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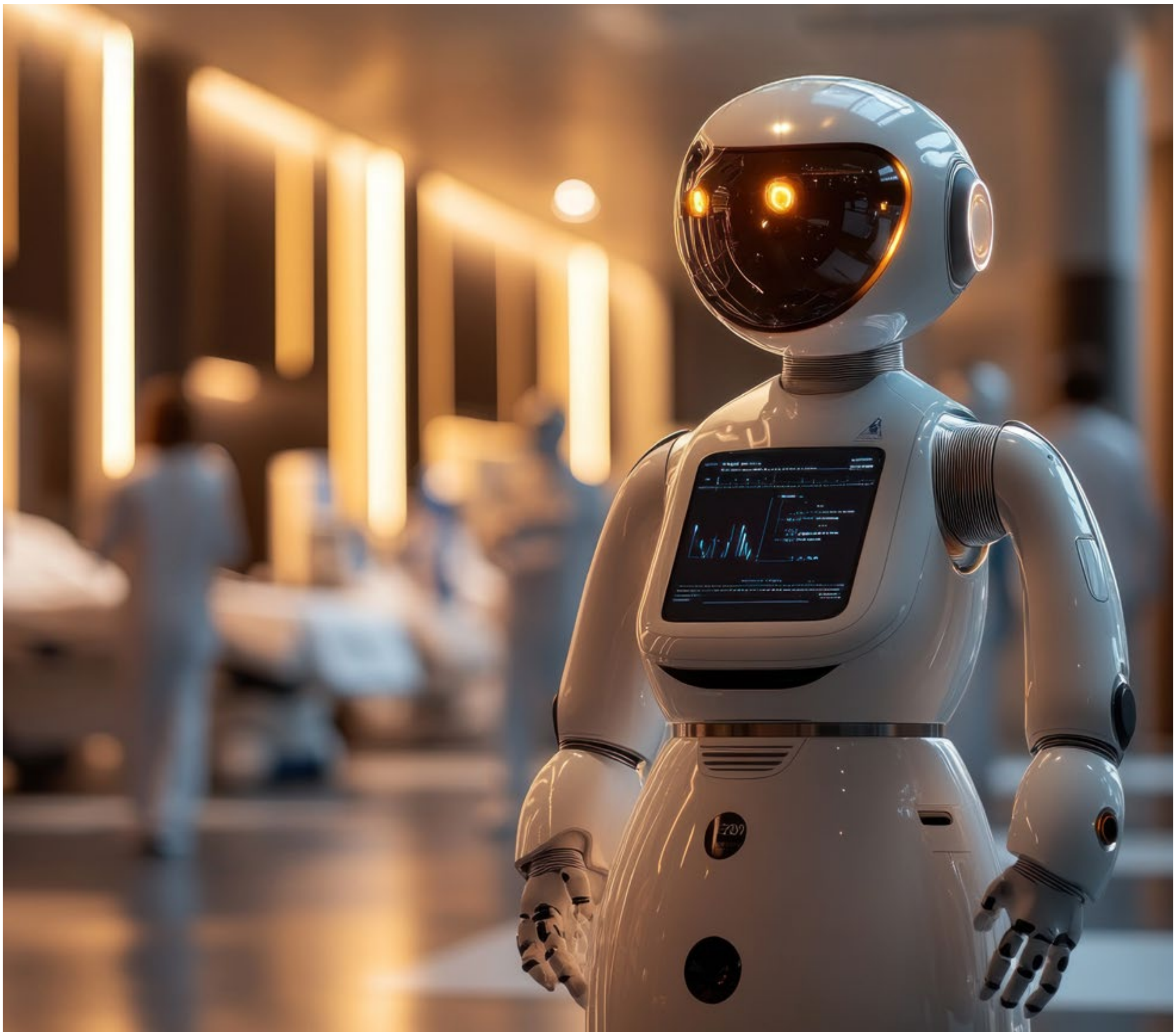
Unlocking the Great Health Productivity Reset

Quantifying the productivity potential of AI, robotics, and quantum for clinical care, pharma, medtech, and payers



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Executive Summary

Global healthcare systems and their subsectors across clinical care, pharma, medtech, and payers are approaching a structural inflection point. Aging populations, persistent workforce shortages, and rising unit costs for each consultation, procedure, and episode of care are colliding with delivery models that remain highly labor-intensive and administratively complex. Without decisive intervention, global healthcare spending is projected to nearly double in real terms — from $11.8 trillion today to $23.1 trillion by 2040.

