In collaboration with Accenture

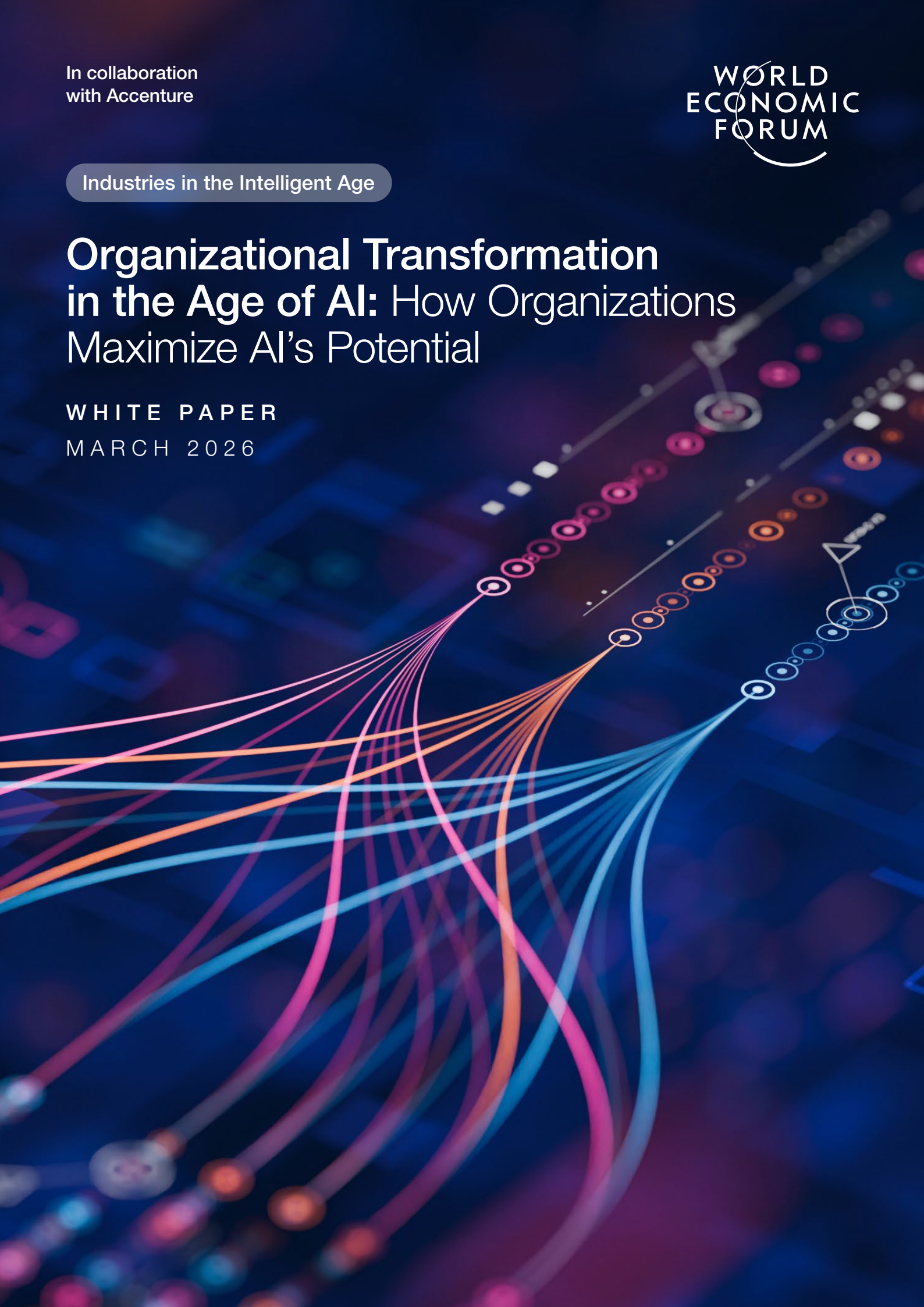
WORLD ECONOMIC FORUM

Industries in the Intelligent Age

Organizational Transformation in the Age of AI: How Organizations Maximize AI's Potential

WHITE PAPER

MARCH 2026



Images: Adobe Stock, Getty Images

Contents

Reading guide

The World Economic Forum's AI Transformation of Industries initiative seeks to catalyse responsible industry transformation across industries and society. It advances understanding of artificial intelligence's (AI) impact on business and society while actively accelerating practical implementation through leadership convening, ecosystem collaboration and the scaling of real-world solutions.

This white paper series examines the transformative role of AI across industries, combining cross-industry analysis with in-depth sectoral and regional perspectives.

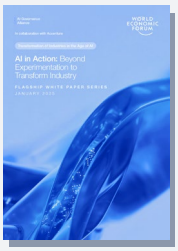
Each paper offers a practical, executive-level view of what transformation looks like on the ground, drawing on real-world case studies, leading practices, emerging data from across industries and figures of impact achievable in selected contexts. While each paper is standalone, common themes emerge: new operating models, evolving roles of leadership, human-AI collaboration and the growing importance of AI governance and orchestration.

As AI adoption accelerates, this series aims to equip leaders with the insight, capabilities and decision frameworks required to build competitive, responsible and future-ready AI-enabled organizations.

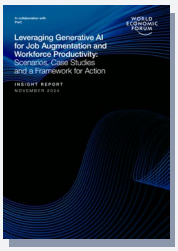
Cross industry

Impact on industrial ecosystems

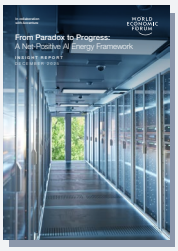
Organizational Transformation in the Age of AI: How Organizations Maximize AI's Potential



AI in Action: Beyond Experimentation to Transform Industry



Leveraging Generative AI for Job Augmentation and Workforce Productivity

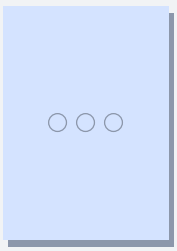


From Paradox to Progress: A Net-Positive AI Energy Framework

Artificial Intelligence and Cybersecurity: Balancing Risks and Rewards

Regional specific

Impact on regions



Upcoming: China

Industry or function specific

Impact on industries, sectors and functions

Media, entertainment and sport

Artificial Intelligence in Media, Entertainment and Sport

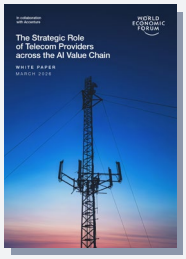
Healthcare

The Future of AI-Enabled Health: Leading the Way

Transport

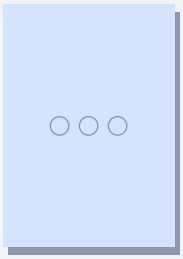
Intelligent Transport, Greener Future: AI as a Catalyst to Decarbonize Global Logistics

Telecommunications



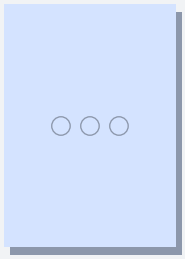
The Strategic Role of Telecom Providers Across the AI Value Chain

Advanced manufacturing and supply chains



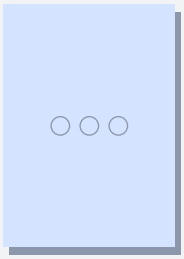
Upcoming

Financial services



Upcoming

Consumer goods



Upcoming

Foreword

Maria Basso
Head, AI Applications and Impact, Centre for AI Excellence, World Economic Forum

Stephan Mergenthaler
Managing Director, Chief Technology Officer, World Economic Forum

Kathleen O'Reilly
Global Lead, Deal Structuring & Pricing, Accenture

Artificial intelligence (AI) is entering a decisive phase. Across industries and regions, organizations are moving beyond experimentation and demonstrating tangible results from AI adoption. Yet as organizations unlock value from isolated AI use cases, a deeper transformation remains elusive: embedding AI into the core processes that define how work gets done and how decisions are made across enterprises.

This paper reframes the challenge facing leaders today: not whether AI works, but how organizations must re-architect their workflows, operating models and decision rights to harness AI as a source of sustained enterprise advantage.

To date, much of AI's impact has been delivered through targeted applications and functional pilots. These efforts have proven that AI works – but they capture only a fraction of its potential. The greatest gains arise when AI is embedded into core workflows, decision-making processes and operating models, reshaping how organizations compete and grow. Achieving this shift is not a primarily technological challenge, but an organizational one.

Scaling AI requires changes in how work is designed, how decisions are made and how accountability is exercised. It calls for new approaches to governance, leadership, skills and trust – particularly as AI systems move from supporting analysis to participating directly in execution. In this environment, organizations must redefine the relationship between people and intelligent systems, ensuring that human judgement, responsibility and oversight remain firmly at the centre.

The World Economic Forum has long championed collaborative approaches to complex systemic challenges. In this spirit, the findings presented here are rooted in cross-industry practice and reflect the collective experience of organizations at the forefront of AI transformation. They also reaffirm a central insight: success with AI is not merely a technological achievement, but an organizational one. It depends on strategic leadership, clear accountability, trust in AI-supported decisions and operating models that balance human agency with machine intelligence.

This white paper is part of the World Economic Forum's *Industries in the Intelligent Age* series and builds on the insights from the AI Transformation of Industries community. We offer this paper as a resource and a call to action. Integrating AI into how value is created and decisions are made is among the most consequential leadership tasks of this decade. Organizations that act with clarity, coherence and commitment will unlock transformative productivity, resilience and growth. Those that do not risk falling behind – not because AI fails them, but because organizational change does.

Executive summary

From pilots to operation models, leading firms embed artificial intelligence into core workflows to deliver enterprise value.

Artificial intelligence (AI) has moved beyond curiosity and early experimentation. Across industries, organizations can now point to measurable gains from AI adoption. Yet for most, these gains remain fragmented – captured through isolated use cases rather than embedded into how the enterprise operates. As a result, the central challenge has shifted: not whether AI works, but how organizations must change to realize its full, sustained value.

This paper examines how leading organizations are making that transition. Drawing on consultations and discussions with the World Economic Forum's AI Transformation of Industries community – comprising more than 450 executives across sectors – it explores how AI is being integrated into core enterprise workflows and reshaping operating models, decision-making and the nature of work itself. The findings build on *AI in Action: Beyond Experimentation to Transform Industries*, moving from proof of concept to organizational redesign.

The analysis focuses on five critical focus areas where community members are actively re-architecting how work is performed, and where AI is already driving enterprise-level impact:

Focus 1

Real-time, individualized customer experiences: Shifting from static journeys to continuous, intent-driven engagement

Focus 2

Efficient and resilient operations: Shifting from forecast-based execution to adaptive, AI-orchestrated systems

Focus 3

Accelerated research and development (R&D) and breakthrough innovation: Shifting from linear development into continuous, evidence-driven learning

Focus 4

Predictive, AI-powered strategic planning: Shifting from periodic planning cycles with ongoing strategic steering

Focus 5

Data-driven, personalized talent experience and workforce planning: Shifting from role-based management to dynamic, capability-based systems

Across the focus areas, three structural shifts are emerging:

- From isolated use cases to connected systems, where customer experience (CX), operations, research and development (R&D), strategy and talent reinforce one another
- From episodic initiatives to continuous processes that sense signals, make decisions and learn in real time
- From task automation to human value creation, with people focusing on judgement, orchestration and accountability while AI accelerates insight and execution

While the focus areas illustrate where AI is transforming value creation, sustaining these shifts at scale depends on how organizations redesign themselves. Scaling AI requires a rethinking of decision ownership, operating structures and governance mechanisms so that intelligent systems are embedded into execution rather than layered onto existing processes. Organizations that succeed keep humans firmly in the lead, redesign operating models around end-to-end outcomes, treat trust and transparency as execution enablers, institutionalize disciplined experimentation and invest in scalable talent systems. In these environments, AI enhances speed and intelligence in execution while humans remain responsible for direction, trade-offs and outcomes.

Taken together, the findings highlight a broader organizational transition. As AI becomes embedded in execution, sustained value depends less on technical sophistication and more on leadership's ability to align governance, incentives and ways of working with intelligent systems. Organizations that succeed act on AI-supported evidence, continuously reallocate resources and adapt how work is done.

Introduction

AI's next phase demands a rethinking of core workflows to unlock enterprise-wide impact, rather than an expansion of pilots.

The past decade marked an important inflection point in the adoption of artificial intelligence (AI). Organizations moved rapidly from experimentation to capability, advancing through pilots, proofs of concept and early deployments. As explored in *AI in Action: Beyond Experimentation to Transform Industries*, many leaders have now demonstrated that AI use cases work. As agentic AI starts being integrated and cost of learning collapses, the next phase of AI adoption requires structural organizational change.

