a system that learns from the work.

Proven applications, emerging pilots, and longer-term capabilities create more value when they operate as part of a connected system rather than as separate tools and workflows.

An Innovation Intelligence System allows evidence, decisions, and outcomes to carry from one initiative to the next, so the organization can build on what it has already learned instead of reconstructing that knowledge each time. This section sets out the architecture required to make that possible.

The architecture begins with people setting strategic direction, defining the boundaries for AI use, and remaining accountable for consequential decisions. An orchestration engine then coordinates the people, AI agents, information, and decision points involved as an opportunity moves from sensing and framing through testing, deciding, building, launch, and learning. The enabling infrastructure supports that work by allowing data and information to move securely across tools and teams.

THE SYSTEM ADVANTAGE

A leading national youth mental health nonprofit holds a level of trust few organizations ever earn. Young people often reach out with experiences they have never shared anywhere else. That trust shapes how the organization designs its work. AI is introduced through workflows built around clear standards of care, governance, and human judgment—not layered onto the existing process as another tool.

"You don't find a workflow and sprinkle AI on it. You redesign the whole workflow, with AI as part of the team."
— Innovation Leader, National Youth Mental Health Nonprofit

Shared innovation intelligence retains the knowledge generated throughout the process. Within this foundation, the Nucleus connects the organization's signals, assumptions, experiments, evidence, decisions, outcomes, learnings, and best practices. It gives the system access to the context created across the innovation lifecycle. Evidence gathered during research remains available when a decision is made, and the assumptions behind that decision can later be compared with what happened in practice.

The system-learning loop uses that comparison to improve how future work is carried out. It identifies which assumptions held, where experiments produced weak evidence, whether decisions led to the expected outcomes, and where the process broke down. Those findings can then shape future workflows, decision rules, experiment templates, agent instructions, governance, and resource allocation. The Nucleus connects and retains what the organization knows, while the learning loop turns that knowledge into changes in how the system operates.

No team in our research has built the full architecture. Those furthest along have connected parts of it, usually beginning with a small number of workflows, information sources, and decision points. Organizations can therefore build toward the blueprint over time rather than attempting to implement every layer at once. This also explains why the previous section protects investment for capabilities that will take longer to develop.

Competitors may be able to buy the same models and tools, but they cannot procure the knowledge and judgement developed through another organization's experiments, decisions, and outcomes. As more initiatives move through the system, that experience becomes more useful to future teams and increasingly difficult to replicate.