This expansion would outpace economic growth in most major regions and materially increase healthcare's share of global gross domestic product (GDP).[1] Of the projected $11.3 trillion increase in spending, roughly $2.7 trillion is structurally locked in due to population growth. The larger share — around $8.6 trillion, or 76% — reflects rising system inefficiencies as healthcare struggles to meet growing demand amid labor shortages, fragmented operating models, and a rising chronic disease burden.

We need to focus on the productivity of our healthcare systems

Incremental reforms and short-term cost containment will not resolve this imbalance. The central question is no longer whether healthcare demand will rise, but whether systems can continue to deliver the care that society expects under tightening workforce and fiscal constraints. This is not primarily a financing problem or a lack of technology: It is a productivity challenge — rooted in labor-intensive, fragmented operating models unable to scale without human labor to meet the challenge.

In this context, productivity will not be achieved by reducing access, coverage, or quality of care. It will be the result of delivering more — and better — health services and products with the same or fewer resources, using redesigned workflows organized, coordinated, and supported by technology.

The convergence of technology capability with economic urgency

Over the next 15 years, we expect three disruptive technologies to reach maturity and deployability in time to help us weather the widening crisis in healthcare.

1. **Artificial intelligence:** With agentic systems based on language models, AI has reached a stage that now shifts from limited task support to full workflow and system orchestration capabilities, enabling disruptive shifts that improve healthcare's productivity.

2. **Robotics (physical AI):** *Specialized robotics* already deliver 15% to 30% time and cost savings and have expanded into a wide variety of areas including surgery, logistics, labs, operations, and support functions. *Humanoid robots* will scale over the coming decade and hold the potential to automate areas facing labor shortages, including home care and other sectors serving a cohort of patients over age 65.

3. **Quantum technology:** Emerging as a longer-term accelerator, it will drastically expand in use and reduce the cost of computing power, while further providing an increase in cryptography needed by future healthcare IT and enabling completely new diagnostic fields with quantum sensing.

This shift is now possible because these technologies are no longer experimental tools. Unlike earlier digital health advances, the latest technology innovations enable system-level redesign rather than narrow task optimization. Early deployments already demonstrate material impact when these technologies are embedded into real workflows.

Breakthrough scenario foresees up to $5.1 trillion in annual cost reductions, 22% productivity gains

To estimate the potential impact on healthcare sectors, we modeled three productivity pathways through 2040, based on the broad Oliver Wyman Healthcare Technology Use Case database of current and future technology applications in AI, robotics and quantum technology. To reflect uncertainty in investment, regulation, and execution, our scenarios do not differ in the technologies assumed to be available, but in the speed of adoption, depth of integration, and discipline of reinvestment.

- **Scenario 1: Incremental adoption.** $1.1 trillion in annual net productivity savings 2040 (4% reduction in cost)

- **Scenario 2: Accelerated adoption.** $2.8 trillion in annual net productivity savings 2040 (12% reduction in cost).
- **Scenario 3: Breakthrough adoption.** $5.1 trillion in annual net productivity savings 2040 (22% reduction in cost)

Net savings refer to the total gross savings achievable minus the technology investment cost per year to enable the change. We estimate that the technology investments needed between 2025 and 2040 would be $3.6 trillion (cumulative) for scenario 1; $4.3 trillion (cumulative) for scenario 2; and $5.6 trillion (cumulative) for scenario 3.

Realizing breakthrough productivity gains requires sizable, long-horizon investment in technology infrastructure, innovation, and capabilities — from public funders, private investors, and system balance sheets. While this scenario's investment is 30% higher than the accelerated's, it produces 82% more savings over the 15 years.

Importantly, this investment does more than fund efficiency gains; it will **create new high-value healthcare technology markets.** At scale, it expands the addressable market and innovation runway for AI platforms, robotics and software-enabled medical devices, data infrastructure, and services.