Increasingly, organizations recognize that the greatest value from AI is not realized through standalone use cases but from embedding AI deeply into core workflows and operating models. At this stage, AI becomes a catalyst for transformation – reshaping how work is done, how value is created and how productivity and growth are achieved.

Much of AI's early value has come from narrowly defined applications that delivered learning, localized efficiency gains and proof of return. Applied in discrete use cases, AI often augments existing workflows but rarely transforms them, constraining the scale and durability of impact. Greater impact emerges when organizations redesign processes end-to-end, creating compounding effects across the enterprise. Yet today, only a small proportion of organizations – approximately 15% – are using AI to fundamentally redesign how work is performed.[1] As more organizations progress beyond segregated pilots, the value generated by AI shifts from incremental improvement towards more transformative outcomes.

While studies show double-digit productivity gains at the task level, these have not consistently translated into enterprise or macroeconomic impact. Without redesigning end-to-end workflows and decision rights, individual gains do not convert into structural value.

As with earlier transitions from analogue to digital, scaling AI requires more than technology adoption. It demands changes to operating models, governance structures, skills and leadership practices. While pathways differ across industries and regions, organizations advancing beyond experimentation are converging on a set of shared principles: clear business ownership of AI, workflow redesign rather than pilot expansion, sustained investment in workforce leadership capability development, and trust and experimentation as foundational capabilities.

Building on *AI in Action: Beyond Experimentation to Transform Industries*, this paper examines how organizations are translating AI ambition into measurable outcomes. Drawing on consultations and observations from the AI Transformation of Industries Community at the World Economic Forum, comprising more than 450 leading adopters advancing AI at scale across industries, it synthesizes the organizational changes observed among successful enterprises. The paper reflects patterns emerging in practice and is not intended as a prescriptive set of recommendations. It highlights five core focus areas where leaders are already embedding AI to drive enterprise-wide impact:

Focus 1: Real-time, individualized customer experience (CX)

Focus 2: Efficient and resilient operations that adapt and evolve

Focus 3: Accelerated research and development (R&D) and breakthrough innovation

Focus 4: Predictive, AI-powered strategic planning

Focus 5: Data-driven, personalized talent experience and workforce planning

Across each focus area, the paper highlights value opportunities, the organizational shifts required and examples of progress towards enterprise-wide impact.

Focus 1

Real-time, individualized CX

AI turns customer journeys into real-time, adaptive systems that predict intent, act autonomously and learn continuously.

CX spans end-to-end processes through which customers discover, evaluate, purchase, use and receive support for products and services. Traditionally, these journeys have been designed as linear flows and managed through fragmented channel interactions.

AI enables organizations to sense customer intent in real time, steer experiences dynamically and act on customers' behalf within clearly defined guardrails. As a result, CX shifts from a series of discrete interactions to continuous, adaptive relationships, anticipating needs, resolving issues earlier and learning from every engagement.

TABLE 1 | **AI-enabled transformation of CX**

At a glance

Awareness	Consideration	Purchase	Service	Retention

Ambition: opportunities to capture	**Action:** how organizations are changing
– **Increase conversion and reduce churn** through timely, predictive and personalized interventions at the moment of risk or opportunity. **Up to 25% higher consumer conversation rates and 21% reduction in churn[2] leading to 5-8% revenue uplift[3]**	1 **From periodic campaign targeting to one-to-one, predictive discovery:** Shift from campaign-led reach and customer-initiated contact to AI-driven inference of latent intent, value and risk.
– **Reduce cost-to-serve while improving experience[4]** by preventing issues, automating resolution and accelerating human-led interactions. **20–30% lower cost-to-serve,[5] 15–30% productivity gains[6]**	2 **From static journeys to dynamic, real-time orchestration tailored to every customer:** Replace static journey maps with continuous, moment-level decisions across channels.
– **Strengthen trust and brand consistency at scale** by consolidating consumer profiles and delivering one coherent relationship across channels. **Up to 15–20% higher customer satisfaction score (CSAT)[7]**	3 **From human-only execution to agentic action on behalf:** Move routine CX execution to AI agents operating within guardrails, with human focus reserved for judgement, empathy and exceptions.
	4 **From reactive outcomes to continuous experience learning and trust optimization:** Shifts from post-hoc churn response to continuous optimization of value, trust and automation thresholds.

FIGURE 1 | **Four operating model shifts in CX**

1

From periodic campaign targeting... → **to one-to-one, predictive discovery**

Discovery shifts from broadcasting the same offers to many customers to sensing personal intent and context in real time and surfacing what's most relevant in the moment.

2

From static journeys... → **to real-time evaluation steering to dynamic,real-time orchestration tailored to every customer**

AI replaces pre-built journey flows with real-time decisions on what content, offer or human intervention is triggered next for each individual interaction.

3

From human-only execution... → **to agentic action on behalf**

AI autonomously executes routine CX actions – such as resolving issues, adjusting terms, routing work and initiating follow-ups – under clearly defined guardrails: e.g. refund limits below a defined financial threshold, escalation triggers for repeated complaints or high-value transactions or human review when model confidence falls below a set level. These parameters ensure that autonomy expands where risk is contained, while accountability for customer outcomes remains explicitly assigned.

4

From reactive outcomes... → **to continuous experience learning and trust optimization**

AI continuously builds customer profiles and updates who receives retention actions, which offers are allowed and when automation is permitted based on observed lifetime values, experience outcomes and trust signals.

Taken together, these shifts transform CX into a real-time value allocation system that continuously optimizes outcomes across key dimensions – enhancing experience quality, reducing stress, accelerating responsiveness and improving accuracy. In such systems, AI dynamically prioritizes attention, autonomy and incentives while guiding human intervention where it matters most, balancing growth, cost, risk and trust.

1.1 From periodic campaign targeting to one-to-one, predictive discovery

Shifts in how CX operates:

- Complement or replace fixed campaign targeting with continuous, AI-driven selection of customers to engage, suppress or defer based on predicted intent, value and risk.
- Combine signals across the journey (browsing, comparison, pauses, retries, device, location, service history) to infer what customers are trying to do now.
- Shift customer discovery from static segmentation to an adaptive process that infers and actively inquires into evolving customer behaviours and preferences, continuously learning as individuals move through the journey.
- Evolve CX and marketing roles from audience and message design to signal definition, guardrails and decision thresholds.

Organizational changes observed:

- Establish cross-functional discovery teams combining different expertise – e.g. marketing, CX, data science and product ownership.
- Shift accountability from campaign planning to real-time decision engines that determine engagement and suppression.
- Expand human roles towards signal curation, policy definition and acceptable actions.
- Introduce shared standards for customer signals, consent rules and confidence thresholds across channels.

Early vs advanced adopters:

- **Early:** Use AI to refine targeting and engagement within existing campaign structures using a limited set of clear intent signals.
- **Advanced:** Operate discovery as a real-time, predictive decision system coordinated across marketing, sales and service.

CASE STUDY 1

Interactive “next best action” to steer customer engagement

Ford used AI-driven decisioning to dynamically move customers in and out of audiences during multi-wave campaigns based on real-time responses, rather than fixed journeys. This enabled rapid adjustment of who to engage, when and with what message. In three weeks, the FordPass Mobile App reported over 300,000 customers engaged and a 26% increase in conversion.[8]

1.2 From static journeys to dynamic, real-time orchestration tailored to every customer

Shifts in how CX operates:

- Shift from predefined, linear paths to real-time steering that adapts dynamically as individuals evaluate, hesitate, compare or change direction.
- AI continuously interprets decision signals (stalling, backtracking, comparison depth, option overload, repeated errors and individual context) to design how the journey adapts next.
- Dynamically reorder steps, content, choice sets and assistance in real time to match individual decision-making.
- Shift journey design from static maps to adaptive rules, pathways and intervention logic.

Organizational changes observed:

- Transition from channel- or campaign-specific ownership to end-to-end journey governance.
- Establish shared journey logic across digital, assisted and human touchpoints.
- Redefine CX roles to focus on adaptive rules, thresholds and decision patterns.
- Deploy real-time orchestration layers that can modify journeys mid-stream.
- Align incentives around journey completion and momentum rather than performance.

Early vs advanced adopters:

- **Early:** Apply real-time nudges or assistance at selected high-friction moments.
- **Advanced:** Run journeys as continuously adaptive processes, dynamically steering each individual's path based on real-time decision signals.

CASE STUDY 2

Continuous customer profiling and adaptive engagement

Rabobank uses its Customer Decision Hub to unify customer profiles and continuously adapt engagement across app, web, online banking and call-centre channels. The AI engine aggregates behavioural and interaction data in real time to deliver **next-best actions** tailored to evolving customer needs, enabling over 1.5 billion personalized interactions per year, a fourfold increase in click-through rates, a 208% lift in conversion, a 4.7% increase in customer lifetime value and a 2.4% reduction in cost to serve.[9]

1.3 From human-only execution to agentic action on behalf

Shifts in how CX operates:

- Execution shifts from primarily human and rule-driven responses to requests towards AI agents acting proactively on customers' behalf within defined guardrails.
- AI agents can complete actions end-to-end (rebook, refund, configure, schedule, escalate).
- As agentic systems mature, competitive advantage will hinge on how effectively organizations let customers govern autonomy by defining what can be automated, what requires confirmation and when a human must intervene.
- Shift trust from firm-defined policies to dynamic, customer-controlled relationships.

Organizational changes observed:

- Define clear guardrails, human accountability frameworks and redress mechanisms for when AI agents act independently, including defined liability ownership, incident response protocols and dispute resolution pathways. Securely integrate AI agents directly with core systems (CRM, billing, inventory, scheduling, fulfilment).
- Integrate AI agents directly with core systems – e.g. customer relationship management (CRM), billing, inventory, scheduling and fulfilment.
- Redesign escalation models based on confidence thresholds and policy limits.
- Human effort shifts to oversight, judgement, policy definition and complex exception handling.
- Establish governance for accountability, auditability and customer consent.

Early vs advanced adopters:

- **Early:** Deploy agents in limited steps under close human supervision.
- **Advanced:** Operate agentic systems that autonomously execute many routine CX tasks, with defined guardrails.

CASE STUDY 3

AI agents act autonomously under consumer-set guardrails to complete purchases

Visa Intelligent Commerce enables AI agents to complete authorized purchases on behalf of consumers. This represents a shift to AI-driven purchasing workflows, combining real-time intent inference with trusted payment credentials and network safeguards.

In total, 47% of consumers now use AI tools for at least one shopping task, from price comparisons to personalized recommendations, creating a strong base of behavioural adoption that agentic payment systems can build on.[10]

1.4 From reactive outcomes to continuous experience learning and trust optimization

Shifts in how CX operates:

- Move from channel-specific views to a continuously updated, unified customer profile used consistently across channels and touchpoints.
- AI tracks behaviour, context and outcomes so each interaction builds on the last.
- Shift experience management from post-hoc measurement to continuous learning.
- Treat trust as a measurable system variable, informed by customer behaviour and outcomes, that adjusts automation levels, escalation thresholds and human involvement.

Organizational changes observed:

- Replace episodic CX reviews with continuous monitoring of experience, outcome and trust signals (such as complaints, reversals and consent changes).
- Establish cross-functional governance forums with defined audit cycles to review automated decisions and trust signals, and update thresholds and policies accordingly. Embed model monitoring, bias detection and outcome validation into CX operations.
- Continuously update policies, thresholds and customer-set permissions governing automation.
- Align incentives and performance metrics around long-term experience quality, trust and lifetime value rather than short-term campaign metrics. Embed privacy-by-design principles into CX systems, including consent-aware automation, data minimization, role-based access controls and transparent data use policies.

Early vs advanced adopters:

- **Early:** Share limited customer context across selected channels and periodically refine rules.
- **Advanced:** Maintain a real-time, unified customer profile that continuously governs decisions and learning.

CASE STUDY 4

AI-orchestrated CX at scale

WPP Open, an AI-powered operating system, unifies creative, media and operational workflows across its global network. AI integrates data, decision-making and execution to steer customer-facing actions in real time, while humans focus on strategy, judgement and oversight.

The platform reduced non-essential tasks by 20%, increased creative capacity by 25% and improved productivity by 29%, demonstrating how AI can orchestrate continuous, individualized CX at scale.

As CX becomes adaptive and real-time, sustained value increasingly depends on an organization's ability to continuously refine the systems that shape interaction. Leading organizations embed mechanisms for updating models, calibrating guardrails and learning from outcomes, treating CX not as a finished product, but as an evolving capability. In doing so, they strengthen resilience, deepen trust and expand long-term customer value.

Focus 2

Efficient and resilient operations that adapt and evolve

AI turns operations into adaptive systems that sense, decide and improve continuously across networks.

