Harnessing AI and Talent Intelligence

A People-Centered Playbook for Institutional Investors

INVESTOR LEADERSHIP NETWORK

People.Culture.Data. Consulting Group

Investor Leadership Network

Investor Leadership Network (ILN) is a CEO-led network of some of the world's leading institutional investors, spanning seven countries with a combined USD 10 trillion in assets under management. Founded in 2018 under the Canadian G7 presidency, ILN was established to leverage the power and influence of large institutional investors to build a more sustainable and inclusive global economy.

ILN's members collectively manage trillions of dollars on behalf of current and future beneficiaries across different geographies, mandates, and regulatory environments. What unites them is not a single investment approach, but a shared commitment to long-term value creation and responsible stewardship through periods of economic transition. Members move at different paces and pursue different strategies, shaped by local context and portfolio needs. This diversity is a core strength of ILN's model.

Through collaboration across Climate Change, Public–Private Partnerships, and Talent and Culture for the Future, members use ILN to exchange insights, develop practical tools, and learn from one another's experience. The Network does not prescribe outcomes, but creates space for informed judgment, adaptation, and disciplined decision-making grounded in fiduciary responsibility.

ILN members include some of the world's largest pension funds, sovereign wealth vehicles, and asset managers. The network operates through peer learning, collaborative research, and collective action — creating shared standards and frameworks that no single institution can develop as efficiently alone.

ILN's thematic agenda, endorsed by the CEO Council under the 'Road to 2030' strategy, focused on three pillars: public-private partnerships, climate change, and talent and culture for the future with AI as a cross-cutting theme.

Our Members

State Street, OMERS, Ontario Teachers' Pension Plan, Sun Life, Future Fund (Australia's Sovereign Wealth Fund), Nordea Asset Management, Natixis Investment Managers, CPP Investments, La Caisse, Ninety One, M&G

People Culture Data Consulting Group

People.Culture.Data. Consulting Group

People Culture Data Consulting Group (PCD Consulting Group) is a global AI, big data, and behavioral science advisory firm founded in 2008 by Dr. Paola Cecchi-Dimeglio.

Operating across several continents with offices spanning North America and Europe, PCD Consulting Group brings together a multidisciplinary team of senior consultants, data scientists, behavioral researchers, and strategic advisors.

The firm has specialized in the intersection of artificial intelligence, big data, behavioral science, leadership strategy, and organizational performance.

PCD Consulting Group has served the financial sector as a core client segment since its founding, alongside global technology companies, top-tier law firms, Fortune 10 to Fortune 1000 corporations, governments, and public-sector organizations across industries, including finance, insurance, accounting, healthcare, energy, real estate, technology, government, law, and education.

In complex, high-stakes engagements, PCD Consulting Group helps organizations identify where technology deployment outpaces governance capacity, where AI-enabled systems introduce opacity or bias, and where decision processes fragment under pressure. By redesigning operating models, accountability mechanisms, and workflow architecture, PCD Consulting Group enables leaders to accelerate innovation while preserving clarity, trust, and execution discipline.

The firm's approach integrates scientific rigor with operational execution, combining proprietary big data analytics, behavioral modeling, sectorial analysis, and AI-driven people intelligence to design decision environments that are more effective, more equitable, and more durable.

PCD helps organizations at all stages to enhance the use of technology for their workforce and to make informed choices — from early-stage AI readiness assessments through enterprise-scale transformation.

Our Leadership

AMY HEPBURN

Chief Executive Officer,
Investor Leadership Network (ILN)

Amy Hepburn is a globally recognized leader in social impact and sustainable finance, serving as Chief Executive Officer of the Investor Leadership Network (ILN), a G7-launched coalition of 12 leading institutional investors across seven countries representing over $10 trillion in assets under management, focused on mobilizing private capital to build a more inclusive, resilient, and sustainable global economy.

Through her leadership of ILN, Amy convenes and advises some of the world's largest institutional investors, working across climate, talent and culture, and public-private partnerships to translate collective member practice into industry-level guidance and cross-sector action. She works directly with investor CEOs, policymakers, multilateral institutions, and philanthropic leaders to unlock capital at scale, and speaks at global convenings including the World Economic Forum, COP, UNGA, and Milken Institute Global Conference.

A delegate to the inaugural G7 Gender Equality Advisory Council and appointed member of the 2025 and 2026 Councils, she serves on multiple boards including the University of Denver Korbel School of International Affairs and the Middle East Children's Initiative, and holds faculty appointments at Duke University and George Washington University.

PAOLA CECCHI-DIMEGLIO

Faculty, Harvard University,
Chief Executive Officer, PCD Consulting Group

Dr. Paola Cecchi-Dimeglio is a globally recognized authority on artificial intelligence, behavioral science, and institutional strategy, bringing more than 20 years of experience at the intersection of big data, AI, and governance. As CEO of PCD Consulting Group and the principal investigator for this research, she advises Fortune 10 and Fortune 500 companies, leading financial institutions, and institutional investors on enterprise strategy at the intersection of big data, AI, and governance. Retained by CEOs, boards of directors, and investment committees as both a strategic advisor and board-level resource, she guides institutions on AI strategy, governance oversight, and fiduciary risk.

Dr. Cecchi-Dimeglio holds senior faculty appointments at Harvard University, where she has served since 2011 as Faculty Chair of the ELRIWMA Initiative. She serves as Co-Chair of the UN ITU Steering Committee on AI and Big Data and Chair of Sustainability, Accessibility, and Inclusion for AI Governance. She was named an "Influencing Mind" by the Edison Electric Institute and holds several patents, including the I.D.E.A. Platform — a patented people intelligence system tailored to leading financial institutions and Fortune 500 corporations for performance, team strengthening, and decision-making.

She is an award-winning author of several MIT Press books: Diversity Dividend (2023) and Building a Thriving Future (2025, Silver Medal, North American Book Awards), and has published more than seventy peer-reviewed articles, regularly contributing to Harvard Business Review, MIT Sloan Management Review, and Forbes. Her work has been featured in The New York Times, The Wall Street Journal, The Washington Post, Bloomberg Law, Thomson Reuters, and Business Insider.

Foreword

Organizations today are operating in an environment characterized by **rapid technological advancement, shifting workforce dynamics, and increasing complexity in decision-making**.

The challenge is no longer access to information, but the ability to interpret it, prioritize effectively, and act with consistency.

In this context, the collaboration between Investor Leadership Network and PCD Consulting Group reflects a shared recognition: that better outcomes depend on better decision systems.

This requires not only data and tools, but also the integration of behavioral insight, institutional experience, and disciplined governance. It equally requires an urgent focus on talent — the learning curve is steep, but the solutions are real, and they are being implemented by the institutions that have chosen to lead rather than wait.

This playbook is grounded in that perspective. It draws on the experience of leading institutional investors and the application of behavioral and data science to real-world organizational challenges.

The methodology used pairs PCD's AI proprietary behavioral analysis and sectorial expertise with quantitative data triangulation, labor market modeling, and publicly available research from leading academic and industry sources.

The result is a scientifically grounded, practitioner-validated intelligence report designed not only for ILN members, but to benefit the financial sector more broadly — providing structured insights that support more informed choices in a period of unprecedented transformation.

In the spring of 2025, the ILN CEO Council endorsed the 'Road to 2030' strategy, including a focused commitment to understanding how AI is reshaping talent, culture, and governance across institutional investing.

This playbook delivers on that commitment. It is practitioner-informed, peer-validated, behaviorally grounded, and governance-rigorous. It is the first report of its kind in institutional investing — and it is designed to serve as a strategic reference and an operational playbook for the future, to be further complemented by instruments developed as ILN members navigate this transformation.

We are thankful to the participating institutions whose CEOs, CIOs, CHROs, CTOs, and senior leaders contributed their time, candor, and expertise under Chatham House Rule. Their willingness to share openly is what makes this research credible and actionable. We invite all ILN members — and the broader financial sector — to use this playbook as a diagnostic tool, a strategic framework, and a springboard for the collaborative work that lies ahead.

Amy Hepburn
Chief Executive Officer,
Investor Leadership Network

Dr. Paola Cecchi-Dimeglio
CEO, PCD Consulting Group |
Faculty, Harvard University

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Acknowledgments

This playbook was made possible by the participation and trust of institutional investor organizations across three continents. All contributions were made under Chatham House Rule, and all institutional and individual identities are anonymized throughout.

We extend our deepest gratitude to every individual who participated in the structured interviews that form the primary research base of this playbook. Their candor, operational insight, and willingness to engage with difficult questions under conditions of confidentiality are what make this work credible and actionable.

We thank the members of the CIO Roundtable and the Talent & Culture Advisory Committee for their engagement and willingness to share operational realities alongside strategic aspirations.

We appreciate the efforts and support of ILN and PCD Consulting group teams dedicated to this project.

Executive Summary

This playbook presents the findings of the first large-scale, cross-border, practitioner-informed study of AI adoption, governance, and workforce transformation in institutional investing.

Investor Leadership Network, partnering with PCD Consulting Group, draws on nearly 20 years of proprietary big data and behavioral analysis, combined with confidential, structured interviews across ILN member institutions, a CIO Roundtable, and an ILN Board session — all conducted under the Chatham House Rule. The evidence base was triangulated against leading academic research, labor market data, and behavioral modeling of sector adoption trends, producing a standard that neither internal surveys nor external benchmarks can match.

Nine integrated parts move from diagnosis to action, culminating in a people-centered implementation framework designed for immediate C-suite application.

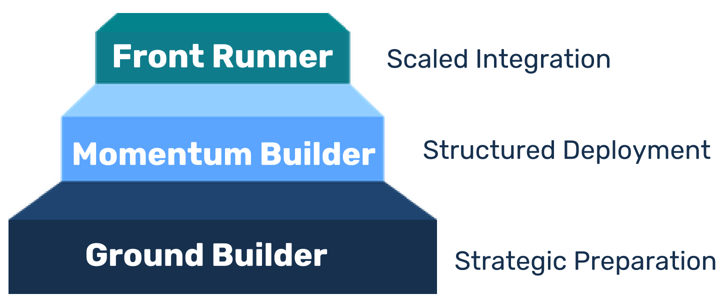
Every institution in this research has deployed AI tools. The transformational value each can still unlock is the defining opportunity of the next three years — the gap lies not in technology but in the governance, leadership behaviors, and organizational structures required to deploy it at scale. Four elements distinguish the winning institutions.

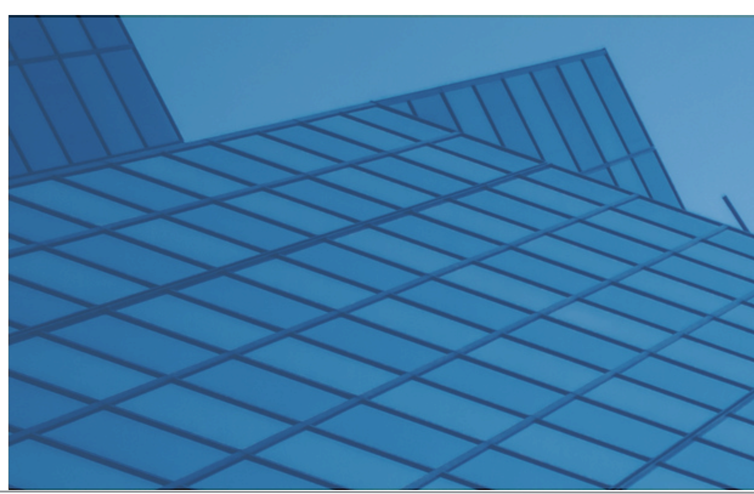
First, leadership behavior: when a CEO or CIO visibly uses AI — not endorses it, uses it in meetings, in their own work, sharing what works and what fails — workforce adoption accelerates within measurable three-month windows. No other variable produces the same effect.

Second, governance reframed: the institutions furthest ahead treat governance not as a compliance gate but as the operating system that makes confident, scaled deployment possible. In multiple institutions, leadership conviction about governance maturity has developed ahead of the measurement systems available to confirm it — a calibration opportunity that, once closed, converts governance into a demonstrable strategic advantage.

> *The central finding is unambiguous: AI transformation in institutional investing is not primarily a technology challenge. It is an adoption, governance, and organizational design challenge. The competitive advantage belongs to the institutions whose leadership, governance architecture, and investment in human capabilities convert technology into sustainable value.*

Three Maturity Profiles





Executive Summary

Third, a talent strategy designed for what is coming: AI is now performing the tasks that defined early-career development in institutional investing, disrupting the succession pipeline that has produced senior leaders for decades. The window to redesign how the next generation is built is three to five years — and it is open now.

Fourth, a financial proof chain: capturing AI's value requires a deliberate sequence, not a single ROI calculation.

Prove AI saves first — through cost avoidance, reduced hiring need, and compliance efficiency. Then prove AI enables — through mandate win rates, revenue per relationship manager, and client retention. Then prove AI creates — through investment alpha, decision quality, and strategic competitive advantage.

Each stage builds the credibility required to invest in the next. The institutions that deliberately sequence this proof chain and rigorously measure it are the ones that will sustain AI transformation when the pressure to demonstrate returns arrives.

10 Findings

1. The transformation is structural and without historical precedent at this scale in institutional investing. AI restructures the cognitive architecture of investment work itself.

2. AI governance is the primary constraint — not technology, not budget. Institutions reframing governance as enabler are measurably further along the adoption curve.

3. Leadership modeling predicts adoption. When CEOs and CIOs visibly practice AI use, workforce adoption accelerates within three-month windows. No other variable produces this effect.

4. Curiosity, not demographics, predicts adoption success. Disposition-based intervention outperforms training segmented by age or seniority.

5. Near-universal tool access collapses to limited impact. 75–100% have access; fewer than 10–15% achieve transformational gains. The gap is organizational, not technological.

6. Three maturity profiles describe the institutional landscape. Each carries distinct risks, strategic logic, and highest-leverage interventions.

7. The gender-AI convergence poses a pipeline integrity risk. The broken rung at director level intersects with AI displacement at precisely those analytical roles.

8. The succession pipeline for future leaders is being disrupted. AI performs the tasks that defined early-career development. The window to redesign the pathway is three to five years.

9. The competitive clock is running. AI-native entrants deliver with three-person teams what previously required a dozen. Fee compression from 100bp toward 10bp is accelerating.

10. Value capture requires a financial proof chain. AI saves → AI enables → AI creates. Each stage requires dollar-denominated evidence appropriate to its deployment reality.

METHODOLOGY

This research was designed to answer a specific question: how AI adoption, governance, and workforce transformation actually work within complex organizations, what enables them, what blocks them, and how leadership shapes the outcomes. That question requires depth, not scale. Eleven leading institutional investors across several continents participated in more than fifty confidential interviews, each lasting up to an hour, all conducted under the Chatham House Rule.

The findings were further validated through an ILN CIO Roundtable and the Q1 2026 ILN Board Meeting. Eleven is the methodologically correct number of institutions for this type of research: the scientific standard sets nine to twelve cases as the point at which new interviews stop producing new themes (saturation criteria).

On the most critical findings, ten or eleven of the eleven institutions independently raised the same issue without prompting (convergence criteria). That level of unprompted agreement is not a coincidence. It is a structural pattern.

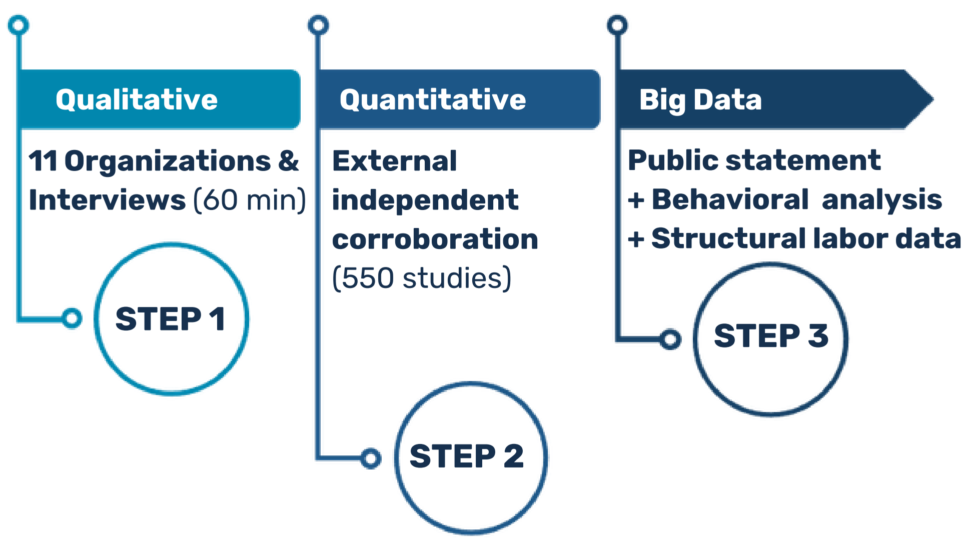
Each finding was then tested in three ways against independent evidence (Big data — transferability and triangulation criteria).

First, against more than 550 external studies across seven fields conducted on different populations. Second, against PCD Consulting Group's proprietary behavioral models — built over nearly twenty years — which predict how professionals in these roles actually behave, independent of what they say. Third, against PCD's structural labor market data on workforce structure and trends across the sector.

Where all three sources align with the interview record, the finding is confirmed. Where they diverge, the divergence itself becomes a finding.

Any claim that survived all five validity tests is presented in this playbook as a sector-level pattern — not a trend, not an opinion, but a finding that held across institutions, continents, and independent methods simultaneously.

This study covers ILN member institutions as of Q1 2026 and does not include the Middle East or Asia.



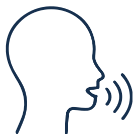
Why this sample size is sufficient
Qualitative saturation is reached at 9–12 cases.

WHO WE SPOKE TO

STAKEHOLDERS

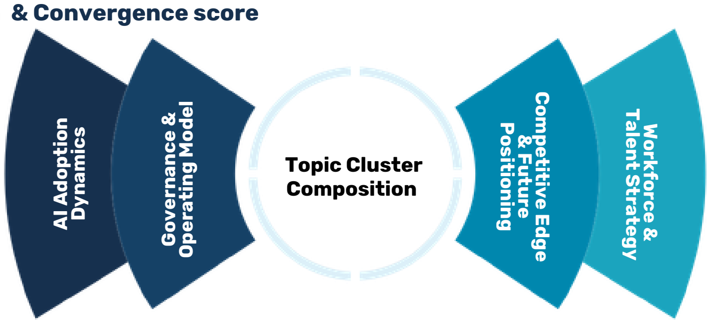
PRIMARY SOURCES INDIVIDUAL INTERVIEWS	**C-SUITE & ENTERPRISE STRATEGY / OVERSIGHT**	**DATA, ANALYTICS & AI DEPLOYMENT LEADERS**
	INVESTMENT & PORTFOLIO MANAGEMENT LEADERS	**HUMAN CAPITAL & ORGANIZATIONAL DEVELOPMENT LEADERS**
SECONDARY SOURCES GROUP VALIDITY CHECK	**ROUNDTABLE 1 – CIO GROUP** CIOS FROM ILN MEMBER INSTITUTIONS	
	ROUNDTABLE 2 – ILN BOARD ILN MEMBERS (Q1 BOARD MEETING)	

STEP 1 – QUALITATIVE STEP



- **LEADERSHIP BEHAVIOR DRIVES ADOPTION**
- **GOVERNANCE IS THE #1 BARRIER**
- **CURIOSITY, NOT AGE, PREDICTS AI ADOPTION**
- **TOOLS ARE UNDERUSED RELATIVE TO THEIR TRUE CAPABILITY**
- **AI IS DISRUPTING TALENT SUCCESSION PIPELINES**

Topic Cluster Composition & Convergence score



STEP 2 – QUANTITATIVE STEP

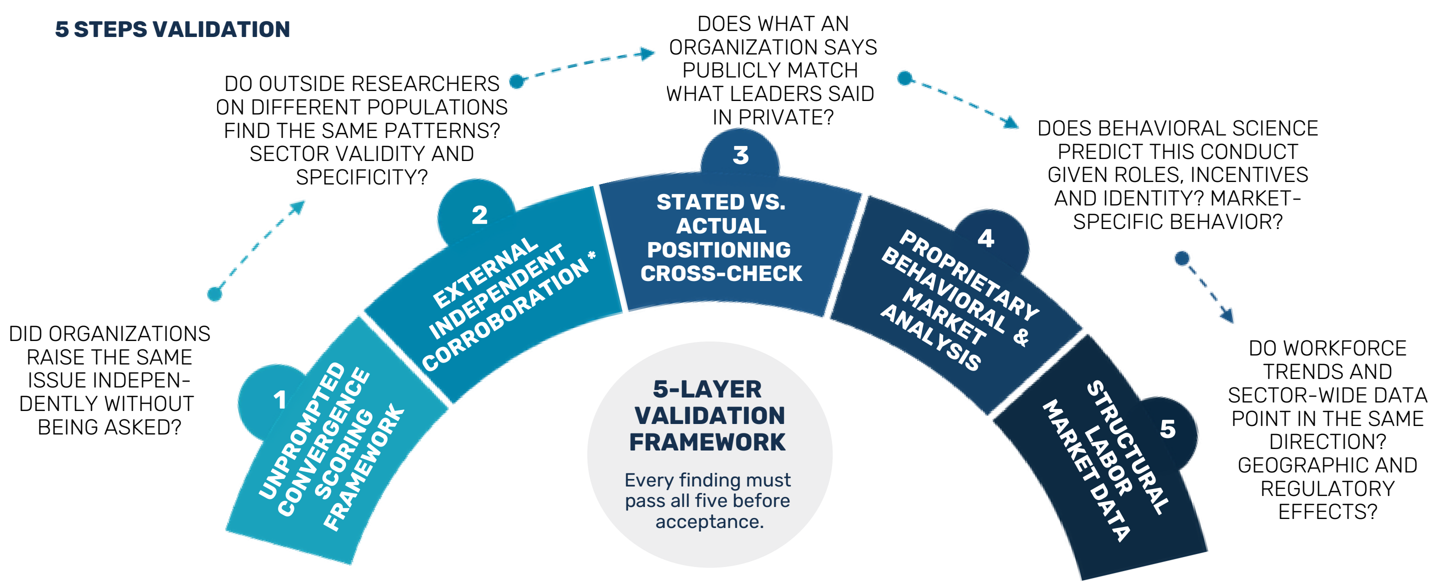
External independent corroboration with

550 Independent studies across 7 fields confirm sector-level findings, using different methods on different populations.

STEP 3 – BIG DATA & PROPRIETARY ANALYSIS

- **STATED VS. ACTUAL POSITIONING CROSS-CHECK**
- **PROPRIETARY BEHAVIORAL & MARKET ANALYSIS**
- **STRUCTURAL LABOR MARKET DATA**

5 STEPS VALIDATION



Setting the Scene

1

The Shifting Landscape, Structural Distinction & Competitive Context

This section establishes the context in which institutional investors are navigating AI transformation. It maps the forces reshaping investment work, introduces the structural distinction between asset owners and asset managers that governs the entire analysis, examines the workforce trends already visible across the industry, and assesses the competitive landscape that defines the urgency. Together, these four dimensions frame the diagnostic on which every subsequent section of this playbook builds.

Shifting Landscape

AI is reshaping the operating logic of every major industry, and the financial sector sits ahead of the curve. From algorithmic trading in the 1980s, through electronic execution in the 2000s, to today's wave of generative and agentic AI (AI systems that operate with increasing autonomy across workflows, requiring new oversight frameworks), financial institutions have consistently deployed transformational technology earlier than their peers in other sectors.