In this sense, productivity transformation functions as both a cost-containment strategy for health systems and a structural growth engine for technology innovation — with the scale, timing and coordination of capital determining whether this upside materializes.

Five enablers will be key to tap the technology productivity potential

Whether productivity gains materialize at scale will depend on how we set the systems up for technology adoption success. We identified five key enablers that will spark the productivity reset.

1. **Technology investment:** AI, robotics, and quantum tech do not deliver durable impact on their own. Enabling the adoption at scale will require fully accessible, open source platforms across core software and hardware fundamentals as well as clear application programming interfaces and standards for healthcare application developers to create workable solutions in the complex healthcare environments.
2. **Capability and talent investment:** These are the missing links between technology and impact. Capability and talent investments convert a technology's potential into durable productivity by building the operational, clinical, and engineering skills to deploy, govern, and continuously improve AI- and robot-enabled systems at scale.
3. **Changing reimbursement systems and liability rules:** Reimbursement and liability reforms determine whether automation is economically viable by shifting incentives from manual effort to outcomes, avoided utilization, and shared accountability for AI-enabled decisions.
4. **Modernizing regulatory frameworks to enable automation innovation:** Modernized regulation enables productivity gains to compound by supporting adaptive, life cycle-based oversight that allows AI and connected devices to learn and evolve safely after deployment.
5. **Moving from labor-centric to technology-enabled health system:** A shift in mindset toward a technology-enabled workforce can transform AI and robotics from cost-cutting tools into capacity multipliers that stabilize care delivery under persistent labor constraints.

The productivity uplift is a systemwide, people-centered leadership choice

Healthcare productivity is no longer a technical question. It is a leadership choice.

What remains uncertain is whether institutions can adapt fast enough and at scale. The existential questions facing healthcare systems over the coming decade can no longer be based on whether productivity gains are possible, because they are, but on how aggressively they will be pursued.

To make sufficient progress, AI, robotics, and quantum technology must be treated as core system infrastructure, not peripheral efficiency tools, with investment, regulation, and operating models aligned across the ecosystem. That makes the next decade a once-in-a-generation window to reset healthcare productivity deliberately — rather than having change imposed by crisis. The chosen path will shape affordability, access, and resilience for decades.

However, healthcare is not manufacturing. It is and needs to stay deeply people-centered. Full automation of end-to-end encounters is neither realistic nor desirable, particularly in high-stakes and emotionally charged settings. The role of technology is to reduce administrative friction, extend human capability, and allow clinicians and caregivers to focus their time and attention where it matters most — nurturing the real human relationships and trust that form the foundation of healthcare. To be accepted and supported, these new technologies must use productivity gains to strengthen people-centered care, not erode it.

01

Unpacking Future Healthcare Spending

1.1

Projections of global healthcare expenditures from 2025 to 2040

> “The growth rate in healthcare spending can be expected to significantly exceed expansion in GDP in advanced economies

Global healthcare spending in 2025 added up to $11.8 trillion, with North America making up roughly 50% of the total at $5.5 trillion, followed by Europe with $2.6 trillion, China at $600 billion, Japan at $500 billion, India at $100 billion, and other developing markets at $2.5 trillion.

To assess the structural forces shaping healthcare affordability in the future, this analysis extends its projections through 2040, based on proprietary modeling that integrates the most robust regional expenditure data available. The most comprehensive and widely cited projections on global healthcare spending, such as those published by the Organisation for Economic Co-operation and Development (OECD), generally extend only to 2030, reflecting both data limitations and rising uncertainty over longer horizons. In a widely recognized article from the Global Burden of Disease Health Financing Collaborator Network in *The Lancet* 2017,[2] global healthcare spending was projected to reach $24 trillion by 2040 — with an uncertainty array of up to $29.7 trillion and underlying compound annual growth rates (CAGR) between 3.8% and 4.8%.

Newer 2025 projections by macroeconomic forecasting firm BMI,[3] covering 186 countries globally, foresee global spending of as much as $18.4 trillion by 2034 with a yearly CAGR reaching 4.9% between 2015 and 2034. This report’s simulation models through 2040 take into account region-specific assumptions on demographic shifts, disease prevalence, and anticipated care needs driving regional CAGRs.