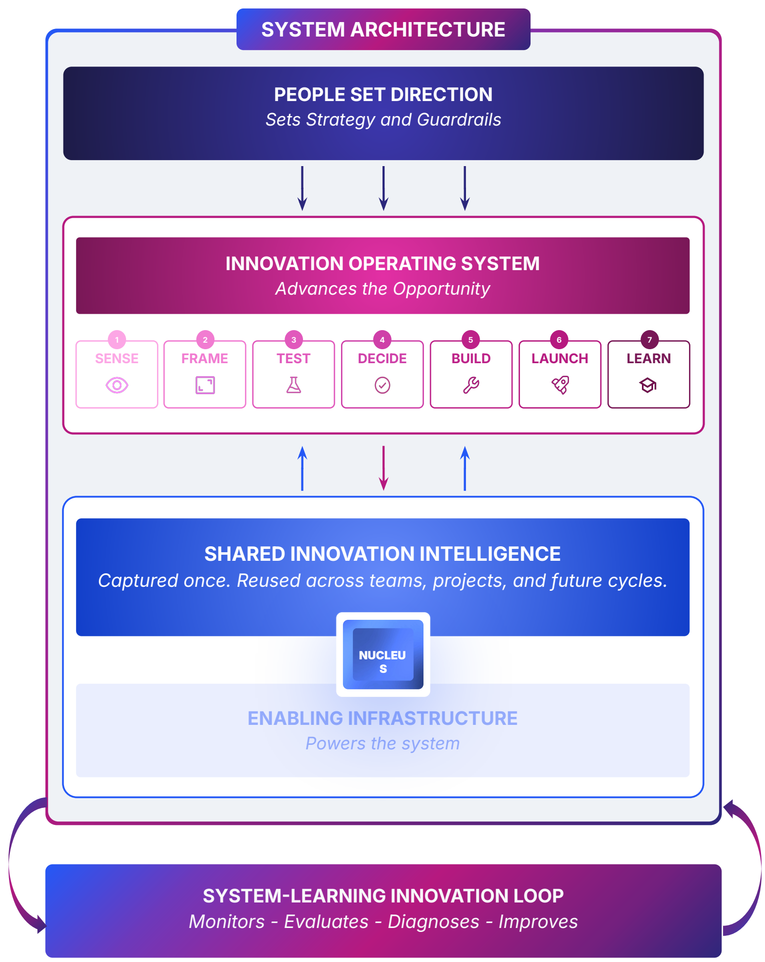


Fig. 7. AI-powered innovation system architecture [simplified]. Connects strategic direction, an orchestrated operating system, shared intelligence, enabling infrastructure, and a continuous learning loop to improve innovation performance over time.

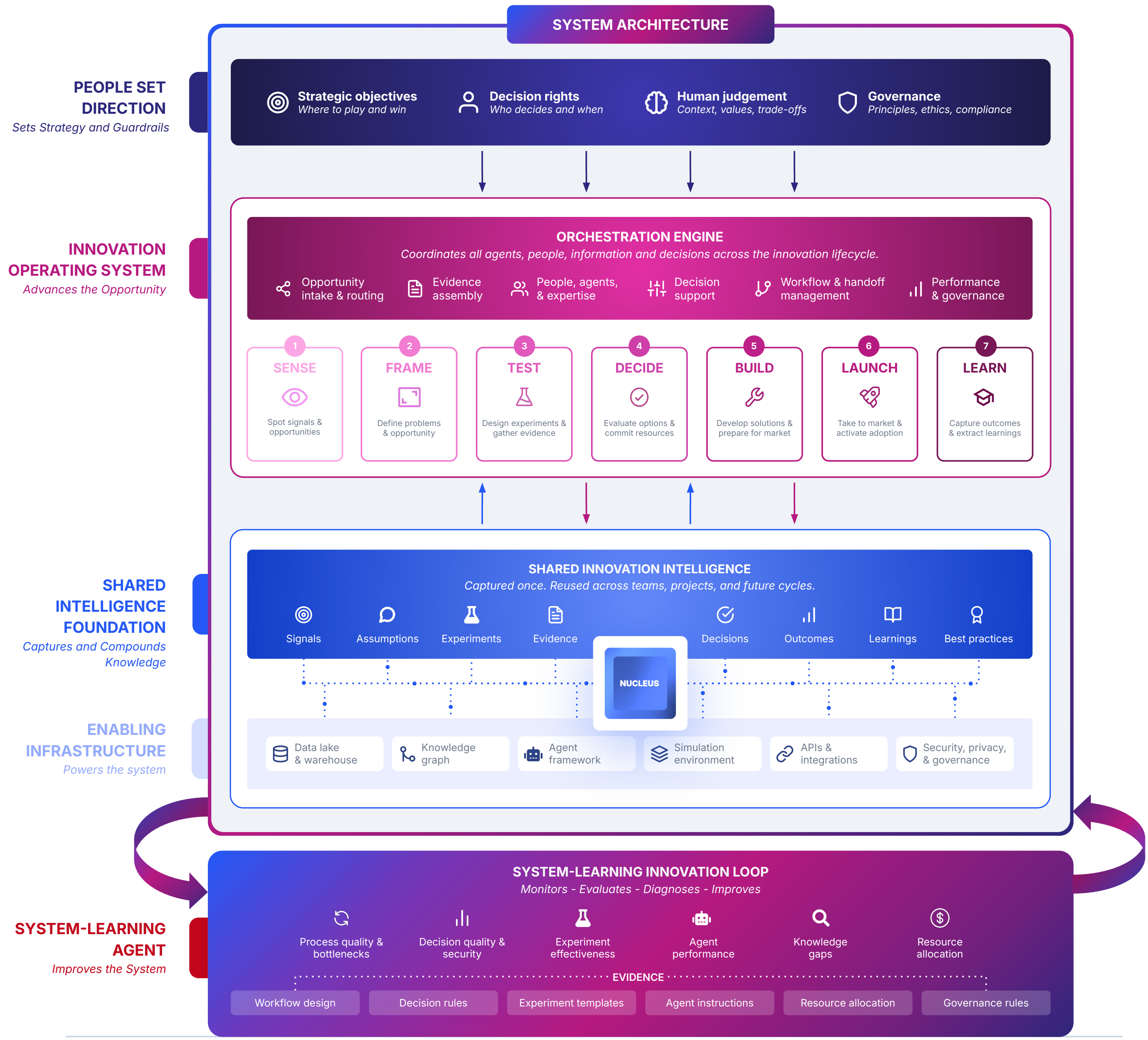
The architecture connects every stage of innovation so learning compounds across cycles.