Adoption rates confirm the trajectory. Recent industry data place financial services among the highest-adopting industries globally, with the majority of firms using AI in at least one business function. The question for institutional investors is no longer whether AI will affect their organizations. It is how quickly the distance between current deployment and full organizational transformation can be closed.

Something fundamental has changed in institutional investing, and it has changed faster than the governance, talent pipelines, and organizational habits built to manage it. AI is not arriving as a discrete technology to be evaluated, procured, and deployed alongside existing workflows. It is arriving as a general-purpose transformation — one that restructures how investment work itself gets done.

This distinction matters. Previous technology waves in institutional investing — the move to electronic trading, the adoption of risk analytics platforms, the integration of ESG data feeds — were additive. They layered new capability onto existing workflows without challenging the underlying logic of how investment professionals think, decide, and create value.

In Brief

1 — Not a Technology Cycle
AI is restructuring investment work itself. Prior playbooks don't apply.

2 — Breadth Without Depth
Everyone has deployed AI. Few see material impact yet.

3 — Two Different Transformations
Asset owners face a talent question. Asset managers face a survival question.

4 — The Pipeline Is Breaking
Junior analyst tasks now take AI minutes. The succession model is failing.

5 — Capacity Over Spend
The winners adapt faster, not spend more.

> *The transformation underway in institutional investing is profound and without historical precedent at this scale. This is not another technology cycle. It is a structural shift in how investment value is created, governed, and sustained.*

AI is different. It does not sit alongside the analyst's workflow; it enters it. It does not supplement judgment; it participates in the formation of judgment. And it compresses the distance between tool deployment and organizational transformation from years to months. The situation is more fragile precisely because AI is no longer experimental at these institutions. Every institution in this research has moved well beyond proof-of-concept. Yet the distance between deploying AI tools and capturing their transformational value is proving far wider than anticipated. Recent industry surveys find that only a small fraction of companies — roughly 1-3 percent — consider their generative AI strategies mature, and roughly 4 in 5 report no significant bottom-line impact from AI investments to date.[1]

This is not another technology cycle. It is a structural shift in how investment value is created, governed, and sustained.

3 Converging Forces

Three forces are reshaping institutional investing at the same time, and they reinforce each other.

The rise of cognitive workload

AI does not eliminate complexity; it redistributes it. Investment teams that once spent days assembling earnings analysis, drafting investment committee memoranda, or screening ESG data now face a different problem: interpreting, validating, and synthesizing AI-generated outputs that arrive in minutes.

The volume of material an investment professional can process has expanded dramatically. So has the cognitive demand of deciding what to trust, what to verify, and what to discard.

Nobel laureate Daron Acemoglu's task-based framework offers the sharpest lens here. AI's employment impact is determined not by aggregate capability but by the balance between two forces. Displacement: machines replacing tasks.[2-3] Reinstatement: new tasks are being created where humans remain productive. Nobel laureate Elinor Ostrom's work on the governance of shared resources reinforces the same point from a different angle. Which force dominates is a design choice shaped by institutional governance, not a technological inevitability.[4]

A new talent economy

The competition for analytical talent in institutional investing is now a competition for a fundamentally different kind of professional. Technical fluency in AI is necessary but insufficient. What separates high-performing investment teams in an AI-augmented environment is the combination of domain judgment, behavioral adaptability, and the capacity to work productively alongside systems that are simultaneously powerful and imperfect.

The World Economic Forum's Future of Jobs Report 2025 — surveying over 1,000 employers representing 14 million workers across 55 economies — identifies analytical thinking as the most sought-after skill globally, followed by resilience, flexibility, and leadership. AI and big-data literacy top the list of fastest-growing skills. But the central finding for institutional investors is that behavioral competencies, more than technical ones, determine whether AI can be deployed at scale.[5]

Technological convergence
AI, automation, and data infrastructure are no longer separate investment categories. They are fusing into a single capability stack that reshapes cost models, decision-making, and competitive dynamics simultaneously. An institution that spent six years building its data foundations before deploying AI applications now finds that investment compounding as AI tools mature. An institution that rushed AI tools onto a fragmented data foundation finds each new application amplifying — rather than resolving — underlying data quality problems.

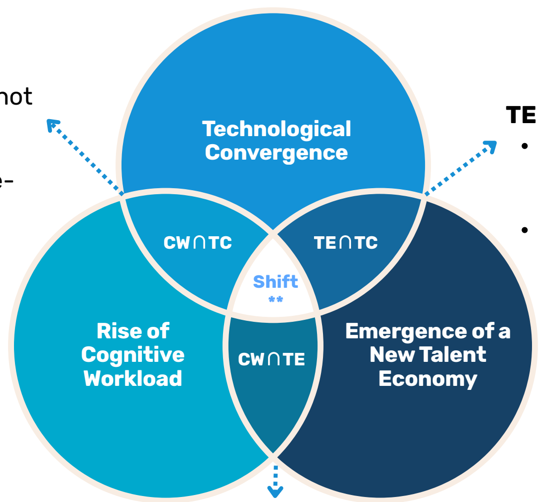
Research from Stanford's Digital Economy Lab characterizes AI as a general-purpose technology. The label is analytically precise. Like electricity or the internal combustion engine, AI's transformative impact comes not from the technology itself but from the complementary investments in organizational design, human capability, and institutional governance that must accompany it.[6]

The same body of research identifies a Productivity J-Curve: measured productivity often declines before it rises, because the reorganization of work required to capture AI's value is itself costly, disruptive, and slow.[7]

Converging Forces Reshaping The Landscape

** The shifting landscape of investment work where all three forces converge

CW∩TC
- AI augments, not replaces, judgment
- Human-in-the-loop becomes official



TE∩TC
- New role architectures emerge
- Hybrid human-AI team design

CW ∩ TE
- Skills revaluation under AI pressure
- Judgment becomes the premium skill

PCD CONSULTING GROUP

- AI adds new layers of decision complexity
- Information noise rises alongside AI
- Analytical requirements expand
- Human judgment increasingly stressed
- Cognitive load redistributed, not reduced

- Competition for analytical, quantitative, and technical talent intensifies
- Skills half-life problem accelerates
- Changing expectations for flexibility, meaning, and growth
- New hybrid roles emerge faster than supply pipelines can fill them
- Career path redesign becomes a strategic urgency

- AI + automation merge into unified systems
- Workforce cost models disrupted
- Operating structures require redesign
- Capability needs shift toward orchestration
- Technology convergence reshapes institutions

The Asset Owner vs. Asset Manager Distinction

The single most important structural variable in this research is the distinction between asset owners and asset managers. It governs everything that follows: the pace of AI adoption, the nature of competitive pressure, the design of governance, the calculus of workforce transformation, and the strategic options available to leadership.

This is not a superficial organizational difference. It is a structural bifurcation that produces different AI risk profiles, governance imperatives, and transformation incentives. Treating asset owners and asset managers as a single category — as most industry AI commentary does — produces analysis that is simultaneously too general to be actionable and too imprecise to be credible.

This playbook recognizes the distinction throughout. The maturity profiles, governance models, and strategic recommendations that follow are calibrated to the different realities each side faces.

At the same time, the core analytical models developed in this research — the adoption depth deficit, the behavioral science of leadership-led change, the governance operating models, and the financial proof chain — apply to both.

The challenges differ in form and urgency. The underlying dynamics of human behavior, institutional governance, and organizational design are shared.

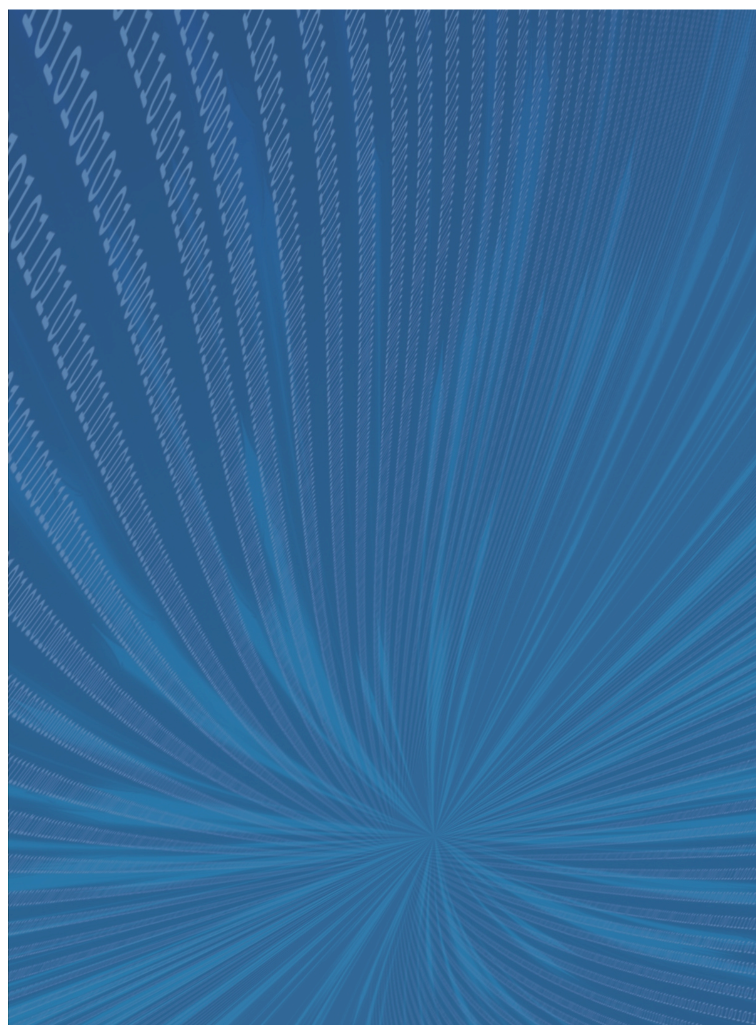
Asset Owners (pension funds, sovereign wealth vehicles, endowments)

Asset owners operate under direct fiduciary obligations to beneficiaries. Their investment horizons are measured in decades. Governance failures compound over those decades in ways that are difficult to reverse and costly to remediate.

Their data environments tend to be more consolidated. Their regulatory exposure is more uniform within jurisdictions. Their cultures are more tolerant of long-horizon investment in infrastructure and capability. Board structures reflect governance authority and institutional stewardship.

For asset owners, AI transformation is primarily an operational and talent question.

How to deploy AI to improve decision quality, manage total portfolio risk, and sustain the institutional capability to fulfill obligations that extend thirty, forty, or fifty years into the future.



Asset managers (whether independent, bank-owned, or insurance-affiliated)

Asset managers operate under shorter performance cycles, direct competitive fee pressure, and the existential threat of AI-native entrants who can deliver comparable analytical capability with a fraction of the headcount and cost structure. Their data environments are more fragmented across products, strategies, and client mandates. Regulatory exposure varies by domicile, product type, and distribution channel.

For asset managers, AI transformation is a competitive survival question. The institutions that fail to capture AI's value — in investment performance, in client experience, in operational cost — face structural disadvantage that compounds with each quarter of inaction.

> *AI's comparative advantage is precisely in extracting signal from unstructured data at scale.*

AI and Workforce Trends Shaping Institutional Investing

The distinction between active, passive, and mixed business models creates further differentiation within asset management. Decades of research on disruptive innovation, most prominently Clayton Christensen's, shows that incumbents whose current revenue depends on the products most vulnerable to technological disruption face a structural disincentive to self-disrupt.[8]

In active management, this dynamic is especially pronounced. The products and client relationships that generate the majority of current revenue are precisely the ones where AI-enabled alternatives are advancing fastest. Fee compression from 100 basis points toward 10 basis points is no longer a projection but an observable trajectory.

Passive managers face a different strategic calculus. AI enables further cost compression in an already low-margin model, but the competitive moat is scale and distribution, not analytical differentiation. Mixed-model firms face both dynamics at once — and the internal politics of resource allocation between active and passive strategies are themselves a governance challenge that AI intensifies.

The workforce implications of AI are not confined to any single cohort of institutions. They are an industry-wide reality that every organization in the financial sector is working through — with varying degrees of intentionality, varying levels of success, and, in many cases, with genuine uncertainty about whether the direction chosen will prove correct.

The AI-augmented investment professional

Across the industry, the rise of the AI-augmented investment professional is the most visible trend. Investment committee papers that required two to three days of analyst preparation are now drafted in hours. ESG scorecards that demanded manual aggregation from multiple data vendors are being generated and updated in near-real time. RFP commentary — once the province of dedicated client service teams working through weekends — is being produced at higher quality and lower cost by AI systems trained on institutional history and mandate-specific language. Earnings analysis that required a team of four can be initiated by one person working alongside an AI system that processes transcripts, financial filings, and market data simultaneously.[9]

These are not marginal improvements. They represent a fundamental compression of the labor content of analytical work — and that compression cascades through the entire talent pipeline of the organization. When the tasks that defined a junior analyst's first three years can be performed by AI in minutes, the question is not whether to hire fewer analysts. The question is how to redesign the early-career experience so that the judgment, contextual understanding, and institutional knowledge that make a thirty-year career productive are still being developed — even when the tasks that historically provided that development are no longer available.

Hybrid investment teams and the forward-deployed engineer

Hybrid investment teams are emerging as the organizational response. The traditional structure — fundamental analysts on one side, quantitative researchers on the other, with limited integration — is giving way to teams that combine domain expertise, quantitative capability, and AI fluency in a single operating unit.

The forward-deployed engineer model — embedding technical AI talent directly within investment teams rather than centralizing it in technology departments — is the operational expression of this shift. It requires new roles, new career paths, and deliberate management of the tension between the people who build AI tools and the people who embed them into investment workflows. These are not the same people. The institutions that conflate them lose value on both sides.

Where the impact lands hardest: the mid-career cohort

The workforce impact is not uniform across demographics, seniority, or function. Early signals suggest the transformation affects different populations in structurally different ways. Mid-career professionals — those with eight to fifteen years of experience whose expertise was built on the very tasks AI now performs — face the sharpest identity challenge. They are too senior to be retrained as entry-level AI users and too junior to redefine their value entirely around governance and strategic judgment. This is the population most at risk of what behavioral scientists describe as workflow identity lock-in: a deep psychological attachment to the specific tasks and methods that define professional competence, which becomes a barrier to adoption even when the individual intellectually understands the case for change. The gender, generational, and functional dimensions of this impact are developed in Part 4.

Research on AI's labor market impact provides a quantitative anchor: workers with demonstrable AI skills now command a wage premium exceeding 50 percent over peers without them — a figure that has nearly doubled year-on-year.[10] The labor market is pricing AI fluency as a scarce and appreciating asset. Institutions that fail to develop it internally will pay an escalating premium to acquire it externally — and will do so in a market where AI-fluent talent increasingly self-selects into organizations that offer the most compelling AI-enabled work environments, not necessarily the highest compensation.

THE COMPETITIVE LANDSCAPE

Who is Winning and Why

During a Roundtable session, a senior leader posed the question that every institution in the financial sector is asking:

'If we put this as a Formula One race — everyone is going very fast, it starts raining, everyone is getting wet — who is actually making gains? How to really manage to overtake others?'

The metaphor is apt. In a wet race, the advantage belongs not to the most powerful car but to the team that adapts fastest under conditions that nullify previous advantages. Tire strategy, risk calibration, and real-time decision-making under uncertainty determine the outcome.

The parallel to AI transformation in institutional investing is direct. **The institutions pulling ahead are those whose leadership, governance, and culture enable faster adaptation under genuine uncertainty — not those with the largest technology budgets.** [11]

From automation to augmentation to value creation

The evidence from this research confirms that some institutions are making gains, moving from automation to augmentation and from augmentation to value creation.

The clearest examples are institutions that have deployed AI not merely to reduce cost but to generate dollar value:

- AI systems that participate in investment analysis.
- Agentic deployments — AI systems that execute multi-step analytical workflows with human oversight at defined checkpoints.
- Organizational designs where AI capability is measured not by usage statistics but by competitive outcomes.

AI-native entrants and the incumbent's dilemma

AI-native entrants represent a structural competitive pressure. Firms built from inception around AI-optimized data infrastructure and workflows can deliver analytical services with significantly smaller teams and fundamentally different cost structures. This advantage is not incremental. It compounds.

For established institutions, the strategic question is whether the pace of internal transformation is sufficient to maintain competitive positioning as these entrants scale.[12] Recent consolidation across mid-tier asset management suggests that for some, the window for independent transformation has already narrowed.

The dynamic that innovation research describes as the incumbent's dilemma is observable across the sector. Established institutions derive the majority of revenue from existing products and client relationships, creating a rational but potentially dangerous disincentive to self-disrupt. The most candid diagnosis of this risk came from practitioners within the industry itself — a useful reminder that awareness of a challenge and organizational capacity to respond to it are not the same thing.

Geography and data sovereignty as competitive variables

Geographic variation is a further dimension of competitive positioning. The maturity of regional AI ecosystems — the density of specialized talent, the depth of vendor infrastructure, regulatory frameworks, and cultural tolerance for experimentation — varies meaningfully across regions.

These structural differences produce measurably different adoption velocities, and they create both challenges and opportunities depending on where an institution operates.[13]

Data sovereignty is emerging as a strategic variable with direct implications for competitive positioning. Institutions operating across multiple jurisdictions face a more fragmented regulatory environment, with compliance complexity that directly shapes how AI is deployed.[14]

> The institutions approaching data sovereignty as a geopolitical and strategic risk factor — rather than a legal compliance exercise alone — are the ones positioning most effectively for the next decade.

Ground Builder

1. Commission a structured executive AI immersion program — working sessions built around real investment and operational challenges, not awareness briefings
2. Conduct a data architecture review: identify where infrastructure investment is compounding and where fragmentation constrains AI deployment.
3. Establish a board-level briefing on the institution's AI strategic positioning, maturity profile, and governance readiness

Momentum Builder

1. Quantify the adoption depth deficit: measure the gap between tool access and transformational impact across the workforce
2. Benchmark competitive positioning: assess organizational AI capability relative to the pace of change in your market segments
3. Map unstructured data surfaces across the organization — identify the highest-value AI applications that current infrastructure has not yet reached

Front Runner

1. Conduct a succession pipeline audit: identify which developmental experiences have been displaced by AI and design structured replacements
2. Stress-test the build-buy-partner portfolio: evaluate vendor concentration risk and the defensibility of proprietary data advantages
3. Develop a three-year competitive positioning scenario model that accounts for accelerating technology capability and evolving market structure

Where Institutions Stand

The Maturity Framework

2

There is no single AI posture across institutional investing. What emerges is meaningful divergence — not in technology access, which is broadly equivalent, but in three variables technology cannot substitute for: leadership engagement, governance design, and deliberate human-capability investment.

Three distinct profiles describe where institutions stand. None is inherently superior. Each carries its own strategic logic, its own risks, and its own highest-leverage next move. This section introduces the profiles, the quantitative evidence that defines them, the five strategic applications that cut across all profiles, the transition pathways between them, and the governance operating models that determine whether AI capability translates into organizational value.

Three Maturity Profiles

The three-profile model — Ground Builder, Momentum Builder, Front Runner — emerged from the research. The profiles are anonymized composites, not descriptions of individual organizations. Each represents a distinct pattern of organizational behavior observed across the cohort.

GROUND BUILDER	MOMENTUM BUILDER	FRONT RUNNER
Strategic Preparation	Structured Deployment	Scaled Integration
• Governance-first. • Data infrastructure compounding. • Champion networks ready. • Leadership signal opportunity.	• High deployment velocity. • 25–90% daily usage. • Governance catching up. • Tool proliferation ungoverned.	• AI embedded in investment decisions. • 70%+ engagement. • Succession pipeline as frontier challenge.

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IN BRIEF

1 — Three Profiles
Ground Builder. Momentum Builder. Front Runner.
2 — The Depth Deficit
Tool access is universal. Impact is single-digit.
3 — Two Strategic Frontiers
Governance and competitive positioning.
4 — Five Parallel Tracks
Not sequential. All running at once.
5 — Transitions Aren't Automatic
Each requires a different binding constraint to break.

Ground Builder: Strategic Preparation

Ground Builders bet on infrastructure before deployment, and the bet is paying off. Years of data architecture investment are compounding as AI tools mature. Governance frameworks are in place. The data is clean. Risk-tolerance protocols are calibrated by activity type: experimental, productionized, agentic.

A consistent pattern across Ground Builder institutions: technical teams and AI champions are building deep operational fluency that the executive layer will draw on next. This is the logical outcome of a governance-first sequencing decision — the foundations were built first.

Visible leadership modeling of AI practice is the next-stage opportunity, and institutions that pair their champion networks with executive immersion close the gap quickly.

The asset under management is the infrastructure advantage. Its compounding accelerates with each quarter the leadership signal is visibly modeled at the senior level. A first-mover advantage in infrastructure appreciates fastest when executive practice extends and reinforces the foundation already built.

Across the Ground Builder tier, approximately 85 percent of the workforce has tool access, regular use sits at roughly 35 percent, workflow integration at around 12 percent, and transformational impact — employees achieving measurable productivity gains — at roughly 3 percent. The infrastructure is ready; the practice is at an earlier stage of development.

> *The data investment is appreciating, and organizational readiness is compounding behind it on a deliberate curve. The next move is not more infrastructure but executive immersion — bringing AI practice into the leadership repertoire as a strategic, owned priority.*

Momentum Builder: Structured Deployment

Momentum Builders are institutions with real deployment velocity. CEO-sponsored sprint programs are running. Daily usage ranges from approximately 45 to 90 percent. Investment committee papers that once took days are drafted in hours. Early pilots of agentic AI (AI systems that operate with increasing autonomy across workflows, requiring new oversight frameworks) are underway.

Deployment velocity has outpaced governance design, and that velocity is the institutional asset to govern. AI committees exist at most of these institutions; their mandates vary — some advisory, others with broad oversight developing the technical capability to match it. Internal inventories surfaced hundreds of AI-enabled tools in active use — a demand signal ready to be channeled through structured oversight.

Headline adoption metrics describe an average; the distribution underneath is where the opportunity sits. In one institution, reported daily usage exceeded 60 percent, while the bottom quartile of users submitted as few as one or two prompts per month. In another, 95 percent monthly usage masked the reality that the top 30 percent of users generated 70 percent of activity, while the bottom half accounted for just 10 percent. Even where 90 percent of staff use AI tools multiple times daily, institutions consistently identify change management — not technology — as the primary implementation challenge.

This is the capability overhang: the gap between what AI can do and what organizations actually ask it to do. **The constraint is not the technology. It is the behavioral and organizational design surrounding it.**

> *You are not behind — you are ahead on deployment. The next move is to bring governance and workflow redesign onto the same accelerating curve, so the two engines compound together. Governing with the same energy that has driven deployment converts velocity into durable institutional capability.*

Front Runner: Scaled Integration

Front Runners have embedded AI in investment decisions, portfolio monitoring, and workforce planning. The aspiration: above 70 percent workforce engagement in a human-in-the-loop capacity within twelve months.

The technology question recedes. Three organizational design challenges take its place.

The succession pipeline. AI is performing tasks that traditionally defined early-career learning. A senior technology leader described concluding that existing AI tools could perform the entire role of a new analyst hire — not theoretical, it happened. When the pathway producing future investment leaders is narrowed without a replacement, the long-term talent implications are material.

The productivity paradox. Non-technical staff building AI tools without engineering support generate real initial gains. The quality assurance, maintenance, and governance requirements remain — a J-curve where short-term productivity becomes a net drag if downstream costs go unmanaged.

The governance complexity spiral. Agentic AI — where systems take actions, not just provide analysis — requires fundamentally different governance. One Front Runner is developing a graduated trust framework: narrow-parameter agents with limited oversight, broad-latitude agents with full human accountability. This is the frontier.