Operations sit at the core of value creation, spanning sourcing, manufacturing, supply chains, logistics, maintenance and field services. Historically, these functions were optimized for efficiency and stability through forecasts, standardized processes and human coordination to manage variability and exceptions.

AI introduces a fundamentally different architecture across this value chain. By embedding real-time sensing and predictive intelligence into execution, it enables operations to shift from reactive, scheduled execution to adaptive, predictive and learning-based systems that respond dynamically to changing conditions.

TABLE 2 | **AI-enabled transformation of operations and supply chain**

At a glance

Planning	Scheduling	Production	Delivery	Fulfilment

Ambition: opportunities to capture	**Action:** how organizations are changing
– **Improve operational efficiency and performance** by proactively reducing bottlenecks, downtime and defects. **20–50% reduction in defect rates; up to 10–30% reduction in scrap and rework, leading to over 10% earnings before interest and taxes (EBIT) impact**[11]	1 **From manual coordination to human-AI coordination and AI-orchestrated execution:** AI and robots take on routine, heavy and hazardous work while humans focus on oversight and judgement within defined guardrails.
– **Increase operational flexibility, stability and resiliency for just-in-time execution** by continuously adjusting production as conditions change. **Up to 27% reduction in order lead time; up to 20–30% reduction in inventory; 5–8% improvements in fill rate through real-time demand/supply balancing**[12]	2 **From reactive fixes to pre-emptive resilience:** Early warning systems detect deviations during execution and trigger predefined responses before disruptions escalate.
– **Turn operations into a source of innovation and growth** by embedding automation, digital simulation and embodied AI directly into the workflow. **Organizations with AI-enabled intelligent operations achieve 2.4 times greater productivity and 2.5 times higher revenue growth**[13]	3 **From forecast-driven planning to real-time sensing:** Fixed schedules give way to continuous sensing of demand, supply and production signals to rebalance workflows dynamically.
– **Improve sustainability and safety** by optimizing energy use and early risk detection. **Approximately 40–60% potential reductions in energy consumption and emissions**[14]	4 **From one-speed execution to outcome-driven, continuous network-wide improvement:** AI learns from execution outcomes and local and tacit knowledge to continuously improve decisions across plants, assets and teams.

FIGURE 2 | **Four operating model shifts in operations and supply chain**

1

From manual coordination... → to human-AI coordination and AI-orchestrated execution

Physical and embodied AI are embedded into production, monitoring and routine coordination. Humans continue to perform core operational work, exercising supervision, judgement, approvals and intervention in complex, safety-critical or novel situations.

2

From reactive fixes... → to pre-emptive resilience

AI augments planners by continuously sensing demand, supply and operational signals and proposing updates, while humans remain responsible for setting priorities, resolving trade-offs and approving changes.

3

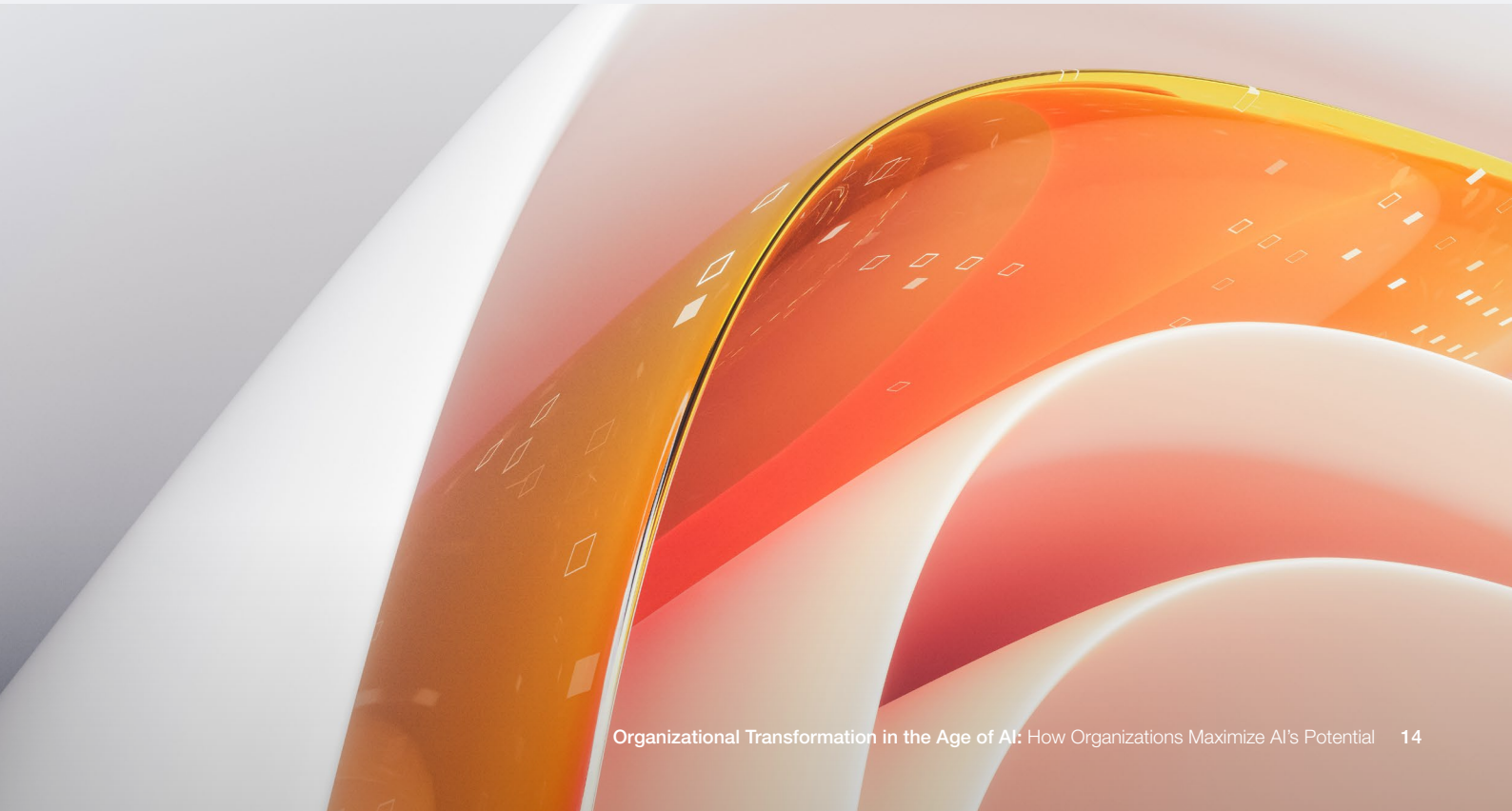
From forecast-driven planning... → to real-time sensing

Disruptions are anticipated and mitigated early through real-time signals and predefined responses. Humans oversee exceptions, refine playbooks and intervene when situations exceed expected bounds.

4

From one-speed execution... → to outcome-driven, continuous network-wide improvement

AI systems learn from execution data and frontline expertise to refine models, codify operator insight and propagate improvements across the network. Humans interpret insights, validate learning and decide how improvements are applied across sites and teams.



2.1 From manual coordination to human-AI coordination and AI-orchestrated execution

Shifts in how operations work:

- Physical execution increasingly involves robotics and embodied systems coordinated by digital agents.
- Manual coordination of production tasks, maintenance schedules and line performance is complemented by AI agents acting as a digital execution layer.
- Advanced manufacturing environments increasingly use autonomous mobile robots (AMRs) and unified data layers to reshape real-time planning.
- AI agents monitor real-time operating conditions and autonomously adjust parameters, dispatch maintenance and optimize process flow within predefined safety and operational guardrails.
- Process variability is increasingly treated as a signal to interpret rather than a deviation to eliminate, enabling adaptive optimization while maintaining consistent outcome quality.
- Accountability expands to include agent performance, with humans retaining override and governance control.

Emerging organizational practices:

- Operators and supervisors shift from direct control to system oversight and approvals in safety-critical situations.
- Engineering, operations and safety teams are expected to define agent behaviour and autonomy boundaries.
- Accountability expands to include additional AI performance monitoring metrics, such as orchestration accuracy and loop-closure metrics.
- Governance frameworks specify which decisions agents can take autonomously versus those requiring human sign-off.

Early vs advanced adopters:

- **Early:** AI generates alerts, task recommendations and performance insights for operators to act on.
- **Advanced:** AI agents autonomously dispatch work orders, adjust line speeds and optimize process parameters and task sequencing within clearly defined safety and business guardrails.

CASE STUDY 5

Scaling efficiency across sites with agentic AI

Allied Systems deployed agentic AI at the production line level to autonomously optimize operating parameters using real-time data and embedded operator expertise. Operators remained in the loop through real-time feedback and approval. The approach scaled across sites, improving overall equipment efficiency by 10%, reducing raw material and energy waste and enabling consistent performance without additional capacity, turning local know-how into a scalable production model.

2.2 From reactive fixes to pre-emptive resilience

Shifts in how operations work:

- Computer vision systems monitor shopfloor activity in real time, detecting safety risks and equipment anomalies with privacy-preserving safeguards.
- AI models monitor real-time signals across quality, supply chain and production, detecting deviations from baseline before failures materialize, pre-emptively predicting issues and initiating corrective actions before performance decline.
- AI agents with pre-defined thresholds execute pre-approved countermeasures, significantly reducing response time.

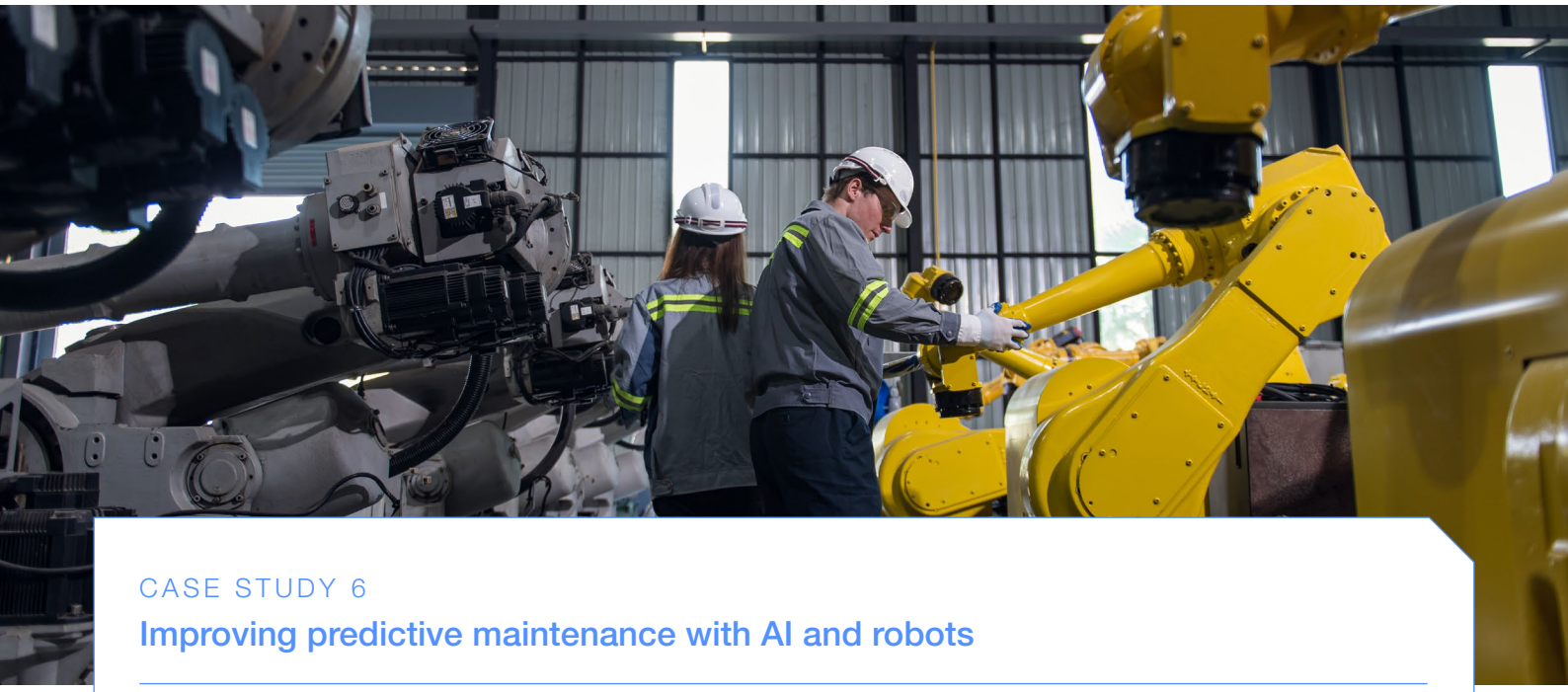
- Embodied AI systems, including inspection drones and mobile robots, detect physical anomalies and trigger response protocols with only human oversight.
- Digital twins simulate changes to equipment settings and operational conditions, allowing adjustments to be tested virtually before physical deployment.