The previous page showed the system's shape. This page shows what's inside it.

The five layers are the same; people set direction, the operating system advances opportunities, shared intelligence compounds what's learned, infrastructure powers it all, and the learning loop improves the whole. What the full view adds is the connective detail: the seven-step lifecycle driven by the orchestration engine.

It also reveals the types of reusable intelligence, along with the specific evidence that feeds the learning loop. Notice what the arrows show, which is that nothing here is a standalone tool. Every step draws on the shared foundation and returns what it learns, and that circulation is the entire point: it is what makes the system compound while a stack of tools cannot.

Fig 8. Expanded view of the system architecture on Fig 7.



The Embedding Method: How leading teams built the system and where everyone else got stuck.

Innovation leaders face competing priorities as they integrate artificial intelligence.

Executive mandates require rapid deployment, software vendors add automated features to existing enterprise contracts, and internal teams develop independent AI prototypes. Despite this activity, 89% of organizations fail to scale their efforts.

High-performing organizations achieve significant cycle-time improvements by focusing on workflow design before technology selection. AI accelerates the performance of the system it enters. When integrated into a well-designed process, it delivers measurable efficiency gains. When added to a broken process, it accelerates failure. To succeed, organizations must map their processes, fix existing inefficiencies, and rebuild key workflows around core AI capabilities. We refer to this as the Embedding Method.

The Embedding Method

A simple, repeatable process that turns AI into an innovation capability that improves every cycle.

STEP 1 **Map where innovation starts and stops.**

Before integrating AI, understand how innovation actually moves through your organization. Reconstruct the journey of a successful concept, from origin to market, documenting every workflow, decision-maker, and phase duration. Most teams have never seen their process end to end; it usually starts later and stops earlier than expected. That picture, plus your baselines, is the map.

STEP 2 **Prioritize the workflows that matter and can work fast.**

List the recurring jobs inside each phase, then screen them twice: for value (time consumed, whether it feeds a decision) and for feasibility (data in reach, fast to build, limited judgement required). Start where the two criteria intersect, selecting those workflows meaningful enough to earn executive attention, and buildable enough to show results in weeks. Choose two workflows. Not ten.

STEP 3 **Rebuild each workflow with AI designed in.**

Map each workflow step by step, marking where AI augments it and where human judgement stays. Design what makes it real: the data each step requires, the formats decision-makers already read, the interface, and the agent orchestration behind it. Ground it in your context, run it on live concepts, and hold one bar: the output is used in a real gate meeting.

STEP 4 **Learn in tight loops, and let each cycle improve the next.**

No team in our research produced a trusted workflow on the first attempt. Capture what the AI got right and wrong, feed both back into its data, prompts, and evaluations, and improve week over week. The result is directional value within one week, and measurable gains within ninety days. Do not start the next workflow until the first two are validated and measurably improved. These tight loops are the workflow-level version of the system-learning loop on previous pages. Once rebuilt workflows share an evidence base, the learning compounds, tests sharpen, and decision rules earn trust.

METHOD IN PRACTICE

Schreiber

Schreiber Foods, a multibillion-dollar employee-owned dairy company, illustrates the Embedding Method in practice. Rather than starting with tools, Schreiber mapped an innovation process that was already performing well, identified where AI could play the strongest role within it, and embedded it into those workflows. The result: cycle times more than 25% faster and an increase in products, capabilities, and business improvements delivery. These gains were ultimately from augmenting a working process rather than replacing it.

A note on who builds it.

Across our research and client work, teams take three primary paths to resource AI workflows, each with distinct trade-offs.

Internal engineering teams launch quickly, but competing priorities often divert technical resources away from operational redesign and toward primary revenue drivers. Off-the-shelf software offers platform stability, yet standard configuration lacks operational depth. Generic tools cannot digest proprietary gate criteria or historical business cases, producing high-level outputs that fail to drive concrete decisions.

Leading organizations resolve this tension by collaborating with specialized partners. These partners bring established workflow architectures and adapt them directly to proprietary enterprise data, decision formats, and governance rules. To sustain value over time, any build approach must balance innovation domain expertise with deep contextual tailoring and ongoing technical support.