We estimate total spending on healthcare to rise from $11.8 trillion in 2025 to $23.1 trillion by 2040 at a 4.6% CAGR (with up- and downside scenarios ranging from $20.8 trillion to $26.1 trillion).

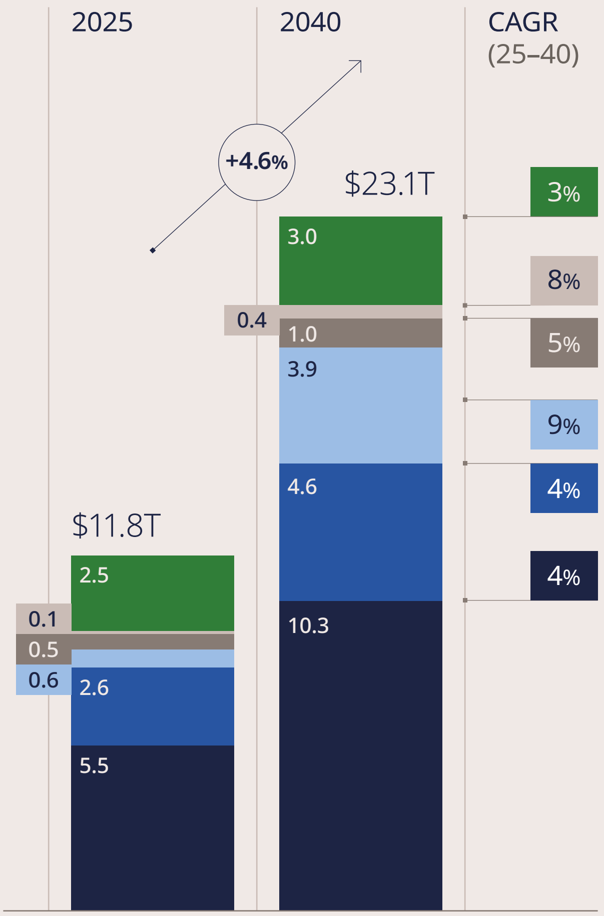
Regardless of which projection one chooses, the growth rate in healthcare spending can be expected to significantly exceed expansion in gross domestic product (GDP) in all advanced economies. For instance, most economic analyses project that the US GDP will grow between 1.7% and 2.3% per annum over the next 15 years. That means in the best case, GDP growth will still be roughly half the annual increase for health spending.

Exhibit 01

Global healthcare spending is projected to double by 2040 (base case)

Global healthcare cost projections 2025-2040 (base case)
In trillions US $

- 🟩 Other Developing Markets
- ▨ India
- ▨ Japan
- ▨ China
- ▨ Europe
- ■ North America



Source: Fitch Solutions (BMI), IHME,[4] Organisation for Economic Co-operation and Development,[5] World Health Organization,[6] UN population growth 2024, Oliver Wyman analysis

The trends driving cost escalation and their regional implications

Healthcare's rapid escalation is driven by several reinforcing trends, including the steady growth in the number of people 65 years old or older in most advanced economies, as well as a rise in the percentage of national populations they represent. By 2029, all living members of the massive baby boom generation will have reached 65 years.

> Aging populations mean a higher prevalence of chronic diseases and a shift toward more frequent, longitudinal, and complex care

Aging populations mean a higher prevalence of chronic diseases and a shift toward more frequent, longitudinal, and complex care, particularly for conditions such as cardiovascular disease, diabetes, cancer, and neurodegenerative disorders. At the same time, recent waves of medical innovation — much of which is designed to benefit this aging demographic — have become increasingly expensive, [8] often relying on specialty biologics and cell and gene therapies, advanced diagnostics and imaging, and technology-enabled interventional procedures. By 2040, these dynamics are expected to push healthcare spending to a materially larger share of GDP across all major regions.