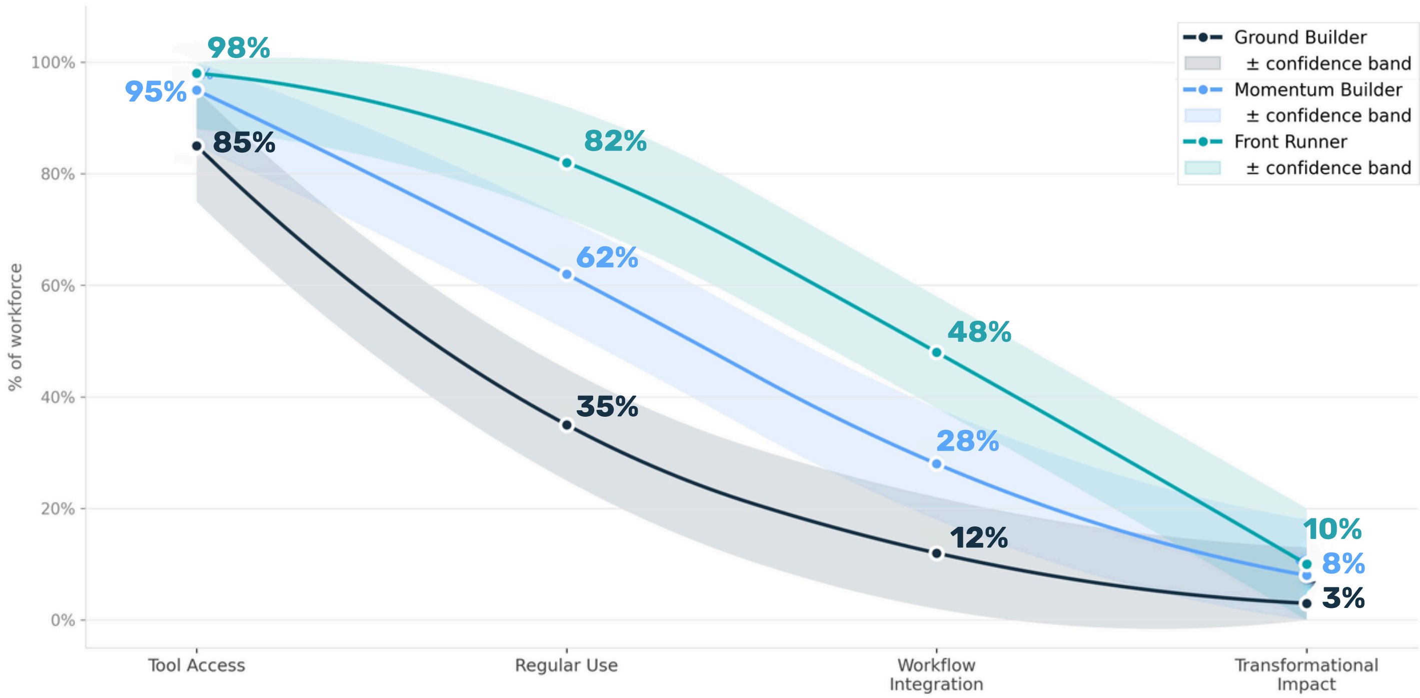
> *The strategic stakes are universal. The pace, sequencing, and binding constraints are not. This playbook is built for both realities.*

The Adoption Depth Deficit

The quantitative evidence produces a single diagnostic finding that anchors the entire maturity framework: near-universal tool access collapses to single-digit transformational impact across every tier. This is the adoption depth deficit — structural, not a function of insufficient tool deployment, but of insufficient organizational redesign.

Adoption Depth Matrix — Tier Averages with ±10pp Brackets

The drop-off from tool access to transformational impact is 82 percentage points for Ground Builders, 87 points for Momentum Builders, and 88 points for Front Runners.



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Even the most advanced institutions see about one in ten employees achieving productivity transformation at a level that justifies the organizational disruption of AI adoption. The funnel does not widen with maturity; it deepens slightly. Moving to a higher tier does not automatically solve the deficit — it requires deliberate intervention at each stage of the funnel.

AI Maturity Profiles: Six-Dimension Diagnostic

Six dimensions surface where institutions diverge most meaningfully:

1. **Breadth of Adoption** (percentage of workforce with active AI tool access and regular use)
2. **Depth of Adoption** (sophistication of use across the investment value chain)
3. **Governance Architecture** (maturity of AI-specific governance)
4. **Workforce Strategy** (existence and sophistication of AI-linked talent frameworks)
5. **Leadership Engagement** (behavioral modeling by senior leaders)
6. **Competitive Positioning** (extent to which AI is framed as competitive differentiator)

AI Maturity Profiles by Tier

Tier	Breadth of adoption	Depth of adoption	Governance architecture	Workforce strategy	Leadership engagement	Competitive positioning
Ground Builder Strategic preparation	Finding momentum	Finding momentum	Finding momentum	Building foundations	Finding momentum	Building foundations
Momentum Builder Structured deployment	Gaining confidence	Gaining confidence	Finding momentum	Gaining confidence	Gaining confidence	Finding momentum
Front Runner Scaled integration	Setting the pace	Operating at scale	Operating at scale	Gaining confidence	Setting the pace	Operating at scale

Maturity Signal Building foundations | Finding Momentum | Gaining confidence | Operating at scale | Setting the pace

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Governance architecture and competitive positioning are the lowest-scoring dimensions for Momentum Builders, despite their relatively stronger breadth and depth of adoption. This is the quantitative expression of the deployment-governance gap: these institutions are deploying faster than they are governing. The gap is not an administrative shortfall; it is fiduciary risk that compounds with each ungoverned application added to the institutional inventory.

Leadership engagement strengthens progressively across the tiers, and at each tier it is expressed differently. For Ground Builders, leadership engagement has been most visible in sponsoring the governance-first strategy itself — leading the infrastructure investment from the front. Visible AI practice is the next expression.

Competitive positioning is consistently among the lowest-scoring dimensions across all tiers — Front Runners excepted. At the Ground Builder level, it shares the lowest score with breadth of adoption and workforce strategy. At the Momentum Builder level, it ties with governance architecture. Most institutions have not yet framed AI as a competitive differentiator and still operate within the efficiency paradigm. The gap between current positioning and the competitive reality in Part 1 — AI-native entrants, fee compression, the incumbent's dilemma — is itself a strategic risk.

AI Transformation Readiness: The Convergence Matrix

Our research identifies not only where individual institutions stand, but what the cohort shares. Twenty-eight topics were coded across all institution interviews. The topics were bundled into four thematic clusters — Leadership and Adoption Dynamics, Governance and Operating Model, Workforce and Talent Strategy, and Competitive Edge and Future Positioning — each comprising seven component topics.

Topic Cluster	Ground Builder	Momentum Builder	Front Runner	All Institutions
AI Adoption Dynamics	65% STRONG	85% STRONG	95% HIGH	82% STRONG
Governance & Operating Model	55% MODERATE	80% STRONG	92% HIGH	76% STRONG
Workforce & Talent Strategy	45% EMERGING	72% STRONG	88% HIGH	68% STRONG
Competitive Edge & Future Positioning	35% EMERGING	62% MODERATE	90% HIGH	62% MODERATE

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Leadership & Adoption Dynamics, Governance & Operating Model, Workforce & Talent Strategy, and Competitive Edge & Future Positioning — seven topics each. The full topic list is in Appendix B.

The convergence matrix reveals a clear gradient: **as institutions mature, their engagement with the full breadth of AI transformation deepens systematically.**

Leadership and Adoption Dynamics is the strongest cluster across all tiers at 82 percent cohort-wide, confirming the primacy of leadership in driving adoption.

Competitive Edge and Future Positioning is the weakest at 62 percent — most institutions have not yet shifted from an efficiency framing to competitive positioning.

The steepest gradient is in Competitive Edge: Ground Builders at 35 percent versus Front Runners at 90 percent. This 55-point gap is the largest in the matrix and marks the strategic pivot that defines the transition from early to advanced maturity. Ground Builders are focused inward — on infrastructure, governance, and foundational adoption. Front Runners are focused outward.

The transition from inward to outward focus is the strategic inflection point of the maturity journey.

Four topics achieved universal convergence — leader-modeled AI adoption, AI governance as primary constraint, productivity-focused AI tools deployment, Succession pipeline disruption — and three near-universal: agile mindset predicting adoption, capability overhang, shadow AI. These six form the foundational layer of AI transformation in institutional investing, the issues every institution is confronting regardless of maturity, geography, or institution type.

5 Cross-Profile Strategic Applications

Regardless of maturity profile, five areas consistently produced the highest return on leadership attention across our research. They are not sequential. They operate in parallel. Think of them as a portfolio allocation decision applied to AI transformation.

1. Personal AI practice at the top. The single most consistent predictor of organizational AI momentum — the highest convergence score in the entire research. A senior leader who spends five minutes in a meeting describing how they used an AI tool to prepare — what worked, what produced errors, what they would do differently — creates measurable adoption acceleration within weeks.

2. Workforce planning integration. Treat AI capability as a talent and organizational design priority, not a technology roadmap item delegated to IT. Revised hiring criteria, skills-based restructuring, adoption metrics embedded in performance reviews.

3. AI governance as CIO-level strategic decision. Reframe governance from constraint to enabler. This shift separates institutions that advance from those that plateau. The convergence matrix confirms: governance topics appear at 76 percent cohort-wide, but the quality of governance varies more than any other dimension.

4. Embedded technical capability within investment teams. The forward-deployed engineer model. Centralize governance, federate execution. The institutions that embed AI talent in investment teams rather than technology departments capture more value from every deployment.

5. Build-buy-partner as portfolio discipline. Partnership for foundations. Internal build where proprietary data creates a moat. Deliberate vendor concentration risk management. Treated as a dynamic portfolio, not a procurement decision.

Transition Pathways and Sequencing

Moving from one profile to the next is not automatic. Each transition is governed by a specific binding constraint — and misidentifying that constraint is itself the most common cause of stalled progress.

Ground Builder → Momentum Builder: The Leadership Activation Threshold

With technology and governance well advanced, the next-stage opportunity is leadership activation: bringing investment committee workflows, board reporting formats, and senior leaders' personal practice into alignment with the AI capability the institution has built. The activation pathway is executive immersion — structured working sessions on real business problems, integration of AI use cases into existing executive routines, and explicit objectives that translate leadership commitment into the visible practice that converts infrastructure investment into operational return.

Momentum Builder → Front Runner: The Change Management Discipline

Deployment momentum creates an illusion of progress that can mask the absence of deep organizational change. One institution built a proprietary AI tool integrating earnings call transcripts, financial filings, and market data into structured investment analysis. Accurate, well-engineered, praised by early users. Six months later: near-zero daily usage. The tool existed. The workflows that would require its use did not.

Four conditions distinguish institutions that successfully make this transition:

1. Leadership at every level with individually measured AI adoption objectives,
2. AI capabilities embedded into workflow requirements rather than offered as optional supplements,
3. Incentive and performance evaluation structures redesigned to make AI use the path of least resistance,
4. Governance frameworks mature enough to enable agentic capabilities rather than constrain them.

> ***Adoption without workflow redesign is not transformation.***
> ***It is experimentation at scale.***

Structural Differences Across Institution Types

Institutions sharing a maturity profile may still face fundamentally different strategic realities. A pension fund at the Momentum Builder stage is driven primarily by operational efficiency and fiduciary obligation. An active asset manager at the same stage is driven by competitive survival — fee compression and AI-native entrants. The same profile points to different binding constraints, different risk calculi, and different highest-leverage interventions.

The playbook's recommendations account for these differences throughout.

Institutions inside larger corporate or banking-group structures face an additional consideration. Parent-level governance frameworks designed for balance-sheet risk and zero-tolerance operational cultures can sit awkwardly against the iterative nature of AI deployment. A governance approval process can extend over months for a tool that, by approval, has been superseded by a more capable alternative. This is not a compliance failure; it is a structural mismatch between the governance tempo of the parent and the deployment tempo of AI.

	Model A — Fragmented	Model B — Transitional	Model C — Integrated
Oversight	Reactive; unclear accountability	Defined but uneven roles	Strategic, embedded ownership
Risk	Identified after the fact	Structured but static	Predictive and dynamic
Human-AI	Ad hoc intervention	Rule-based oversight	Calibrated human–AI system
AI Literacy	Low awareness	Role-based capability	Organization-wide fluency

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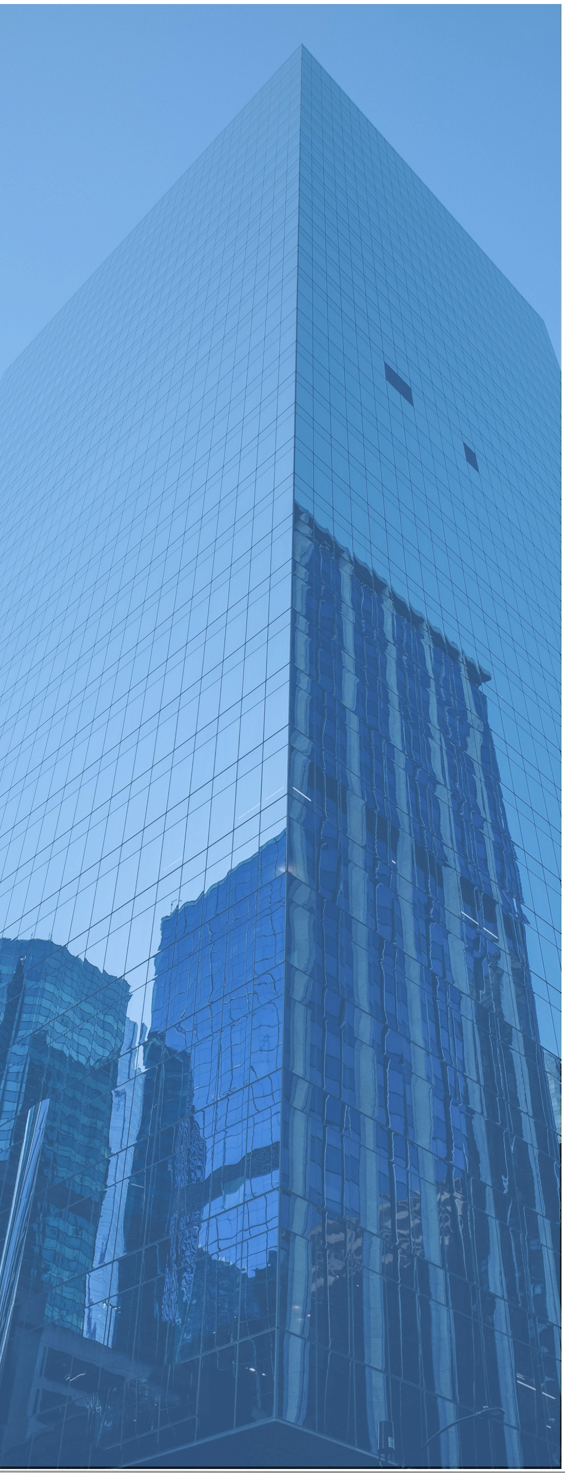
These governance models apply at organizational, functional, and individual levels simultaneously. A Front Runner can exhibit minimal-governance practice in specific functions, and frequently does. The most common pattern is a gap between aspiration and practice. Organizations aim for AI governance that is built into decisions and ahead of risks. In the functions, governance is formal but reactive — and in some pockets, no one yet owns it. Section 3 develops the full operating models in detail.

The greatest near-term governance opportunity across the sector lies in closing the gap between policy design and daily practice. Where oversight cadences and human-in-the-loop requirements exist on paper, the implementation question is whether they shape actual behavior under operational conditions. Institutions that close this gap convert governance from a compliance exercise into a strategic asset. Letter of the policy, met. Purpose of the policy, the opportunity.

The question for every board: What does governance look like in the daily practice of the people on your team? Not what the policy says. What actually happens.



Strategic Implications: The Diagnostic Architecture

The five dimensions of this framework do not operate in isolation. They form a diagnostic architecture and the institutions that read them as a system will extract more strategic value than those that treat each as a standalone metric.

The adoption depth deficit is the anchor. Near-universal tool access collapsing to single-digit transformational impact reveals that the constraint is organizational design, not technology. Every other finding in this section gains its significance in relation to this central diagnostic.

The profiles expose where the system is weakest under stress. Governance architecture and competitive positioning are the lowest-scoring dimensions for the largest cohort segment — Momentum Builders — confirming that deployment velocity has outpaced governance maturity. The gap is not administrative but fiduciary, and compounds with each ungoverned application added to the institutional inventory.

The convergence matrix shows where institutional attention has concentrated — and where it has not. Leadership and governance are the strongest clusters at 82 percent and 76 percent cohort-wide. Competitive positioning is the weakest at 62 percent. The pivot from efficiency framing to competitive positioning is the inflection point of the maturity journey, and it remains the weakest signal across the cohort.

Maturity itself is granular, not binary. A Front Runner can exhibit minimal-governance practice in specific functions. The framework is a diagnostic tool, not a scorecard — its value lies in surfacing the internal variation that aggregate labels conceal. Structural differences between institution types run through every dimension. Competitive dynamics, governance design, and transformation incentives differ materially by mandate, time horizon, and competitive context. The playbook's recommendations are calibrated to these differences throughout.

YOUR PLAY:
Maturity Self-Assessment

All Institutions

1. Score your organization across the six radar dimensions (Breadth, Depth, Governance, Workforce, Leadership, Competitive) using the 1–5 rubric provided.

2. Identify your maturity profile: Ground Builder, Momentum Builder, or Front Runner

3. For each dimension, assess whether you operate at Model A, B, or C governance — at the organizational, functional, and individual levels.

4. Identify the single binding constraint preventing your transition to the next maturity tier — this is your highest-leverage intervention point.

The Leadership Imperative and the

Behavioral Science of Adoption

3

One finding emerged with consistency across every institution studied, every geography, and every maturity tier: AI adoption is leader-led, or it does not happen. No amount of budget, tooling, training, or policy compensates for the absence of visible, behavioral leadership commitment.

AI Adoption Is Leader-Led or It Fails

The research identifies a J-curve of adoption: when the CEO and CIO together model AI use — not endorse it, not announce it, but visibly practice it in meetings, in decision-making, in daily work — the trajectory of workforce adoption accelerates, and anxiety decreases within measurable three-month windows. No other variable produces this combined effect.

The mechanism is behavioral, not managerial. When a senior leader opens a meeting by describing how they used an AI tool to prepare — what worked, what produced errors, what they would do differently — three things happen simultaneously. Professional legitimacy is conferred on AI use. Imperfection is normalized. And permission for experimentation is granted without the need for formal policy. Counter-intuitively, leaders who share failed AI experiments produce nearly as much adoption momentum as those who share successes.

This is psychological safety operating at the leadership level: when the most senior person in the room treats imperfect AI output as learning material rather than evidence of incompetence, the social cost of experimentation collapses for everyone else.[15-16]

The strength of this signal varies meaningfully across the cohort. One senior participant observed that leadership commitment to AI is most catalytic when it shifts from verbal endorsement into visible personal practice. Where commitment is expressed primarily through endorsement, adoption develops more slowly than where the same commitment is expressed through behavior.

This is the activation distinction — the opportunity to translate existing commitment into the practice that unlocks the organizational permission structure.

The behavioral dynamics are well understood: the design of AI deployment environments — how tools are presented, how defaults are set, how first experiences are structured — determines adoption outcomes more reliably than the technology itself.

Every AI recommendation interface is a choice architecture that predictably influences behavior.[17] Professionals default to fast, automatic evaluation of AI outputs, anchoring to first impressions, and systematically overweighting the risk of errors relative to equivalent gains. The result is a consistent preference for familiar methods over AI-assisted alternatives — even when the AI demonstrably outperforms.[18-21]

IN BRIEF

1 — Leader-Led and It Moves
When leaders practice AI visibly, adoption follows.
2 — Curiosity Is the Predictor
The best catalysts are already inside the organization.
3 — Four Levers Reframe identity. Redesign workflows. Recalibrate effort. Close the disposition gap.
4 — Fastest Value Available
2–4x gains at home already. The workplace gap is a design fix.
5 — Connected System
Permission → targeting → sequencing. It works as a chain.

> *Loss aversion is the dominant adoption barrier. The perceived risk of using AI — errors, exposure, identity threat — is systematically overweighted relative to the potential gains. Until the perceived cost of not using AI exceeds the perceived cost of using it, adoption will remain shallow regardless of tool access.*

The Learning Mindset Finding

The second finding that carries strategic weight demolishes one of the most common assumptions driving AI training programs: the assumption that adoption resistance is demographic. It is not. Curiosity, growth mindset, tolerance for uncertainty, and the habit of personal AI experimentation are the most consistent predictors of adoption success across the cohort. Age, seniority, and technical background are not predictive as such.[21-22]

Psychometric data from internal assessments at several institutions revealed a striking pattern: the professionals who scored highest on deep domain specialization — the organization's most experienced investment talent — scored lowest on learning agility. Conversely, professionals with moderate domain depth but high curiosity and cross-functional orientation were substantially further along the AI adoption curve.

The implication is that organizations designing AI training by demographic segment — millennials get advanced training, senior leaders get awareness sessions — are misallocating their investment. The evidence supports disposition-based intervention: identify the curious regardless of seniority, invest in them as adoption catalysts, and use their success to generate the social proof that pulls peers forward.

The behavioral science of organizational change offers a deeper explanatory layer.[23] Deep specialists resist AI adoption not out of ignorance or technophobia, but from a psychologically coherent immunity: their expertise is their identity, and the very system of beliefs and practices that produced their career success now actively resists the adaptation it requires.

This is not a training deficit. It is an identity challenge — and the intervention that addresses it is not more information but a structured process that surfaces the hidden commitments competing with the stated commitment to adopt. Organizations that design for this dynamic — rather than defaulting to skills-based remediation — produce more durable behavioral change.

Across institutions in this research, the individuals who emerged as internal AI champions were not the most technically proficient members of their teams. They were the ones operating across boundaries, treating disruption as a learning opportunity rather than a threat to established practice.

Four Behavioral Root Causes of Adoption Resistance

PCD's proprietary behavioral diagnostic tools and frameworks — built on more than 18 years of applied research across behavioral science, technology adoption, and institutional performance — identifies four interconnected root causes. Validated across the full cohort, these dynamics explain why AI adoption stalls and how to design interventions that address actual barriers rather than assumed ones.

Workflow identity lock-in. Professionals who have built their careers on specific analytical methods experience AI not as a productivity tool but as an identity threat. The sunk cost of expertise — years of developing a particular analytical approach — creates psychological resistance that rational argument cannot overcome. When a portfolio manager's self-concept is built around a specific research methodology, the suggestion that an AI system can perform that methodology is experienced as a challenge to professional identity, not as an offer of assistance.

Categorical misperception. Many professionals categorize AI as another tool in the same class as existing analytics platforms or risk management software. This framing dramatically underestimates the scope of transformation required and produces adoption behavior calibrated to a technology upgrade rather than a workflow redesign. The result: tool access without workflow integration — the capability overhang that characterizes the majority of the cohort.

Effort-reward miscalibration. The immediate cost of AI learning is concrete and visible; the future benefit is abstract and uncertain. This is present bias in its most practical form.[24] Most professionals who eventually become power users begin as struggling beginners. Our proprietary research identifies a 20-hour threshold: meaningful AI competence requires approximately 20 hours of deliberate practice, but most resistors abandon after a single unsuccessful attempt. The organizations that have crossed this barrier are those that structured the first 20 hours as guided experimentation, not self-directed exploration.

Technology disposition gap. Individuals differ in their baseline orientation toward new technology — from enthusiastic early adopters to deliberate skeptics. This disposition is stable across contexts and only weakly correlated with age or seniority. The practical implication: segmenting AI training by disposition rather than demographic category produces measurably faster adoption.