The teams furthest along built a culture where AI could take hold.

Across our interviews, the teams furthest along were not relying on architecture or tool access alone.

Instead, they tended to treat AI integration as a change in how people worked, made decisions, and learned together. Employees had clearer permission to use AI, managers had greater visibility into how outputs were reviewed, and the people responsible for the work remained involved in shaping how AI was introduced.

In these teams, AI was often connected to an outcome the organization already cared about, with ownership made explicit. Leaders provided sanctioned tools, practical guardrails, and visible permission to experiment. Workflow owners helped determine where AI fit, how outputs would be reviewed, and which decisions remained human.

CASE STUDY

Colgate-Palmolive, the 220-year-old multinational CPG company, successfully scaled AI by prioritizing organizational structure over tools. By deploying 240 cross-functional ambassador leads, integrating responsible-AI principles into its code of conduct, and focusing on advanced use cases like deep analysis, the company grew weekly white-collar advanced AI adoption to over 50%.

Confidence appeared to grow when AI was used in real workflows and its contribution could be examined. Teams compared outputs with existing evidence, discussed where AI added value or fell short, and reviewed errors openly. This gave people a clearer view of when AI could support the work, where judgement was still required, and who remained accountable for the outcome.

Over time, AI also became part of regular operating routines. Its contribution was discussed alongside cycle time, evidence quality, and decision outcomes. Useful practices spread through peer examples, shared standards, and existing team forums rather than through one-time training alone. Lessons from the work were carried into subsequent workflows.

These patterns point to six principles that appeared repeatedly in cultures supporting deeper AI integration. They were reflected in what leaders expected, what employees were permitted to try, how outputs were challenged, and how the organization responded when something did not work.

Six principles of a healthy AI-forward culture

These six principles reflect the cultural conditions that appeared most consistently in teams further along in their use of AI. Each is paired with a question leaders can use to assess whether that condition is present in their own organization.

Leaders Make AI Part of the Mandate

Do leaders clearly connect AI to the organization's priorities and signal where thoughtful use is expected?

Responsible Experimentation Is Encouraged

Can people test new approaches, raise concerns, and share weak results without losing permission to continue?

The People Doing the Work Shape the Change

Are the people closest to the work involved in deciding where AI fits and how it should be used?

Accountability Remains Human

Is it clear who owns the quality of the work and the decisions made with AI support?

Trust Is Earned Through Evidence

Are AI outputs challenged, compared with other evidence, and judged by their contribution to real work?

Learning Is Shared Openly

Do useful practices, limitations, and failed approaches move beyond the individuals who discovered them?

This report is grounded in 119 leaders accountable for innovation outcomes.

This is not a poll of anonymous respondents. It is a picture of how real innovation functions in global enterprises, health systems, financial institutions, transit authorities, and scale-ups are putting AI to work.

By role

Manager/Senior Manager	32%
VP/Head of Innovation, Strategy, R&D	24%
Director of Innovation/Portfolio/Foresight	19%
Innovation Practitioner	13%
C-Suite (CINO, CSO, or Equivalent)	8%
External Advisor	4%

By industry

Manufacturing	16%
Retail/Consumer	16%
Healthcare/Pharma	14%
Other	14%
Financial Services	11%
Professional Services	11%
Tech/TMT	9%
Energy/Utilities	7%
Transport/Logistics	2%

By Region

20+ Countries Represented

Collaborators

Disruptive Edge
An AI-first strategy and innovation firm that bridges strategy and execution, helping teams turn emerging technology into real-world impact.

Aucctus AI
An AI-powered platform that enables teams to rapidly generate, test, and refine ideas across the innovation lifecycle.

Innov8rs
A global community of corporate innovators, helping organizations share best practices and turn innovation into measurable results

Research approach

This benchmark draws on responses from 119 corporate innovation professionals across 20+ countries and multiple industries. The Innovation Intelligence Curve places each team at a stage based on reported behaviours across funnel adoption, structural integration, measurement, and governance. Adoption and cycle-time findings are self-reported, while quotes come from survey responses and 1:1 interviews. Results should be viewed as directional, as the sample is community-based rather than randomized.

Contributors

Tyler Anderson, Toronto
June Barrage, New York
David Duncan, Boston
Kyle Edmonds, Toronto
Lauren Biricz, Toronto
Victor Chao, Toronto
Vincent Atallah, Toronto
Roberto Mill, Toronto

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