North America

The US population is aging rapidly as baby boomers move into their senior years. US Census Bureau projections indicate that by 2040, roughly 23% of Americans will be age 65 or older, up from about 17% today.[9]

> US digital health startups raised $14.2 billion in venture funding in 2025, the highest since 2022, with firms focused on AI attracting more than half of the capital

This demographic shift places significant pressure on healthcare resources, particularly the availability of skilled healthcare workers, given the sector's high labor intensity. Workforce shortages extend beyond physicians and nurses to administrative and clinical support roles such as case managers, utilization reviewers, coders, and customer service staff — adding strain to already complex payer and provider organizations.

At the same time, the US has seen in recent years a surge in investment in digital health, AI, and automation across research and development (R&D), care delivery, and administration.[10] In 2025, US digital health startups raised roughly $14.2 billion in venture funding, the highest since 2022,[11] with companies focused on AI attracting more than half of that capital. Health technology startups in the US and Europe raised about $8.2 billion in the first half of 2025 alone, with a large share tied to AI-enabled tools designed to address administrative and clinical needs.

Despite the investment, measurable productivity gains at the system level have been uneven, reflecting persistent barriers such as fragmented delivery, reimbursement and incentive misalignment, regulatory complexity, and the operational challenge of integrating new tools into frontline workflows.[12] In practice, many technologies have improved performance in targeted use cases, while adding implementation and documentation burden in others. This can contribute to the administrative workload rather than reduce labor intensity at scale.[13]

Canada faces many of the same demographic pressures as the US, with the share of the population age 65 and older projected to increase from about 19% today to around 24% in 2035.[14]

While some growth is expected in select provider categories such as nurse practitioners, according to the Canadian Institute for Health Information,[15] shortages in family medicine, geriatrics, home care, and long-term care are likely to persist. These constraints heighten interest in technologies that can extend and supplement scarce clinical capacity, particularly outside acute care settings.

Europe

The European Union and United Kingdom are also experiencing a rapidly aging population,[16] with sustained growth in both the 65+ and 85+ cohorts expected over the coming decades. As in other advanced economies, this demographic shift is placing more pressure on already strained health systems. In Europe's predominantly publicly funded models, however, consumers will experience the rising demand in the form of constraints on access, capacity, and service availability rather than higher prices. Governments, on the other hand, will contend with higher costs from the spike in demand, which could mean higher taxes.

These pressures interact with structural characteristics of European health systems. Administrative overhead is generally lower than in the United States,[17] reflecting centralized payers and simplified billing. At the same time, rigid labor frameworks, fragmented procurement and reimbursement mechanisms, and regulatory heterogeneity limit the ability of health systems to reallocate capacity or scale new care models. Workforce shortages — particularly in nursing, primary care, geriatrics, and long-term care — are becoming increasingly burdensome, while regulations on scope of practice and task reallocation across clinical roles limit workforce flexibility.

Significant investment has been mobilized to support digital transformation and the adoption of artificial intelligence across European health systems. While investment flows are more fragmented than in the US, $5 billion to $6 billion was deployed across Europe in 2025[18,19] in AI-enabled health solutions spanning diagnostics, clinical decision support, and workflow automation. This has been achieved through a combination of venture funding, national health system programs, and EU initiatives. Despite this level of investment, systemwide productivity gains have been uneven.

> $5 billion to $6 billion was deployed across Europe in 2025 in AI-enabled health tools spanning diagnostics, clinical support, and workflow automation with uneven gains in system productivity

Fragmented data infrastructure, interoperability challenges, and complex procurement processes slow deployment of the latest technologies at scale. As a result, digital and AI solutions have not yet translated into sustained gains in labor productivity or throughput systemwide, despite incremental efficiency improvements in specific settings. Thus, demographic pressure is tightening capacity faster than institutional and operational structures are adapting, reinforcing access constraints even as overall spending growth remains comparatively contained.

