The age of co-intelligence

How humans, AI agents and robots are redefining value

accenture | Wharton University of Pennsylvania

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Executive summary

AI has progressed from a novelty to a driver of performance faster than any technology before it. Use of AI has shifted from simple augmentation, where AI supports a task, to co-intelligence, where AI can interpret intent, reason through options, coordinate steps, and execute bounded work across functions at machine speed. While benchmarks indicate AI may surpass people in specific domains, only humans bring the full view, including context, values, legitimacy, and accountability. That is why humans are not merely “in the loop.” Humans must stay in the lead by setting direction, defining guardrails, challenging analysis, making trade-offs, and owning outcomes.

This shift raises a new leadership mandate: redeploy expanded capacity into measurable value and sustained growth. As AI compresses analysis, decision cycles, and delivery, it expands both human and digital capacity, and that capacity can be redirected toward reinvention. That includes faster product iteration, new offerings, sharper customer response, and smarter capital allocation. Leaders need human-led operating systems where people orchestrate human and AI collaboration and AI executes within clear constraints, so speed and scale increase while responsibility remains firmly human.

> Humans must stay in the lead by setting direction, defining guardrails, challenging analysis, making trade-offs, and owning outcomes.

In our previous report, Humans, AI and Robots (2024), we focused on productivity: how humans and machines could work better together. This year, the focus shifts to value. Specifically, how the collaboration of human and artificial intelligence reshapes value creation across four fronts:

Economics

The next source of value is growth

AI-enabled ways of working deliver measurable productivity gains, but the true dividend comes from how leaders deliberately redirect that capacity toward expansion, innovation and market advantage.

Individuals

Job titles give way to skills as the new currency of work

Work is no longer organized around static roles, but around skills. The Wharton-Accenture Skills Index (WAsX), developed by Wharton and Accenture, provides an empirical view of this shift by mapping jobs at the task and skill level and linking them to economic value in an AI-enabled economy. As WAsX shows, breaking jobs down into skills gives leaders a practical way to redesign work and align compensation with both human and AI capabilities.

Workforce

Designing work with people in the lead

An organization's workforce strategy must align closely with its business goals and technology strategy. Creating value at scale requires redesigning jobs around the work that only people can do and regularly recalibrating roles and workflows as AI capabilities expand. Technology can then extend reach, coordination and execution. This approach puts people in the lead, supported by AI, and depends on building trust, effective models of human-AI interaction and continuous skill development to sustain performance and growth.

Society

Responsibility, trust and legitimacy in an AI-enabled economy

As intelligence becomes more scalable through human-AI systems, responsibility does not scale in the same way. Society must reshape education, work and governance so that AI increases human capacity and progress, while legitimacy, accountability and stewardship remain firmly human.

Leaders who master co-intelligence by integrating human, digital and physical artificial intelligence into a cohesive workforce will define how value, growth and purpose are created in the next decade.

01

The new reality

From augmentation to co-intelligence

AI, in some critical areas, has reached parity with human intellect. The latest generation of large language reasoning models are no longer limited to pattern recognition or narrow optimization. They can reason, generalize and solve novel problems at levels comparable to people with a PhD-level education. In fact, they have outperformed human experts on a number of rigorous benchmarks. These tests, once considered the frontier of human reasoning, include the GPQA (the Google-Proof Question and Answer assessment, the standard set of which contains 448 questions focused on physics, chemistry and biology)[1], and ARC-AGI (Abstraction and Reasoning Corpus for Artificial General Intelligence)[2]. Additionally, GPT 5.2 outperformed human baselines in 71% of 1,320 tasks across 44 occupations in GDPval (Gross Domestic Product Evaluation), a test that not only includes knowledge questions but also tasks that generally take humans up to eight hours to complete.[3]

It's a decisive shift. AI is no longer augmenting human intelligence at the margins. It is dramatically expanding the scale, speed and scope at which human judgment can be applied. AI removes limits on how much thinking and analysis can be done, while humans still decide what matters, set strategy and own the outcomes. This asymmetry is critical. Intelligence may be scalable, but accountability is not. AI can expand the range of options considered and accelerate analysis, but only humans define ambition, determine acceptable risk, resolve trade-offs and take responsibility for consequences. In a co-intelligent enterprise, leadership does not diminish as AI improves, it becomes more consequential.

With humans in the lead, agents extend intelligence across the enterprise

As AI capabilities have advanced, organizations are rethinking how work is led, organized and executed. Agentic AI represents a step-change in enterprise design, with agents embedded directly into workflows, systems and operating models. Within human-defined boundaries and factors that build trust, these agents support reasoning, learning and execution at a different level of performance.

People must remain in the lead—to frame problems, apply judgment and to build trust. Agents can be assigned goals, operate within defined boundaries, coordinate across systems and adapt their behavior over time. When combined with physical robots, they extend execution in a **Human+ workforce**: a blended system in which people set direction and accountability, and AI agents and machines increase speed and scale of delivery.

> AI is no longer augmenting human intelligence at the margins. It is dramatically expanding the scale, speed and scope at which human judgment can be applied.

Critically, this is not a zero-sum dynamic. Rather, it's about adopting an abundance mentality, where humans are supported by agents. It brings the vision of the "10× enterprise" into focus—where one person can increasingly direct and oversee the work of multiple AI-enabled systems, while retaining responsibility for outcomes, risk and judgment.

Meanwhile, AI and agents are already spreading rapidly across the enterprise value chain, often ahead of formal strategy and governance. Nearly three-quarters of knowledge workers now use AI, frequently through unsanctioned, bring-your-own tools[4]; and roughly a third of enterprise applications are expected to embed agentic capabilities by 2028.[5] As intelligence becomes pervasive by default, the challenge for leaders will be how to systematically balance speed, risk and return at scale.

The impact is immense

The impact of agentic AI extends beyond tasks and workflows to the core of how decisions are made.

According to a report by Gartner, Inc., by 2027, roughly half of business decisions are expected to be augmented or automated by AI agents, with 15% made autonomously by 2028. In some domains, the shift is even more pronounced: customer operations are trending toward nearly 80% autonomous resolution by 2029.[6] As automation increases, the leadership challenge intensifies: leaders must determine which decisions to delegate, where human judgment must remain central, and how governance, accountability and trust are designed into the system. The implications for governance and value creation are profound, as leaders must decide more deliberately what to delegate and why.

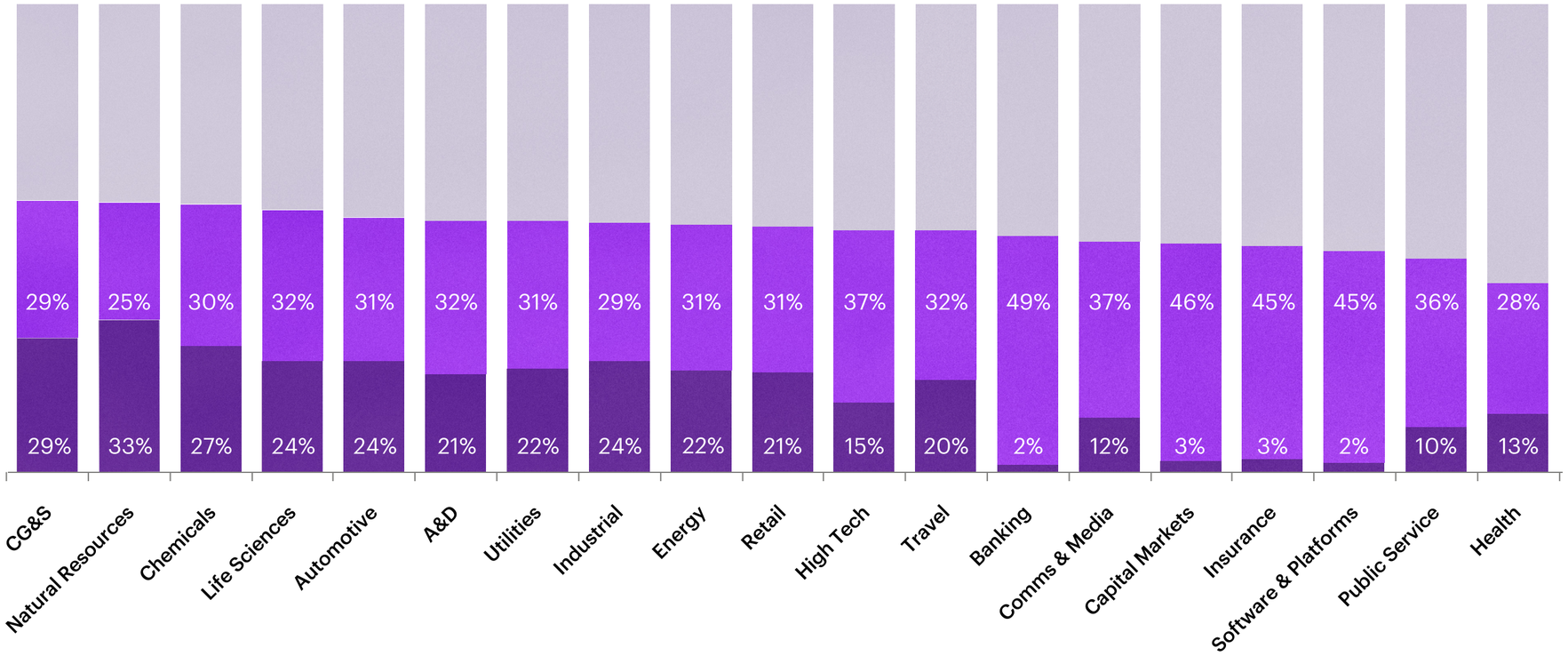
To understand what this means in practice, we conducted a bottom-up analysis of work across 18 industries. Our analysis showed that on average, more than **50% of working hours** are expected to be impacted by AI agents. This represents a reshaping of how work is performed and how value is created. Some industries will feel this shift sooner and more deeply than others, driven by task composition, data intensity and operational complexity. (See chart for detail on next page.)