Organizational changes observed:

- Issue detection is embedded in shared dashboards, agent alerts and inline quality systems accessible to frontline teams.
- Risk detection and intervention planning occur earlier, with predefined intervention roles across operations, logistics and procurement.
- Resilience is increasingly incorporated into design, supported by playbooks validated through simulation.
- Performance is measured by disruption contained and impact avoided, not just recovery speed.
- Development and oversight of AI-driven resilience systems becomes a shared responsibility across operations, engineering, data science, information technology (IT) and risk functions.

Early vs advanced adopters:

- **Early:** Predictive analytics flag risks and alert human teams.
- **Advanced:** Multi-agent systems simulate risks and reconfigure operations automatically within defined tolerances.



CASE STUDY 6

Improving predictive maintenance with AI and robots

Nestlé Purina uses AI-powered robots and fleet management software to automate routine equipment inspections and enable predictive maintenance. Robots equipped with thermal and acoustic sensors regularly scan motors and gearboxes for anomalies; AI analyses the data to flag issues early. This approach detects problems before failures, reducing unplanned downtime and allowing operators to focus on higher-value work.[15]

CASE STUDY 7

Accelerated problem detection and resolutions

At Siemens, generative AI enables frontline workers to flag design and quality issues through natural language, automatically summarizing and routing insights to the right teams. Automation engineers use AI co-pilots to generate and debug programmable logic controller (PLC) code, reducing errors and cycle time, while real-time computer vision detects defects in the factories. These capabilities accelerate problem resolution, improve quality and enhance operational resilience.[16]

2.3 From forecast-driven planning to real-time sensing

Shifts in how operations work:

- Real-time simulation continuously adjusts energy consumption, material use and production parameters to achieve the same output with lower resource intensity.
- AI continuously ingests signals across demand, supply, labour, inventory and asset availability to adjust schedules, logistics levels and workflows as conditions change.
- AI dynamically adjusts production and logistics based on real-time signals, constraints and upstream disruptions.
- Live sensing improves both speed and decision quality, reducing reaction lag.
- Coordination shifts from handoffs and escalation meetings to shared, AI-mediated execution logic with human approval thresholds.

Organizational changes observed:

- Planning teams increasingly focus on static schedule generators, decision supervision and guardrail settings.
- Cross-functional coordination deepens across planning, operations and logistics.
- Accountability is expected to be traceable across human and AI decisions.
- Success metrics expand beyond plan adherence to flow stability and responsiveness.

Early vs advanced adopters:

- **Early:** AI generates plan alternatives and bottleneck insights for manual execution.
- **Advanced:** Multi-agent orchestration autonomously coordinates scheduling, inventoryrebalancing and work assignments across sites and networks within defined operational constraints.

CASE STUDY 8

AI-orchestrated supply chains at scale

Lenovo embedded an AI agent, iChain, at the core of its global supply chain to continuously monitor demand, supplier constraints and transport flows. The agent predicts disruptions and dynamically re-optimizes shipments, coordinating across manufacturing, inventory and logistics in real time. This shift improved shipment accuracy by 30%, increased delivery predictability and sustainability at scale.

2.4 From one-speed execution to outcome-driven, continuous and network-wide improvement

Shifts in how operations work:

- Best practices propagate automatically across similar assets and sites.
- In practice, site leadership typically validates propogation ahead of broader deployment.
- Operator actions, overrides and recovery steps are captured at the company level.
- AI models are periodically retrained and updated using execution feedback, adjustments and setpoints aggregated across locations.
- AI connects signals across factories, warehouses, suppliers and transport to coordinate network-level adaptation.

Organizational changes observed:

- Human-AI interfaces are redesigned to capture decision rationale and exception handling.
- Continuous improvement increasingly harnesses digital tools, with insights embedded directly into execution logic.
- Cross-site coordination increasingly incorporates AI-derived performance data into continuous improvement forums.
- Workforce development may include efforts on preserving institutional know-how amid turnover.

Early vs advanced adopters:

- **Early:** Share benchmarks, key performance indicators (KPIs) and standard operating procedures across sites to reduce process variability and encourage knowledge exchange.
- **Advanced:** Automatically retrain and deploy orchestration logic based on execution outcomes.

CASE STUDY 9

Scaling learning and performance with agentic AI

Essity embeds agentic AI into high-volume procurement and finance workflows to move beyond static automation towards continuous learning. Agents learn from exceptions, feedback and human judgement, turning individual decisions, such as pricing dispute resolution, into training signals that drive double-digit productivity gains and enterprise-wide improvement.[17]

CASE STUDY 10

Translate local learning into network-wide knowledge

Every warehouse or production site has its own operational DNA – layouts, workflows and constraints that make it unique. Claryo's AI agents adapt to each facility, learning its specific patterns while carrying transferable insights across sites. This creates a balance between local precision and global scalability, ensuring that each implementation reflects on-the-ground realities while benefitting from enterprise-wide learning.[18]

Focus 3

Accelerated R&D and breakthrough innovation

AI turns R&D into a continuous learning engine that expands options, tests earlier and reallocates resources faster.

R&D is emerging as one of the areas where organizations are realizing the greatest productivity gains from AI. Nearly 40% of senior executives identify R&D among the top functions benefitting from AI investment.[19]

AI transforms R&D by turning linear execution into continuous learning, expanding the range of options explored and shifting risk assessment from late failure to early calibration.

AI reshapes the R&D value chain by expanding exploration upstream, shifting decisions earlier, virtualizing validation and embedding continuous learning across stages.

Similar test–learn–adjust dynamics are emerging in areas such as AI-assisted radiology, where continuous model refinement based on diagnostic outcomes improves accuracy and reshapes clinical workflows.

TABLE 3 | **AI-enabled transformation of R&D and innovation**

At a glance

Research	Development	Prototype testing	Market launch

Ambition: opportunities to capture	**Action:** how organizations are changing
– **Shorten time from idea to launch** through earlier hypothesis testing and faster human-AI learning cycles. **Up to 50% reduction in time-to-market**[20]	1 **From narrow exploration to expanded option space:** Automate low-value tasks and use generative models to generate many more hypotheses early and prioritize candidates more efficiently.
– **Increase R&D success rates** by expanding the exploration of design and solution spaces and evaluating risks earlier. **Up to 70% increase in R&D success rates;**[21] **30–50% improvement in R&D productivity;**[22] **Expected 20–80% acceleration in R&D cycle times across product industries**[23]	2 **From late failure to early risk calibration:** Move go/no-go decision gates earlier using partial but richer evidence (surrogate models, automated assays) to stop weak options sooner and scale better candidates.
– **Improve portfolio risk and return** by screening more options and focusing human effort on the most promising candidates. **20–30% fewer redesigns;**[24] **50% reduction in rework**[25]	3 **From physical-first to virtual-first validation:** Shift most early testing to simulations, digital twins and virtual labs, reserving physical prototypes for high-confidence validation.
	4 **From linear execution to short, evidence-driven learning cycles:** Close the loop by feeding experimental, production and market data back into models so R&D becomes a continuous learning engine.

FIGURE 3 | **Four operating model shifts in R&D and innovation**

1 From narrow exploration... → to expanded option space

AI-augmented discovery increases the number and diversity of hypotheses explored early.

2 From late failure... → to early risk calibration

Decision gates move earlier, using partial but richer evidence. Activities shifted upstream: manufacturability, regulatory and quality considerations become inputs earlier, guided by AI sims.

3 From physical-first... → to virtual-first validation

Virtual simulations replace most forms of early physical testing in the value chain. Activities eliminated or automated include manual screening, routine data aggregation and repetitive experiment documentation.

4 From linear execution... → to short, evidence-driven learning cycles

Insights flow continuously across research, development, testing and launch. New activities: model training/validation, data curation, AI oversight; the trained model becomes an asset.

3.1 From narrow exploration to expanded option space

Shifts in how R&D operates:

- AI expands the number and diversity of ideas, designs and hypotheses explored early.
- AI integrates signals from customers, operations and regulators to improve problem framing and prioritization.
- AI will expand the option space by automating early search and screening while scientists and engineers remain central and become stewards of judgement, focused on problem framing, evidence quality and strategic trade-off.

Example use cases:

- Scanning target and patent landscapes
- Designing and prioritizing candidate molecules
- Automating the setup of assay and experiment protocols
- Interpretating results with evidence packaged for the next “decision gate”

Organization changes observed:

- Capturing this opportunity requires shifting how decisions are made, who owns them and how teams collaborate early in the R&D process.
- Establish dedicated AI-enabled discovery teams combining domain experts, data scientists and product owners.
- Redefine scientist and engineer roles to reduce manual searches and increase evaluation and prioritization.
- Introduce shared front-end standards (data formats, ontologies, model validation criteria).
- Clarify ownership for early-stage down-selection decisions.

Early vs advanced adopters:

- **Early:** Use AI to accelerate search and screening and improve protocol drafting.
- **Advanced:** Combine generative design, simulation and lab automation to run high-throughput discovery.

CASE STUDY 11

Using AI to expand the chemical search and compress the hypothesis to viable molecule process

Merck KGaA is accelerating early-stage pharmaceutical R&D by using AI to digitalize and automate compound optimization. Through an AI-augmented in-silico platform, generative models can virtually screen over 60 billion potential chemical targets in minutes, narrowing options to a shortlist for human review and lab testing. This integrated workflow significantly compresses the journey from hypothesis to viable molecule, saving up to 70% in time and cost, while enhancing accuracy, efficiency and novelty in molecular discovery.[26]

CASE STUDY 12

AI accelerates early drug discovery by expanding the pool of viable candidates

Insilico Medicine uses a generative-AI drug discovery platform to rapidly generate and explore large numbers of candidate molecules. Early predictive models and assays are used to prioritize which options merit further investigation, allowing teams to focus downstream experimentation on the most promising candidates. Across its portfolio, Insilico reports an average of approximately 13 months to nominate a preclinical candidate, with multiple programmes progressing towards clinical trials.[27]

3.2 From late failure to early risk calibration

Shifts in how R&D operates:

- Go/no-go decisions move earlier in the R&D process, reducing mid- and late-stage resets, increasing the share of projects that reach launch and boosting confidence that the concept matches customer needs before major spending.
- Partial but richer evidence is used to assess technical, performance, manufacturability and compliance risk.
- As a result, weak options are stopped sooner; stronger options receive resources earlier.

Organizational changes observed:

- Redesign portfolio governance with earlier, lighter-weight decision gates and explicit authority to stop work.
- Improving R&D success rates requires stronger early-stage governance, with shared evaluation criteria and a shift in how teams view validation and failure.
- Reframe early project termination as a success, not a failure.
- Establish cross-functional risk review forums spanning R&D, regulatory, quality and manufacturing.

Early vs advanced adopters:

- **Early:** Implement structured early gates and screening to trim low-value options.
- **Advanced:** Use continuous portfolio management systems that dynamically rebalance in near real time based on model outputs and scenario simulations.

CASE STUDY 13

Applying AI knowledge graphs to identify drug targets

Lundbeck built a domain-specific knowledge graph for headaches and migraines, integrating 54 million electronic medical records with biological, genetic and disease data. Machine learning models were applied to predict the probability of gene–disease links in the knowledge graph and infer new connections that were not explicitly stated by the graph, allowing potential novel drug targets to be identified 80% more quickly.[28]

CASE STUDY 14

AI diagnoses toxicity early, enabling safe redevelopment of abandoned drug candidates

Ignota Labs acquires drug candidates abandoned late in development due to safety or toxicity issues. Its AI platform identifies the molecular causes of toxicity and redesigns compounds for a second development attempt. By narrowing the number of possible biological pathways, the platform provides a clearer, safer way forward. This can return a redesigned compound to clinical trials in under two years and for less than $1 million – versus the $10 million and 7–8 years typically required.[29,30]

3.3 From physical-first to virtual-first validation

Shifts in how R&D operates:

- Use simulations, digital twins and early models to compare candidates before committing to expensive studies.
- Lower the cost and cycle time of early validation, screening and experimentation, allowing more R&D programmes to be explored simultaneously.

Organizational changes observed:

- Build or strengthen simulation and digital twin capabilities as core R&D infrastructure.
- Integrate simulation teams tightly with experimental labs and engineering groups.
- Update validation and quality processes to recognize virtual evidence alongside physical testing.
- Invest in data pipelines linking experimental, simulation and production data.
- Shift digital prototyping from complex manual model-building towards defining specifications and orchestrating model-based workflows.

Early vs advanced adopters:

- **Early:** Pilot virtual testing for selected products or processes.
- **Advanced:** Embed end-to-end virtual validation across design, testing and scale-up.