AI Adoption Barriers Matrix — Asset Management Ecosystems

These four behavioral root causes map onto a broader structural taxonomy of adoption barriers, organized by whether they originate internally or externally, and whether they are strategic or operational in nature.

AI Adoption Barriers Matrix

Executive Insight: The real constraint is misalignment across all four quadrants.

	◀ *Internal (People & Culture)*	*External (Systems & Governance)* ▶
Strategic (Long-term) ▲	**Talent & Culture** Internal / Strategic •Limited time to learn or upskill •Lack of targeted training & real use cases •Fear of job displacement or role redefinition •Risk of skill atrophy, cultural resistance	**Governance & Risk** External / Strategic •Lack of trust in AI outputs •Regulatory & fiduciary uncertainty •Cybersecurity & data privacy risks •Model risk & accountability gaps
Operational (Day-to-day) ▼	**Workflow & Value** Internal / Operational •Burden of validating AI outputs •Fragmented adoption across workflows •Unclear ROI and business case •Limited end-to-end process embedding	**Technology & Ecosystem** External / Operational •Legacy systems & data fragmentation •Maintenance & technical-debt concerns •Integration challenges with vendors •Limited interoperability & scalability

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The Capability Overhang and the Human-AI Contracting Paradox

The capability overhang is the gap between what AI tools can do and what organizations actually ask them to do. Professionals report capturing only a fraction of AI's productivity potential in the workplace, while using the same tools at home to achieve twofold to fourfold improvements on comparable tasks. The same technology. The same person. Radically different utilization.

This is the clearest indicator that institutional environments have not yet been configured to capture AI's full capability. The constraint is not the technology. It is the governance design, the permission structures, and the workflow designs that surround the technology within the institutional environment.

The capability overhang reveals the human-AI contracting paradox at the institutional level. AI's efficiency gains are real — but so are the oversight costs required to deploy it responsibly. Every AI-assisted decision in a fiduciary context requires a human who remains accountable: accountable for validating the output, accountable for the decision informed by that output, and accountable to the beneficiaries whose assets are at stake. **This accountability is non-delegable.**

No AI system, however capable, can bear full fiduciary responsibility. Named human individuals must remain in the chain of accountability, and maintaining that chain can partially offset the efficiency gains AI provides. This is not a failure of AI. It is a structural feature of fiduciary institutions that must be designed for, not wished away.

AI Adoption: Eight Stages from Manual Work to Autonomous Orchestration

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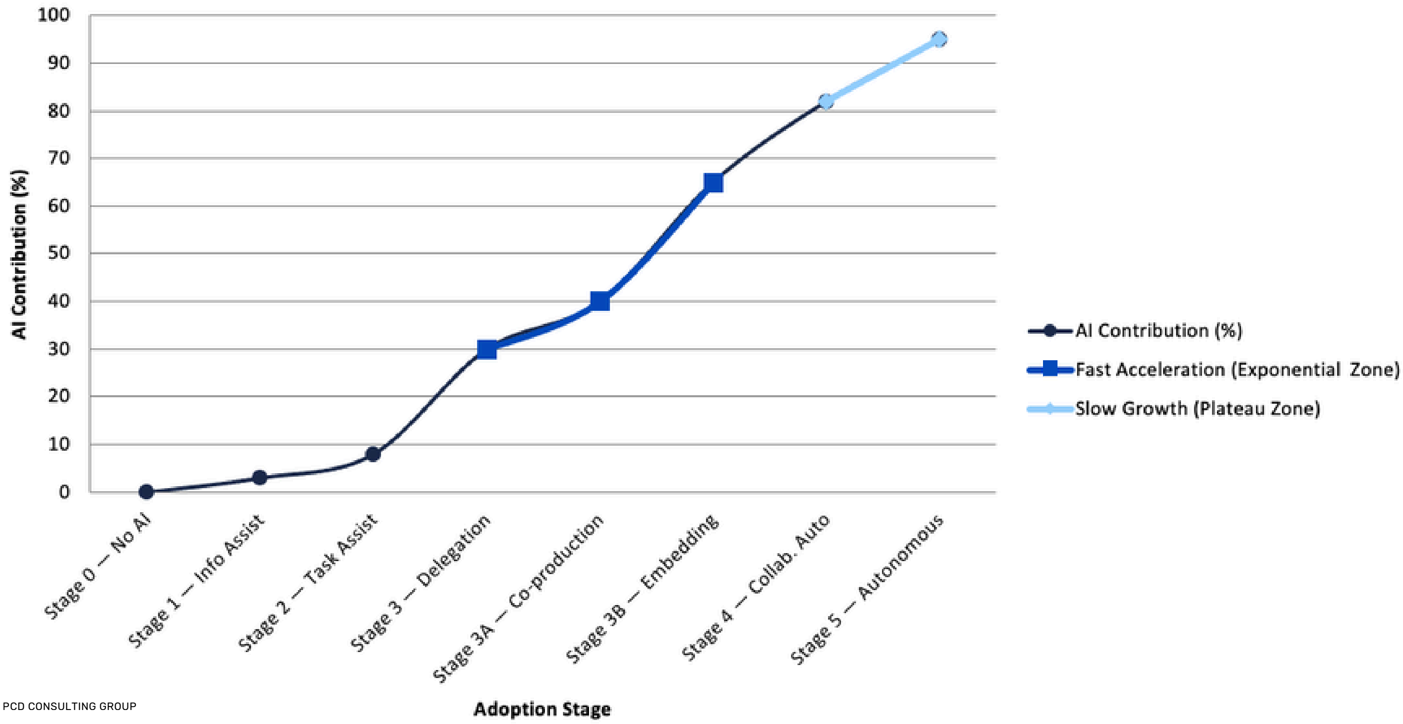
	TRADITIONAL	AI - ASSISTED					AGENTIC AI	
	STAGE 0 **Manual** *AI: 0%*	**STAGE 1** **Lookups** *AI: 1-5%*	**STAGE 2** **Drafts** *AI: 6-10%*	**STAGE 3** **Delegation** *AI: 30%*	**STAGE 3A** **Co-production** *AI: 30-50%*	**STAGE 3B** **Embedded** *AI: 50-80%*	**STAGE 4** **Collaboration** *AI: >80%*	**STAGE 5** **Autonomous** *AI: >95%*
AI ROLE	Absent	Queries Lookups	Drafts Suggestions	Near-final outputs	Real-time co-draft	Workflow participant	Co-pilot Multi-step	Self-initiates Sub-agents
HUMAN ROLE	Full ownership	Directs & applies	Reviews & edits	Prompts & checks	Steers direction	Governs & monitors	Sets goals & criteria	Oversight governance
VALUE	Baseline	Minimal uplift	Modest time save	Meaningful productivity	High quality jump	Enterprise gains	Step-change capacity	Systemic transform
BEHAVIORS	Loss aversion	Novelty bias	Confirmation bias	Automation bias	Rapid Acceleration	Identity shift	Plateau onset	Deep plateau

AI ADOPTION S-CURVE — BEHAVIOURAL & ECONOMIC DYNAMICS



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STAGES 0–2: SLOW INCLINE (0–10%)
Individual convenience only. Behavioral barriers dominate: loss aversion • status-quo bias • confirmation bias. No enterprise impact. Complementary investment not yet begun.

STAGES 3–3B: RAPID ACCELERATION (30–80%)
Steepest S-curve segment. Trust calibration → fluid human-AI collaboration. Cognitive offloading frees higher-order capacity. Role identity shifts. Each AI increment amplified by workflow redesign + top-down mandate.

STAGES 4–5: SLOW PLATEAU (80–95%+)
Constraint shifts: AI performance → human governance capacity. Dominant risks: automation bias • accountability diffusion • moral disengagement. Marginal AI gains require disproportionate oversight + ethics investment.

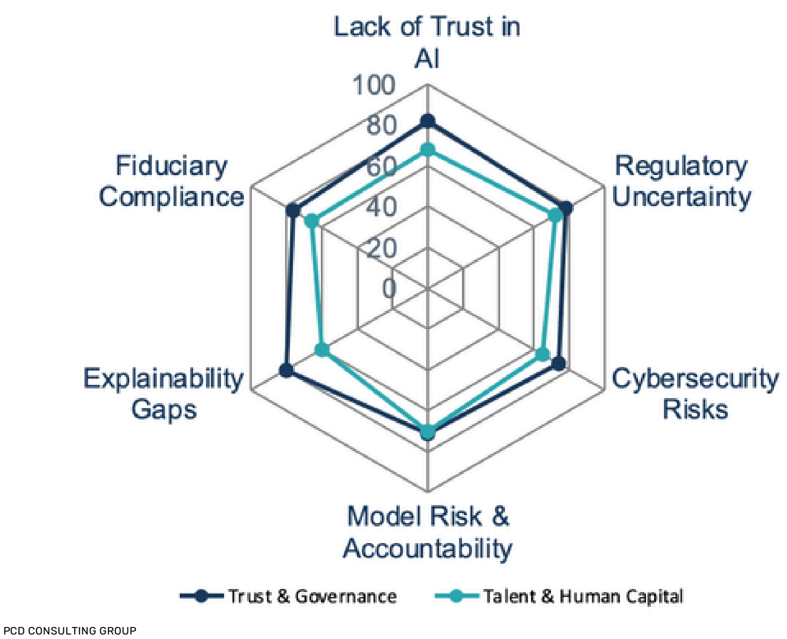
From Resistance to Fluency: Designing the Adoption Journey

The transition from no adoption to shallow use to deep use follows a well-established behavioral progression — organized around three binding constraints that shift as adoption matures.[25] At the no-adoption stage, the barrier is motivation: the perceived cost of trying exceeds the perceived benefit. At the shallow-use stage, the barrier is capability: professionals have access but lack the skill to extract value. At the deep-use stage, the barrier is trust: professionals can use AI effectively but do not yet trust it enough to integrate it into consequential decisions.

The institutions making the most progress have designed interventions matched to each stage. Safe-to-fail environments where the current error rate of AI systems is communicated not as a warning but as a trust-calibration signal — telling professionals precisely when and how much to verify, rather than leaving verification to instinct. Champion networks that create visible social proof by peer, not by policy. Microlearning integrated into existing meeting rhythms rather than delivered as standalone training programs. And choice architecture that makes AI the path of least resistance: pre-configured tools, default integration, and guided first experiences that compress the time from first use to first productive use.[26]

Barrier Severity Assessment: Radar Profile

Perceived severity of AI adoption barriers among institutional investors — based on ILN member interviews and cross-industry benchmarking.



How to Read

80-100: *Critical Barrier*
requires immediate governance action

60-79: *Significant Barrier*
targeted programs needed

40-59: *Moderate Barrier*
monitor and address over time

Below 40: *Emerging Barrier*
track but lower priority

The adoption journey maps directly onto the J-curve dynamics. The critical inflection occurs between Stages 3 and 3B — the zone where AI contribution moves from roughly 30 percent to 80 percent. This is where trust calibration unlocks fluid human-AI collaboration, where cognitive offloading frees capacity for higher-order reasoning, and where each increment of AI capability is amplified by organizational redesign. The institutions that reach this zone through deliberate, top-down workflow redesign generate substantially greater productivity gains than those that arrive through bottom-up experimentation alone.

Beyond 80 percent AI contribution, the binding constraint shifts from AI performance to human governance capacity: automation bias, accountability diffusion, and the risk of moral disengagement become the dominant challenges, and marginal AI gains require disproportionate investment in oversight and ethics infrastructure. The organizations that treat AI adoption as a technology deployment problem will capture a fraction of the available value. **The organizations that treat it as a behavioral design challenge — applying the same rigor to adoption design as they apply to investment decisions — will capture the rest.**

Strategic Implication: The Behavioral System

The behavioral dynamics documented in this section form a connected system — and institutions that treat them as such will outperform those that address them in isolation.

Leadership behavior activates the system. Without visible, practiced AI use at the senior level, the permission structure remains dormant — and every downstream investment in training, tooling, and governance produces diminishing returns. The J-curve is not one variable among many; it is the precondition on which all others depend.

Disposition-based segmentation determines where investment lands. The four root causes of adoption resistance — identity lock-in, categorical misperception, effort-reward miscalibration, and technology disposition gap — operate differently across populations. Institutions that design for this variation, rather than deploying uniform training, convert the same budget into measurably faster adoption.

The capability overhang reveals where value is being left on the table. The twofold to fourfold gap between home and workplace AI utilization is not a technology gap. It is a governance and workflow design gap — and closing it is the single fastest path to capturing value that already exists within the organization.

The J-curve defines the sequencing. Motivation at the base, capability in the middle, trust at the top. Institutions that design interventions matched to each stage accelerate through the inflection zone. Institutions that treat adoption as a single undifferentiated challenge stall at each transition and misdiagnose the cause. These four dynamics are the behavioral architecture of AI transformation.

The technology is available to everyone. The institutions that design the human system around it will determine who captures the value.

YOUR PLAY: Leadership and Adoption

Ground Builder

1. Launch a 90-day senior leadership AI immersion: structured sessions on real investment problems, sharing results (including failures) with direct reports

2. Identify your top 10% curiosity-driven professionals regardless of seniority — invest in carrying them past the 20-hour competence threshold

3. Conduct a shadow AI audit: quantify the home-vs-work capability gap and use findings to justify governed tool expansion

Momentum Builder

1. Embed adoption metrics in performance reviews for all people managers — measure behavioral AI use, not just tool access

2. Deploy disposition-based training: segment the workforce by learning agility, not demographics, and design interventions accordingly

3. Implement 'AI moments' as standing agenda items in leadership meetings — five minutes per meeting, shared experiments and learnings

4. Link AI adoption to financial incentives within performance evaluation frameworks — the behavioral rationale is that financial signals convert optional behavior into expected behavior, but the design must match institutional context: mandating usage without supporting capability produces compliance without adoption

Front Runner

1. Formalize champion networks with dedicated time allocation, measured impact, and career recognition

2. Design choice architecture audits for the three highest-value workflows: is AI the path of least resistance, or does using it require extra steps?

3. Build a trust calibration program: teach teams precisely when to verify AI outputs based on task type and risk tier, not instinct

4. Tie adoption depth metrics to leadership compensation — not as a blunt mandate, but as a governance signal that the institution treats AI transformation with the same seriousness as investment performance

Gender, Inclusion, and the AI Transition

4

This section addresses a structural finding with direct implications for the long-term talent pipeline of institutional investing. The pattern emerged independently across participating institutions with sufficient consistency to warrant dedicated analysis — not as a supplementary topic, but as a core dimension of the AI transformation challenge.

The Broken Rung and AI Displacement Convergence

Two structural dynamics are converging in institutional investing, and the convergence is occurring without deliberate design. Neither dynamic is new in isolation. Together, they constitute one of the most consequential talent pipeline risks the research has identified.

The broken rung

The first dynamic is the well-documented broken rung at the director level — the point in the organizational hierarchy where female representation drops sharply.

Several studies have documented this pattern across its membership: women enter the industry in proportions approaching parity at the analyst and associate levels, progress at or near parity through the first promotion cycle, and then encounter a structural narrowing at the director and principal tier.

The OMFIF 2025 Gender Balance Index confirms the pattern across the broader financial sector: fewer women in senior and revenue-generating roles create a bottleneck for leadership progression that has persisted despite sustained institutional attention.[27]

The AI displacement dynamic

The second dynamic is the AI automation risk profile, which concentrates near-term displacement pressure on precisely the analytical, process-oriented roles that women disproportionately hold at the director tier. These are the roles responsible for structured analysis, report preparation, compliance coordination, portfolio monitoring, and client communication — tasks where AI's current capability is strongest and where the productivity compression documented throughout this playbook is most advanced.

IN BRIEF

1 — Two Forces Converging
Broken rung meets AI displacement. Multiplicative effect.

2 — Parity Today
Senior women use AI at parity — but they're a filtered group.

3 — Not Self-Renewing
Today's parity can fade without action.

4 — Framing Matters
Capability framing broadens adoption. Headcount framing opens the gender gap.

5 — Measure or Miss
Aggregate averages hide the risk. Disaggregate.

When the two forces converge

When these two forces compound without intervention, the effect on the leadership pipeline is not additive but multiplicative. The pool of professionals positioned for senior leadership narrows at the same moment that the roles providing their current foothold are being transformed by AI.

The broken rung becomes a broken pipeline — not through any single decision, but through the accumulated effect of undesigned technological change operating on a structure already weakened by existing patterns.

The evidence from the research indicates that this convergence is recognized by a significant proportion of participating institutions but actively managed by very few. The gap between awareness and action aligns with the broader behavioral pattern documented throughout this playbook: institutions frequently identify structural risks accurately but underinvest in the organizational design required to address them.

The behavioral science explanation is straightforward: the convergence risk is abstract, long-horizon, and probabilistic; the competing demands on leadership attention are concrete, immediate, and measurable.

The long-horizon risk will be systematically underweighted relative to immediate operational pressures — and that is exactly what the research observes.

The structural distinction between institution types applies with particular force here. Institutions with longer time horizons and governance cultures oriented toward institutional sustainability are better positioned to invest in pipeline preservation over decade-plus horizons. Institutions facing shorter performance cycles and more intense competitive pressure are more likely to optimize headcount in ways that accelerate the convergence risk. Both face the same structural dynamic; the institutional capacity to respond differs markedly.

The Convergence

The Broken Rung: *Women enter at near parity (47%) and progress through first promotion cycles, then encounter a structural narrowing at the director and principal tier - dropping to 22%. This pattern has persisted despite sustained institutional attention.*

AI Displacement Risk: *Near-term displacement pressure concentrates on analytical process oriented roles - where AI capability is strongest and where women are disproportionately represented at the director tier.*

Governance Implication: *When these forces compound without intervention, the effect is not additive but multiplicative. The pool of professionals positioned for senior leadership narrows at the exact moment their current roles are being transformed by AI.*

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AI Displacement Risk by Role Type

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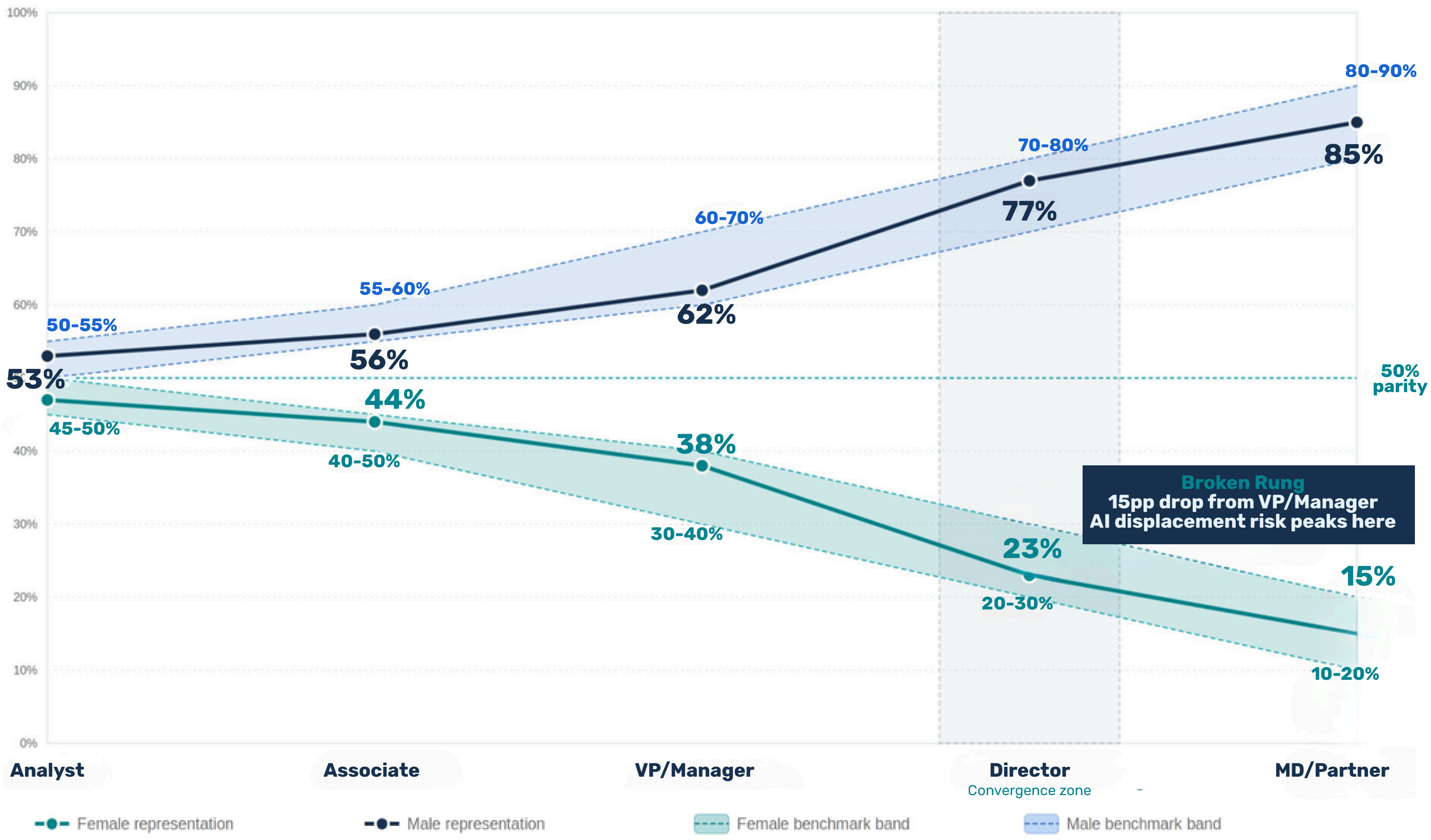
Female Representation Across Career Pipeline



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1. **Education in mathematics, computer science, or finance** — fields where self-selection already skews toward risk tolerance and analytical confidence.[28]
2. **Entry into finance** — where networks and demonstrated credibility matter disproportionately at the hiring stage.
3. **The broken rung** — first promotion to manager, the sharpest single drop in female representation, where the gap opens decisively.[29]
4. **Mid-career retention through what research terms the motherhood penalty** — the documented drop in earnings, advancement probability, and performance evaluation scores that accompanies parenthood for women but not men in professional environments.[30]
5. **The senior-to-director cut** — the second structural narrowing documented across the sector.
6. **C-suite and investment leadership** — where female representation reaches its floor, at approximately 18 percent across the sector.

Combined, these filters mean that only a small and highly selected population reaches senior roles in finance. That selection process changes the behavioral profile of the group that remains — in ways that are directly relevant to AI adoption.

Our finding
No gender gap detected in AI use

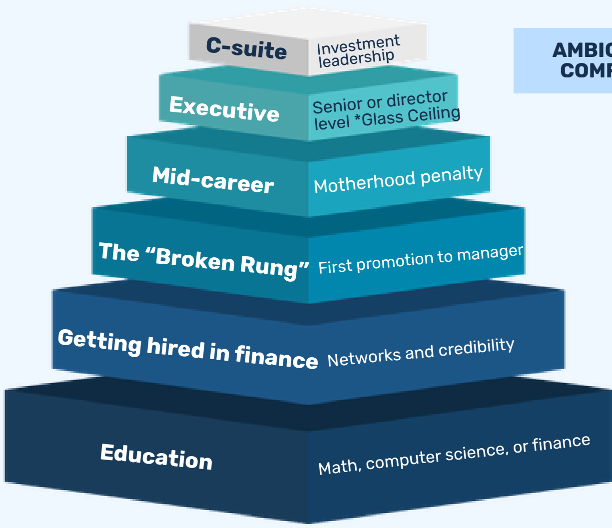
Why this happens

The Survivor Effect

The women we see have already passed through many career filters.
Each filter removes a non-random group.
Combined, only a small, highly-selected group of women reaches senior roles.