A task-level view of work

To anticipate how companies will integrate AI, we analyzed tasks and roles using occupation-level data from O*NET and the U.S. Bureau of Labor Statistics (BLS). Each task was evaluated according to the critical human inputs required and then mapped to a digital or physical agent using an LLM that interprets both task and agent descriptions, and then validated by a subject matter expert. This task-level approach moves beyond job titles to reveal where agents can realistically assist or perform work and with how much autonomy.

Figure 2

% hours impacted by approximately 60 agents across industries



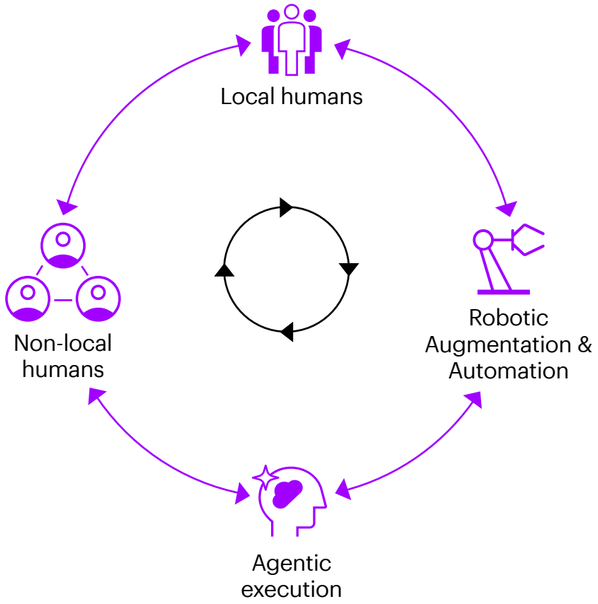
Source: Accenture Research proprietary model developed as part of the partnership with the Wharton School of Business, using data from ONET, BLS.

The scale of this impact is already visible in practice. Talent reinventors are creating value by continually redesigning work and reshaping the workforce to align around shared goals and emerging opportunities enabled by AI, ensuring that people grow, contribute and thrive alongside technology. As the examples on this page illustrate, this shift is already delivering measurable improvements in productivity, cycle time, cost efficiency and operational performance across industries.

How redesigned work is already creating value

A new architecture of work

The **Human+ workforce** seamlessly integrates on-site and remote employees with AI agents and intelligent robots redefining productivity, collaboration and decision-making



What changes when work is redesigned

accenture

Accenture's marketing and communications team reimagined how work gets done by embedding AI into its operating model and core workflows. Through platform consolidation, centralized data and 14 AI-powered agents, the team created a continuous human-AI learning loop across research, content, planning and execution. This has driven a 67% reduction in manual steps for creative briefs, enabled first drafts 90% faster and set the stage to cut campaign steps from 135 to 85. The result is a 25–35% faster time to market, while elevating creativity, agility and impact.

ECOLAB

Ecolab is reinventing itself by leveraging AI to transform its end-to-end processes automating routine tasks, reducing errors and streamlining workflows across sales, billing and fulfillment to enhance both customer and associate experiences.

These outcomes show how organizations that move beyond isolated use cases and intentionally design for agentic intelligence at the enterprise level can realize measurable improvements in outcomes.

Agentic execution within the intelligent enterprise

A clear structural pattern emerges. As intelligence scales, leading organizations are moving beyond isolated solutions and instead relying on a coordinated set of digital and physical agents that operate under human direction. Our analysis identified a minimum viable organization of approximately 60 enterprise agents—35 digital agents and 25 physical agents (robots)—supporting work across areas of research and development (R&D), manufacturing, human resources (HR), finance and customer service.

Importantly, many of these agents recur across functions and industries. The same core agents support multiple parts of the enterprise, creating **economies of scale** and reducing the need for one-off experimentation. This shift reflects a move away from siloed use cases toward a more deliberate approach to how work gets done.

While this overall pattern is consistent across industries, its impact varies by sector based on task and role composition and industry value chain. To illustrate this, we modeled the agentic organization for a grocery retailer, mapping digital and physical agents to the value chain and estimating the share of work hours affected by function.

As shown in figures 2, 3 and 4, more than half of work hours in key areas, including product design & development, manufacturing, distribution and logistics, supply chain planning, customer experience and sales and channel and commerce, are expected to be materially impacted by digital and physical agents.

Figure 2

A one-page organization of agents for grocery retailers

Non-Exhaustive

% of total enterprise hours digital and physical agents could impact across Retail – Grocery

Digital AI Agents

Orchestrator agents

Agent name	% Hours impacted
Smart Query Agent	1.02%
Strategic Advisor	0.50%
Learning Guide	0.04%

Super agents

Agent name	% Hours impacted
Supply Chain Companion	2.55%
Finance Companion	1.75%
Customer Companion	1.64%
Procurement Companion	1.58%
Sales Companion	1.41%
Merchandising Companion	0.84%
Infrastructure Companion	0.83%
Compliance Companion	0.80%
HR Companion	0.62%
Marketing Companion	0.48%
Legal Companion	0.39%
Critical Thinker	0.37%
R&D Companion	0.25%
Production Companion	0.23%

Utility agents

Agent name	% Hours impacted
Advisor	2.93%
Author	2.79%
Analytics Agent	2.27%
Master Data Management	1.50%
Quality Control Agent	1.22%
Research Agent	1.14%
Knowledge Base Agent	1.10%
Crystal Ball	1.00%
Learning and Development	0.74%
Assistant	0.73%
EHS (safety)	0.62%
Tech Support	0.47%
Reporting	0.42%
Capacity & Skill	0.31%
Designer	0.19%

Physical AI Agents

Robotic automation

Agent name	% Hours impacted
Robotic Cleaning and Scrubbing Systems	2.32%
Vision Inspection Systems	2.04%
Robotic Storage and Retrieval Systems	1.72%
Disinfection and Sanitization Robots	1.69%
Dispensing Robots	1.66%
Robotic Palletizing & Depalletizing	1.56%
Robotic Palletizing	1.54%
Weighing and Sorting Robots	1.44%
Automated Guided Vehicles (AGVs)	1.10%
Specialized Blister Packaging Robots	1.08%
Seal Integrity Testing Robots	0.97%
Carton Filling, Sealing, and Labeling Robots	0.96%

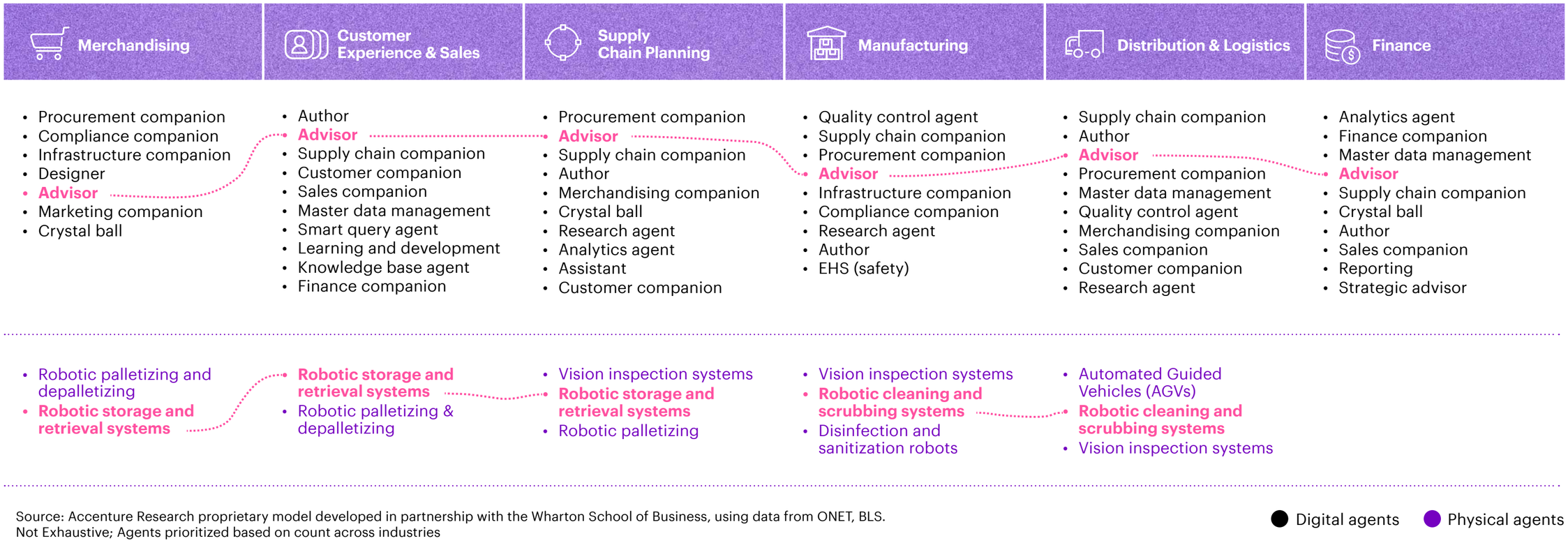
Source: Accenture Research proprietary model developed as part of the partnership with the Wharton School of Business, using data from ONET, BLS.