Japan

Japan represents the world's most advanced example of a "super-aged" society — defined as having 20% or more of the population age 65 or older.[20,21] With nearly 30% of its population already above this threshold,[22] Japan's total population is projected to shrink materially by 2040.[23] This demographic reality has translated into persistent labor shortages and sustained pressure on productivity across healthcare and related care sectors.[24]

> Even without a sizable aging population, India struggles with one of the lowest healthcare worker densities among big economies, with only 0.7 doctors per 1,000 people

In response, policymakers and industry have increasingly turned to automation, robotics, and AI, particularly in elder care delivery and long-term support systems,[25] to help offset workforce constraints. Japan has become an early testing ground for these approaches. Government initiatives, including the Moonshot Research and Development Program,[26] alongside private-sector investment, have supported the deployment of AI-enabled robotics and digital tools for monitoring, logistics, and patient engagement in care settings.[27]

Evidence to date suggests these technologies can partially alleviate staffing pressures in selected workflows — especially in non-clinical and support functions — while their impact in complex, hands-on care remains more limited.[28] Japan's experience highlights both the potential and the limits of technology-led productivity gains in the absence of a broader redesign of care models, roles, and incentives.[29]

China

China is moving rapidly from "aged" to "super-aged" status. In 2023, the population age 60+ reached almost 300 million, or about one-fifth (21.1%) of the population,[30] and the cohort is expected to exceed 400 million by 2035,[31] which would put it at more than 30%. On a 65+ basis, China is not yet "super-aged" today (65+ represented about 14.7% in 2024), but multiple outlooks project a steep rise over the next decade — implying a transition to super-aged status in the 2030s under the common 20% (65+) definition.

Unlike Japan — already deep into super-aging — China's challenge is from the speed and scale of the shift, compounded by population decline and uneven care capacity across regions.[32,33] In 2025, China's birth rate dropped to a record low of 5.63 per 1,000 people, marking the fourth consecutive year of population decline. Total births plummeted to 7.92 million, down 17% compared with 2024 and the lowest since records began in 1949.

While the policy response is accelerating — with "silver economy" initiatives and national disease burden planning for such old-age afflictions as dementia — the core question is whether technology and service model innovation can expand eldercare capacity fast enough to address the growing demand and insufficient workforce supply.[34,35]

India

India's productivity challenge is driven less by an aging population and more by a severe workforce scarcity at scale. Despite major improvements in access and coverage, India continues to struggle with one of the lowest healthcare worker densities among large economies. According to the World Bank, World Health Organization (WHO), and OECD data, India has about 0.7 physicians per 1,000 people,[36] compared with 2.5 for China and significantly higher levels across other large economies. There are similar workforce shortfalls across Southern and Southeast Asia. In 2023, WHO estimated that Southern and Southeast Asia accounted for about 37% of the global health workforce shortfall,[37] with India a major contributor in absolute terms.

These constraints are compounded by a rapidly rising burden of non-communicable diseases, alongside persistent communicable disease challenges. The proliferation of disease places sustained pressure on primary and secondary care in these regions.

In this context, productivity gains through technology are not primarily driven by cost containment but instead by efforts to extend the effective reach of scarce clinical resources. AI-enabled decision support, task-shifting to nurses and community health workers, and digital triage and diagnostics offer a credible pathway to partially offset workforce gaps when deployment is aligned with frontline workflows and public sector delivery models rather than specialist-centric care.

Other developing markets

Like high-income economies, many developing markets are also battling rapidly rising healthcare costs. Some of the pressures are the same — in particular severe labor shortages that may top 11 million by 2030. Where high-income countries face burnout and baby boomer and early retirement within a relatively large professional base, less advantaged nations face insufficient training pipelines, persistent emigration of skilled professionals to high-income countries, and an internal brain drain from public to private sectors. Unlike many of the more advanced economies, they do not have burgeoning populations of 65 and older.