Structural Process

Six sector-specific filters women pass through



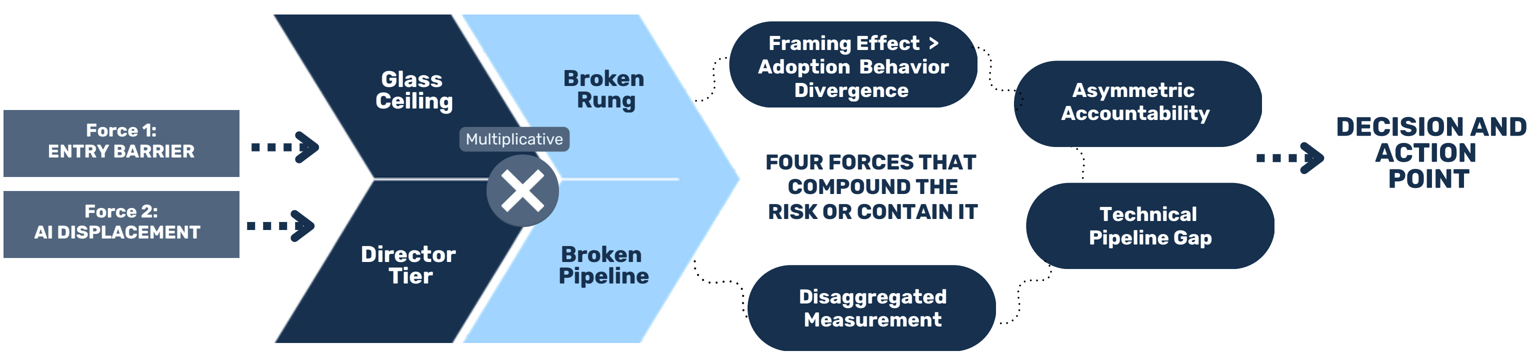
Structural Traits

Behavioral characteristics explaining

- AMBIGUITY COMFORT
- NEGOTIATION WILLINGNESS
- HABITUATED NEED FOR EVIDENCE
- RISK TOLERANCE
- PERSISTENCE
- LESS OVERCONFIDENT
- MORE LIKELY TO ANSWER "DON'T KNOW" THAN GUESS
- MORE CAUTIOUS VERIFYING AI OUTPUT

This is an advantage in high-stakes judgment domains.

The Incoming AI Transition Risk



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Three mechanisms that explain why the selected population shows parity

The risk-perception driver switches off. The gender gap in AI adoption documented in the general population is driven by risk perception, not capability. Women who have reached senior roles in institutional investing have navigated the same competitive, high-variance environments as their male counterparts. The trait that drives the broader gap is simply not operating in this population — the career path has already filtered for it.

Evidence-production habits meet an evidence-generating tool. Senior women in finance are typically promoted on demonstrated performance; men more often on perceived potential. The practical consequence is that women at each career stage have assembled more structured evidence than male peers to obtain equivalent credibility. Generative AI produces structured evidence on demand. The alignment between user habit and tool capability is unusually tight, and this group extracts more value from the tool than populations whose prior workflow did not depend on structured evidence assembly.

The institutional environment matters. ILN member firms have cleared a higher governance bar than the sector average. Willingness to experiment in public depends on the perceived cost of visible failure. The asymmetric penalty for AI-assisted errors documented in the broader literature — where women face higher scrutiny for the same mistakes — is partially neutralized by the governance environments these institutions have built.

A strength worth naming: calibration as an asset
Women in finance and technology contexts consistently demonstrate stronger calibration between self-assessed and actual knowledge — less prone to overconfidence, more likely to verify AI output before acting on it, more likely to acknowledge uncertainty rather than project false confidence.

In the general-population literature, this trait sometimes reads as slower or more cautious adoption. In institutional investment — where the most expensive errors come from overconfident judgment, and where the published evidence shows female fund managers achieve equivalent average returns with less extreme portfolio positioning — this same calibration reads as higher-quality AI integration.

> ***The caution is a feature, not a lag. Institutions that measure AI adoption by volume of use rather than quality of judgment may systematically misread this pattern.***

Why the current parity is fragile

The parity observed at ILN member firms is real and welcome. It is also not self-renewing. The junior cohorts below the six filters reflect the general-population pattern. If the adoption gap documented in the broader literature compounds through five to ten years of promotion cycles, the senior parity observed today will quietly disappear — because the junior cohort being promoted into senior ranks will carry the differential AI fluency that the broader literature documents.

The finding is a reassuring snapshot and a pipeline warning simultaneously. It describes a current strength that depends on active management to persist.

Adoption Behavior Divergence by Gender

The findings below apply to the general workforce and junior cohorts — the pipeline from which tomorrow's senior talent is drawn, not the senior ILN cohort where parity has been established. These dynamics matter because they determine whether today's parity is preserved, and the mechanisms they reveal apply at every level.

The external evidence base for gender divergence in AI adoption has grown substantially in recent years, and the patterns observed in our research are directionally consistent with, and further build upon, findings from large-scale studies across industries and geographies. A large-scale meta-analysis synthesizing 17 studies encompassing approximately 140,000 individuals finds that women use generative AI 10 to 40 percent less than men.[31] The gap is driven by risk perception, not skills. A 2026 study surveying approximately 3,000 respondents in the United States and Canada confirms the pattern with additional granularity: women are approximately 20 percent less likely to use generative AI at work, with the gap driven by two factors — women's greater general risk aversion and women's higher perceived exposure to AI-related employment risks.[32]

The experimental part of this research is especially revealing for institutional investors. As the probability of net job losses from AI increases, women's support for adoption falls more steeply than men's. When AI is framed as creating jobs, the gender gap narrows significantly. When framed as potentially eliminating jobs, women's support drops sharply while men's remains stable. This is a framing effect, not a capability difference — and it has direct design implications for how institutions communicate AI transformation.

Across participating institutions, a directionally consistent pattern with the external evidence was observed. Women may adopt AI more readily when the transformation is framed as professional empowerment expanding capability, improving decision quality, enabling higher-value work but disengage more quickly when the same transformation is framed as headcount reduction or efficiency extraction. The framing of AI communications is therefore not a messaging exercise; it is a design variable that directly affects the breadth and equity of adoption across the workforce.

The asymmetric accountability dynamic adds a further dimension that the research surfaced at multiple institutions.

Research on gender and professional accountability consistently shows that errors made with new technologies are attributed differently depending on the professional's gender. In AI-assisted investment decisions, the observational evidence suggests that this asymmetry may create a rational disincentive for risk-averse adoption among women not because of lower capability, but because the professional consequences of an AI-assisted error are perceived as greater. A portfolio manager who uses AI and makes a correct call receives the same credit regardless of gender. A portfolio manager who uses AI and makes an error may face differential scrutiny. Under these conditions, the rational decision for a professional who perceives higher scrutiny is to adopt less aggressively — not because they cannot use the tool, but because the risk-reward calculus is structurally different.

The productivity gap risk. Emerging evidence on AI's impact on professional productivity documents a concrete divergence: men's research productivity increased measurably more than women's following the release of generative AI tools, widening an existing gap.[33] Whether AI ultimately delivers net benefits or harms, those who engage with these technologies accumulate different skills, networks, and opportunities than those who abstain creating new axes of occupational differentiation independent of the technology's ultimate success or failure.[34] For institutional investors, allowing differential AI adoption to compound into differential career outcomes over a five-to-ten-year horizon is a governance failure that erodes the breadth and quality of the senior talent pool.

The Technical Pipeline Gap, Governance Design

Female representation in technical AI roles remains low across the financial sector, despite strong adoption behavior in business functions. This gap creates a governance risk that extends beyond workforce composition: when the teams designing AI systems, selecting training data, and defining algorithmic parameters are homogeneous, the resulting systems are more likely to encode and amplify existing patterns.

Research on algorithmic bias consistently demonstrates that systems not tested for differential impact across groups will reproduce and amplify the very patterns they were intended to improve upon. The logic applies with full force to institutional investing, where AI is increasingly used in hiring, promotion, compensation, performance evaluation, and client allocation decisions.[35-37]

The governance implication is direct. AI systems used in people-facing decisions hiring, promotion, compensation, performance evaluation, and workforce planning must meet fairness standards at least equivalent to those applied to human decision-making processes. The academic literature on behavioral design for institutional fairness, including the work of Cecchi-Dimeglio and also of Bohnet, offers a framework: structural system-level interventions, rather than relying on individual awareness, lead to more durable and scalable outcomes.[38-39] For institutional investors, these findings point toward several governance considerations worth examining. Regular audits of people-facing AI applications — with results reported to the AI governance committee — help ensure that algorithmic decisions meet the same standards applied to human decision-making. Broad representation on AI governance committees and tool selection processes serves as a structural safeguard against design blind spots. And explicit fairness standards for algorithmic decisions, monitored with the same discipline as financial compliance, provide the accountability architecture that fiduciary environments require.[40]

A further dimension deserves attention. If the oversight costs of AI-assisted decisions are distributed unevenly across the workforce, and if some professionals face higher scrutiny for AI-assisted errors, then the efficiency gains of AI may not be evenly captured.[41] The institution benefits from the productivity of AI-assisted work while the individual professional bears a disproportionate share of the accountability risk.

This asymmetry does not surface in aggregate adoption metrics. It becomes visible only when adoption data is disaggregated by gender, function, and seniority, which is why disaggregated measurement deserves consideration not as an optional enhancement to the KPI framework, but as an integral part of understanding how AI is operating across the organization.[42-43]

Strategic Implications: The Pipeline Architecture

The dynamics documented in this section are not independent observations. They form a connected risk architecture and the institutions that treat them as such will protect capabilities that those addressing them in isolation will lose.

The broken rung and AI displacement convergence is the structural foundation. It establishes the pipeline risk that every other finding in this section amplifies. Without this convergence, the adoption behavior gap would be a workforce analytics observation. With it, the adoption gap becomes a compounding force that narrows the leadership pipeline from two directions simultaneously.

Adoption behavior divergence is the transmission mechanism. The framing effect empowerment versus headcount reduction is not a communications challenge. It is a design variable that determines whether the convergence risk accelerates or decelerates. Institutions that frame AI transformation as capability expansion will sustain broader adoption. Institutions that frame it as efficiency extraction will lose the very professionals whose progression through the pipeline is already structurally constrained.

The technical pipeline gap is the governance vulnerability. Homogeneous teams building AI systems for heterogeneous workforces produce systems that encode the patterns the institution should be correcting. Structural safeguards — audits, representation, fairness standards are not compliance additions. They are the governance infrastructure that prevents AI from amplifying the very risks it was deployed to manage. Disaggregated measurement is the diagnostic that makes the system visible. Aggregate adoption metrics conceal the differential patterns that drive the convergence risk. Until adoption data is disaggregated by gender, function, and seniority, the risk architecture remains invisible to the governance bodies responsible for managing it.

> *The institutions that proactively address the gender-AI convergence are protecting their leadership pipeline, their governance integrity, and their adaptive capacity over the decade-plus horizons that define fiduciary obligation.*
>
> *The institutions that do not will discover the cost of inaction compounding silently in a narrowed talent pool, in governance blind spots, and in competitive disadvantage that becomes visible only when it is too late to reverse.*

YOUR PLAY:
Talent Pipeline Architecture

Ground Builder

1. Frame all AI communications as professional empowerment and capability expansion — test messaging across workforce segments before deployment to ensure the framing sustains broad adoption

2. Establish baseline workforce analytics disaggregated by gender, function, and seniority to identify differential adoption patterns early

3. Ensure broad representation on AI governance committees and tool selection processes as a structural safeguard against design blind spots

Momentum Builder

1. Conduct a convergence risk assessment: map the overlap between mid-career pipeline data and AI automation exposure by role tier to identify where the two dynamics compound

2. Design adoption support programs that address risk-perception barriers specifically, with structured experimentation environments calibrated to the populations where adoption is still developing

3. Implement regular audits for all people-facing AI applications (hiring, performance evaluation, promotion) with results reported to the governance committee

Front Runner

1. Build a succession pipeline preservation framework that explicitly accounts for the convergence of structural workforce patterns and AI displacement over a five-year horizon

2. Establish fairness standards for AI-assisted decisions that are monitored and enforced with the same rigor as financial compliance

3. Establish internal reports on AI adoption rates and AI-assisted decision outcomes, disaggregated as a governance quality signal

An Integrated Framework

Data and AI Governance

5

AI governance emerged as the primary implementation constraint. This section outlines the governance framework that the research indicates yields the most effective results — governance viewed not as a mere compliance layer, but as the organizational operating system that facilitates confident, scaled deployment in fiduciary contexts. The distinction matters: institutions that treat governance as a constraint deploy slowly, govern reactively, and accumulate ungoverned risk. Institutions that treat governance as an enabler deploy confidently, govern proactively, and build the institutional trust that accelerates adoption.

Governance Foundations: Data Governance and AI Governance Distinguished

Most institutions arrived at AI governance through existing data governance frameworks — a logical starting point, but not the final destination. The distinction between these two domains must be maintained with analytical precision, because conflating them produces governance designs that address one challenge while leaving the other unmanaged.

Data governance addresses the asset: is the information accurate, provenance-documented, and compliant with regulatory requirements? Is lineage traceable from source to decision? It is the foundation — necessary, well-understood, and increasingly mature across the cohort.

AI governance addresses the actor. Are the decisions made by or with AI accountable? Are they auditable and appropriately risk-tiered? Is there a named human in the accountability chain for every consequential AI-informed decision?

Can the institution explain, to a regulator, a beneficiary, or a board, why a particular AI-assisted decision was made and who is responsible for its outcome? AI governance requires distinct ownership, distinct frameworks, and tiered risk calibration.

A minority of institutions in the cohort have AI governance frameworks that are clearly distinguished from their data governance infrastructure.

IN BRIEF

1 — Constraint or Operating System
Governance as enabler deploys faster with less risk.
2 — Two Distinct Disciplines
Data governance manages the asset. AI governance manages the actor.
3 — Four-Tier Risk Model
Calibrate governance burden to decision consequence.
4 — Policy vs. Practice
Leaders overestimate governance maturity by a full tier. Design fixes it, not more policy.
5 — Six Principles Hold Across Jurisdictions
Regulation is fragmenting. Six governance principles provide a stable framework regardless.

The shift from control-oriented governance to AI-enabling governance is observable in the language institutions use. Institutions with fragmented governance talk about what AI is not allowed to do.

Institutions with integrated governance talk about what governance makes possible — producing a trusted pathway that professionals can navigate with confidence and governance teams can monitor without becoming bottlenecks.

The Four-Layer Architecture

The governance architecture operates across four layers, each with distinct accountability, AI governance requirements, and behavioral dynamics. Across these layers, 12 areas of AI governance require explicit, structured attention.

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Layer 1: Board and Trustees — fiduciary oversight of AI strategy, risk appetite, and the AI literacy required to exercise meaningful oversight.

Layer 2: C-Suite and AI Committee — strategic direction and cross-functional coordination, with the CIO as the governance architect.

Layer 3: Business Units and Risk Functions — operational governance where the design-enactment gap is most acute, with governance burden proportionate to decision consequence.

Layer 4: Technology and MLOps — model lifecycle governance, continuous monitoring, drift detection, and vendor accountability.

Governance is not the brake. Governance is the road. The institutions that conceptualize governance as the architecture enabling confident, scaled deployment will systematically outperform those that treat it as a gate to pass through, a checklist to complete, or a compliance burden to minimize.

The reframing from constraint to enabler is the single most important strategic shift in this domain and the institutions that have made it are measurably further along the adoption curve.

12 Areas of AI Governance

These 12 areas are derived from the governance challenges institutions in this research actually confront, the regulatory requirements they face, and the behavioral dynamics that determine whether governance translates from policy into practice.

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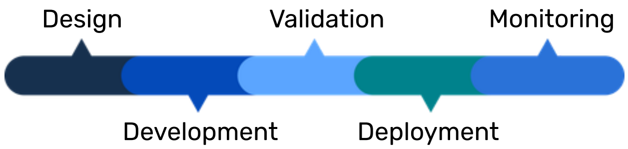
AI Risk Tiering and Model Lifecycle Governance

The most operationally mature institutions in the cohort have moved to a four-tier risk classification for AI applications. The tiering is not a theoretical exercise; it is the operational mechanism that determines the governance burden for each AI deployment, making governance proportionate to consequence rather than uniform across all applications.

The four tiers calibrate governance to consequence: Tier 1 (Critical) covers investment decisions with direct portfolio impact — requiring the most rigorous oversight. Tier 2 (High) covers client-facing and regulatory applications. Tier 3 (Medium) covers internal productivity and research support. Tier 4 (Low) covers personal productivity and information retrieval.

The five-phase model lifecycle — design, development, validation, deployment, monitoring — requires governance at each phase.



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The most common failure mode is governance concentrated at the deployment gate: a thorough review before launch, followed by minimal ongoing monitoring.

AI systems drift. Training data ages. External conditions change. An AI model that was well-calibrated at deployment may produce systematically different outputs six months later. Continuous monitoring with defined drift thresholds and automated alerting is the minimum standard for Tier 1 and Tier 2 applications.

One Front Runner institution is developing a graduated trust framework for agentic AI — systems that take actions, not just provide analysis. This represents the frontier of institutional AI governance. Narrow-parameter agents, operating within tightly defined decision boundaries, receive limited human oversight with automated monitoring. Broad-latitude agents, with authority to take actions with wider consequences, operate under full human accountability with real-time oversight.

The override rate (the frequency with which human operators override AI recommendations), is treated as a leading indicator. Too high suggests the AI system is miscalibrated or the use case is mismatched.Too low suggests that humans have ceded judgment to the system, a governance risk that may not manifest until the system produces a consequential error.

Governance Maturity: The Behavioral Dimension

The governance maturity spectrum — from minimal-governance through formal-but-reactive to integrated-proactive — takes on its fullest analytical significance through the behavioral lens. AI governance maturity is defined not by the existence of policies but by how consistently governance shapes actual behavior.

Two organizations can have comparable frameworks on paper and deliver fundamentally different outcomes in practice.

The critical distinction is between governance as designed and governance as enacted. The gap between the two is the single most diagnostic variable in the governance framework.

Three behavioral dynamics explain why the design-enactment gap persists. Motivation barriers — low salience and status quo bias — cause governance to be deprioritized relative to investment deadlines. Capability barriers — friction and cognitive load — cause well-intentioned processes to be simplified under time pressure. Trust barriers — professional identity threats and permission bias — cause formal compliance while substantively bypassing governance requirements.

Industry-wide evidence consistently shows that human-in-the-loop requirements, even when formally documented, are vulnerable to practical dilution under time pressure — output review compressing from substantive evaluation to brief error-scanning. This pattern is corroborated by the broader academic literature on automation bias, and is not uncommon across institutional settings where deployment pace has outrun governance design.

Behavioral Interpretation

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Model A - Fragmented System

BEHAVIORAL PATTERN
- Reactive, silenced decision-making
- Ownership unclear and shifting
- Governance perceived as constraint

WHAT IT LOOKS LIKE
- AI initiatives emerge bottom-up
- Limited unity across business, IT, and HR
- Employees experience ambiguity and inconsistency

KEY RISKS
- Hidden exposure
- Misaligned decisions
- Low Trust

LOW MATURITY

Model B - Transitional System

BEHAVIORAL PATTERN
- Structured but partially aligned
- Governance framework exists but unevenly applied

WHAT IT LOOKS LIKE
- Policies and roles defined
- Tension between innovation and control
- Execution gaps across functions

KEY RISKS
- Governance fatigue
- Over-standardization
- Cross-functional friction

MID MATURITY

Model C - Integrated System

BEHAVIORAL PATTERN
- Governance as a strategic capability
- Coordinated, system-wide decision-making

WHAT IT LOOKS LIKE
- AI embedded in strategy and operations
- Alignment across business, IT, and HR
- Employees understand roles and boundaries

KEY STRENGTHS
- Scalable trust
- Faster and better decisions
- Organizational resilience

HIGH MATURITY

AI Governance Maturity Matrix

(see also appendix)	Model A — Fragmented *Reactive, Siloed, Low Trust*	Model B — Transitional *Structured, Partial, Improving*	Model C — Integrated *Strategic, Embedded, Resilient*
Oversight & Accountability	Reactive ownership; unclear accountability	Defined but uneven roles	Strategic, embedded ownership
Risk Management	Risks identified after the fact	Structured but static approach	Predictive and dynamic risk management
Documentation	Incomplete and inconsistent	Standardized but siloed	End-to-end traceability
Human Oversight	Ad hoc intervention	Rule-based oversight	Calibrated human-AI system
Transparency	Minimal and reactive	Policy-driven disclosures	Trust-driven, proactive transparency
Data Governance	Fragmented practices	Managed but not unified	Lifecycle-based governance
Testing & Validation	Late and inconsistent	Periodic validation	Continuous validation
Incident Management	Crisis-driven response	Formal processes exist	Predictive and resilient
Supply Chain Governance	Limited visibility	Controlled vendors	Ecosystem-wide governance
AI Literacy & Culture	Low awareness	Role-based capability	Organization-wide fluency
Compliance Monitoring	Sporadic checks	Regular reviews	Continuous monitoring
Enforcement Awareness	Reactive to events	Monitored environment	Anticipatory positioning

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> *The question is: what does governance look like in daily practice — not what the policy says, but what actually happens when professionals use AI tools in their work? The distance between that answer and the answer your governance framework assumes is your institution's most important governance variable.*

AI Governance Maturity Matrix

The most valuable diagnostic in the research is the calibration opportunity between leadership's view of governance maturity and the operational evidence revealed by audits and practitioner interviews. Where governance conviction leads measurement systems, a meaningful calibration opportunity emerges — one that, once addressed, converts governance maturity into a demonstrable and sustainable strategic advantage for institutions that move deliberately.

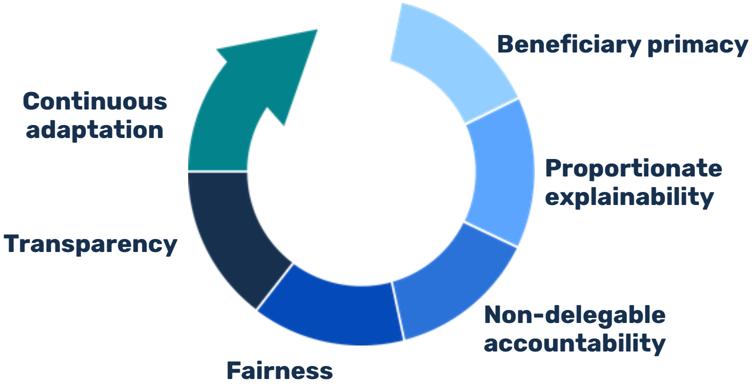
This perception-reality alignment is not a communication exercise; it is a governance design opportunity. The decisions being made at the leadership level anticipate a governance infrastructure that the operational level is still building. Closing the alignment requires not more policies but better behavioral design: making the governed behavior easier, more salient, and less psychologically costly than the ungoverned alternative.

Regulatory Landscape and Governance Principles

The regulatory environment for AI in institutional investing is fragmenting along jurisdictional lines in [44-45] ways that directly shape deployment architecture. For institutions operating across multiple geographies, the fragmentation is not merely a compliance cost. It is a strategic variable that shapes the feasibility of AI-enabled investment strategies.