Note: Only top agents by agentic category are displayed. Hours impacted are non-exclusive and may involve various combinations of the agents listed. Manual intervention may still be required in supervision and orchestration of agentic workflows.

Figure 3

Agents are redeployed/reused across functions to maximize the ROI of each agent and enable continuous learning

Top digital and physical agents by function for a grocery retailer (a subset of functions)

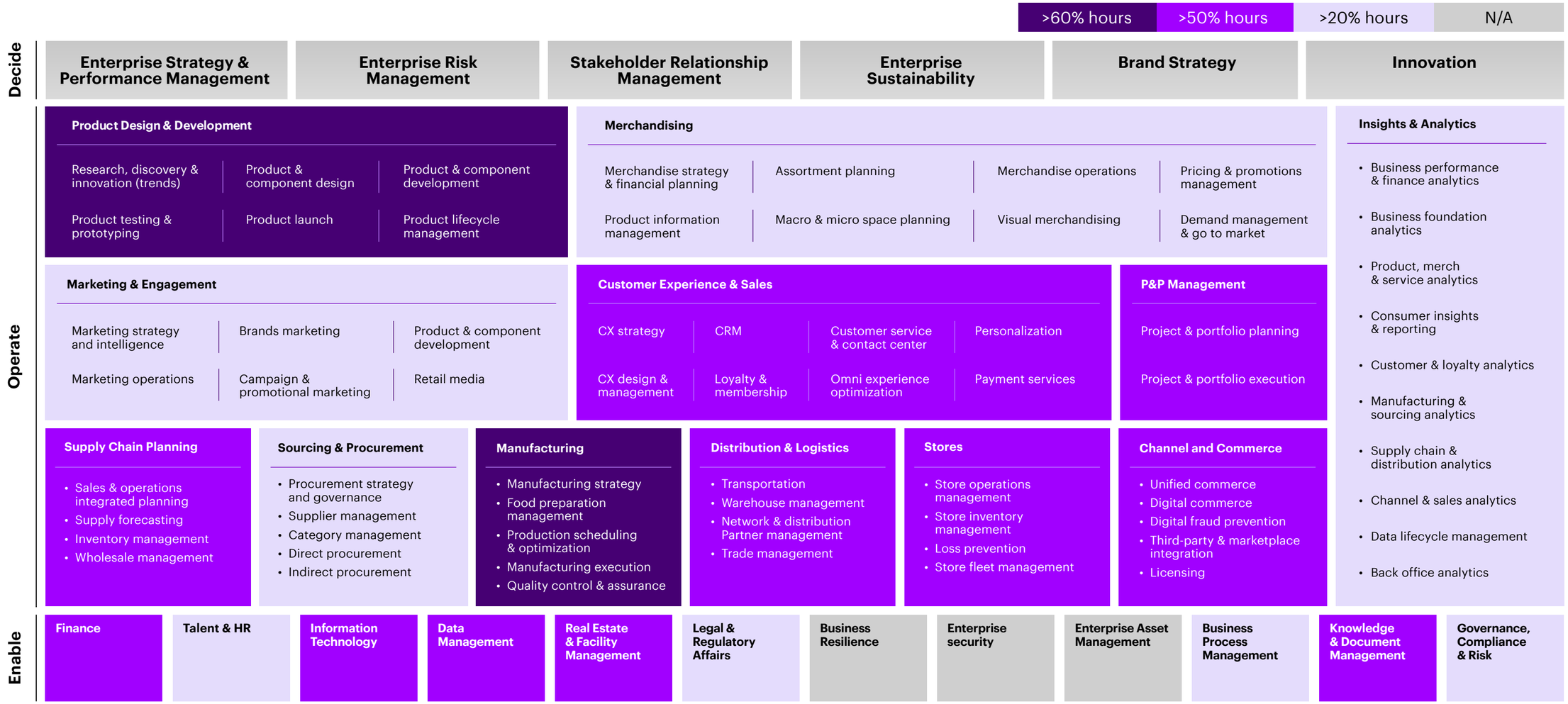


Source: Accenture Research proprietary model developed in partnership with the Wharton School of Business, using data from ONET, BLS.
Not Exhaustive; Agents prioritized based on count across industries

Figure 4

Across Grocery Retail value chain, over 50% of work hours across functions could be impacted by agents

For a grocery retailer:



Source: Accenture Research proprietary model developed in partnership with the Wharton School of Business, using data from ONET, BLS.

Intelligence is no longer scarce; it is scalable. The next source of competitive advantage will be how effectively organizations combine human judgment with agent-enabled execution, and how deliberately they redeploy their newfound capacity.

This raises the next critical question:

If more than half of all work hours are being reshaped, how does that impact show up on financial statements?

02

Economics

The next source
of value is growth

As agents move from pilots to production, the leadership question shifts from **“What can AI do?” to “How much value can it create, and where does it actually come from?”**

Our bottom-up economic modeling shows that the agentic dividend is substantial, but it does not emerge evenly. It does, however, follow clear patterns. Leaders who understand and intentionally act on those patterns stand to capture far more value than others.

Specifically, we found that:

Growth, not efficiency, is the dominant value lever.

While productivity gains are meaningful, the primary economic upside of agentic AI comes from improved decisions, faster execution and higher-quality outcomes that translate into revenue growth. Cost reduction alone captures only a fraction of the available value.

Productivity becomes growth only through redeployment.

A significant share of productivity manifests as capacity freed rather than costs removed. Unless leaders deliberately redeploy that capacity toward higher-value work, productivity gains stall at efficiency and fail to translate into growth.

Value is unevenly distributed across functions and tasks.

Economic impact does not diffuse evenly across the enterprise. It clusters in specific functions and in a small number of task groups that recur across those functions. The implication is clear: targeted deployment, starting with priority functions and scaling the highest-value task groups across the enterprise, maximizes returns.

Governance needs of agentic AI depend on where tasks fall across a volume-risk spectrum.

In areas where agents operate at high volumes and carry high decision risk, more rigorous governance is required. Leaders will need to assess exactly where decision risk resides before deploying agents, and design governance accordingly. This targeted approach focuses controls where they matter most, rather than applying uniform guardrails across the enterprise.

How we modeled the agentic economy

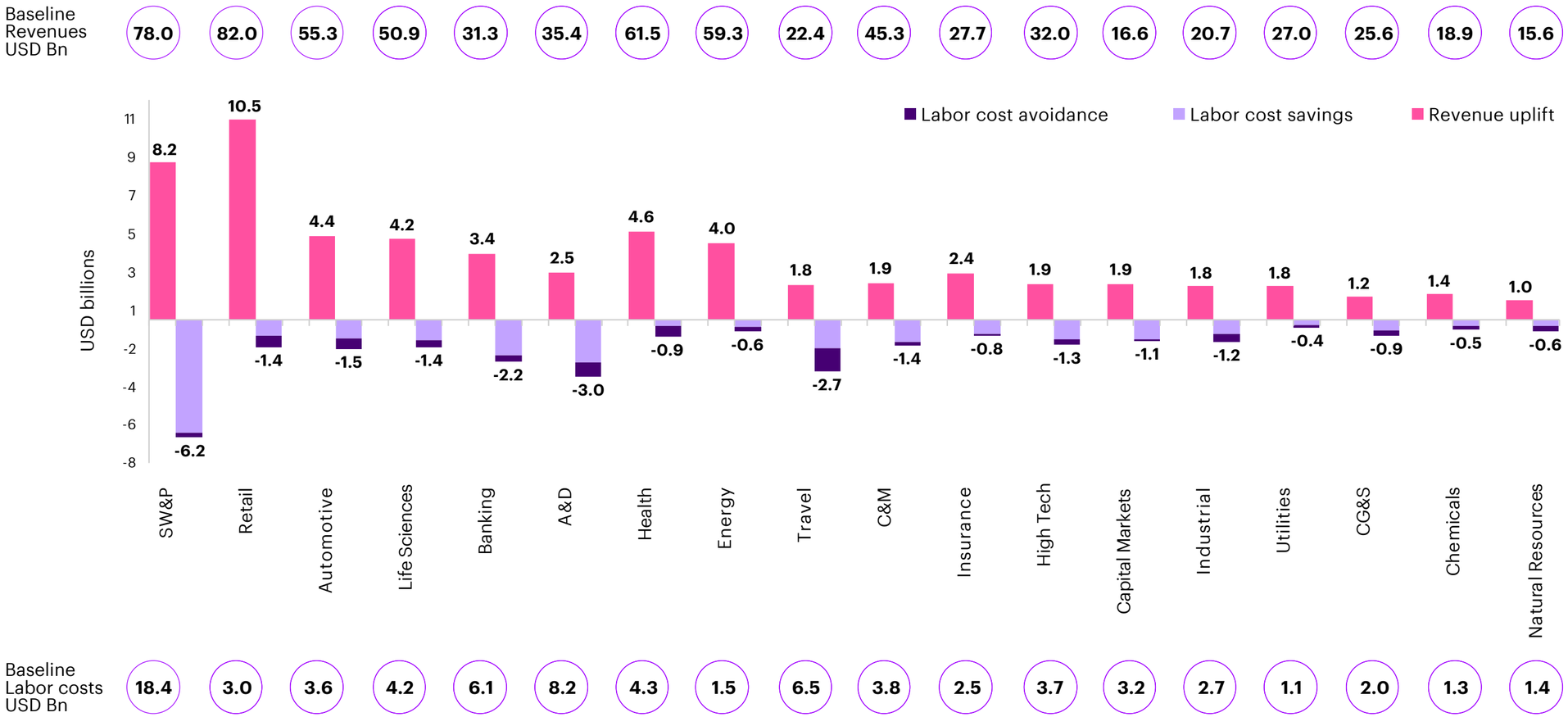
We modeled agentic impact using a task-level framework that captures both cost efficiencies and output growth from alternative workflow modes between humans and machines. The analysis reflects how enterprises progress from human-only work to AI-augmented roles, supervised agents and human-led autonomous digital and physical agents. We grounded estimates in observed time savings and quality improvements from experimental research and industry use cases, calibrated to current agentic capabilities and realistic enterprise adoption paths. We simulated economic value across companies, functions, roles and tasks, capturing both productivity effects and growth dynamics.