CASE STUDY 15

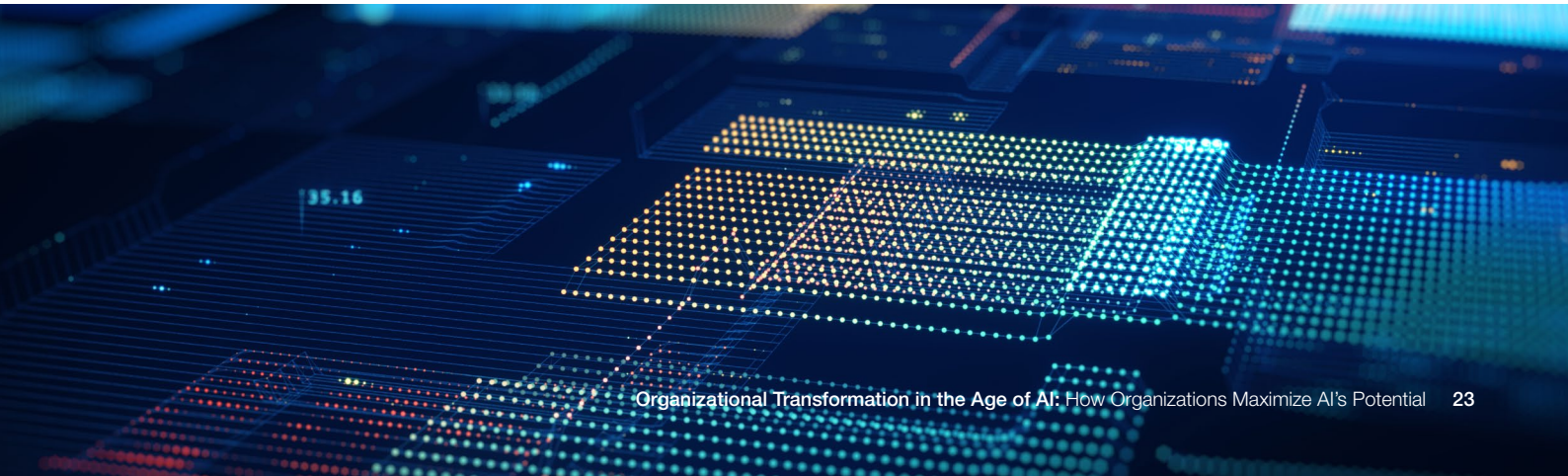
AI-powered engineering acceleration and safety testing

Google integrates AI deeply into its product development and engineering workflows to drive speed, safety and creativity. Within research, large language models (LLMs) now generate synthetic user interactions and adversarial prompts, thereby automating safety testing and accelerating model refinement. Beyond validation, AI also supports continuous engineering improvement by automatically addressing 12% of duplicate issues without human input.

CASE STUDY 16

Expanding cervical cancer diagnosis through automated digital slide analysis and remote review

Landing Med integrates automated image analysis and remote pathology review to digitize cervical screening samples and pre-screen slides for abnormal cells before specialist assessment. Deployed across China, the redesigned workflow shifts interpretation from traditional on-site manual review to digitally enabled triage with distributed expert oversight. Since 2017, more than 13 million screenings have been conducted using this model, increasing productivity fivefold (from 12 to 60 samples per hour). The approach improves diagnostic consistency and reduces reliance on local specialist availability, demonstrating how virtual-first validation can scale population-level diagnostics.



3.4 From linear execution to short, evidence-driven learning cycles

Shifts in how R&D operates:

- R&D shifts from sequential phases to short "test–learn–adjust" cycles.
- Insights from experiments, production and market use feed back into discovery.
- Decisions are updated continuously as new evidence emerges, allowing flexible portfolio rebalancing.

Organizational changes observed:

- Evolve performance management to reward evidence quality, adaptability and learning speed.
- Shift from rigid stage gate models to learning loop operating models with more frequent reviews.
- Form persistent, cross-functional teams accountable for outcomes across phases.
- Track velocity as a key performance metric.
- Introduce data and machine learning operations (MLOps) capabilities to support continuous model updating and monitoring.
- Adjust performance management to value learning speed, evidence quality and adaptability.
- Consider more regular resource reallocation as a standard.

Early vs advanced adopters:

- **Early:** Introduce faster iteration cycles within existing stage–gate structures.
- **Advanced:** Fully integrate learning systems where data continuously informs discovery, development and portfolio decisions.

The transition from early to advanced adoption is driven less by technical capability than by leadership confidence in AI-supported evidence justifying real resource reallocation.

CASE STUDY 17

Using end-to-end AI enablement to dramatically reduce development

JLL piloted an end-to-end AI enablement – including automated gathering of requirements for code generation and testing and streamlined GitHub workflows. This delivered 75–85% time savings for frontend teams and reduced development resource needs by 30%, allowing senior engineers to focus on higher-value problem-solving and experimentation.

CASE STUDY 18

Agentic AI co-researcher to orchestrate drug discovery experiments at scale

SandboxAQ developed an agentic AI "co-researcher" – a hierarchical network of semi-autonomous virtual scientists that orchestrate multi-step experiments, data analyses and simulations that were once managed by human experts. The system is expected to achieve fourfold increases in project throughput, double its concurrent project capacity and unlock a 50% reduction in competition time. This agentic layer serves as the foundational reasoning engine that unlocks SandboxAQ's broad set of modular scientific workflows and democratizes access to high-fidelity scientific simulation.

Focus 4

Predictive, AI-powered strategic planning

AI turns strategy into a living system that senses change, compares options and reallocates resources continuously.

Strategic planning encompasses enterprise and business-unit decisions on where to compete and how to win, including interpretation of market and internal signals, evaluation of strategic options and trade-offs, prioritization of initiatives and allocation of capital, talent and capacity.

Traditionally, strategic planning has been a periodic coordination exercise anchored in annual cycles, static assumptions and delayed feedback from execution. AI turns strategic planning into a "living" process by continuously sensing signals, testing assumptions and linking decisions to execution.

TABLE 4 | **AI-enabled transformation of strategic planning**

At a glance

Analyse | **Plan** | **Execute** | **Review**

Ambition: opportunities to capture	**Action:** how organizations are changing
– **Improve decision speed, robustness and confidence under uncertainty** by continuously updating strategic assumptions based on real-time market, customer, competitor and internal signals. **Approximately 30% faster planning cycles; 20–40% improvement in forecast accuracy**[31]	1 **From periodic sensing to continuous signal interpretation:** Shift from calendar-driven strategy reviews to always-on interpretation of market, customer, competitor and internal signals. New data continuously challenge, update and reframe strategic assumptions.
– **Improve capital and resource allocation quality** by reallocating capital, talent and capacity more dynamically towards the highest-value options as conditions change. **Potential 2–3 percentage point decrease in costs; approximate 15–30% reduction in inventories**[32]	2 **From single-plan convergence to ongoing option comparison:** Move away from committing to one approved plan towards maintaining a live portfolio of strategic options and trade-offs that are continuously compared as conditions evolve.
– **Strengthen the link between strategy and execution** by embedding AI-supported assumptions directly into operating metrics, funding triggers and performance management. **2–4 percentage point annual increase in revenues;**[33] **approximate threefold increase in likelihood of superior financial outcomes from stronger KPI alignment**[34]	3 **From fixed allocation to dynamic resource reallocation:** Shift from annual, fixed commitments to trigger-based reallocation of capital, talent and capacity when performance, risk or opportunity thresholds are met.
	4 **From strategy handoff to execution-linked steering:** Embed strategic choices directly into operating plans, funding flows and performance metrics, creating continuous feedback loops between strategy and execution.

FIGURE 4 | **Four operating model shifts in strategic planning**

1

From periodic sensing... → to continuous signal interpretation

AI continuously ingests and interprets market, customer, competitor and operational signals. Strategy and finance teams shift from preparing periodic reports to monitoring assumption health. Analysts spend less time compiling data and more time validating signals and implications.

2

From single-plan convergence... → to ongoing option comparison

AI generates, maintains and evaluates multiple strategic options in parallel. Quantify trade-offs, risks and confidence ranges continuously as conditions change. Strategy teams stop "locking the plan" early and instead manage portfolios of options.

3

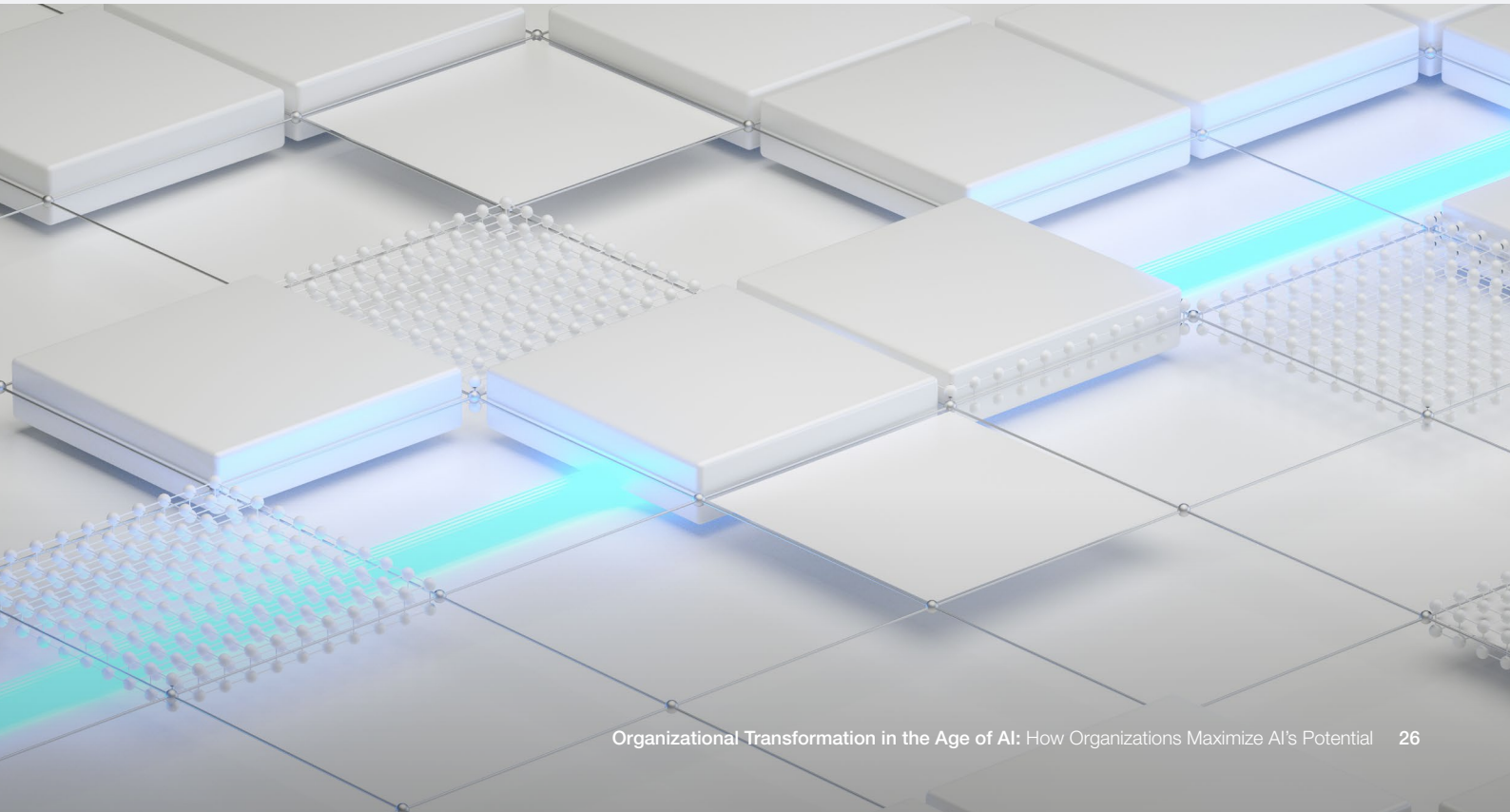
From fixed allocation... → to dynamic resource reallocation

Reallocate capital, talent and capacity incrementally based on performance and risk signals. Trigger funding increases, pauses or exits without restarting the planning cycle. Business leaders are accountable for releasing resources from underperforming initiatives.

4

From strategy handoff... → to execution-linked steering

Strategy leaders stay engaged through execution instead of handing off plans. Operating teams execute against living priorities, not static plans.



4.1 From periodic sensing to continuous signal interpretation

Shifts in how strategic planning operates:

- AI does not just refresh data – it helps reinterpret what signals mean as context changes, continuously testing and updating strategic assumptions.
- The analysis phase becomes a persistent capability, not a discrete step at the start of planning.
- Human strategists shift from compiling inputs to questioning assumptions, validating signal relevance and interpreting implications for strategic choices.