Regulatory exposure varies by institutional structure, mandate, and geography. Institutions with public governance mandates face transparency and political accountability requirements. Institutions within banking group structures inherit prudential requirements that may constrain the experimental deployment of AI. Independent institutions face lighter regulatory governance but correspondingly greater competitive pressure to deploy at pace. The governance architecture must account for these structural differences without creating separate systems that fragment institutional oversight. [46-47]

Six governance principles emerged from the research as the foundation for AI deployment in institutional investing. These are not abstract values; they are design considerations that institutions at the forefront of this transformation have found effective in structuring governance decisions.



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> *Data sovereignty is emerging as financial sovereignty. Institutions operating across jurisdictions face an increasingly fragmented regulatory landscape that directly shapes the architecture of AI deployment. The institutions approaching data sovereignty as a geopolitical and strategic risk factor — rather than a legal compliance exercise alone — are the ones positioning most effectively for the next decade of institutional investing.*

Strategic Implications: The Governance System

These governance dynamics form a connected system — and institutions that treat them as such will build the infrastructure on which sustained AI value capture depends.

The data-AI governance distinction is the foundation. Institutions that conflate the two leave decision accountability unmanaged even when data quality is well governed. Separating the two — with distinct ownership, distinct frameworks, and distinct reporting — is the precondition for everything that follows.

The four-layer governance design determines where governance is exercised. Board-level AI literacy, CIO-level governance ownership, business-unit risk tiering, and technology lifecycle monitoring each address a distinct dimension of the challenge. Institutions where all four layers are active and coordinated deploy faster, with less ungoverned risk.

The risk tiering framework makes governance proportionate. Uniform governance produces over-governance of low-risk tools and under-governance of high-risk applications. The four-tier classification resolves this — and institutions that have implemented it report both faster deployment and stronger risk management.

The behavioral dimension reveals whether governance is functioning. The perception-reality audit — comparing leadership's assessment of governance maturity against operational evidence — is the single most revealing diagnostic in this research. Institutions that have conducted it consistently discover that the gap is wider than assumed.

The regulatory landscape defines the boundaries within which governance must operate. Jurisdictional fragmentation is a design constraint, not merely a compliance cost. The six governance principles — beneficiary primacy, proportionate explainability, non-delegable accountability, fairness, transparency, and continuous adaptation — provide the decision framework that holds across jurisdictions even as specific requirements diverge.

> *Governance is the binding constraint on AI value capture in institutional investing. The institutions that build governance as an enabling architecture — proportionate, behavioral, adaptive, and embedded in daily practice — will capture the value. The institutions that treat governance as a compliance layer will continue to deploy tools without transforming outcomes.*

YOUR PLAY: Governance Architecture

Ground Builder

1.Distinguish data governance from AI governance explicitly — assign separate ownership, separate frameworks, and separate reporting lines

2. Implement a four-tier AI risk classification for all current AI applications, with documented human-in-the-loop standards per tier

3. Conduct a governance perception-reality audit: survey leadership on governance maturity, then compare against operational evidence

Momentum Builder

1. Complete a full AI tool inventory with documented function, ownership, data sources, and audit history for every application in use

2. Establish a quarterly governance review cycle that escalates the override rate as a leading indicator to the AI committee

3. Build a regulatory compliance map across all jurisdictions in which you operate — identify constraints and opportunities by product and geography

Front Runner

1. Design a graduated trust framework for agentic AI: narrow-parameter agents with limited oversight versus broad-latitude agents with full human accountability

2. Implement continuous model monitoring with automated drift detection and defined escalation protocols

3. Develop board-ready AI governance reporting: quarterly dashboards covering all 12 governance areas with trend analysis

Workforce, Talent, and Succession

6

The workforce implications of AI in institutional investing are no longer projections. They are observable, accelerating, and producing organizational design challenges that existing talent frameworks were not built to address. This part moves from diagnosis to design: operating model restructuring, shadow AI governance, talent strategy for an AI-transformed investment function, and the succession challenge that AI is creating at the entry level of the investment profession.

Operating Model Shifts Required for AI Adoption

The highest-performing institutions in this research are not adding AI to existing operating models. They are redesigning operating models around AI-enabled workflows. The distinction is the difference between AI-Enabled and AI-First organizations and it requires fundamentally different investment sequencing, organizational architecture, and leadership commitment. [48]

An AI-Enabled organization layers technology onto existing structures. Workflows remain essentially unchanged; AI accelerates specific tasks within them. The organizational chart looks the same. The governance architecture is unchanged. Career paths are unmodified. Reporting lines are undisturbed. This is where the majority of the cohort currently sits and it explains the central paradox of this research: why near-universal tool access has produced only single-digit transformational impact. The tools are present. The operating model has not changed to use them. Industry research confirms this is not unique to institutional investing: only half of companies have moved beyond tool deployment to workflow redesign, and only 1-3 percent consider their strategies mature.

An AI-First organization requires the reorganization of teams, workflows, and decision rights around AI-augmented capability.

The unit of analysis shifts from the role to the workflow. Teams are structured around outcomes, not functions. Decision-making moves to integrated, AI-enabled pods where domain expertise, quantitative capability, and AI orchestration sit within a single operating unit.

The forward-deployed engineer — technical AI talent embedded directly within investment teams rather than centralized in technology — is the operational expression of this shift. It requires new roles, new career paths, and deliberate management of the tension between the people who build AI tools and those who embed them in investment workflows. These are not the same people, and the institutions that conflate them lose value on both sides.[49]

IN BRIEF

1 — AI-Enabled vs. AI-First Tools deployed.
Operating models unchanged. That's the gap.
2 — Shadow AI is a Signal
Match consumer AI inside the governed environment.
3 — Three Trajectories
Accelerate, Displace, Augment. Plan for all three.
4 — Three-to-Five-Year Window
Redesign junior development before the pipeline narrows.
5 — T to W
AI disrupts how careers are built. Apprenticeship models rebuild them.

Productivity is demonstrated in tasks; value is captured in outcomes. The organizational design gap between the two is where most institutional AI investments currently lose their value. A team builds a proprietary AI tool integrating earnings call transcripts, financial filings, and market data into structured investment analysis. Accurate, well-engineered, praised by early users. Six months later: near-zero daily usage. The tool exists. The workflows that would require its use do not. This is the last-mile problem in its most concrete institutional expression.

The question is not where AI can automate — it can automate broadly — but where AI-enabled workflow redesign creates structural advantage that compounds over time.

The investment value chain has distinct segments — research and idea generation, portfolio construction, risk management, trading and execution, client reporting, compliance and governance — each with different AI impact profiles. The institutions capturing the most value are those that have mapped these segments, identified the highest-leverage redesign opportunities, and concentrated organizational energy on two or three workflow transformations that produce compounding returns.

Most institutions are converging on a hybrid model: centralized governance with federated execution. Centralized governance sets the standards, risk tiering, and accountability framework; investment teams build and deploy within those guardrails. Build-buy-partner decisions are treated by leading institutions as a dynamic portfolio allocation: partnership for foundational capability; internal build where proprietary data creates a defensible moat; and deliberate management of vendor concentration risk, evaluated with the same rigor as any portfolio concentration.

Shadow AI: From Prohibition to Governed Enablement

Shadow AI — the use of AI tools outside approved institutional channels — is a cybersecurity and data governance risk widely documented across the financial services sector. Industry research confirms it is not a compliance problem to be solved through prohibition alone. It is a demand signal to be channeled through governance.

Employees will use the tools that are most capable regardless of institutional policy. If the approved internal AI tools are materially less capable than the consumer tools available on a personal device, shadow AI is the logical response. Prohibition drives it underground, where it becomes ungoverned, unmonitored, and invisible to the risk management framework. The most effective response is a data-parity principle: rather than restricting access, ensure approved tools match or exceed the capability of consumer alternatives and build the governance pathways that make using them the path of least resistance. When the governed tool is better than the ungoverned alternative, shadow AI tends to resolve itself.

A related dynamic is emerging across the sector: non-technical users building AI-powered tools without engineering support or governance review. The initial productivity gain is real, but quality assurance, maintenance, and governance requirements remain — creating a dynamic where short-term productivity becomes a net drag if downstream costs go unmanaged. The organizations confronting this most effectively have built lightweight governance pathways for user-built tools: a structured review that catches consequential risks without stifling innovation.

Talent Strategy

The ADA Labor Market Trajectories: Accelerate, Displace, Augment

Dr. Cecchi-Dimeglio's labor market research, presented at the Stanford 100 Global Business Summit in March 2026, identifies three primary trajectories for how AI reshapes the workforce in institutional investing and the broader financial sector.[50]

Accelerate. AI advances exponentially. Productivity soars and new roles emerge faster than old ones disappear. But governance frameworks and social safety nets struggle to keep pace. The institutions that invest in adaptive governance and continuous reskilling capture disproportionate value. Those that rely on the technology alone discover that productivity without governance is fragile.

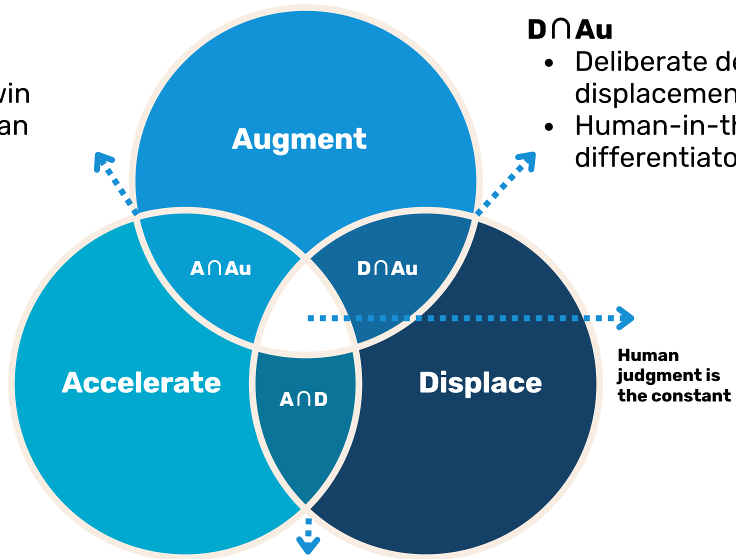
Displace. AI outpaces the workforce's ability to adapt. Displacement concentrates in mid-career analytical and operational roles. In this trajectory, the AI dividend question — whether employers have an obligation to support professionals whose institutional knowledge trained the models that now displace them — becomes a governance and reputational imperative.

Augment. AI advances gradually, with deliberate focus on augmentation over automation. Human-AI teams reshape value chains together and the developmental pipeline is redesigned rather than eliminated. This is the trajectory most consistent with the human-first framing that emerged across the research.

The ADA Model

A∩AU
- Reskilling is essential
- Adaptive institutions win
- Speed + governance can coexist

D∩Au
- Deliberate design prevents displacement
- Human-in-the-loop is the differentiator



A∩ D
- AI pace outstrips human readiness
- Skills half-life crisis
- Governance urgency

Which trajectory materializes will depend not on the technology — which is advancing regardless — but on institutional design choices made in the next three to five years.

Three Talent Strategies in Practice
Three distinct talent strategies are observable across participating institutions.

Expanding. Some institutions are increasing entry-level hiring: AI makes junior professionals more productive from day one, entry-level talent trained alongside AI develops potentially more valuable capabilities, and early-career investment compounds as AI matures. One large-scale institution doubled entry-level hires over two years precisely because AI expanded what junior professionals could contribute. The question: whether the expansion is reaching all talent segments equally, or whether the AI-native talent pool is skewed in ways that compound existing pipeline patterns.[51]

Contracting. Other institutions are reducing entry-level hiring: AI eliminates the tasks that justified those roles, a smaller and more senior workforce augmented by AI is the more efficient structure, and the scarce resource is senior judgment, not entry-level analytical capacity. [52]

3 Big ideas

1.Human Judgment is Non-Negotiable
2.Governance is the Strategic Variable
3.Institutions Choose the Trajectory

This approach is more common among institutions facing direct competitive fee pressure and shorter performance cycles.

Holding and observing. A third group maintains current hiring levels while waiting for AI's workforce impact to clarify, relying on natural attrition to adjust workforce size and using the interval to upskill existing staff and observe how AI reshapes role requirements before committing to structural changes. The risk: the window for deliberate redesign narrows with each quarter of inaction. The advantage: it preserves optionality while the technology and regulatory landscape stabilize.

The research does not resolve which strategy is correct — the answer depends on institutional structure, time horizon, fiduciary mandate, and strategic ambition. What it establishes is that the choice must be made deliberately, not defaulted into through accumulated individual hiring decisions made without a strategic framework.

The T→W Shape Framework: What Skills-Based Restructuring Is Building Toward

Skills-based restructuring requires a concrete model for what the target knowledge profile looks like at each career stage. The T→W Shape Framework developed from this research provides that model.

The **T-shape** describes the developing investment professional in their first three years: broad familiarity across domains — investment basics, data literacy, AI fluency, behavioral awareness, regulatory fundamentals — combined with one area of genuine depth, typically core investment analysis. The vertical bar of the T is built through doing the analytical work that AI now threatens to automate. If those tasks are automated before the junior professional has built that depth, the T-shape never forms. This is why the succession challenge is urgent.

The **W-shape** is the target profile for a seasoned investment professional. The two vertical bars of the W represent two distinct areas of deep expertise. At the mid-level: investment strategy and AI-human decision design — the ability to both make analytically sound calls and to deliberately map where human judgment must govern AI-assisted decisions. At senior level: leadership and governance, and judgment and ethics — setting the conditions under which AI operates responsibly and making the final calls where AI cannot. The horizontal bar across the top is the integrating breadth that holds both deep domains together.

The developmental journey from T → W is the progression the succession pipeline exists to enable — and AI is disrupting it at its foundation. Orchestration apprenticeships, deliberate senior-junior pairing, and in-person collaboration on consequential decisions are not optional. They are the mechanism by which the T-shape acquires the second vertical bar it needs to become the W.[53-54]

> *The framing that emerged most powerfully from the research is human-first: institutional investing remains a fundamentally human enterprise, augmented by AI rather than replaced by it. The institutions that invest in the judgment, relationships, and institutional knowledge that compound over a career are making a competitive bet — not bearing a cost.*

Skills-based restructuring therefore requires changes across every dimension of the talent system: hiring criteria that weight curiosity and learning agility alongside domain expertise; performance evaluation systems redesigned to assess AI-augmented output rather than unassisted effort; career paths that recognize AI orchestration as a premium capability; and workforce planning models that account for the differential impact of AI across different populations.

The AI-Ready Professional:

A 6 Competency Blueprint for Institutional Investing

Critical Thinking	AI Collaborations	Ethical Judgement
• Analytical Reasoning • Causal Reasoning • Evidence Evaluation • Logical Structure • Hypothesis Testing	• AI Tool Fluency • Workflow Redesign • Output Validation • Prompt Engineering • Human-in-the-Loop	• Bias Awareness • Ethical Oversight • Privacy & Governance • Responsible AI Norms • Transparency

Agility & Resilience	Leadership	Depth of Learning
• Learning Agility • Change Adaption • Ambiguity Tolerance • Uncertainty Acceptance • Bounce-Back	• Vision & Strategy • Team Influence • Stakeholder Mgmt • Governance Design • Talent Development	• Expertise Depth • Continuous Upskilling • Knowledge Reapplication • Cross-Domain Synthesis • T→ W Transition

A team evaluating whether to hire a new analyst assesses the role's responsibilities against the capabilities of existing AI tools. The conclusion: the AI can perform everything the new hire would do. Not in theory. Not in a pilot. In production. Not a projection — an operational assessment of what AI has already replaced. The hiring decision is deferred.

The dilemma was described with precision across these conversations: agentic AI is now performing better than junior team members and, in some dimensions, better than senior skilled talent. Senior professionals remain essential for their capacity to validate AI outputs — to exercise the judgment that distinguishes correct analysis from confident hallucination.

But that judgment was itself developed through years of performing the tasks that AI now handles. If the tasks that build judgment are automated before the judgment is built, the profession faces a generational discontinuity — and the supply of senior professionals capable of validating AI output will eventually thin.

The traditional learning-by-osmosis model is being disrupted from two directions simultaneously. The tasks that created developmental opportunities — building financial models, drafting investment memoranda, conducting preliminary research — are increasingly delegated to AI systems, removing the learning content from early-career work.

And remote and hybrid arrangements reduce the incidental exposure that osmosis requires: the junior analyst who once absorbed contextual judgment by sitting in the room while a portfolio manager debated a position is now at home, interacting with AI tools rather than senior colleagues.

The compounding nature of this risk makes it urgent. If pipeline narrowing begins today and the typical path from analyst to senior leadership spans fifteen to twenty years, institutions that fail to redesign the developmental pathway will discover the consequences in the 2035–2040 leadership cohort — a generation whose judgment was formed without the foundational experiences their predecessors relied on. By then, the window for correction will have passed.

A counterintuitive approach to the succession challenge lies in unstructured data repositories — due diligence memoranda, valuations, legal documents, loan covenants — that have never been systematically leveraged. AI's comparative advantage in extracting signal from unstructured data creates an opportunity to redeploy junior talent from data processing to judgment-intensive work earlier in their careers. This is a potential redesign of the developmental pathway, not merely an efficiency gain. But it requires deliberate institutional design.

Left to default, the same professional is simply reassigned to supervise AI document extraction — developing monitoring skills but not investment judgment.

Three design principles emerged from the research for preserving the succession pipeline — and for enabling the T-to-W developmental journey that institutional investing depends on.

First, redesign early-career development around judgment formation rather than task execution — the tasks will be automated; the judgment must still be developed. Second, create orchestration apprenticeships: structured programs where junior professionals manage AI systems, validate outputs, and apply contextual judgment to AI-generated analysis. This is how the T-shape acquires its second vertical bar. Third, protect the exposure that builds institutional knowledge: deliberate senior-junior pairing, structured mentoring, and in-person collaboration on consequential decisions that AI cannot replicate.

Strategic Implications: The Workforce Architecture

These workforce dynamics form a connected system — and institutions that treat them as such will build the organizational capability that those addressing them in isolation will lack.

The operating model shift is the structural foundation. The AI-Enabled vs. AI-First distinction determines whether every subsequent investment in talent, governance, and workflow redesign compounds or dissipates. Institutions that layer AI onto unchanged operating models will continue to experience the adoption depth deficit regardless of how much they invest in tools and training.

Shadow AI is the demand signal. It reveals where the governed AI environment is failing professional needs and where the risk management framework has blind spots. Institutions that channel this signal through governance rather than suppressing it through prohibition convert a compliance risk into an adoption accelerator.

The talent strategy determines how the organization positions for the three labor market trajectories. The human-first framing and the 10-20-70 principle — 10 percent of AI transformation investment to technology, 20 percent to process redesign, and 70 percent to people and behavior change — provide the decision framework. The talent strategy must be stress-tested against all three ADA scenarios.

The succession pipeline is where the long-term consequences of today's decisions will be felt most acutely. The T→W developmental journey that produces future investment leaders is being narrowed from two directions. The three design principles — judgment formation, orchestration apprenticeships, and protected exposure — provide the framework for preservation. ILN's network provides the mechanism.

YOUR PLAY:
Workforce and Succession

Ground Builder

1. Maintain or increase junior hiring levels — but redesign the first-year experience around AI orchestration, not task execution

2. Conduct a shadow AI audit and build a governed alternative tool stack that matches consumer AI capability

3. Map every role against the AI-Enabled vs. AI-First distinction: which roles require workflow redesign, not just tool access?

Momentum Builder

1. Design orchestration apprenticeships: structured programs where juniors learn through managing AI systems, validating outputs, and applying judgment

2. Implement skills-based hiring criteria: weight curiosity and learning agility alongside domain expertise in all recruitment

3. Embed forward-deployed engineers in the three highest-value investment teams within six months

Front Runner

1. Build a five-year succession pipeline model that accounts for AI displacement of entry-level developmental tasks

2. Create a private markets AI exploitation roadmap: identify unstructured data repositories and design AI extraction programs with junior development built in
3. Redesign career paths to recognize AI orchestration, governance capability, and human-AI collaboration as promotion-track competencies

KPIs, Value Capture, and Implementation Roadmap

7

A well-designed KPI does three things simultaneously: it measures an outcome, it signals what the organization values, and it shapes the behavior of the people being measured. In AI adoption, the third function is the most consequential. During one of the Roundtables we organized, a direct question was posed that crystallized the measurement challenge facing every institution in the financial sector: how do you demonstrate, in measurable terms, that AI adoption is producing competitive advantage and, specifically, that it is generating money?

The question is legitimate, urgent, and genuinely difficult to answer with the precision that CIOs, CFOs, and boards require. This section presents a KPI framework based on primary research and PCD's proprietary tools, a financial proof chain that links value evidence to maturity stages, a governance measurement KPI, and a three-horizon implementation roadmap aligned with the maturity profiles in Part 2.

The KPI Challenge: Productivity vs. Financial Impact

AI is a general-purpose technology, and traditional ROI frameworks do not fit. This is not an evasion of the measurement question; it is the most important thing to understand before attempting to answer it.

Industry research surveying more than 1,800 organizations finds that most achieve satisfactory AI ROI only within two to four years. Only 6 percent reported payback within the first year, while 37 percent reported payback in two to three years. Research on productivity dynamics argues that aggregate gains are more modest than forecasts because reallocation costs — the organizational disruption of moving from old ways of working to new — are systematically undercounted in optimistic projections. [57-58]

The value concentration finding is directly relevant to institutional investors: 72 percent of global AI market value is in information-based activities, and the top 1.6 percent of work activities account for over 60 percent of all AI market value. AI deployment spread thinly across all functions will capture far less value than AI deployment concentrated on the specific information-creation activities where the market value is highest.

Only 1 percent of companies view their generative AI strategies as mature, and 80 percent report no significant bottom-line impact.[59-61]

IN BRIEF

1 — KPIs Shape Behavior
Start with 3–5 for your tier. Expand from there.
2 — Saves → Enables → Creates
Each stage builds credibility for the next.
3 — Model Integrity
New KPIs answer the trust question before regulators ask it.
4 — Three Failure Modes
Premature ROI. False activity signals. Wrong metrics for the maturity level.
5 — Three Horizons Foundations. Capability. Optimization. Sequencing matters.

The problem is misallocated deployment — horizontal AI spread versus vertical AI targeting — combined with unrealistic timelines and measurement frameworks designed for discrete software rather than transformational infrastructure.[62]

One institution in this research has made a deliberate strategic choice not to measure dollar-denominated ROI on AI — a sophisticated application of real options thinking that treats early AI investments as options on future capabilities. The analogy: no one measures the dollar ROI of giving employees a cell phone. The question is whether you can compete without one. The four-domain AI framework — productivity, sales, investment management, and risk — provides the KPI scaffold that ensures measurement covers AI's full institutional footprint.

The Financial Proof Chain: AI Saves, AI Enables, AI Creates

The revenue-generation KPIs in this framework use PCD's proprietary measurement methodology and are tailored to the ILN research context. They follow a deliberate behavioral sequence, mapped to the maturity framework and to the psychology of how organizations build trust in a new technology. The sequence is not arbitrary: it starts with the metrics that are easiest to prove and most psychologically compelling, then progresses to those that require more sophisticated attribution.

This sequence maps directly to the behavioral adoption framework's transition from shallow to deep use. At the shallow stage, motivation is driven by satisficing — people adopt AI minimally because they have been told to. The 'AI saves' metrics provide the external evidence that converts satisficing into genuine engagement. At the deep stage, the barriers shift to legitimacy, identity, and permission. The 'AI creates' metrics address all three: they confer legitimacy (AI is measured by the institution's defining metrics), resolve identity threats (using AI is how the best professionals work), and grant explicit permission (the organization has declared that AI-augmented returns are the standard).

AI Saves (Ground Builder Metrics)

At the earliest maturity stage, the financial proof that AI generates value is anchored in loss prevention.