We also explicitly assessed risk-sensitive decision-making by identifying how many decisions are made across functions, what share of those decisions are risk-sensitive and which can realistically be performed by agentic AI. This allowed us to distinguish between digital autonomy risks and physical autonomy risks and to factor governance requirements directly into the decision-making.

Figure 5

Potential economic impact of AI by industry, S&P 500 firms

Full-maturity (upper-bound) annual potential of digital and physical AI agents for the average S&P 500 company, by industry



Source: Accenture Research analysis based on data from S&P Capital IQ, US ONET, US Bureau of Labor Statistics, International Labor Organization, and Lightcast. Baseline: 2024 revenues and labor costs for the average S&P 500 firm in each industry, except for Automotive and Health for which we use a matched equivalent sample.

Case study

Modeling value creation at an enterprise with $60 billion annual revenue

To make these dynamics concrete, we applied our reinvention and value-modeling approach with a real-world client: a large enterprise with **$60 billion in annual revenue** and **$4.5 billion in labor spend.**

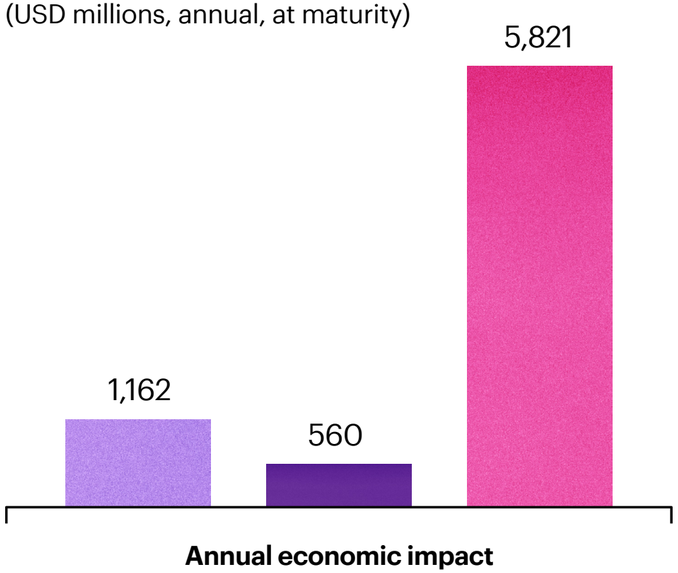
The first step in the reinvention process was to **set the ambition.** While the client had several AI initiatives in flight, they lacked a compelling enterprise-level value target, a clear view of where value would be created across the organization and alignment among senior leaders on the importance and scale of change required.

Using our model, we identified the functions and company-wide areas that matter most, along with the revenue gains and productivity improvements tied to each. This enabled the CEO to recast the enterprise horizontals with more specific, outcome-oriented targets, selectively add functions for AI-driven transformation and align the C-suite around both the magnitude of the opportunity and the commitment required to capture it.

Figure 6

Total opportunity at the company level

(USD millions, annual, at maturity)



- **Revenue uplift**: revenues generated by higher volume and/or price driven by output quality improvements from AI
- **Labor cost savings**: change in current wage bill given time savings from AI
- **Labor cost avoidance**: potential cost changes for roles that could not be allocated

Source: Accenture Research proprietary model developed in partnership with the Wharton School of Business, using data from ONET, BLS, S&P CapIQ, and Lightcast.

We modeled the value potential, which is approximately **$6 billion in annual revenue growth**, driven by better decisions, faster execution and improved quality, alongside **$1.7 billion in productivity gains**, reflecting both efficiency improvements and capacity freed for redeployment.

Importantly, the model demonstrated that productivity does not translate cleanly into lower costs. Instead, roughly two-thirds of productivity gains materialized as direct cost savings, while one-third appeared as cost avoidance, capacity freed to do different, higher-value work. Without intentional redeployment, that avoided cost does not become growth.

Where value concentrates and where risk scales

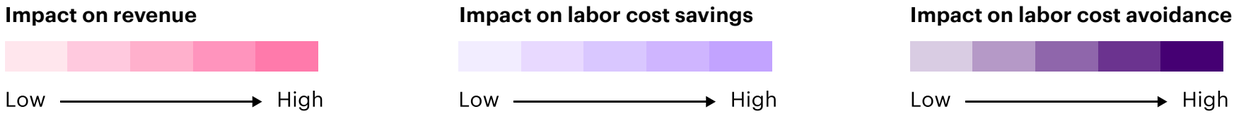
Revenue growth was most heavily concentrated in sales, R&D and market access, functions that shape demand, define products and make offerings accessible to the market. Together, these functions accounted for nearly half of the potential rise in total revenues in the enterprise, reflecting where better decisions, faster execution and higher-quality outputs translate most directly into growth. (See figure 7)

Productivity gains, by contrast, were broader. While productivity improvements spanned many functions, they were dominated by a small set of recurring task groups performed across the enterprise. Management, business strategy, writing and recording and data analysis together accounted for most of the productivity opportunity. (See figures 9 and 10)

Figure 7

Monetary impact from autonomous AI

(USD millions, annual, at maturity)



Annual

USD Millions	Sales	R&D	Market Access	MFG	Supply Chain	EHS	Cust. Service	Mkt.	P&P Mgt.	Sourcing & Proc.	IT	W&L	Quality Mgt.	Finance	Insights & Analy.	HR	Legal	Reg. Affairs	Facility Mgt.	Know. Mgt.	Total
Revenue uplift	1,102	1,040	698	397	366	350	350	335	288	215	164	127	90	87	71	55	40	29	11	7	**5,821**
Labor cost	271	205	152	128	113	69	65	62	163	74	151	52	35	61	28	54	17	12	8	3	**1,722**
Labor cost savings	223	34	67	103	95	4	4	62	162	71	150	29	15	42	27	52	10	7	3	2	**1,162**
Labor cost avoidance	47	171	84	25	18	65	61	1	1	3	1	23	19	19	1	2	7	5	5	1	**560**

Source: Accenture Research proprietary model developed in partnership with the Wharton School of Business, using data from ONET, BLS, S&P CapIQ, and Lightcast
Notes: Labor Cost Savings are reductions in current wage bill given time savings from AI for roles scoring high in Reallocation Index.
Labor Cost Avoidance are potential cost changes given time savings from AI for roles scoring low in Reallocation Index.
Revenue Uplift refers to additional revenues generated by higher volume and/or higher price driven by output quality improvements from AI for roles that contribute to revenue generation using a revenue generation score.
R&D = Research and Development; MFG = Manufacturing; EHS = Environment, Health and Safety; MKT = Marketing; Proc = Procurement; W&L = Warehouse and Logistics; Know. Mgt = Knowledge Management

Figure 8

Revenue uplift

(USD millions, annual, at maturity)