Organizational changes observed:

- Establish continuous sensing capabilities that integrate external data (market, competitor, macro) with internal signals (financial, operational, customer).
- Redesign strategy processes so insight generation runs in parallel with execution (not only before planning cycles).
- Shift ownership from individual strategy teams to shared signal interpretation forums spanning strategy, finance, operations and risk.
- Introduce governance to decide which signals matter, how often assumptions are revisited and when reinterpretation is required.

Early vs advanced adopters:

- **Early:** Use AI to automate data collection and monitoring to inform periodic strategy reviews.
- **Advanced:** Continuously reinterpret signals and update assumptions in near real time.

CASE STUDY 19

Interpreting market signals from executive communication

S&P Global used AI to analyse over 190,000 earnings call transcripts, extracting forward-looking market signals from how executives addressed analysts' questions and emerging risks. The analysis showed that companies whose leaders communicate clearly and anticipate key issues consistently outperform peers, illustrating how AI can turn unstructured communication into predictive strategic insight.

4.2 From single-plan convergence to ongoing option comparison

Shifts in how strategic planning operates:

- Planning moves away from convergence on one approved plan towards maintenance of a live portfolio of strategic options and trade-offs.
- AI enables rapid generation, comparison and stress-testing of multiple strategic pathways under different assumptions.
- Strategy becomes a comparison engine, not a document – options remain active and revisable as conditions evolve.

Organizational changes observed:

- Replace static planning documents with option portfolios that are continuously evaluated.
- Redesign planning cadences to support ongoing scenario comparison, not one-off approvals.
- Introduce common metrics and assumptions so options are comparable across business units.
- Clarify decision rights for when options are promoted, deprioritized or retired.

Early vs advanced adopters:

- **Early:** Use AI to test alternative scenarios during annual or major planning moments.
- **Advanced:** Maintain a continuously updated set of strategic options that guide decisions throughout the year.

4.3 From fixed allocation to dynamic resource reallocation

Shifts in how strategic planning operates:

- Capital, talent and capacity shift from fixed, annual commitments to trigger-based reallocation as performance, risk or opportunity thresholds are met.
- Resource allocation becomes an active step in the value chain, not a one-time outcome of planning.
- AI monitors execution signals and recommends when resources should be scaled, paused or reallocated.
- Strategy and finance become tightly linked through more frequent allocation decisions.

Organizational changes observed:

- Redesign budgeting and workforce processes to allow mid-cycle reallocation.
- Define clear triggers and thresholds that activate reallocation decisions.
- Integrate planning tools with financial, human resources (HR) and operational systems so reallocation is executable, not theoretical.
- Shift governance from budget control to allocation effectiveness and speed.

Early vs advanced adopters:

- **Early:** Use AI to highlight under- or over-performing initiatives for periodic reallocation discussions.
- **Advanced:** Dynamically move capital and talent more frequently as signals and priorities change.

CASE STUDY 20

Faster planning cycles and improved forecast accuracy

Canada Goose used an AI scenario planning system to make financial planning and analysis faster, with greater consideration for different potential outcomes, so finance teams could reallocate budgets and rerun scenarios quickly as assumptions changed. The company reported a 60% reduction in planning cycle time and a 4% improvement in revenue forecast accuracy.[35]

4.4 From strategy handoff to execution-linked steering:

Shifts in how strategic planning operates:

- Strategy no longer ends at approval – it becomes embedded in execution through operating plans, funding flows and performance metrics.
- AI can detect when execution is drifting from the assumptions behind the strategy and then quantify the likely impact.
- Execution outcomes continuously feed back into strategic assumptions, options and allocations.
- The traditional "review" phase collapses into a continuous steering loop.
- Leaders focus on course correction, not post-hoc explanation.

Organizational changes observed:

- Strategic priorities translate changes into clear operating, KPI and management dashboards.
- Replace episodic, "all hands on deck" crisis meetings with a continuous dialogue where decisions are refined through rapid, iterative learning.
- Align incentives so leaders are rewarded for adapting strategy based on evidence, not just delivering against static plans.
- Establish clear accountability for updating strategy as execution data emerges.

Early vs advanced adopters:

- **Early:** Track execution metrics against strategic goals and adjust plans periodically.
- **Advanced:** Continuously steer execution using live feedback to update strategy, options and allocation.

Predictive, AI-powered strategic planning shifts leadership from **deciding once** to **steering continuously**. The greatest value comes not from sophisticated models, but from the ability to act on AI-supported evidence – reallocating resources, revisiting assumptions and adjusting course as conditions evolve.

Focus 5

Data-driven, personalized talent experience and workforce planning

AI turns workforce planning into a dynamic capability system that aligns skills, capacity and AI support with demand.

Talent strategy spans how organizations attract, develop, deploy and retain their workforce.

A holistic, personalized talent experience reduces time-to-staff, accelerates time-to-skill and improves retention by making growth and mobility more transparent. AI enables near real-time skills mapping, opportunity matching, personalized learning and early risk detection – shifting talent management from discrete HR processes to a continuous, adaptive system.

TABLE 5 | **AI-driven transformation of talent experience and workforce planning**

At a glance

Planning	Recruitment and selection	Performance and enablement	Evaluation and adaptation

Ambition: opportunities to capture	**Action:** how organizations are changing
– **Optimize workforce deployment and skills matching** by aligning people to work based on inferred capabilities rather than job titles. **Approximate 30% reduction in time to fill roles;**[36] **21% increase in the quality of recruits**[37]	1 **From fixed job titles to capabilities that can be built and redeployed:** Shift from static roles to dynamic capability frameworks that identify, build and redeploy skills in real time as strategic needs evolve.
– **Expand workforce capacity and productivity** by augmenting human expertise with AI agents. **4 times faster skill deployment;**[38] **Approximate 33% increase in worker productivity with each hour of AI use**[39]	2 **From periodic, static workforce data to AI-generated talent intelligence:** Use AI to synthesize skills data, performance and workforce patterns into continuous talent intelligence that reveals capability, gaps and internal mobility resources.
– **Reduce bias and increase fairness in hiring and promotions** by making growth, mobility and contribution more visible and continuous. **Increase diversity of hire by 21%**[40]	3 **From layered organizational structures to flatter, human-led teams supported by agents:**[43,44] Workforce models are evolving into flatter, cross-functional teams where human expertise leads, supported by embedded AI agents and fewer layers of oversight.
– **Improve retention and employee engagement** by identifying early signals of disengagement, burnout or attrition risk and acting proactively. **21% boost in talent retention;**[41] **5 times higher workforce engagement**[42]	4 **From fragmented learning to continuous upskilling, reskilling and adaptive retention:**[45] Embed AI-enabled, personalized learning into daily work to support ongoing capability development and proactive retention.

FIGURE 5 | **Four operating model shifts in talent experience and workforce planning**

1

From fixed job titles... → **to capabilities that can be built and redeployed**

AI breaks work into capabilities and tasks, enabling rapid recombination across the value chain. Organizations shift from role-based structures to capability-based deployment.

2

From periodic, static workforce data... → **to AI-generated talent intelligence**

AI generates real-time talent insights and scenarios, enabling continuous resource reallocation. Planning shifts from fixed headcount decisions to portfolio management; leaders validate trade-offs and risk.

3

From layered organizational structures... → **to flatter, human-led teams supported by agents**

AI agents execute routine and analytical tasks across workflows. Humans oversee, intervene in and optimize outcomes rather than performing each step.

4

From fragmented learning... → **to continuous upskilling, reskilling and adaptive retention**

AI embeds learning into work and predicts future skill needs. Roles evolve continuously, with humans prioritizing creativity, leadership and system stewardship.

5.1 From fixed job titles to capabilities that can be built and redeployed

Shifts in how talent operates:

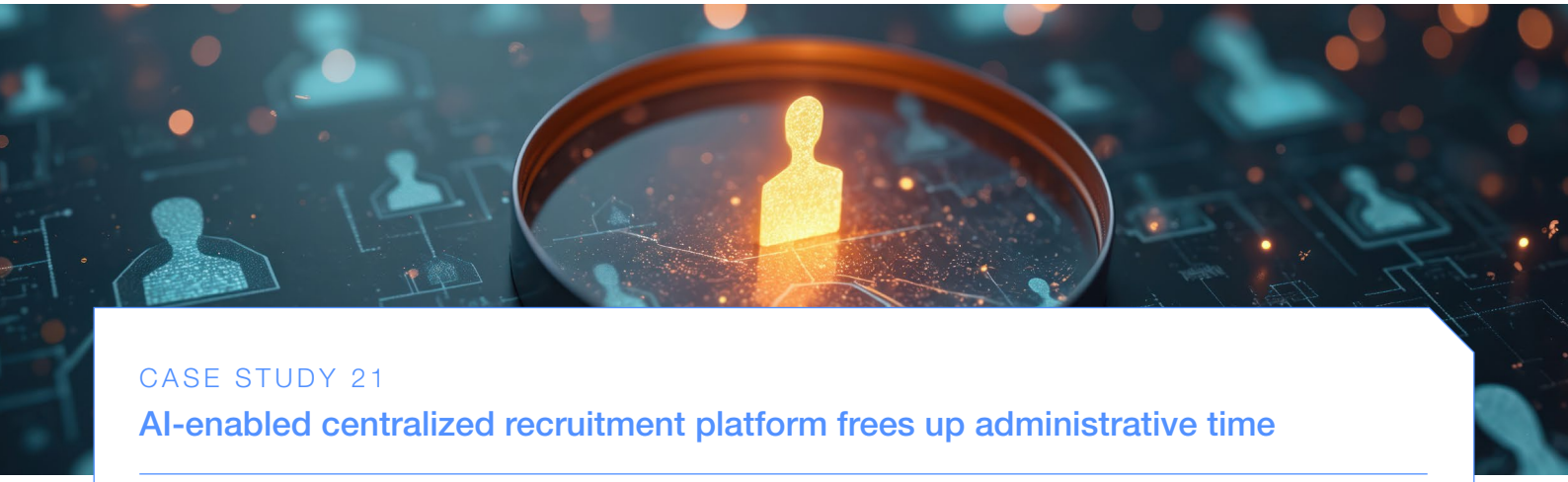
- Workforce planning moves from roles to capabilities and skills as the primary units of work.
- AI translates business needs into dynamic capability requirements and identifies near-ready internal talent.
- AI forecasts emerging capability gaps and estimates internal build-versus-buy scenarios, while digital systems support the coordination of internal transitions.
- Transitions are supported through repeatable pathways combining learning with real work.

Organizational changes observed:

- The workforce is managed as a capability system that can be reconfigured as strategy shifts.
- Leaders treat capabilities as strategic assets, not HR metadata. Capability taxonomies and skills profiles are continuously updated using strategic and operational signals.
- HR, learning and development, and line managers shift from primarily sourcing external talent towards orchestrating internal mobility, capability development and redeployment.
- Internal mobility and transition pathways are embedded into workflow systems rather than standalone training programmes.

Early vs advanced adopters:

- **Early:** Define capability sets for priority roles and pilot internal mobility for targeted teams.
- **Advanced:** Operate the workforce as a dynamic capability system; reconfigurable as strategy shifts.



CASE STUDY 21

AI-enabled centralized recruitment platform frees up administrative time

Yum China deploys neuro-linguistic programming (NLP) and AI algorithms to match millions of applicants to positions, chatbots to schedule interviews and LLMs to analyse interviews and make recommendations. The platform fulfils about 89% of restaurant hiring needs across over 16,000 stores, with average fulfilment as fast as 1–2 weeks. Yum's restaurant managers' turnover rate dropped from 9.7% in 2024 to 7.8% in 2025.

CASE STUDY 22

AI-powered internal marketplace

Unilever uses an AI-powered internal marketplace to match employees to short-term projects and assignments across the company, based on skills and development goals. Managers post a need, AI suggests near-ready people, and employees build capability by doing real work instead of formal role changes. Unilever has reported 70% cross-functional assignments, approximately 500,000 hours of capacity unlocked and 41% improvement in productivity.[46]

5.2 From periodic, static workforce data to AI-generated talent intelligence

Shifts in how talent operates:

- AI synthesizes skills, learning activity, performance trends and work history into real-time talent intelligence.
- Latent skills and mobility opportunities facilitate AI-enabled, proactive workforce planning.
- Leaders gain foresight into where to build, buy, borrow or augment talent, including digital labour.

Organizational changes observed:

- Expand definitions of "talent data" beyond HR records to include learning, performance signals and execution outcomes.
- Integrate AI-driven analytics into workforce planning and talent decision processes.
- Clear governance is established for data quality, fairness, transparency and explainability.