Three metrics are primary. **Avoided hiring cost**: if AI productivity gains eliminate the need for planned hires, the dollar value is the number of avoided hires multiplied by the average loaded cost per hire a figure that shows up directly in the headcount budget and requires no attribution modeling. By way of illustration, if ten hires are avoided at a loaded cost of one hundred and fifty thousand dollars each, the annual value is one and a half million dollars. **Compliance cost reduction**: reduction in hours spent on regulatory reporting, audit preparation, and manual compliance checks, expressed in dollars. **Working capital freed**: capital previously tied up in processes that AI has accelerated, now available for redeployment.

The behavioral logic is grounded in loss aversion: losses are experienced approximately twice as intensely as equivalent gains. Proving that AI saves money builds credibility with the CIO, CFO, and the board before attempting the harder argument that AI creates money. The 'AI saves' metrics are the foundation of the financial proof chain not because they represent the highest value, but because they represent the most psychologically credible entry point.

What this measures. AI Saves is the loss-prevention layer — dollars AI keeps the institution from spending, plus the discipline metrics that make those savings defensible. This is where credibility lives.

AI Enables (Momentum Builder Metrics)

At the structured deployment stage, the financial evidence shifts from cost avoidance to competitive advantage. Four anchor metrics: **mandate win rate** (conversion rate on competitive mandates where AI-assisted pitch preparation was used versus mandates without); **revenue per relationship manager** (A/B comparison between AI-augmented and non-augmented relationship managers — when colleagues see that AI-using peers generate measurably higher revenue, adoption accelerates through social proof); **information creation productivity** (analytical output per investment professional versus pre-AI baselines); and **client retention value** (financial impact of AI-enhanced client service on retention rates).

What this measures. AI Enables is the competitive-advantage layer — dollars AI brings IN that would not otherwise have come in, plus the rollup metrics that net those gains against investment. This is the first cluster where a single net dollar figure can be defended to the board.

AI Creates (Front Runner Metrics)

At the scaled integration stage, AI is measured by the metrics that define institutional excellence. **AI-attributed alpha**: the proportion of investment returns attributable to AI-assisted analysis, requiring control portfolios, time-series comparison, and factor decomposition — the most technically demanding metric but the one that answers the Roundtable question most directly. **Decision augmentation yield:** measurable improvement in decision quality when AI-assisted analysis is used versus unassisted. **AI value concentration ratio**: proportion of AI value captured in top-quartile activities versus dispersed across low-value applications. **Token cost-to-value ratio and token-to-insight conversion efficiency**: operational metrics tracking the economic efficiency of AI inference costs against insights produced.

What this measures. AI Creates is the value-creation layer — dollars that would not exist at all without AI (alpha attributable to AI, decision quality gains, AI-generated EBITDA), plus the value-to-investment multiple that tests whether the institution sits inside the winners' financial profile.

The Model Integrity and Technical Governance: The Trust Layer That Boards Will Ask About Next

The financial proof chain answers whether AI is generating revenue. But the next question is already arriving from regulators, from boards, and from CIOs who have seen what happens when AI systems fail publicly: is the AI trustworthy?

Most institutions cannot answer this today. They can report adoption rates, cost savings, even early revenue attribution. What they cannot yet demonstrate — and what they will increasingly be required to — is that the AI systems producing those results are explainable, auditable, and fair. This is not a theoretical gap. For instance, the EU AI Act now categorizes AI systems by risk level and imposes graduated obligations on high-risk applications. FINRA has clarified that existing securities regulations apply fully to AI-generated outputs, including compliance reporting and client communications.

The direction of travel is unambiguous: what is encouraged today will be required tomorrow.

The framework incorporates additional KPIs — organized into two clusters — that give institutions the measurement infrastructure to answer the trustworthiness question before the regulator asks it.

Cluster 1: Explainability and Trust

What this measures. Cluster 1 is the regulatory-and-fiduciary protection layer — dollar exposures avoided (regulatory action, litigation, reputational impact, fiduciary risk), valued at the expected cost of the events it helps prevent. The value is often invisible until tested.

Model explainability score: percentage of production AI models with documented XAI methods (SHAP values, feature importance, local interpretable explanations). For institutional investors making decisions that affect beneficiaries, the ability to explain why an AI recommended something is a fiduciary expectation, not a technical nicety. Institutions deploying AI models without explainability documentation are accumulating governance debt.

Hallucination and output reliability rate: percentage of AI-generated outputs flagged as factually incorrect by human review or secondary validation. In multi-agent AI pipelines, a hallucinated output can propagate silently through the entire chain — making this metric operational before most financial KPIs is a prerequisite for institutions deploying LLMs in analytical or compliance workflows.

Algorithmic bias audit frequency: formal fairness testing cycles per year per model. Where AI is used in talent assessment, portfolio allocation, or client segmentation without bias testing, the institution faces regulatory and reputational exposure that no financial return will offset.

Human-in-the-loop compliance rate: percentage of governed outputs passing required human review. The most common failure mode is not that humans disagree with AI — it is that they stop checking. Regulators treat the gap between documented governance and actual practice as a material compliance risk.

The Cluster 2: Investment-Specific Model Quality

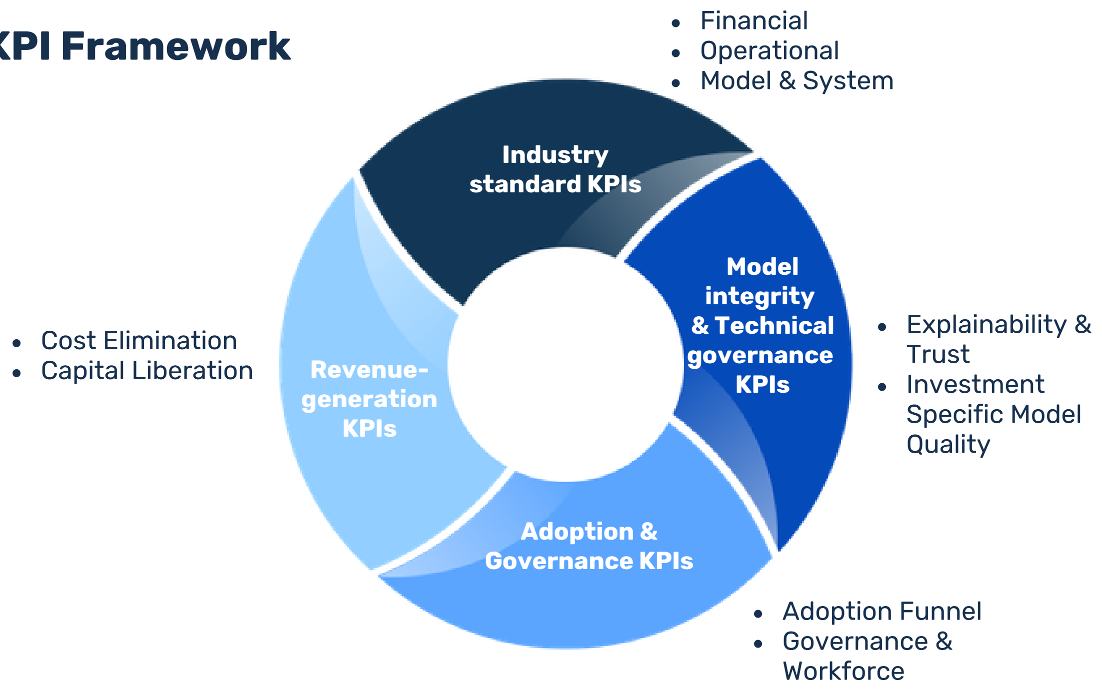
What this measures. Cluster 2 is the investment-quality layer — whether AI is improving decision quality, operational efficiency, and analytical edge. These are the metrics that show AI is not just deployed, but generating dollars by improving the activities that produce returns.

Signal-to-noise improvement ratio: predictive power of AI-generated signals versus traditional signals over time — whether AI is sharpening or diluting the institution's analytical edge. **AI-augmented decision quality index**: accuracy, consistency, and risk-adjusted outcomes of AI-augmented decisions versus unaugmented baselines.

Synthetic data utilization rate: percentage of model validations incorporating synthetic stress data — a competitive advantage in model robustness for Front Runners. **Regulatory readiness index**: percentage of AI deployments mapped to applicable regulatory requirements by jurisdiction. **Cross-functional AI integration depth**: number of AI applications spanning two or more organizational functions. **SLA compliance %**: percentage of AI-assisted service deliveries meeting defined service-level agreements. **Total model operating cost efficiency**: total cost per unit of AI-assisted output — tokens plus human review, validation, and operational overhead — surfacing the true cost of responsible AI deployment.

Financial performance without technical integrity is a liability waiting to materialize. Technical integrity without financial performance is an expense without a sponsor.

AI KPI Framework



The Measurement Trap: What Happens When You Get the KPIs Wrong

Premature ROI mandates as innovation constraints. Requiring dollar-denominated ROI for every AI experiment creates a harness on innovation — when measurement emphasizes preventing losses, the organization shifts from exploration to defense. One institution in the research has deliberately declined to measure dollar ROI precisely to avoid this trap.[63]

Activity metrics as false signals. Organizations measure AI success through activity-based metrics — 'productivity,' 'adoption rates' — rather than outcomes. The behavioral consequence is predictable: when a measure becomes a target, it ceases to be a good measure (Goodhart's Law). The framework addresses this by pairing adoption metrics with financial outcome metrics — ensuring that activity is always interpreted in the context of the value it produces.

Uniform measurement across asymmetric maturity. Applying the same KPIs to a Ground Builder and a Front Runner simultaneously produces two kinds of damage: unachievable targets for the less mature institution (disengagement) and insufficiently ambitious targets for the more mature institution (complacency). The maturity-aligned structure of this framework is a behavioral design choice, calibrated to organizational absorptive capacity.

Governance KPI Dashboard

Alongside the financial proof chain, the research produced a +10-metric governance KPI dashboard designed for board-ready reporting across three domains.

AI governance metrics: AI inventory coverage rate, model validation rate, drift response time, human override rate, and incident rate.

Data governance metrics: data quality score, lineage documentation rate, and privacy impact assessment completion rate.

Behavioral and workforce metrics: board AI literacy assessment, human-in-the-loop compliance rate, AI training completion rate, bias audit rate for people-facing AI applications, and the inclusion index by gender, seniority, and function.

What this dashboard is. A board-ready reporting layer that gives the board enough visibility on AI risk to move faster on AI value with confidence — protecting against the pauses, scale-backs, and external audits that quietly destroy more value than governance overhead ever costs.

Implementation Roadmap: Three Horizons

The roadmap is structured across three horizons, calibrated to organizational capacity for change rather than arbitrary timelines. The horizons are designed to be sequential but overlapping — each horizon's investments create the preconditions for the next.

	KEY ACTIONS	PRIMARY TIER
HORIZON 1 MONTHS 1-6 | FOUNDATIONS	• Establish governance architecture • Complete AI risk tiering • Launch leadership immersion • Baseline adoption metrics • Shadow AI audit • Data governance audit	• Ground Builders (Foundation building) • Momentum Builders & Front Runners (Governance calibration)
HORIZON 2 Months 6-18 | CAPABILITY	• Workflow redesign • Embed forward-deployed engineers • Formalize champion networks • Align incentives to adoption • Pipeline convergence audit • Skills-based hiring criteria	• Momentum Builders (Primary transformation horizon) • Ground Builders advancing (Capability expansion)
HORIZON 3 Months 18-36 | OPTIMIZATION	• Agentic AI governance • Redesign succession pipeline • Board-ready quarterly KPI reporting • Rebalance build-buy-partner • AI-attributed alpha methodology • Competitive positioning tied to AI	• Front Runners (Primary strategic horizon) • Momentum Builders (Optimization for the ones that have transitioned)

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Horizon 1 (Months 1–6): Foundations.
Governance design established or validated. AI risk tiering completed for all current applications. Leadership immersion launched — structured working sessions on real investment problems, not awareness briefings. Baseline adoption metrics collected. Human-in-the-loop compliance rate baselined — establishing whether the review checkpoints governance documents mandate are actually being executed in practice. Regulatory readiness index initiated: every current AI deployment mapped to applicable requirements by jurisdiction. Shadow AI and data governance audits completed. Within AI Saves: Total AI investment ($) tracking initiated from day one to establish the denominator every later ROI metric will reference; Time to breakeven J-curve baselined; Stage-gate conversion rate established.

For Ground Builders, this is the primary implementation horizon — the foundation on which everything else is built. For Momentum Builders and Front Runners, this is a governance and measurement calibration phase that frequently reveals gaps between perceived and actual maturity.

Horizon 2 (Months 6–18): Capability.
Workflow redesign initiated for the highest-value use cases identified through value chain mapping. Forward-deployed engineers embedded in priority investment teams. Champion networks formalized with dedicated time allocation and career recognition. Incentive structures aligned with adoption objectives; AI use embedded in performance reviews for all people managers.

Model explainability documentation completed for all production AI models before AI moves from experimentation into portfolio and client decisions. Hallucination tracking operational for all LLM-based workflows with escalation protocols. Algorithmic bias audit cycle launched for people-facing and portfolio-influencing AI applications. Cross-functional AI integration depth tracked. Pipeline convergence audit completed. Skills-based hiring criteria implemented. Within AI Enables: Net AI value captured ($) reporting operational; Domain concentration index measured, confirming AI investment is reaching the 1–3 business domains being reinvented rather than dispersing horizontally. For Momentum Builders, this is the primary transformation horizon.

Horizon 3 (Months 18–36): Optimization
Agentic AI governance frameworks operational with graduated trust models. Succession pipeline redesigned to account for AI displacement of entry-level developmental tasks. Signal-to-noise improvement ratio and AI-augmented decision quality index operational — providing the first rigorous evidence of whether AI is improving the quality of investment decisions, not just their speed. Synthetic data utilization integrated into model validation for stress testing and scenario analysis.

KPI framework producing board-ready quarterly reporting across all four domains and all governance and model integrity metrics. Build-buy-partner portfolio rebalanced based on twelve to eighteen months of deployment evidence. Competitive positioning explicitly tied to AI capability metrics. AI-attributed alpha measurement methodology developed and tested. Within AI Creates: AI EBITDA impact (% and $) and Value-to-investment multiple ($ EBITDA / $ invested) calibrated against the winners' benchmark of approximately 20 percent EBITDA uplift and 3.0x multiple at scale. For Front Runners, this is the primary strategic horizon.

Sequencing by Maturity Profile

The roadmap is not one-size-fits-all. For each maturity profile, the implementation sequence follows an Invest Now, Build Capability, Monitor, and Defer logic calibrated to the binding constraint at that profile level.

Ground Builders

Invest now in leadership immersion, governance design, and baseline adoption measurement. Establish human-in-the-loop compliance rate from day one — the metric that reveals whether governance exists on paper or in practice — and initiate regulatory readiness mapping across all operating jurisdictions. Defer enterprise-level workflow redesign until governance foundations are in place. Within AI Saves, initiate Total AI investment ($) tracking, the Time to breakeven J-curve, and Stage-gate conversion rate from day one: the ROI plumbing must be in place before the dollar values become material.

Starting set (metrics): usage depth distribution • leadership modeling index • AI literacy rate • governance coverage rate • human-in-the-loop compliance rate • regulatory readiness index • avoided hiring cost • compliance cost reduction • unrecognized opportunity cost • total AI investment ($) • time to breakeven • stage-gate conversion rate (the last three within AI Saves).

This set establishes the measurement foundation without overwhelming an organization still building governance capacity.

Momentum Builders

Invest now in workflow redesign for highest-value use cases and incentive alignment.

Complete model explainability documentation before AI moves from experimentation into portfolio and client decisions. Launch hallucination tracking and algorithmic bias audit cycles. Track cross-functional AI integration depth to identify where AI value compounds across boundaries. Within AI Enables, layer in Net AI value captured ($) and the Domain concentration index: at this stage the framework should be able to roll gross line items into a single net figure and to test whether deployment is concentrated on the 1–3 domains that distinguish winners.

Add (metrics): adoption velocity • workflow integration rate • shadow AI incidence • cross-functional AI integration depth • process cycle time • automation rate • model explainability score • hallucination and output reliability rate • algorithmic bias audit frequency • mandate win rate • revenue per relationship manager • information creation productivity • working capital freed • AI value concentration ratio • net AI value captured ($) • domain concentration index (the last two within AI Enables).

Front Runners

Invest now in agentic AI governance, succession pipeline redesign, and AI-attributed alpha measurement methodology. Operationalize the AI-augmented decision quality index — evidence of whether AI is improving decision quality, not just speed. Integrate synthetic data into model validation. Within AI Creates, layer in AI EBITDA impact (% and $) and Value-to-investment multiple ($ EBITDA / $ invested): at this stage the framework must be calibratable against the winners' benchmark — approximately 20 percent EBITDA uplift and 3.0x multiple at scale. Without these two metrics, the Front Runner cannot test whether it sits inside the winners' financial profile or merely adjacent to it.

Add (metrics): AI-attributed alpha • decision augmentation yield • client retention value • token cost-to-value ratio • token-to-insight conversion efficiency • signal-to-noise improvement ratio • AI-augmented decision quality index • synthetic data utilization rate • transformational impact score • agentic AI readiness score • AI EBITDA impact (% and $) • value-to-investment multiple (the last two within AI Creates).

Strategic Implications: The Measurement System

The measurement dynamics documented here form a connected system — and institutions that treat them as such will build the evidence base on which sustained investment in AI depends.

The four-domain framework is the scaffold and the financial proof chain determines the sequencing. Every AI deployment maps to one of four domains — productivity, sales, investment management, risk. Starting with 'AI saves' builds credibility with the CIO, CFO and board before attempting the harder argument that AI creates alpha. Each tier of evidence makes the next tier psychologically accessible. Institutions that skip stages undermine their own credibility. The ROI discipline metrics embedded inside each stage — denominator and breakeven inside Saves, net rollup and concentration inside Enables, EBITDA and multiple inside Creates — anchor each tier's gross dollar evidence to a benchmarked, board-ready ROI story.

The model integrity layer provides technical trust; the governance dashboard provides assurance. The model integrity metrics — explainability, hallucination rates, bias audits, human-in-the-loop compliance, signal quality, decision quality — demonstrate that value is being generated responsibly. For boards, the governance dashboard converts AI from an opaque technology investment into a governed, auditable institutional capability. Financial performance without technical integrity is a liability. Technical integrity without financial performance is an expense without a sponsor.

The implementation roadmap translates measurement into action. The three horizons — foundations, capability, optimization — ensure institutions invest in measurement capacity before demanding measurement outcomes. The maturity-aligned sequencing prevents premature ROI mandates that constrain innovation and uniform measurement that mismatches targets with institutional readiness.

> Together, these four dimensions — the domain framework, the proof chain (with ROI discipline metrics embedded inside each of its three stages, calibrated to the winners' financial profile), the model integrity layer, the governance dashboard, and the implementation roadmap — constitute the measurement design of AI transformation. The institutions that build it will be able to answer the question that opened this section. The institutions that do not will continue to invest in AI without knowing whether it is working — or whether it is working responsibly.

YOUR PLAY:
KPIs and Implementation

Ground Builder
Start with Metrics

1. Adoption: Usage Depth Distribution, Leadership Modeling Index, AI Literacy Rate
2. Governance: Governance Coverage Rate, Human-in-the-Loop Compliance Rate, Regulatory Readiness Index
3. Money — AI Saves: Avoided Hiring Cost, Compliance Cost Reduction, Unrecognized Opportunity Cost, Total AI Investment ($), Time to Breakeven, Stage-Gate Conversion Rate
4. Establish the ROI plumbing — denominator, J-curve, gate conversion — from day one. Resist financial-return targets beyond bounded use cases; premature requirements constrain innovation

Momentum Builder
Add new Metrics

1. Adoption: Adoption Velocity by cohort, Workflow Integration Rate, Shadow AI Incidence, Cross-Functional AI Integration Depth
2. Operations: Process Cycle Time reduction, Automation Rate, Model Explainability Score, Hallucination Rate, Algorithmic Bias Audit Frequency
3. Money — AI Enables: Mandate Win Rate, Revenue per RM, Information Creation Productivity, Working Capital Freed, AI Value Concentration Ratio, Net AI Value Captured ($), Domain Concentration Index (1–3 domain test)
4. Begin A/B cohort comparisons between AI-augmented and non-augmented teams; confirm investment is reaching the 1–3 domains being reinvented, not dispersing

Front Runner
Layer Strategic Financial Metrics

1. Money — AI Creates: AI-Attributed Alpha, Decision Augmentation Yield, Client Retention Value, Token Cost-to-Value Ratio, Token-to-Insight Conversion, AI EBITDA Impact,Value–to–Investment Multiple(EBITDA / $ invested)
2. Adoption: Transformational Impact Score (% of workforce at Stage 3B+), Agentic AI Readiness Score; Model integrity: Signal-to-Noise Improvement Ratio, AI-Augmented Decision Quality Index, Synthetic Data Utilization Rate
3. Build the two-tier measurement architecture: bounded use cases with standard KPIs; diffuse AI with proxy metrics and longitudinal tracking
4. Calibrate against the winners' benchmark — c.20% EBITDA uplift, 3.0x multiple at scale — using attribution methodology with control portfolios, time-series, and factor decomposition

The People-Centered Future of AI in Investing

8

The question facing institutional investors is no longer whether AI will transform the industry. That question was settled by the evidence presented in Sections 1 through 7 of this playbook. The question now is whether the transformation will be designed deliberately, with governance, with attention to the people who must execute it and the beneficiaries who depend on it or whether it will happen to institutions that failed to design it for themselves. The difference between these two outcomes is measured in decades of institutional capability, in the quality of the leadership pipeline, and in the fiduciary trust that is the foundational asset of every organization represented in this research.

Vision for Human-AI Collaboration

The destination is not AI as a technology overlay on existing institutional structures. It is AI as an organizational operating system — embedded in investment decision-making, portfolio monitoring, client engagement, governance, and workforce development simultaneously. The most advanced institutions in this research are already beginning to operate this way: AI does not sit in a technology department; it runs through the organization, touching every workflow, every decision, and every professional interaction.

The vision is not one of replacement but of augmentation. The institutions capturing the most value from AI are not those that have automated the most tasks — they are those that have most effectively redesigned the collaboration between human judgment and AI capability. A senior investment professional who uses AI to process a thousand earnings transcripts in an hour, and then applies thirty years of contextual judgment to the synthesis, produces work that neither party could produce alone. That collaboration is the competitive unit.

Three governance imperatives structure the path to this vision. The research suggests they are most effective when pursued simultaneously, not sequentially.

In Brief

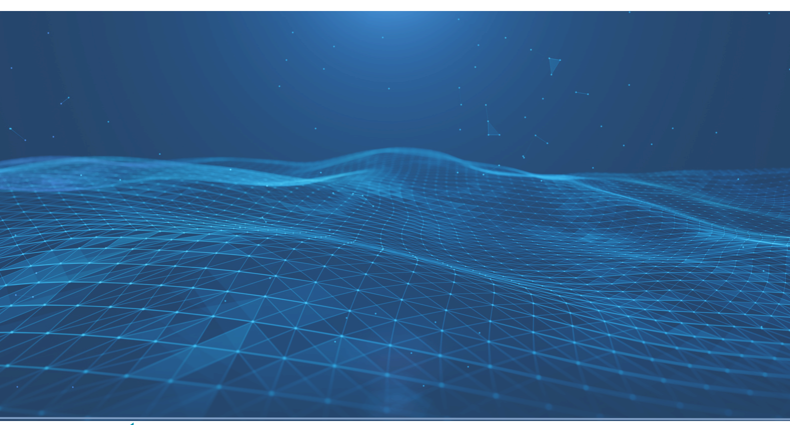
1 —The transformation is coming.
The only question is whether it's deliberate.
2 — Operating System, Not Overlay
Human judgment plus AI capability. Neither alone.
3 — Three Imperatives
Enable. Accountability. Adapt. Simultaneously.
4 — Three Scenarios
Incremental. Accelerated. Disrupted. Position for all three.