Impact on revenue

Low → High

Annual

Task Cluster	Sales	R&D	Market Access	MFG	SC Planning	EHS	CS	MKT	P&P Mgt.	Sourcing & Proc.	IT	W&L	Quality Mgt.	FIN	I&A	HR	Legal	Reg. Affairs	Facility Mgt.	Know. Mgt.	Total	
Management	161	194	163	78	85	86	87	68	62	55	14	21	11	22	6	13	9	6	3	1	1,145	**20%**
Business Strategy	156	87	70	40	43	20	20	57	42	34	3	8	5	7	3	1	0	1	1	0	598	**10%**
Writing and Recording	144	99	55	16	22	41	42	45	11	2	10	5	7	4	1	5	4	3	1	1	519	**9%**
Evaluation	76	105	58	27	22	39	39	62	8	4	20	11	13	14	9	6	1	2	1	1	518	**9%**
Monitor Resources	27	75	68	42	29	45	45	2	25	18	1	20	11	10	2	2	0	2	1	0	426	**7%**
Knowledge Sharing	123	87	35	14	13	21	21	38	8	1	8	10	9	6	10	12	1	2	1	1	423	**7%**
Planning and Coordination	22	72	65	29	31	36	35	1	23	21	11	4	5	2	6	0	0	0	0	0	366	**6%**
Data Analysis	15	50	49	45	47	1	0	17	46	39	18	7	2	6	12	1	4	1	1	0	362	**6%**
Buy, Sell and Service	155	28	25	22	21	0	2	12	24	18	0	10	1	5	1	0	0	1	1	0	328	**6%**
Advising and Instructing	60	65	38	21	21	17	16	18	16	12	9	7	5	5	3	7	5	2	1	1	327	**6%**
Engineering	0	44	26	30	17	13	12	1	10	8	15	6	3	0	3	0	0	0	0	0	189	**3%**
Software	1	31	30	2	1	30	30	2	1	0	40	1	0	0	9	0	0	0	0	0	180	**3%**
Obtain Information	44	38	8	15	5	0	0	9	7	1	5	5	1	0	2	4	6	3	0	0	155	**3%**
Legal Work	0	36	9	1	1	0	0	0	0	0	3	5	1	4	2	1	8	3	0	0	75	**1%**
Handling and Moving Objects	40	11	0	4	1	0	0	0	1	0	0	4	5	0	0	0	0	0	0	0	66	**1%**
Clerical	41	0	0	0	0	0	0	0	3	0	0	0	0	1	0	2	0	1	0	0	49	**1%**
Machine Operation and Maintenance	1	14	0	8	5	0	0	0	1	0	2	2	6	0	0	0	0	0	0	0	39	**1%**
Design and Create	25	1	0	1	0	0	0	1	1	0	4	0	0	0	3	0	0	0	0	0	37	**1%**
Manual Work	10	0	0	2	2	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	19	**<1%**
Total	1,102	1,040	698	397	366	350	350	335	288	215	164	127	90	87	71	55	40	29	11	7	**5,821**	
	19%	**18%**	**12%**	**7%**	**6%**	**6%**	**6%**	**6%**	**5%**	**4%**	**3%**	**2%**	**2%**	**1%**	**1%**	**1%**	**1%**	**1%**	**<1%**	**<1%**		

Source: Accenture Research proprietary model developed as part of the partnership with the Wharton School of Business, using data from ONET, BLS, S&P CapIQ, and Lightcast
Note: Revenue Uplift refers to additional revenues generated by higher volume and/or higher price driven by output quality improvements from AI for roles that contribute to revenue generation using a revenue generation score.

Figure 9

Labor cost savings

(USD millions, annual, at maturity)

Impact on labor cost savings

Low → High

Annual

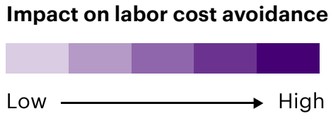
Task Cluster	Sales	R&D	Market Access	MFG	SC Planning	EHS	CS	MKT	P&P Mgt.	Sourcing & Proc.	IT	W&L	Quality Mgt.	FIN	I&A	HR	Legal	Reg. Affairs	Facility Mgt.	Know. Mgt.	**Total**	
Management	27	4	16	20	23	0	0	12	26	18	12	4	1	10	2	12	2	1	1	0	192	**17%**
Business Strategy	31	0	10	11	12	0	0	10	21	11	2	1	1	2	1	1	0	0	0	0	116	**10%**
Data Analysis	2	5	12	13	14	0	0	3	23	12	16	1	0	2	5	1	1	0	0	0	110	**9%**
Writing and Recording	33	1	1	4	5	0	1	8	12	1	10	2	1	3	0	5	2	1	0	0	89	**8%**
Knowledge Sharing	27	4	1	2	2	0	0	7	10	0	7	2	1	2	4	13	1	1	0	0	84	**7%**
Evaluation	14	2	2	5	4	0	0	11	6	1	17	2	2	7	3	6	0	0	0	0	84	**7%**
Buy, Sell and Service	32	0	6	6	6	0	1	2	12	6	0	2	0	2	0	0	0	0	0	0	77	**7%**
Monitor Resources	7	2	5	11	7	0	0	1	14	6	0	4	2	6	1	2	0	0	0	0	70	**6%**
Advising and Instructing	10	2	4	5	5	1	0	3	8	4	8	1	1	4	1	7	1	0	0	0	66	**6%**
Planning and Coordination	5	1	6	8	9	0	0	0	9	7	11	1	1	2	2	0	0	0	0	0	64	**5%**
Software	0	1	0	1	0	0	0	1	1	0	39	0	0	0	4	0	0	0	0	0	47	**4%**
Engineering	0	3	3	8	4	0	0	0	6	2	14	1	1	0	1	0	0	0	0	0	44	**4%**
Obtain Information	8	3	0	4	2	0	0	2	9	0	5	1	0	0	1	5	1	1	0	0	43	**4%**
Handling and Moving Objects	10	3	0	2	0	0	0	0	1	0	0	2	2	0	0	0	0	0	0	0	20	**2%**
Clerical	9	0	0	0	0	0	0	0	3	1	0	0	0	0	0	1	0	0	0	0	15	**1%**
Design and Create	6	0	0	0	0	0	0	0	1	0	4	0	0	0	1	0	0	0	0	0	14	**1%**
Machine Operation and Maintenance	0	3	0	2	1	0	0	0	1	0	2	1	1	0	0	0	0	0	0	0	12	**1%**
Legal Work	0	0	0	0	0	0	0	0	0	0	2	1	0	1	1	1	2	1	0	0	9	**1%**
Manual Work	2	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	5	**<1%**
Total	223	34	67	103	95	4	4	62	162	71	150	29	15	42	27	52	10	7	3	2	**1,162**	
	19%	**3%**	**6%**	**9%**	**8%**	**0%**	**0%**	**5%**	**14%**	**6%**	**13%**	**2%**	**1%**	**4%**	**2%**	**4%**	**1%**	**1%**	**<1%**	**<1%**		

Source: Accenture Research proprietary model developed as part of the partnership with the Wharton School of Business, using data from ONET, BLS, S&P CapIQ, and Lightcast
Note: Labor Cost Savings are reductions in current wage bill given speed improvement from AI for roles scoring high in Reallocation Index

Figure 10

Labor cost avoidance

(USD millions, annual, at maturity)



Annual

Task Cluster	Sales	R&D	Market Access	MFG	SC Planning	EHS	CS	MKT	P&P Mgt.	Sourcing & Proc.	IT	W&L	Quality Mgt.	FIN	I&A	HR	Legal	Reg. Affairs	Facility Mgt.	Know. Mgt.	Total	
Management	4	32	19	3	3	15	15	0	0	0	0	3	2	5	0	0	2	1	2	0	108	9%
Evaluation	4	18	9	3	3	7	7	0	0	0	0	2	2	3	0	0	0	0	0	0	60	5%
Writing and Recording	8	17	9	2	2	8	7	0	0	0	0	1	1	1	0	0	0	0	1	0	59	5%
Monitor Resources	2	12	9	3	2	9	8	0	0	0	0	4	3	2	0	0	0	0	1	0	55	5%
Knowledge Sharing	6	13	6	2	2	4	4	0	0	0	0	2	1	1	0	0	0	0	0	0	44	4%
Business Strategy	5	14	6	1	1	3	3	0	0	0	0	1	1	2	0	0	0	0	0	0	41	4%
Planning and Coordination	1	12	8	1	1	6	6	0	0	0	0	1	1	0	0	0	0	0	0	0	38	3%
Advising and Instructing	2	10	4	1	1	4	3	0	0	0	0	1	1	1	0	0	1	0	0	0	31	3%
Software	0	5	5	0	0	5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	22	2%
Buy, Sell and Service	7	5	1	1	1	0	0	0	0	0	0	2	0	1	0	0	0	0	1	0	19	2%
Engineering	0	6	3	1	1	2	2	0	0	0	0	1	1	0	0	0	0	0	0	0	17	2%
Data Analysis	0	8	1	1	1	1	0	0	0	0	0	1	0	2	0	0	1	0	0	0	15	1%
Obtain Information	1	6	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	13	1%
Legal Work	0	6	1	0	0	0	0	0	0	0	0	1	0	1	0	0	2	1	0	0	12	1%
Handling and Moving Objects	3	2	0	1	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	11	1%
Machine Operation and Maintenance	0	3	0	2	1	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	8	1%
Clerical	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	<1%
Manual Work	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	<1%
Design and Create	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	<1%
Total	47	171	84	25	18	65	61	1	1	3	1	23	19	19	1	2	7	5	5	1	**560**	
	8%	**30%**	**15%**	**4%**	**3%**	**12%**	**11%**	**<1%**	**<1%**	**1%**	**<1%**	**4%**	**3%**	**3%**	**<1%**	**<1%**	**1%**	**1%**	**1%**	**<1%**		