Early vs advanced adopters:

- **Early:** Use AI to uncover hidden skills and near-matches for specific roles or projects.
- **Advanced:** Operate continuous talent intelligence systems that proactively guide mobility, workforce planning and capability investment.

CASE STUDY 23

AI "skills inference" for talent intelligence

Johnson & Johnson (J&J) uses AI to infer employees' proficiency across 41 future-ready skills by combining signals beyond job titles, including learning activity and internal experience data. Leaders use a "skills heatmap" to assess capability strength by business line and geography, and decide where to build skills internally versus hire. The approach increased use of J&J's learning ecosystem by 20% after the first round, with 90% of technologists accessing the platform.[47]

5.3 From layered organizational structures to flatter, human-led teams supported by agents

Shifts in how talent operates:

- Organizational structures flatten into human-led, cross-functional teams supported by AI agents, often starting with limited scopes due to change resistance and risk concerns. This shift introduces new accountability tensions, particularly when agent outputs conflict with expert judgement or established practice.
- Humans remain central-leading, making decisions and applying soft skills while AI agents assist with execution, coordination and insight generation, with clear expectations on where humans must review, approve or override.
- AI agents operate across a spectrum: assisting individuals, collaborating within shared workflows and executing multi-step processes semi-autonomously under human-defined goals and guardrails.
- Workforce planning accounts for combined human/agent capacity (including where agents create throughput but also introduce new review and exception-handling loads).

Organizational changes observed:

- C-suite expands to include AI-focused leadership, while middle manager roles shift towards orchestration, coaching and enabling both human and agent contributions.
- Middle-management roles evolve from supervising task execution to orchestrating human-AI workflows, resolving exceptions, coaching teams on judgement and system stewardship, and continuously refining guardrails and autonomy thresholds.
- AI proficiency and soft skills become increasingly vital, with managers playing key roles in team cohesion, development and performance support,[48] and in resolving tensions when agent outputs conflict with established practices or expert judgment.
- Functions such as HR and IT align under shared leadership to co-govern human and agent capacity, with new hybrid roles emerging.
- Workforce models codify agent participation – including capacity planning, access rights, autonomy boundaries, escalation paths and life cycle governance, because accountability is often contested when agents take actions across workflows.
- Performance and accountability frameworks evolve to cover AI agents, including explicit human sign-off, productivity monitoring and retraining or retirement of underperforming agents.

Early vs advanced adopters:

- **Early:** Deploy agents in controlled workflows with clear human oversight, and invest in change management to address trust, workload concerns and role ambiguity.
- **Advanced:** Redesign elements of organizational structures with flattened hierarchies, new orchestration roles, merged functions (e.g. HR/IT) and integrated agents in coordinated workflows, backed by clear accountability models and manager role redesign.

CASE STUDY 24

Scaling human-agent workflows

Repsol is reinventing core operations through a human-in-the-loop, agentic AI model. Repsol designed workflows where custom AI agents execute discrete tasks, gathering inputs, running checks, drafting outputs and triggering actions within guardrails while humans retain control through review, approval and exception handling. Today, 22 agents are live across 38 use cases, delivering smarter customer energy solutions and streamlined IT operations. Repsol plans to scale to over 90 agents and empower over 3,000 IT employees by early next year.

CASE STUDY 25

Redesigning organization for the agentic AI era

Moderna combined its HR and IT functions under a single Chief People and Digital Technology Officer. The company redesigns teams around "what work should be done by humans versus AI tools", deploying thousands of custom generative pre-trained transformers (GPTs) across business functions to automate routine tasks and elevate human judgement. This integrated model accelerates AI adoption, improves workflow design and ensures decisions about people and technology are made in concert.[49]

5.4 From fragmented learning to continuous upskilling, reskilling and adaptive retention

Shifts in how talent operates:

- Learning moves from episodic to continuous, AI-embedded capability-building tied directly to work.
- AI captures tacit and frontline knowledge from real work, converting it into reusable, system-wide guidance embedded in workflows.
- Personalized learning pathways align with capability gaps, demand forecasts and real work requirements.
- Retention shifts from standalone programmes to an adaptive system linked to career progression, capability growth and predictive risk signals.
- Agents surface the right checklist, template, example or expert, capture what works and escalate complex cases to humans.

Organizational changes observed:

- Learning systems are integrated with workflow tools and capability maps, not segregated learning management systems (LMS) platforms.
- AI is used to anticipate future skill needs and adapt development pathways proactively.
- Retention strategies are aligned with capability evolution and employee growth journeys.
- Organizations invest in systematically capturing, structuring and reusing institutional and frontline knowledge.
- Establish collaboration with intelligent agents as foundational workforce skills, not specialist capabilities limited to technical roles.

Early vs advanced adopters:

- **Early:** Deliver AI-personalized learning recommendations for targeted roles.
- **Advanced:** Build enterprise-wide adaptive capability pipelines that support continuous reskilling, redeployment and retention at scale.

AI shifts talent and workforce planning from a role-based HR function to a continuous capability system that aligns human and digital capacity with evolving work and priorities. Leading organizations treat talent as a strategic execution asset, building skills ahead of demand, redeploying capabilities fluidly and adapting continuously.

Key principles enabling adoption at scale within organizations

Enterprise AI succeeds through accountable leadership, operating model redesign, transparent governance, disciplined experimentation and scalable talent aligned with execution.

Across the chapters, three trends emerge. AI is turning linear and separate workflows into continuous, adaptive and interconnected systems. Decisions are moving earlier and becoming faster and cheaper as AI lowers the cost of learning. As AI moves into execution, humans move up the value chain – focusing on judgement, orchestration and accountability. Realizing AI's full potential requires changes to operating models, governance, skills and leadership.

The following principles describe how organizations are enabling this at scale and are most powerful when applied as an integrated system rather than as isolated initiatives.

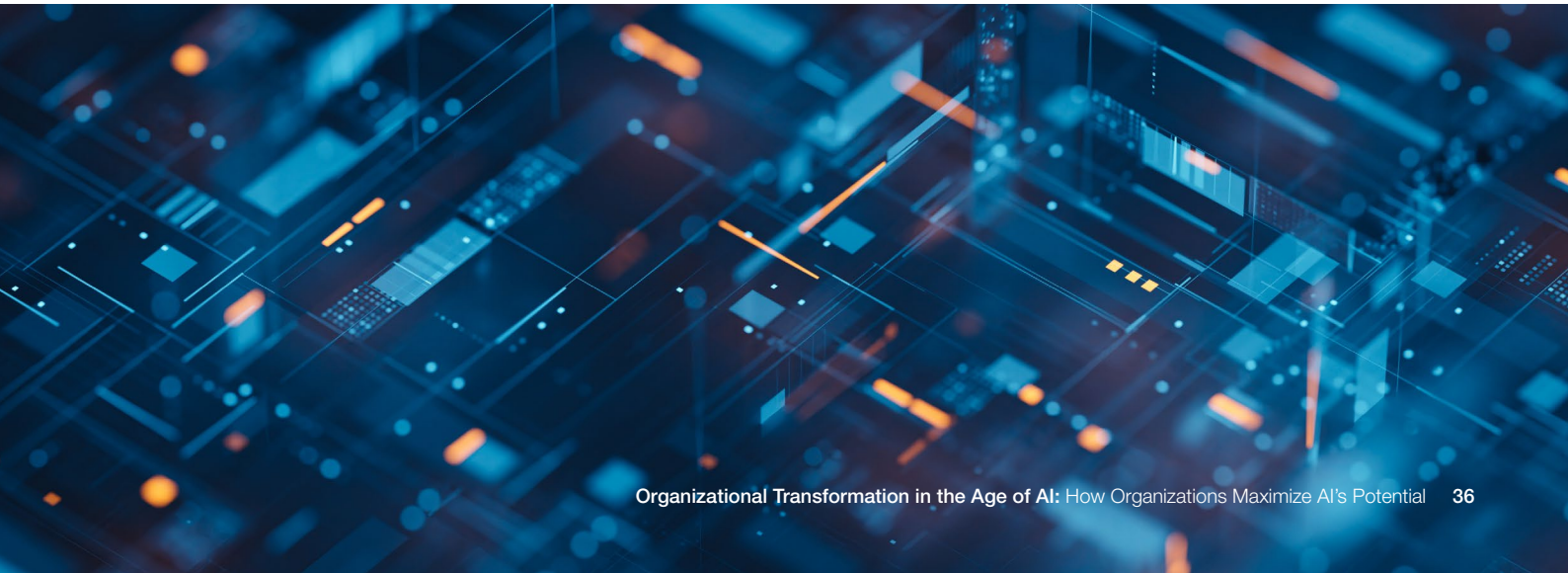
1 **Human accountability at scale:** keeping judgement where value is created

As AI systems increasingly support analysis, execution and decision-making, organizations should be explicit about where accountability resides. Moving from "human-in-the-loop" to **"human-in-the-lead"** means clearly defining decision ownership, autonomy thresholds and escalation paths before, during and after deployment at scale.

AI accelerates insight and execution, allowing people to focus on higher-value judgement, customer engagement and innovation. While AI informs decisions, accountability for outcomes remains with people, and leadership ownership is essential to building confidence and adoption.

2 **End-to-end operating model redesign:** from functional efficiency to outcome ownership

Scaling AI requires more than expanding pilots or automating individual tasks. Organizations that achieve enterprise impact redesign operating models around shared, **end-to-end outcomes** rather than optimizing isolated functions. Fragmented handoffs are replaced by unified ownership, cross-functional teams and shared backlogs. AI agents increasingly support orchestration across workflows under human oversight. Without operating model redesign, AI amplifies complexity – with it, AI simplifies how value flows through the enterprise.



3 **Scalable talent systems:** aligning skills, incentives and roles

At scale, technology is rarely the limiting factor. People, incentives and ways of working determine whether AI delivers sustained value. Leading organizations invest deliberately in scalable talent systems and treat change as a permanent capability. This includes broad-based upskilling focused on how work changes, the creation of new roles such as AI product owners, workflow architects and model stewards, and performance measures that reward adoption and reuse. Change is managed through short learning cycles, frequent feedback and ongoing workflow redesign informed by real use data.

4 **Transparency-driven trust:** from risk mitigation to scale enabler

Trust has emerged as one of the most decisive factors in scaling AI. Organizations that succeed treat responsible AI not as a compliance exercise, but as a **core execution capability** that enables adoption, experimentation and speed.

Rather than relying on restrictive controls, leaders emphasize transparency: making AI behaviour understandable, defining clear boundaries and accountability and encouraging constructive challenge. Governance evolves alongside technology through continuous monitoring, clear accountability and adaptive oversight.

In an environment where AI increasingly operates with autonomy, trust becomes the foundation that allows organizations to move faster, not slower.

Trustworthy AI requires measurable baselines, continuous evaluation and governance integrated early into experimentation. As agents increasingly interact across organizational boundaries, organizations must extend monitoring and accountability beyond internal workflows and use telemetry and AI-supervising-AI approaches to ensure governance enables innovation rather than becoming a gatekeeper.

5 **Disciplined experimentation and learning loops:** scaling through safe failures

Leading organizations treat experimentation as an execution discipline, not an innovation exception. They design AI-enabled workflows to experiment continuously, absorb small failures safely and translate learning into improved workflows and decisions.

Failures are expected, contained and informative. Autonomy thresholds, decision policies and escalation rules are adjusted based on real-world performance rather than theoretical assumptions. This approach accelerates productivity, reduces rework and strengthens trust because failures are surfaced, contained and learned from rather than hidden, preventing prolonged misalignment. It reduces rework by identifying failure modes early.

Conclusion

AI's impact is no longer defined by isolated use cases or technical capability. Across CX, operations, R&D, strategic planning and talent, leading organizations are redesigning how work is performed, embedding AI into core workflows and treating learning, adaptation and reallocation as continuous capabilities. The differentiator is not model sophistication, but the ability to align people, processes and intelligent systems around shared outcomes.

Organizations that succeed build the confidence, governance and operating discipline to act on AI-supported evidence, continuously evolve how work is done and keep human judgement firmly at the centre. Those that do not risk falling behind – not because AI does not work, but because their organizations do not change.

Progress, however, will not happen in isolation. Advancing from experimentation to organizational redesign requires shared standards, practical governance and collective learning across industries and regions. The AI Transformation of Industries initiative will continue to convene organizations to exchange real-world insights, co-develop approaches and accelerate responsible AI adoption.

By working together, leaders can move beyond pilots, translate ambition into measurable outcomes and ensure AI contributes to resilient growth and broader societal value.