First, enable. The institutions furthest along the adoption curve have built governance design that allows confident deployment at scale. Their frameworks are proportionate to risk; their approval pathways move at the speed of AI development; their tool infrastructure matches or exceeds consumer alternatives. The gap between institutions still debating whether to permit AI use and those already governing agentic AI — systems operating with increasing autonomy that require new oversight frameworks — is widening. Enablement is the precondition for everything else.[64]

Second, make accountability explicit. In fiduciary contexts, named human individuals must remain in the chain of responsibility for every consequential AI-informed decision. No AI system, however capable, can bear fiduciary responsibility to beneficiaries. The institutions designing accountability into workflows from the outset — rather than layering it on after the fact — are building the governance credibility that sustains trust over time.

Third, build adaptive governance. The pace of AI development is faster than the pace of institutional governance revision. Static governance applied to dynamic technology produces the design-enactment gap documented in this research. The most effective frameworks include defined triggers for review, thresholds for escalation, and mechanisms for updating standards as capabilities evolve.

The AI Safe and AI for Good distinction provides an essential lens. In institutional investing, 'Safe' means model risk management, explainability, and non-delegable accountability. 'Good' means fiduciary duty to beneficiaries — using AI to create long-term value, not merely short-term efficiency. These are complementary but pull in opposite directions under resource constraints. Institutions that conflate them end up over-governed on safety and under-designed for beneficiary value. The design must serve both.



Scenario Analysis: Three Futures

The research supports three plausible scenarios for the trajectory of AI in institutional investing over the next three to five years.

None is a prediction. Each describes a pathway, the conditions that produce it, and the implications that follow. The institution that has modeled multiple futures is better positioned to respond to whichever one materializes.

Scenario A: Incremental Adaptation

Institutions continue to deploy AI tools, achieve personal productivity gains, and struggle with the transition from tool use to workflow transformation. Governance remains reactive — catching up to deployment rather than enabling it. The adoption depth deficit persists: broad tool access, shallow transformational impact. Competitive advantage accrues slowly and unevenly.

The J-curve trough persists because the complementary organizational investments required to exit it — workflow redesign, incentive realignment, governance design, succession pipeline redesign — have not been made at sufficient scale. Institutions interpret the initial plateau as evidence that AI's value has been overstated, rather than recognizing that organizational design has not yet caught up.

This scenario is stable but not competitive. Institutions in Scenario A will not fail catastrophically; they will fall behind gradually, losing competitive positioning quarter by quarter. For institutions under direct competitive fee pressure, this trajectory leads to consolidation. For institutions with longer fiduciary horizons, it leads to rising operational costs relative to peers and a governance gap that exposes fiduciary risk.

Scenario B: Accelerated Transformation

Coordinated action across stakeholders accelerates the transition. Shared governance standards — developed collaboratively through the peer network — reduce the per-institution cost of governance development. Institutions that would have spent twelve to eighteen months building frameworks independently can adopt shared standards in a fraction of that time. Peer learning on adoption best practices compresses the time from deployment to workflow integration.

Shared investment in talent development creates the infrastructure for succession redesign. Orchestration apprenticeship models, cross-institutional rotation programs, and skills-based hiring criteria are network-level assets no single institution can develop as efficiently alone. The succession pipeline challenge, identified in Section 6 as a structural problem requiring sector-level response, is addressed through the peer-learning platform that ILN provides.

The J-curve inflection arrives faster in this scenario because the complementary investments are made collaboratively rather than independently. The institutions making those investments — in training, process redesign, and governance — exit the trough first. This scenario requires deliberate design and sustained commitment from member leadership. It will not emerge spontaneously.

Scenario C: Disruption by AI-Native Entrants
AI-native firms built without legacy systems, legacy governance, or legacy organizational structures capture market share through structural cost advantage and AI-enabled investment capability.

Three-person teams deliver analytical services that previously required more than a dozen. Fee compression from 100 basis points toward 10 accelerates beyond current projections. Consolidation intensifies.

Research on AI labor market dynamics warns that if AI-native entrants focus on automation without creating new human-productive tasks, the industry risks a structural loss of the judgment capacity that distinguishes institutional investing from algorithmic trading. The succession pipeline does not merely narrow — it disappears for segments of the industry. The expertise that took a generation to build cannot be recreated once the developmental pathway has been eliminated.

For institutions with longer fiduciary horizons, Scenario C creates a distinct challenge. The external managers in their allocation portfolios may no longer exist in their current form, and AI capability must now be evaluated as a governance and survival variable — not merely a performance enhancement. The question is not whether Scenario C is likely, but whether an institution's current trajectory positions it to compete if it materializes.

Three Futures: Comparing Scenarios

	Scenario A Incremental Adaptation	**Scenario B** Accelerated Transformation	**Scenario C** Disruption by AI Native Entrants
Adoption Trajectory	Tool access broad / Workflow integration shallow / J-curve trough persists	Coordinated peer learning / Shared standards compress timelines / J-curve inflection accelerated	AI Coordinated peer learning / Shared standards compress timelines / J-curve inflection accelerated
Governance Posture	Reactive — catching up to deployment	Collaborative — shared standards reduce cost	Fragmented — legacy governance overwhelmed
Competitive Outcome	Stable but gradually falling behind	Accelerated positioning across the membership	Structural disruption for unprepared institutions
Talent Pipeline Impact	Adoption depth deficit persists; pipeline narrows slowly	Succession redesigned; pipeline preserved	Pipeline disappears for segments of the industry
Action Required	Invest in governance and leadership foundations	Commit to coordinated action and shared frameworks	Stress-test current trajectory against disruption scenario

Strategic Implications: From Diagnosis to Action

For Leadership: CEO, CIO, CHRO, and Boards

AI transformation is a shared C-suite and board responsibility. The CIO spans the full investment value chain and governs the AI operating model — but governance designed in isolation from talent strategy, competitive positioning, and fiduciary oversight will stall. The CEO sets direction, allocates resources, and sends the behavioral signal that determines whether the organization treats AI as a strategic imperative or an optional efficiency measure. The CHRO owns the talent pipeline, the skills-based transition, and the workforce analytics that reveal whether the transformation is broadening or narrowing institutional capability. The board exercises fiduciary oversight — asking the right questions about accountability, risk concentration, and long-term pipeline implications is its irreducible contribution.

Personal AI practice at the leadership level — visible, behavioral, shared with direct reports — remains the single highest-leverage action available. The design-enactment gap determines whether AI investment compounds or evaporates. Closing it requires coordinated leadership, not delegated responsibility.

For Senior Leaders: EVP, Managing Directors, Portfolio Managers, Department Heads

Senior leaders are the bridge between C-suite strategy and operational reality. They make investment decisions, manage teams, and shape the daily experience of AI transformation. Their role has three parts. Model AI adoption visibly within their teams — creating the permission structure that accelerates adoption at the operational level. Champion workflow redesign over tool deployment — ensuring AI capability translates into changed practice, not unchanged workflows with faster tools. Protect the judgment pipeline — redesigning mid-career development so that the next generation builds the contextual understanding and institutional knowledge that AI cannot replicate.

For the Individual: All Professionals Across the Organization

Curiosity — not seniority or technical background — predicts who succeeds in the AI-transformed investment profession. Cross the 20-hour competence threshold: the point at which deliberate AI practice converts from frustration to fluency. Adopt AI as a professional practice now, rather than waiting for organizational mandate — the professionals who engage earliest accumulate skills, networks, and career advantages that compound over time. Build the T-to-W knowledge profile: breadth across AI fluency, data literacy, and behavioral awareness, alongside deepening domain expertise. Treat AI fluency as a career asset that appreciates, not a compliance requirement to be minimized.

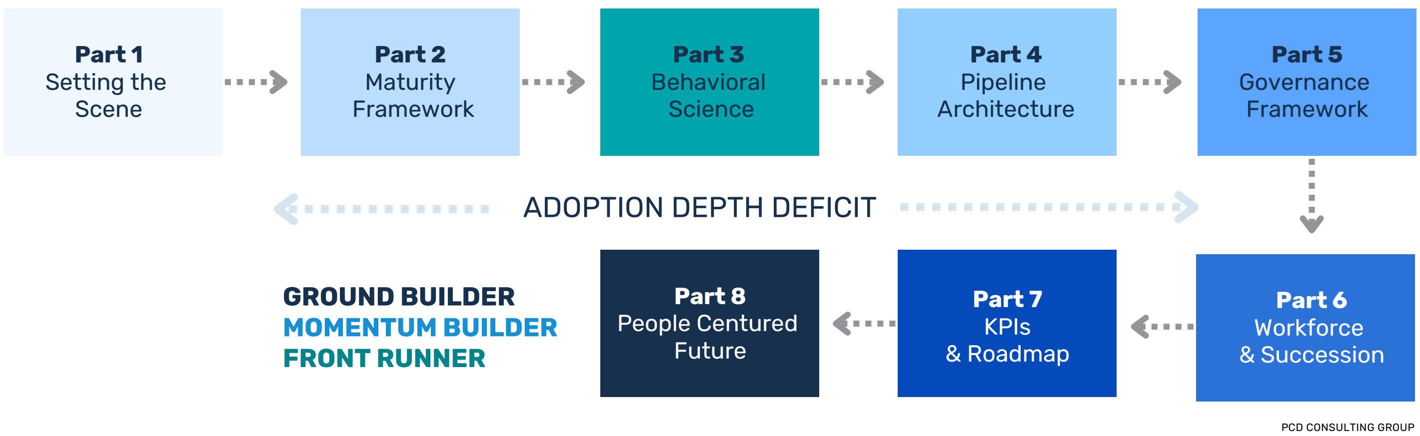
ILN as a Collaborative Platform

AI governance in institutional investing is fundamentally a shared challenge: shared AI systems, shared data dependencies, shared governance risks, shared vendor relationships, shared reputational stakes. No single institution can set governance standards for the industry, solve the succession pipeline challenge, or build the talent development frameworks, KPI benchmarks, and peer-learning infrastructure that the transformation requires.

Research on the governance of shared resources demonstrates that communities which design their own governance rules — with clear boundaries, graduated standards, and participatory decision-making — manage shared challenges far more effectively than either top-down regulation or uncoordinated individual action.

ILN is uniquely positioned to serve this function — a CEO-led network spanning seven countries and USD 10 trillion in combined assets under management, providing the peer-learning infrastructure that no single institution can build alone. The Road to 2030 AI and talent agenda provides the mandate. This playbook provides the foundation. The work that follows is where the value is captured.

Playbook Integration Map



YOUR PLAY:
Strategic Positioning

For Leadership
CEO, CIO, CHRO, and Boards

1. Present this playbook's maturity self-assessment results to the board within 60 days

2. Designate a named AI transformation owner at C-suite level with cross-functional authority and board reporting

3. Commit to one ILN peer-learning session per quarter focused on shared governance standards

4. Begin personal AI practice in visible team settings this week — share what works and what does not

For Senior Leaders
EVP, MD, PM, Department Heads

1. Champion governance as enabler: reframe the conversation from 'what can't we do?' to 'what does confident deployment require?'

2. Sponsor one cross-functional AI pilot that integrates investment, technology, and governance perspectives

3. Identify the two or three workflows in your team where AI-enabled redesign would produce the highest compounding returns

For the Individual
All Professionals

1. Invest 20 hours of deliberate AI practice over the next 90 days — the competence threshold that converts frustration to fluency

2. Identify one recurring analytical task and redesign it as a human-AI collaboration rather than a manual process

3. Share your AI experiments — including failures — with colleagues, contributing to the social proof that accelerates organizational adoption

Conclusion: The Decisive Moment

This playbook has mapped the landscape of AI transformation across a microcosm of the institutional investment industry — a cohort that, while bounded, is representative of the dynamics shaping the sector at large. It has introduced the maturity framework, documented the behavioral science of adoption, examined the pipeline architecture risks, laid out the governance architecture for confident deployment, confronted the workforce and succession challenges, built the KPI framework that translates AI activity into competitive evidence, and modeled the strategic scenarios ahead. What remains is the strategic choice.

Five conclusions carry forward.

The transformation is structural. This is not another technology cycle. It is a fundamental shift in how investment value is created, governed, and sustained. The institutions that treat it as an organizational design challenge — with leadership, governance, talent, and culture as co-equal priorities — will capture the value. Those that treat it as a technology upgrade will not.[65]

The binding constraint is organizational design, not technology. The adoption depth deficit — near-universal tool access collapsing to limited transformational impact — reveals that the limiting factor is leadership engagement, governance architecture, behavioral change, and workflow redesign. The technology is available. The question is whether the organizational architecture exists to use it.

Leadership is the catalyst; governance is the infrastructure. AI adoption is leader-led or it does not happen. But leadership without governance is ambition without architecture. The institutions making the most progress are those where leadership models AI practice visibly, where governance enables rather than constrains, and where the behavioral signal from the top is reinforced throughout the organization.

The succession pipeline is at risk and the window is closing. AI is performing the tasks that built the judgment of every senior investment leader in the industry today. If the developmental pathway that produces the next generation is narrowed without replacement, the consequences are irreversible. This is a three-to-five-year window. The advantage compounds for decades. The cost of inaction does too.

This is a people-centered transformation. The technology is available to everyone. The data is increasingly commoditized. The competitive advantage that endures is the quality of human judgment, the depth of institutional knowledge, and the capacity to develop talent over careers that span decades. The evidence from this research supports the bet that human capability compounds in ways that technology alone cannot replicate.

Appendix

AI Governance Behavioral Evidence Matrix

	Model A – Fragmented ***Reactive, Siloed, Low Trust***	**Model B – Transitional** ***Strucutred, Partial, Improving***	**Model C – Integrated** ***Strategic, Embedded, Resiliant***
Oversight & Accountability	Who owns AI decisions in practice when something goes wrong?	Are accountability roles clearly defined and consistently applied across functions?	How is AI decision-making embedded within strategic leadership structures?
Risk Management	Are risks identified before or after they have already had an impact?	Where do formal risk frameworks fall short in day-to-day practice?	How are emerging AI risks continuously anticipated and modeled before deployment?
Documentation	Can decisions made by AI systems be reconstructed after the fact?	Where do documentation silos limit visibility across teams?	How is end-to-end traceability maintained and used in active decision-making?
Human Oversight	When humans intervene in AI outputs, is that intervention predictable or ad hoc?	Where do intervention rules create friction rather than clarity?	How are human and AI roles deliberately co-designed within workflows?
Transparency	Is communication about AI systems reactive, or driven by obligation rather than intent?	Where do stakeholders continue to struggle with understanding AI outputs?	How is transparency actively designed to build stakeholder trust over time?
Data Governance	Do teams consistently know the origin and quality of the data powering AI systems?	Where do data quality policies fail at the point of execution?	How is data quality continuously monitored and linked to strategic governance priorities?
Testing & Validation	Is AI system testing conducted consistently, or only after failures expose gaps?	Where do gaps exist between testing protocols and real-world operating conditions?	How are validation processes designed to be continuous rather than point-in-time?
Incident Managment	Are incident responses reactive and crisis-driven, or guided by clear escalation paths?	Where do delays or role confusion slow the response to AI-related incidents?	How are lessons from incidents systematically embedded into governance improvement?
Supply Chain Governance	How visible are the AI systems embedded in third-party vendor relationships?	Where do blind spots in vendor oversight create unmanaged exposure?	How is the full AI ecosystem—including third parties—governed on a continuous basis?
AI Literacy & Culture	How uneven is AI understanding and adoption across teams and seniority levels?	Where do capability gaps prevent staff from applying AI training in practice?	How do teams actively and continuously engage with evolving AI capabilities?
Compliance Monitoring	Are compliance reviews sporadic and dependent on individual initiative?	Where is compliance monitoring manual, inconsistent, or slow to surface findings?	How is compliance monitoring automated and embedded into ongoing operations?
Enforcement Awareness	Does the organization act on regulatory expectations only after external pressure?	Where do interpretation gaps slow the organization's adaptation to new requirements?	How does the organization anticipate regulatory trends and embed awareness in decisions?

AI KPI Framework

INDUSTRY STANDARD KPIS	**Financial**	**Operational**	**Model & System**
MODEL INTEGRITY & TECHNICAL GOVERNANCE KPIs	**Explainability & Trust**	**Investment Specific Model Quality**	
ADOPTION & GOVERNANCE KPIs	**Adoption Funnel**	**Governance & Workforce**	
REVENUE GENERATION KPIs	**AI Saves (Cost Elimination & Capital Liberation)**	**AI Enables Revenue Acceleration**	**AI Creates Value That Would Not Otherwise Exist**

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AI KPI Framework

Mapped by maturity tier
P = Primary | • = Applicable | — = Not yet |

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Part A-1: Industry-standard KPIs

FINANCIAL

#	KPI Name	Description	Ground Builder	Momentum Builder	Front Runner
1	**Cost reduction %**	Direct savings from automation	P	P	·
2	**Revenue uplift**	Income from AI-driven improvements	—	·	P
3	**Cost per transaction**	Unit economics pre- vs. post-AI	P	P	·
4	**Payback period**	Months until value = investment	—	·	P
5	**Cost avoidance**	Estimated losses prevented	—	·	P
6	**Employee NPS (eNPS)**	Engagement pre/post AI deployment	·	P	P

#	KPI Name	Description	Ground Builder	Momentum Builder	Front Runner
OPERATIONAL					
1	**Process cycle time**	Time reduction in key processes	—	P	P
2	**Automation rate**	% tasks handled without human input	—	P	P
3	**Throughput increase**	Volume processed pre- vs. post-AI	—	P	·
4	**Time to value**	Time from initiation to first impact	P	P	·
5	**Error rate reduction**	% fewer errors with AI	·	P	P
6	**Sales conversion rate**	AI-assisted vs. baseline	—	·	P
7	**SLA compliance %**	% of AI-assisted service deliveries meeting defined service-level agreements	·	P	P
8	**Total model operating cost efficiency**	Total cost per unit of AI-assisted output: tokens + human review + validation + ops overhead	—	·	P
MODEL & SYSTEM					
1	**Prediction accuracy**	Correctness linked to cost of errors	·	P	P
2	**Model adoption rate**	% users actively using AI outputs	·	P	P
3	**Decision override rate**	How often humans reject AI	—	P	P
4	**System uptime / latency**	Availability and responsiveness	·	P	P
5	**Model drift monitoring**	Performance degradation tracking	—	·	P

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Part A-2: Model integrity & technical governance KPI

#	KPI Name	Description	Ground Builder	Momentum Builder	Front Runner
EXPLAINABILITY & TRUST					
1	**Model explainability score**	% production models with XAI methods (SHAP/LIME) documented	–	P	P
2	**Hallucination / output reliability rate**	% AI outputs flagged as factually incorrect by review	–	P	P
3	**Algorithmic bias audit frequency**	Formal fairness testing cycles per year per model	–	•	P
4	**Human-in-the-loop compliance rate**	% governed outputs passing required human review	P	P	P
INVESTMENT-SPECIFIC MODEL QUALITY					
1	**Signal-to-noise improvement ratio**	Predictive power (IC) of AI vs. traditional signals	–	•	P
2	**AI-augmented decision quality index**	Accuracy + consistency of AI-assisted vs. unassisted decisions	–	•	P
3	**Synthetic data utilisation rate**	% model validations incorporating synthetic stress data	–	–	P
4	**Regulatory readiness index**	% deployments mapped to applicable regs by jurisdiction	•	P	P

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Part B: Adoption & governance KPIs

#	KPI Name	Description	Ground Builder	Momentum Builder	Front Runner
ADOPTION FUNNEL					
1	**Usage depth distribution**	Frequency shape: missing middle exposed	P	P	P
2	**Adoption velocity**	Days from deploy to active use by cohort	P	P	•
3	**Leadership modelling index**	% senior leaders visibly using AI	P	P	P
4	**Workflow integration rate**	% core processes with AI embedded	—	P	P
5	**Transformational impact score**	Has AI changed decisions or products?	—	—	P
GOVERNANCE & WORKFORCE					
1	**Governance coverage rate**	% deployments in formal framework	P	P	•
2	**AI literacy rate**	% trained beyond tool access	P	P	•
3	**Shadow AI incidence**	Ungoverned tools/artefacts identified	—	P	P
4	**AI talent pipeline health**	AI-capable professionals vs. needs	•	P	P
5	**Inclusion index for AI**	Adoption by gender, seniority, function	P	P	P
6	**Agentic AI readiness score**	Infrastructure + governance for autonomy	—	•	P
7	**Cross-functional AI integration depth**	# AI apps spanning 2+ organisational functions	—	•	P

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Part C: Revenue-generation KPIs

AI SAVES — COST ELIMINATION & CAPITAL LIBERATION					
#	KPI Name	Description	Ground Builder	Momentum Builder	Front Runner
1	**Avoided hiring cost ($)**	Planned hires eliminated × loaded cost	P	P	•
2	**Compliance cost reduction ($)**	Hours saved + penalties avoided in $	P	P	•
3	**Working capital freed ($)**	Capital released via AI-optimised ops	–	P	P
4	**Token cost-to-value ratio**	Token spend per unit of business output	–	–	P
5	**Total AI investment ($, fully loaded)**	Licenses + compute + AI-allocated FTE time + governance + training + change-mgmt overhead	P	P	P
6	**Time to breakeven (months, cumulative)**	Months until cumulative AI value >= cumulative AI investment, tracked as quarterly J-curve	P	P	P
7	**Stage-gate conversion rate (%)**	% of AI initiatives passing each gate: Pilot -> Production -> Scale -> Embedded	P	P	P

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AI ENABLES — REVENUE ACCELERATION					
#	**KPI Name**	**Description**	**Ground Builder**	**Momentum Builder**	**Front Runner**
1	**Mandate win rate (AI-assisted)**	% mandates won with AI RFP vs. baseline	—	P	P
2	**Revenue per RM (augmented vs. not)**	A/B: AUM growth with AI tools vs. without	—	P	P
3	**Client retention value ($)**	AUM retained via AI engagement vs. churn	—	—	P
4	**Information creation productivity**	$ output per analyst hour, AI vs. manual	—	P	P
5	**Net AI value captured ($)**	Sum of AI Saves + Enables + Creates, minus Total AI investment ($)	•	P	P
6	**Domain concentration index (1-3 domain test)**	% of AI investment concentrated in top 1-3 business domains being reinvented	—	P	P
7	**Value-to-investment multiple ($ EBITDA / $ in)**	Cumulative AI EBITDA $ / cumulative AI investment $	—	•	P

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AI CREATES — VALUE THAT WOULD NOT OTHERWISE EXIST					
#	KPI Name	Description	Ground Builder	Momentum Builder	Front Runner
1	**AI-attributed alpha (bps / $)**	Incremental return from AI-enhanced process	—	—	P
2	**Decision augmentation yield ($)**	$ value of AI-improved decisions vs. without	—	—	P
3	**AI value concentration ratio**	% AI spend on core vs. peripheral activities	—	P	P
4	**Unrecognised opportunity cost ($)**	Applicable but undeployed AI	•	P	P
5	**Token-to-insight conversion**	Insight value generated per unit compute	—	—	P
6	**AI EBITDA impact (% and $)**	Incremental EBITDA attributable to AI, in $ and as % of base EBITDA	—	•	P
7	**Value-to-investment multiple ($ EBITDA / $ in)**	Cumulative AI EBITDA $ / cumulative AI investment $	—	•	P

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