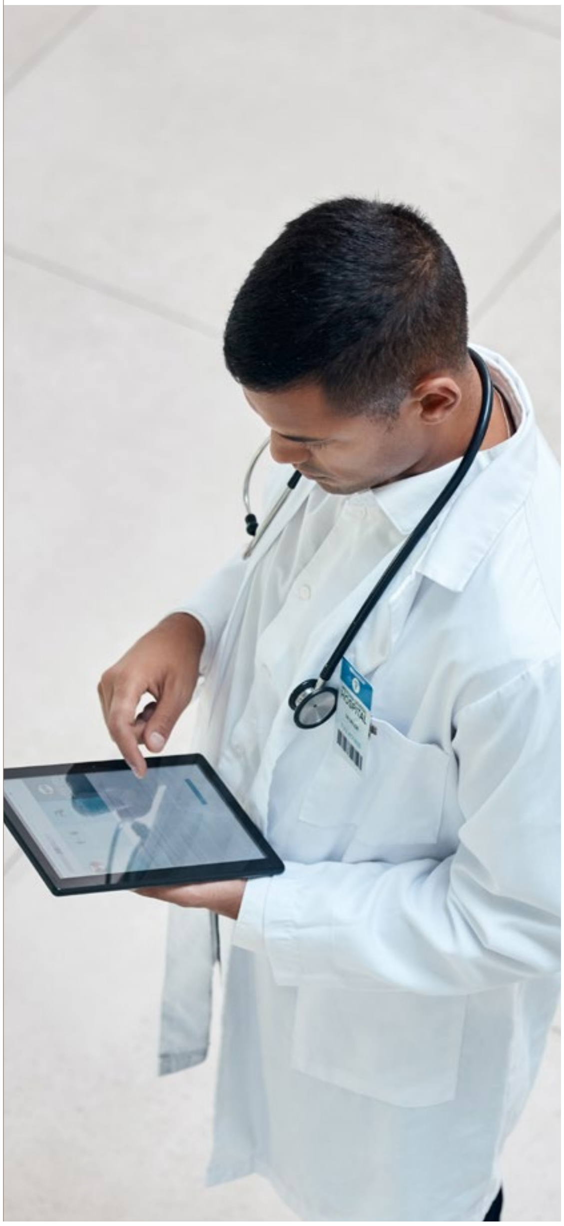
Still, healthcare costs are rising. From 2000 to 2019, public health spending in low-income countries more than doubled in real terms, from $6 to $12 per capita, while low- and middle-income countries saw a similar rise, from $15 to $38 per capita.[38] Unlike high-income economies, what's pushing up costs in these countries is the deliberate and necessary scaling of health insurance coverage to achieve universal health coverage. In most of these countries, less than one-third of the population has coverage. While expanding the number of insured is essential for equity and health security, it compounds already severe affordability constraints.

> “
> In low- and middle-income nations, drug costs represent a disproportionate share of health expenditures because of limited domestic production, a fragmented supply chain, and weak negotiating power

Rising drug costs pose another threat to healthcare affordability. Pharmaceutical spending has become a disproportionate share of total health expenditures and is in fact significantly higher than in advanced economies. At the same time, weak negotiating power, limited domestic manufacturing capacity, and supply chain fragmentation mean low- and middle-income countries pay premium prices for the same drugs and devices that richer economies purchase at volume discounts.

That said, new digital technologies represent an opportunity for many of these nations. With sufficient investment, they could leapfrog richer nations because they have no legacy systems to accommodate or replace. But without a deliberate plan of attack, health systems in these low- and middle-income countries risk either remaining disconnected from the digital health revolution or, more problematically, adopting fragmented, non-interoperable solutions that embed inefficiency and inequity rather preventing them.

But they do have one advantage. Mobile networks are already ubiquitous in most low- and middle-income countries, even in remote areas. These provide a foundation for telehealth, remote diagnostics, and AI-enabled care coordination without requiring traditional hospital-based IT infrastructure.[39] Examples like PharmAccess' MTIBA platform (East Africa) and MomCare (sub-Saharan Africa) demonstrate that these nations can rapidly scale value-based care models, real-time data transmission, and clinical decision support using mobile-first technology. These platforms integrate mobile technology with cloud analytics and AI-driven risk stratification, delivering both quality improvement and efficiency gains in settings where traditional electronic health record implementation would be neither feasible nor culturally appropriate.