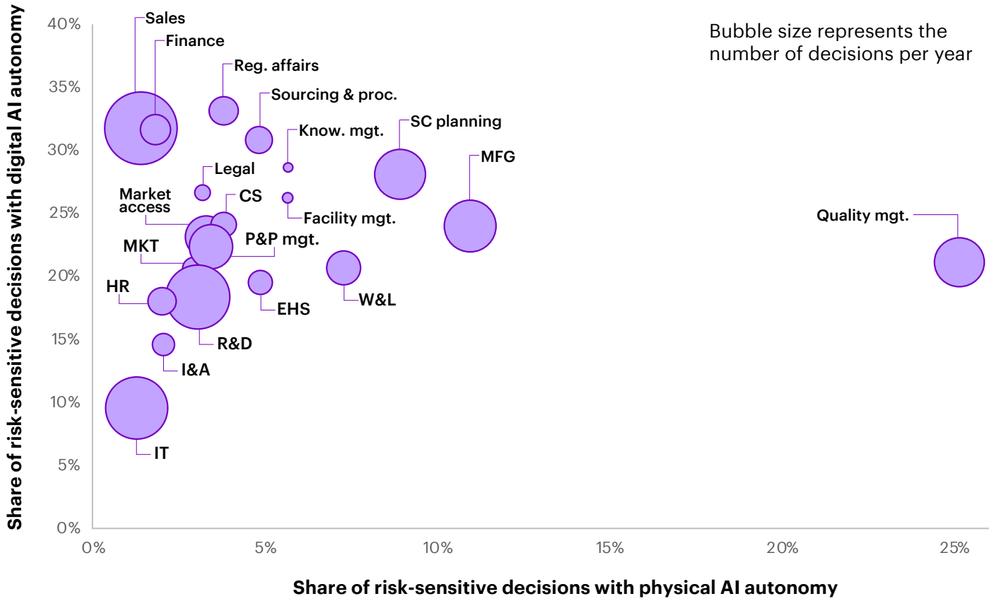
Source: Accenture Research proprietary model developed as part of the partnership with the Wharton School of Business, using data from ONET, BLS, S&P CapIQ, and Lightcast
Note: Labor Cost Avoidance are potential cost changes given speed improvement from AI for roles scoring low in Reallocation Index.

Value and risk scaled together.

Sales, the function with the largest revenue opportunity, was also one of the areas with the highest volume of risk-sensitive decisions, as they include customer interactions, pricing and commercial judgment. This made Sales not only the top priority for investment, but also an area where trust, bias, transparency and accountability had to be carefully designed and managed from the outset.

Figure 12

How risk-sensitive decisions are distributed



Note: R&D = Research and Development; MFG = Manufacturing; SC = Supply Chain; EHS = Environment, Health and Safety; CS = Customer Service; MKT = Marketing; P&P = Project and Portfolio Management; Proc = Procurement; W&L = Warehouse and Logistics; FIN = Finance; I&A = Insights and Analytics; Know. Mgt = Knowledge Management

Each bubble represents a function. Axes show the share of risk-sensitive decisions suited for Digital vs. Physical AI agent autonomy; bubble size reflects total annual decision volume.

Decisions were identified at the **micro-task level** using O*NET data, translated into annual decision volumes per role, classified across multiple dimensions of **organizational risk**, and then assessed for **agentic AI suitability.** Tasks were subsequently aggregated to functions.

The figure highlights a critical asymmetry: Sales, for example, combines a high volume of decisions, high digital agent suitability, and elevated exposure to risk. This makes it both a top candidate for early agent deployment and a governance-critical domain where trust, accountability, and human oversight must be deliberately designed.

As a result, the client's path forward became clear:

Start vertically
in Sales with the right governance in place, focusing first on high-value management, business strategy and writing and recording tasks

Scale horizontally
by extending those same task-level agentic capabilities across the rest of the enterprise

By grounding ambition in a clear, quantified view of enterprise value and linking it directly to functions, tasks, and governance, the organization moved from disconnected AI initiatives to a focused, CEO-led reinvention agenda with both growth and execution at its core.

03

Individuals

Job titles give way to skills as the new currency of work

As AI reshapes work at the task level, salaries are no longer determined by job titles, but by the specific skills that drive outcomes. This shift from a role-based to skills-based labor market is the central finding of the Wharton–Accenture Skills Index (WAsX). Developed by Wharton and Accenture, WAsX is an empirical skills-mapping and economic benchmarking index that analyzes labor market dynamics at the task and skill level to measure how skills translate into economic value in an AI-enabled economy.

WAsX measures the real economics of skills by tracking four key dynamics: which skills are in oversupply or undersupply; which skills materially influence wages, revealing where the market assigns monetary value; how AI is reshaping skill demand over time as tasks migrate between humans and intelligent systems and how these patterns vary across industries and roles, exposing micro-economies within job families that traditional labor data often obscures.

WAsX surfaces three structural mismatches that matter directly to employers:

First, AI is redistributing economic value across the skills spectrum.

The demand for routine, structured cognitive skills is decreasing while the premium on skills rooted in judgment, coordination, compliance and domain-specific execution is increasing. WAsX shows that as tasks migrate between humans and intelligent systems, the market increasingly rewards skills that complement AI rather than compete with it. This complementarity is evident in recent experiments described by Wharton professor Ethan Mollick, where students achieved outsized outcomes by applying core human capabilities such as problem framing, prioritization, delegation, and evaluation to direct AI effectively. The primary driver of success was a human-led model of co-intelligence, in which human judgment orchestrates machine intelligence into a coherent system of work.[7]

Second, skills have price tags, and those prices are highly contextual.

Skill value is not universal; it is governed by the micro-economics of specific roles and industries. A capability that commands a wage premium in one context may be neutral or even value-reducing in another. This challenges long-held assumptions embedded in job architectures and compensation systems, where broad skill categories are often treated as inherently “high value.” For employers, this means workforce strategy must move beyond generic capability frameworks toward role- and industry-specific skill economics, by identifying which skills explicitly move performance and aligning pay and development accordingly.

Figure 13 illustrates this dynamic in Life Sciences: some skills are both scarce and rewarded, while others remain undersupplied despite limited wage premiums, and a separate set of skills earns meaningful wage impact even when supply is relatively abundant. Taken together, the distribution highlights why employers need role- and industry-specific skill economics, not broad ‘high-value skill’ assumptions, to guide hiring, development, and compensation.

Third, the labor market operates with a persistent signaling gap:

Workers overwhelmingly signal broad, generalist traits, while employers consistently pay for a narrower set of specialized, execution-oriented capabilities. These generalist skills are abundant and weakly differentiated, while scarce technical, analytical and operational skills remain undersupplied, creating friction in hiring and slowing execution.

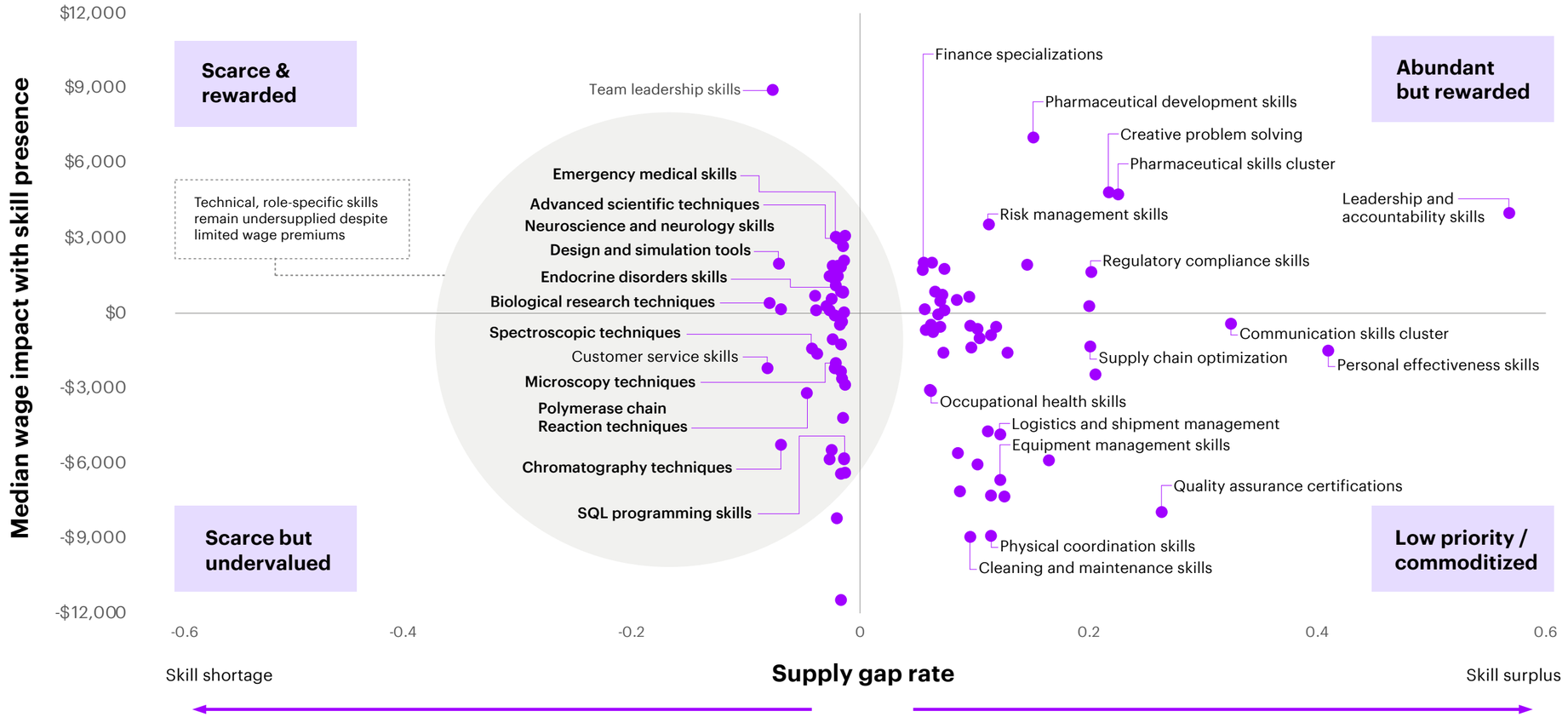
For employers, these findings point to the need for structural redesign grounded in skill-level visibility. As work is increasingly decomposed into tasks and augmented by AI, leaders need systematic ways to map roles to the underlying skills that drive performance, differentiate outcomes and create economic value. Skill mapping supports precise hiring, targeted workforce development and closer alignment of compensation with the real economics of work, helping organizations invest in the capabilities that matter most.