Contributors

Lead authors

World Economic Forum

Fatima Gonzalez Novo
Specialist, AI Applications and Impact,
Centre for AI Excellence, World Economic Forum

Jill Hoang
Initiatives Lead, Applied AI,
Centre for AI Excellence, World Economic Forum

Accenture

Karen O'Regan
Managing Director, Accenture Strategy;
World Economic Forum Executive Fellow

Acknowledgements

The authors extend their gratitude to members of the AI Transformation of Industries Community and all other individuals who shared their valuable insights for the Industries in the Intelligent Age white paper series. A complete list of acknowledgements can be found in the Appendix.

World Economic Forum

Neil Allison
Head, Education, Skills and Learning Mission,
Centre for New Economy and Society

Abhi Balakrishnan
Initiatives Lead, AI Innovation,
Centre for AI Excellence, World Economic Forum

Andre Belelieu
Head, Financial Services Industries; Head,
Business Engagement, North America

Federico Capaccio
Specialist, Applied AI, Centre for AI Excellence

Mattia Damati
Early Career Program, Centre for Artificial Intelligence

Tarik Fayad
Lead, Strategic Integration, MENA,
Centre for AI Excellence

Zara Ingilizian
Head, Consumer Industries; Member of the
Executive Committee

Devendra Jain
Initiatives Lead, Frontier Technologies for
Operations, Centre for Advanced
Manufacturing and Supply Chains

Adinda Khairunnisa
Coordinator, Centre for AI Excellence

Cathy Li
Head, Centre for AI Excellence; Member of the
Executive Committee, World Economic Forum

Na Na
Lead, Industrial and Tech Transformation
Content and Programming

Drew Propson
Head, Technology and Innovation in Financial
Services, Centre for Financial and Monetary Systems

Harsh Sharma
Lead, Artificial Intelligence and Machine Learning

Bart Valkhof
Head, Information and Communication
Technology Industry

Karla Yee Amezaga
Initiatives Lead, AI and Data Governance,
Centre for AI Excellence

Accenture

Muqsit Ashraf
Group Chief Executive, Strategy

Karalee Close
Global Lead for Talent and Organization

Rami El Debs
Senior Managing Director, Global AI Strategy Lead

Anne Groeppelin
Managing Director, Tech Strategy & Advisory

Lan Guan
Chief AI & Data Officer

Reine Khoury
Strategy Manager

Kevin Millan
Principal Director, Growth & Strategy

Matteo Orsenigo
Senior Manager, Communications and Media Industry

Santiago Salinas
Thought Leadership Research Manager

Production

Louis Chaplin
Editor, Studio Miko

Laurence Denmark
Creative Director, Studio Miko

Jay Kelly
Designer, Studio Miko

Cat Slaymaker
Designer, Studio Miko

Endnotes

1. Accenture (2025). *The front-runners' guide to scaling AI: Lessons from industry leaders*. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Front-Runners-Guide-Scaling-AI-2025-POV.pdf.
2. El-Warraky, N. (2024, 15 November). *Reinventing consumer experiences*. Accenture. https://www.accenture.com/us-en/blogs/consumer-goods-services/reinventing-consumer-experiences.
3. Accenture. (2024). *Thrive with responsible AI: From risk mitigation to value creation* (Report). Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Responsible-AI-From-Risk-Mitigation-to-Value-Creation.pdf.
4. McKinsey & Company. (n.d.). *Next-best experience: How AI can power every customer interaction*. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/next-best-experience-how-ai-can-power-every-customer-interaction.
5. Fiedler, L. et al. (2025). *Next best experience: How AI can power every customer interaction*. McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/next-best-experience-how-ai-can-power-every-customer-interaction.
6. Tordjman, K. et al.. (2025). *How AI agents are opening the golden era of customer experience*. Boston Consulting Group. https://web-assets.bcg.com/9d/87/52ec9fab46e3881ad96e74c312e0/agents-ia-une-revolution-pour-lexperience-client.pdf.
7. Fiedler, L. et al. (2025, October 9). *Next best experience: How AI can power every customer interaction*. McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/next-best-experience-how-ai-can-power-every-customer-interaction.
8. Pegasystems. (n.d.). *Ford: Driving CX improvements with next-best-action*. https://www.pega.com/customers/ford-decision-hub.
9. Pegasystems. (n.d.). *Rabobank Customer Decision Hub*. https://www.pega.com/customers/rabobank-customer-decision-hub.
10. Visa. (2025). *The rise of agentic commerce*. https://www.visa.co.uk/content/dam/VCOM/regional/ve/unitedkingdom/PDF/agentic-payments.pdf.
11. McKinsey & Company. (n.d.). *Harnessing the power of AI in distribution operations*. https://www.mckinsey.com/industries/industrials/our-insights/distribution-blog/harnessing-the-power-of-ai-in-distribution-operations.
12. Blanchet, M., McDivitt, C., & Meyer, S. (2025, 20 May). *Making autonomous supply chains real*. Accenture. https://www.accenture.com/us-en/insights/supply-chain/making-autonomous-supply-chains-real; Oca, A., Panikkar, R., Sampat, C., & Brown, T. (2024, 15 November). *Harnessing the power of AI in distribution operations*. McKinsey & Company. https://www.mckinsey.com/industries/industrials/our-insights/distribution-blog/harnessing-the-power-of-ai-in-distribution-operations.
13. Rao, B., & Chakraborty, A. (2024). *Reinventing enterprise operations: How reinvention-ready companies are driving growth and relevance with gen AI* (Accenture Report). Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Reinventing_Enterprise_Operations.pdf.
14. Accenture. (2024). *Thrive with responsible AI: From risk mitigation to value creation*. Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Responsible-AI-From-Risk-Mitigation-to-Value-Creation.pdf.
15. Boston Dynamics. (n.d.). *Digital transformation at Nestlé Purina*. https://bostondynamics.com/case-studies/digital-transformation-at-nestle-purina/.
16. Microsoft. (n.d.). *Siemens and Microsoft drive industrial productivity with generative artificial intelligence*. https://news.microsoft.com/de-de/siemens-and-microsoft-drive-industrial-productivity-with-generative-artificial-intelligence/.
17. Accenture. (2025, November 11). *Essity collaborates with Accenture and Microsoft to accelerate adoption of AI agents to drive productivity and growth*. https://newsroom.accenture.com/news/2025/essity-collaborates-with-accenture-and-microsoft-to-accelerate-adoption-of-ai-agents-to-drive-productivity-and-growth.
18. Claryo. (n.d.). *Home*. https://www.claryo.co/.
19. Accenture. (2025, 5 September). *Pulse of Change: Business and technology trends. Accenture*. https://www.accenture.com/us-en/insights/pulse-of-change.
20. New source: World Economic Forum. (2025). *Transforming consumer industries in the age of AI*. https://reports.weforum.org/docs/WEF_Transforming_Consumer_Industries_in_the_Age_of_AI_2025.pdf.
21. Accenture. (2025). *The future of demand: Opportunities for chemicals to capture growth* (Report). Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Chemicals-Future-Demand-Growth-Opportunities.pdf.
22. Toner-Rodgers, A. (2024). *Artificial intelligence, scientific discovery, and product innovation*. *arXiv*. https://doi.org/10.48550/arXiv.2412.17866.
23. Singla, A., Sukharevsky, A., Berteletti, E., Yee, L., & Chui, M. (2025, 20 June). *The next innovation revolution—Powered by AI*. McKinsey & Company. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-next-innovation-revolution-powered-by-ai.

24. Boston Consulting Group. (2025). *Reshaping R&D for the AI era*. https://www.bcg.com/assets/2025/225-weekly-brief-reshaping-r-and-d-for-the-ai-era.pdf.
25. Bain & Company. (n.d.). *Better, faster, cheaper: How digital transforms R&D*. https://www.bain.com/insights/better-faster-cheaper-how-digital-transforms-r-and-d/.
26. Merck Millipore. (n.d.). *AIDDISON™ AI drug discovery*. https://www.merckmillipore.com/BN/en/services/software-and-digital-platforms/aiddison-ai-powered-drug-discovery/.
27. Hale, C. (2025). *Insilico Medicine provides benchmark timelines from its 22 AI-designed drug candidates*. Fierce Biotech. https://www.fiercebiotech.com/medtech/insilico-medicine-provides-benchmark-timelines-its-22-ai-designed-drug-candidates.
28. Lundbeck. (2024, 18 March). *How Lundbeck used AI to qualify new drug targets for headache disorders* [Press release]. https://www.lundbeck.com/global/press/news-archive/2024/how-lundbeck-used-AI-to-qualify-new-drug-targets-for-headache-disorders.
29. Business Insider. (2025). *Ignota Labs is using AI to reinvent drug discovery*. https://www.businessinsider.com/ignota-labs-funding-pitch-deck-ai-drugs-2025-3.
30. Nature. (2025). *AI-driven drug discovery gains momentum*. https://www.nature.com/articles/d43747-025-00034-0.
31. Boston Consulting Group. (2024). *The power of dynamic steering in financial planning*. https://www.bcg.com/publications/2024/power-of-dynamic-steering-in-financial-planning.
32. Boston Consulting Group. (2023). *AI-driven integrated business planning platforms*. https://www.bcg.com/publications/2023/ai-driven-integrated-business-planning-platforms.
33. Ibid.
34. Massachusetts Institute of Technology (MIT) Sloan Management Review & Boston Consulting Group. (2024). *The future of strategic measurement: Enhancing KPIs with AI*. https://web-assets.bcg.com/54/43/28953bcd41d99e7dd354f5517e13/the-future-of-strategic-measurement-enhancing-kpis-with-ai.pdf.
35. Accelytics. (n.d.). *Canada Goose case study*. https://www.accelytics.com/case-studies/canada-goose.
36. Hancock, B., Schaninger, B. & Yee, L. (2023). *Generative AI and the future of HR*. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/generative-ai-and-the-future-of-hr.
37. Accenture. (2024). *Thrive with responsible AI: How embedding trust can unlock value* [Infographic]. Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Thrive-Responsible-AI-Infographic.pdf.
38. Accenture. (2025). *Learning Reinvented 2025: Accelerating collaboration between humans and AI* (Accenture Report). Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-2/Functions-Learning-Reinvented-2025-Report-Design.pdf.
39. Federal Reserve Bank of St. Louis. (2025). *The Impact of Generative AI on Work Productivity*. https://www.stlouisfed.org/on-the-economy/2025/feb/impact-generative-ai-work-productivity.
40. Accenture. (2025). *Learning Reinvented: Accelerating human–AI collaboration* (Accenture Report). Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-2/Functions-Learning-Reinvented-2025-Report-Design.pdf.
41. Accenture. (2024). *Thrive with responsible AI: From risk mitigation to value creation*. Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Responsible-AI-From-Risk-Mitigation-to-Value-Creation.pdf.
42. Accenture. (2025). *Learning Reinvented: Accelerating human–AI collaboration*. Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-2/Functions-Learning-Reinvented-2025-Report-Design.pdf.
43. McKinsey & Company. (n.d.). *HR's transformative role in an agentic future*. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-organization-blog/hrs-transformative-role-in-an-agentic-future.
44. Nolan, B. (2025, August 7). *AI is already upending the corporate org chart as it flattens the distance between the C-suite and everyone else*. Fortune. https://fortune.com/2025/08/07/ai-corporate-org-chart-workplace-agents-flattening/.
45. McKinsey & Company. (n.d.). *HR's transformative role in an agentic future*. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-organization-blog/hrs-transformative-role-in-an-agentic-future.
46. Gloat. (n.d.). *How Unilever uses AI to retain, engage, and develop employees*. https://gloat.com/wp-content/uploads/How-Unilever-Uses-AI-to-Retain-Engage-and-Develop-Employees.pdf.
47. MIT Sloan Management Review. (n.d.). *How companies can use AI to find and close skills gaps*. https://mitsloan.mit.edu/ideas-made-to-matter/how-companies-can-use-ai-to-find-and-close-skills-gaps.
48. Nolan, B. (2025). AI is already upending the corporate org chart as it flattens the distance between the C-suite and everyone else. *Fortune*. https://fortune.com/2025/08/07/ai-corporate-org-chart-workplace-agents-flattening/.
49. Bousquette, I. (2025). Why Moderna merged its tech and HR departments. *The Wall Street Journal*. https://www.wsj.com/articles/why-moderna-merged-its-tech-and-hr-departments-95318c2a.

WORLD ECONOMIC FORUM

COMMITTED TO IMPROVING THE STATE OF THE WORLD

The World Economic Forum, committed to improving the state of the world, is the International Organization for Public-Private Cooperation.

The Forum engages the foremost political, business and other leaders of society to shape global, regional and industry agendas.

World Economic Forum
91–93 route de la Capite
CH-1223 Cologny/Geneva
Switzerland

Tel.: +41 (0) 22 869 1212
Fax: +41 (0) 22 786 2744
contact@weforum.org
www.weforum.org