The Wharton–Accenture Skills Index provides one empirical example of how this approach can be applied at scale.

Figure 13

Skill scarcity vs. wage premiums for top/bottom 50 skills by supply gap rate, Life Sciences

Supply Gap Rate represents the skill gap as a share of the workforce, telling us how widespread a skill shortage or surplus is, independent of workforce size.
SHAP values are expressed in salary units and represent the marginal contribution of each skill present to predicted compensation.



Source: Accenture Research analysis in collaboration with Wharton on Lightcast job postings data. NAICS = 3254.

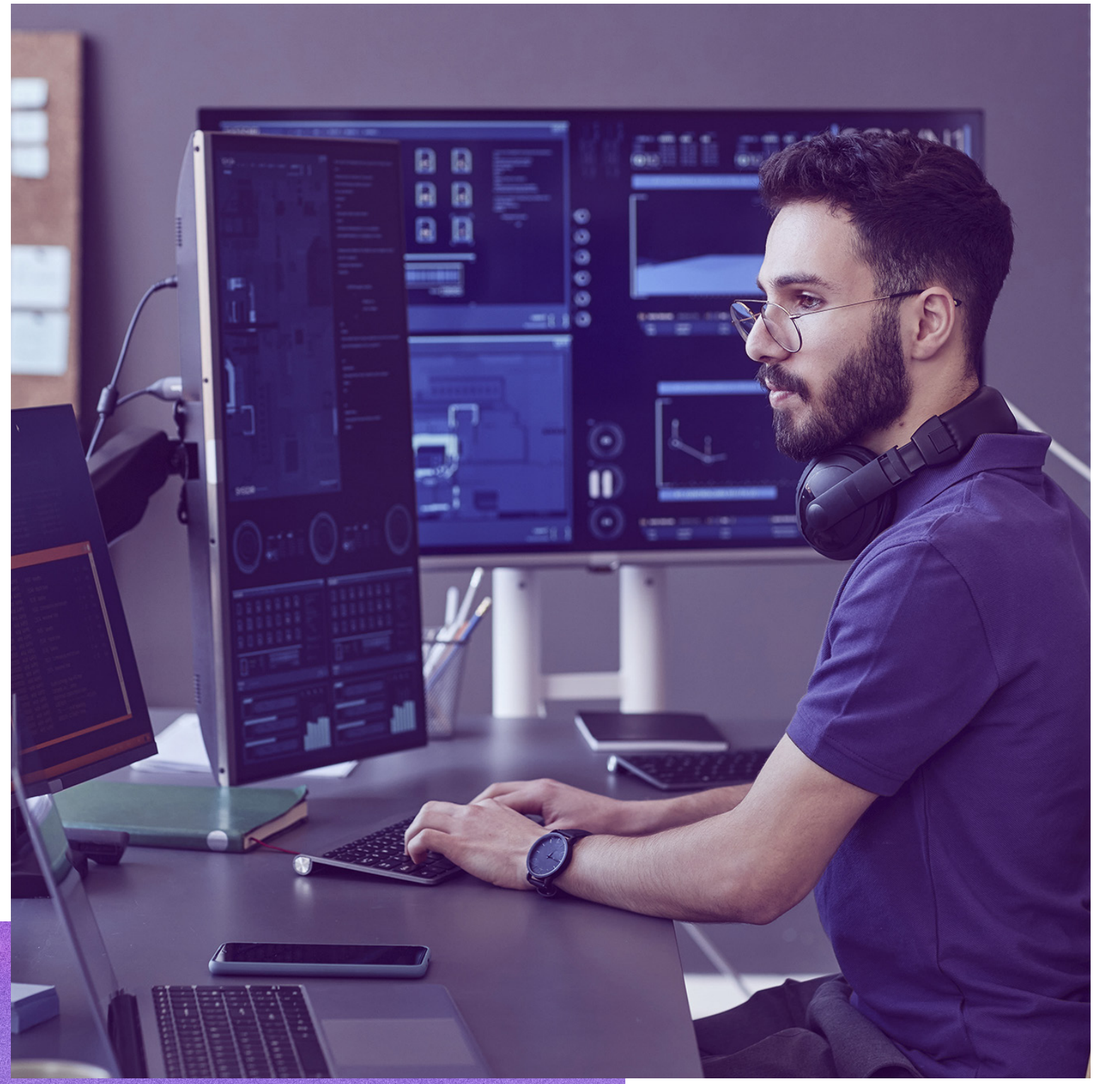
04

Workforce

Architecting for agentic scale means putting people in the lead

At its core, capturing the agentic dividend is a dynamic, organizational challenge: ensuring that talent strategy keeps up with business goals and technology. The small group of companies meeting that challenge successfully today is already pulling ahead of others on several fronts. Among these companies, which we call Talent Reinventors, almost all (96%) reported having a talent strategy that is fully integrated with technology and AI through strong HR and IT collaboration.

As a result, they are reshaping work and the workforce around a shared set of goals. They're using data and AI to help them do this, but critically, they're not asking workers to layer AI onto existing processes. Nor are they demanding that people bend to new ways of working that have been established at a distance. Instead, they are reinventing what and how work gets done with humans in the lead, so that people and technology can elevate each other's performance to meet and exceed business goals. They enable people and technology to grow, contribute and thrive together. (These concepts are explored in detail in the report Talent Reinventors: Delivering value with and for people in the age of AI.)



Six mutually reinforcing characteristics differentiate these organizations from all others. Not every Talent Reinventor is equally strong across all six; however, each characteristic is well represented across all. They are:

Clarity

Having a single definition of value across talent, technology and strategy that compels a shared focus on measurable outcomes. This shared definition helps individual functions align more closely and advance.

Intelligent teaming

Using AI to understand team health, skills and performance, giving leaders greater visibility into workforce capabilities, needs and potential. Talent Reinventors are 1.6x more likely than peers to track behavioral adoption with advanced AI tools and 1.7x more likely to use AI-generated matching to assess fit, guide assignments and flag risks such as burnout or exclusion.

Talent mobility

Placing people with precision based on their skills and emerging roles. At most organizations, internal mobility is not knit tightly into talent strategy. Talent Reinventors are 16.5x more likely than peers to have dynamic, AI-informed skills data embedded in their workforce systems.

Co-learning

Enabling people and AI to evolve together in the flow of work. With co-learning, people teach technology and simultaneously learn from it while on the job, applying the knowledge they gain in a continuous cycle of advancement.

Breakthrough leadership

Cultivating leaders who prioritize coaching over control and guide their teams through change. At Talent Reinventors, leaders are 1.3x more likely to delegate, develop and coach talent than at peer organizations. They do this even if it slows execution, signaling that building capability matters more than short-term output.

Personalized experiences

Creating tailored career development and learning pathways anchored in meaningful work, for every employee. Talent Reinventors provide clear lines of sight into career opportunities and personalized guidance and development support. They also make good use of tailored reminders and personalized suggestions for development, giving employees the nudges they need to take action and simultaneously showing them that the organization sees their individual potential to thrive, contributing to future success.

Already, Talent Reinventors saw revenue growth that was 1.8 percentage points higher and profit growth that was 1.4 percentage points higher than their peers in 2025. Critical to those gains, they are 7x more likely to strengthen organizational culture, 6x more likely to improve employee experience and 4x more likely to enhance workforce adaptability. They also report an 11% improvement in innovation-related skills. All these advantages also benefit workers outside of the organization, leading to uplifts for society, the topic of the next section.

05

Society

Responsibility, trust and legitimacy in an AI-enabled economy

As individuals and organizations adapt to working alongside intelligent systems, society has an opportunity to strengthen **structures that support work, learning and trust.** The rise of co-intelligence is more than a technological shift. It is a chance to expand how humans create value, solve problems and contribute to collective progress.

Co-intelligence is prompting a deeper understanding of where human judgment, creativity and responsibility matter most. It invites practical questions: How can humans and AI complement one another most effectively? What forms of collaboration unlock the greatest societal benefit? How should institutions evolve to support this new partnership?

A growing body of research from Wharton faculty and other global studies suggests that as AI capabilities advance, institutions and leaders must revisit established assumptions about how work is organized and supported, while keeping accountability, legitimacy and stewardship firmly human.

Traditional limitations of AI are challenged

AI as a Creativity Multiplier

Evidence indicates that AI-assisted idea generation can substantially expand both the diversity and quality of innovations, highlighting AI's role as a catalyst for enhancing human creativity and exploration while improving efficiency.[8]

AI as an Advanced Reasoner

Advanced reasoning models now perform at levels comparable to people with doctorates on graduate-level benchmarks, demonstrating how AI can complement human problem-solving in complex domains.[9]

AI as a Compassionate Communicator

Studies showing that AI-generated responses are often rated as highly compassionate reveal new possibilities for support, communication and access.[10] It also, however, opens a world of questions about the kinds of relationships people can forge with AI personas, and the nature and extent of controls needed to ensure human safety while preserving the benefits of those connections.

AI as an Ethical Advisor

Early research suggests that people perceive ethical guidance from AI and humans similarly in some contexts, pointing to a future where AI and human insights together enrich how ethical questions are approached and evaluated.[11]

Yet capability parity does not imply responsibility parity. While AI may generate ideas, reasoning and even ethical guidance at high levels of sophistication, it does not bear moral accountability, institutional legitimacy or long-term societal obligation. Those remain human responsibilities. In a co-intelligent economy, the uniquely human role shifts from performing every task to stewarding direction, safeguarding trust and defining the boundaries within which intelligent systems operate. As intelligence becomes distributed across human–AI systems, responsibility does not distribute in the same way.

The societal implications of this responsibility asymmetry are profound. Co-intelligence challenges how education systems prepare people for work, how institutions define meaningful contributions and how responsibility is assigned when decisions are co-created by humans and machines. Governments, employers and educators must respond by building systems that support continuous skill renewal, ensuring people can effectively direct, supervise and collaborate with intelligent systems over time. Adding such training could help drive significant AI investment returns and add between $4.8 and $6.6 trillion to the US economy alone by 2034.[12]

> Working successfully with AI is an ongoing human responsibility: people must continuously refresh and redevelop their skills.

Ultimately, to unlock Human+ performance, leaders across sectors need to remove the barriers and disparities between AI haves and have-nots. This may mean crossing some traditional boundaries. Gone are the days when a person could spend four years at a university and be prepared for a 30-year career. New forms of collaboration between governments, academia and employers are needed. As enterprises reinvent themselves, educators and policymakers will need to engage and reinvent their approaches as well.

06

Conclusion

The leadership imperative

The opportunities are significant, but so is the risk of fragmentation, misalignment and missed value. Creating value requires leaders to take a deliberate, enterprise-wide approach to how co-intelligence is translated into economic, individual, organizational and societal outcomes. This means clarifying how value is defined, redesigning how decisions flow through the organization, building skills at scale and modernizing technology and governance so technology compounds safely.

The path forward requires leaders to take five actions:

1 Set explicit, top-down profit and loss (P&L) priorities

The economics of agentic AI show that value concentrates unevenly across functions and tasks. Leaders must make deliberate choices about where to invest and redeploy capacity, focusing on the areas that drive growth and differentiation. This needs to be owned and driven at the C-suite and not delegated. Leaders of functions with trapped value will need to commit to transformation while balancing disruption. In-flight enterprise AI initiatives will need to be recast with value targets by function and task cluster. Without this top-down focus, agentic initiatives will become isolated productivity efforts rather than transformative growth engines.

2 Design human-led operating models for agentic work

Every organization, regardless of how it sources or limits agents, needs a clear point of view on what an “agent” is and how agents are embedded into workflows and decision flows. Leaders must define boundaries, escalation paths, decision rights and accountability so responsibility for outcomes, risk and trust remains clearly owned. Agentic hire-to-retire processes as well as agentic performance management approaches, like evaluation and monitoring of agentic decisions, need to be created. Governance should reinforce these processes as intelligence scales across the company, potentially through a Chief Agentic Resources Officer (CARO) or similar role.

3 Reinvent the enterprise around a Human+ workforce

Capturing value at scale requires rethinking how people and AI deliver work across roles, teams and workflows. Adding AI to existing processes will not generate meaningful value. Leaders need to reshape how work is performed across humans and agents. Most importantly, leaders need to create a value proposition at the individual level that shows employees that a redesigned, human-in-the-lead role is not only more effective, but often a better experience, as routine tasks are delegated to agents and employees focus on higher-level skills. Organizations pulling ahead are tightly integrating talent, technology and business strategy to redesign how work gets done, supporting new ways of teaming, learning and leadership that allow people and technology to grow and contribute together.

4 Evaluate talent through a skills lens versus a roles lens

As AI decomposes jobs into tasks and recomposes work in new ways, organizations need clear visibility into the skills that drive outcomes. This requires moving beyond static job architectures to a skills-based view of the workforce, informed by data. Tools like the Wharton–Accenture Skills Index (WAsX) provide a way to identify which skills create value, which are becoming commoditized and how roles must be rebuilt with a Human+ mindset that deliberately blends human and AI-augmented capabilities. Leaders need to architect this change, embed it into key performance management processes and communicate to individuals in the language of skills.

5 Embrace opportunities as employer, educator and learner

The pace of change makes one-time reskilling insufficient. Governments, employers and educational institutions must support continuous learning so people can effectively supervise, guide and collaborate with intelligent systems. This is both an economic and societal imperative: preparing people not just for their next role, but for lifelong participation in a co-intelligent economy. We expect employees to increasingly seek employers who differentiate on AI skill building and exposure to the latest technology. Leaders need to examine the robustness of their training programs and the space they create for self-learning, as well as forging new partnerships with academia and other learning organizations to ensure continuous development with content that matches the pace of AI. To do this, leaders will also need to be fluent and therefore accountable for their own learning and development.

Co-intelligence will not deliver value by default. Value emerges only when leaders make deliberate, coordinated decisions across operating models, economics, talent and learning, while preventing fragmentation and drift.

The new leadership mandate is to design, guide and oversee the human–agent system, ensuring humans remain central to how value is created and how opportunity is distributed within the enterprise and across the broader economy, for sustainable benefit of all.

About the research

Methodology

Estimating impacts of agents on work hours:

We utilize a structured approach to assess how digital and physical AI agents could impact work at the task level, using an LLM-enabled matching and estimation workflow. We start with standardized labor and task data from O*NET and the Bureau of Labor Statistics (BLS), mapping approximately 300 tasks across 90 roles. We then compile a library of agent definitions, digital and physical, initially seeded from Accenture projects and expanded as the analysis surfaced tasks not well-covered by existing agents.

An LLM reads both the task definitions and the agent definitions, matches agents to tasks and estimates the share of each task that could be performed by agents (expressed as a percent of task time). This replaces a purely manual mapping process and provides a consistent, repeatable method for evaluating “agentability” across the task set. In line with the Human-in-the-Lead principle, the model output is reviewed with subject matter experts to validate alignment with real-world delivery constraints and to calibrate assumptions based on client experience.

Where tasks can be addressed by both digital and physical agents, we tag the task accordingly and allocate the impactable share across virtual and robotic agents based on the nature of the work (e.g., information processing versus physical execution) and the degree of autonomy required. Because many tasks are associated with multiple roles, we translate task-level results into role- and function-level impacts by distributing impactable hours across roles using a weighted average, ensuring that aggregate estimates reflect how work is actually spread across the workforce.

The result is a task-grounded view of potential agent-driven capacity impact that is traceable from agent capabilities to specific tasks, and scalable from tasks to roles and functions.

Estimating the potential economic value of AI by industry:

We estimate the potential economic value of AI by industry using a task-level model that connects observed AI performance to real work activities and then translates those impacts into financial outcomes under explicit baseline and adoption assumptions. The approach is designed to be comparable across industries while still reflecting differences in occupational mix, wage structures, revenue profiles and the pace at which AI is likely to be adopted.

The analysis begins with a task-level evidence base. We synthesize findings from workplace experiments that compare outcomes with and without AI assistance, complemented by structured evaluations of AI agents and tools by researchers and practitioners. This evidence is used to quantify two core impact channels: time savings (how much faster work can be completed with AI) and quality improvements (how output quality changes, such as reduced errors/variance, higher accuracy, faster iteration or improved customer outcomes). Where direct evidence exists for a task, we apply the measured effects; where it does not, we extrapolate using similarity-based methods that account for task characteristics, required skills and the degree of critical human input or judgment needed.

Next, we map these task-level impacts to occupations and industries. Using a standardized occupation-to-task framework (e.g., O*NET-style task mappings), we estimate weighted average time and quality effects for each role based on the mix of tasks performed. We then scale role-level effects to the industry level using the industry's occupational composition. To translate task and role impacts into economic value, we anchor the model in industry baselines. On the cost side, we estimate baseline labor spend by combining industry employment by occupation with wage benchmarks, producing an industry labor cost pool that can be adjusted by role-level time savings. On the growth side, we estimate baseline revenues and allocate revenue contribution across roles based on proximity to products and customers, seniority and decision rights. This enables quality improvements where they affect customer experience, throughput, commercialization speed or decision effectiveness to be expressed as potential revenue uplift. Realized value depends heavily on adoption, so we explicitly model adoption trajectories by industry. We apply diffusion-style adoption curves based on US Census enterprise surveys calibrated to observable readiness signals (e.g., process digitization, data availability, regulatory constraints and change capacity), recognizing that value accrues over time rather than immediately. Finally, we aggregate results to produce industry-level estimates of potential value across two lenses: AI-driven labor impact (cost takeout and/or capacity released, adjusted for the practical constraints of redeployment) and AI-driven revenue uplift (incremental revenue associated with measurable quality improvements). All outputs are scenario-based and should be interpreted as potential value under stated assumptions: actual outcomes depend on execution, governance and sustained adoption.

Wharton-Accenture skills index:

Please refer to The Skills Mismatch Economy: Insights from the Wharton-Accenture Skills Index

Acknowledgements

Research team

This report draws on research efforts and reflects contributions from teams across Accenture and Wharton.

Economic modeling

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Talent reinventors research

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