1.2

Reducing 2040’s $8.6 trillion challenge

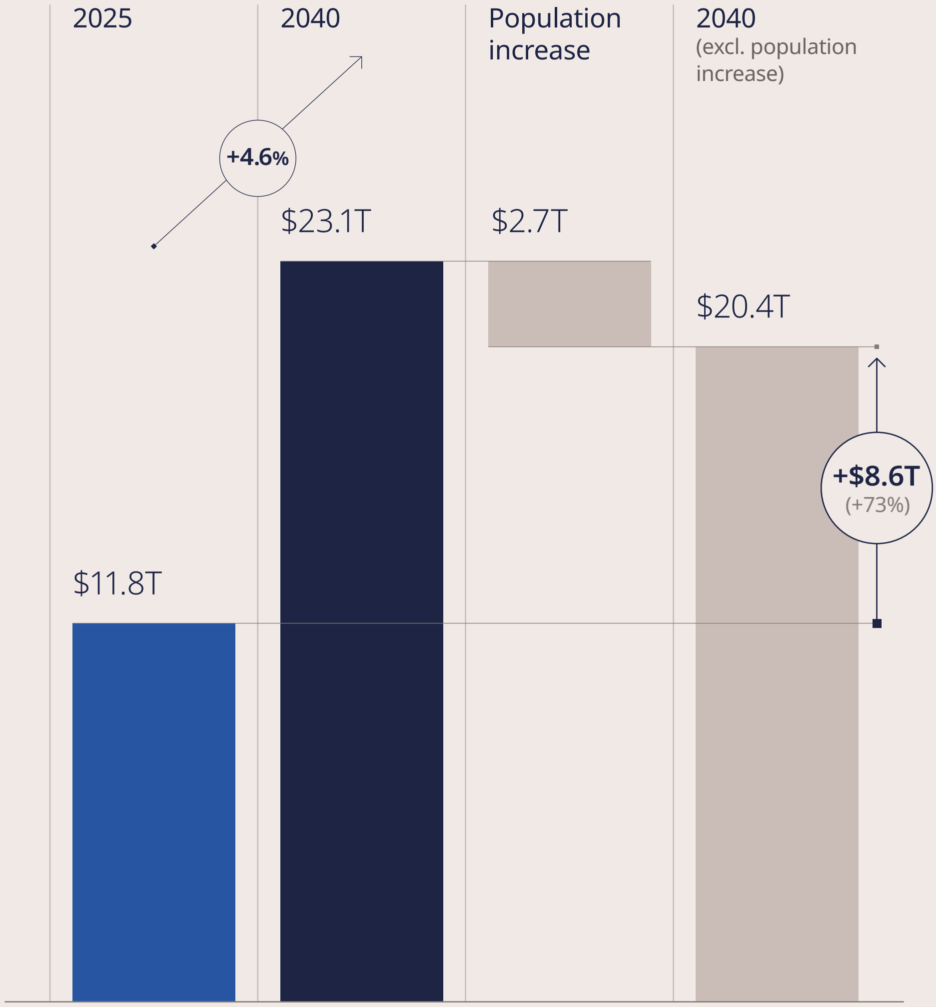
The accelerating trajectory of global healthcare spending does not reflect a single failure or shock, but rather the interaction of powerful structural forces: demographic aging, rising unit costs of care delivery, and deepening workforce constraints. These dynamics are layered on top of long-standing inefficiencies embedded across healthcare systems that have accumulated over decades.

Exhibit 02

Global healthcare spending is projected to double by 2040

Global healthcare cost estimates 2025-2040

In trillions US $



Source: Fitch Solutions (BMI), IHME, Organization for Economic Co-operation and Development, World Health Organization, Oliver Wyman analysis

> “
> Globally, the number of people age 65 and older is expected to reach about 1.3 billion by 2040, up from roughly 850 million in 2025 — raising the percentage of older adults to 14% from 11% in 2025

To clarify the nature of this challenge, the analysis separates unavoidable cost growth from spending increases that can plausibly be influenced by productivity improvements. Between 2025 and 2040, global healthcare spending is projected to rise by approximately $11.3 trillion. Of this increase, $2.7 trillion stems from population growth.

The remaining $8.6 trillion, representing a 76% increase in expenditures, reflects rising health service costs — that is, an increase in the real labor, time and administrative resources required to deliver a given episode of care. These cost pressures are driven by care delivery models, labor intensity, innovation complexity, and system design.

Demographic aging and changing system economics drive spending growth

The aging global population is the most visible and pervasive driver of rising healthcare demand. According to the United Nations’ *World Population Prospects 2022*,[40] the number of people age 65 and older is expected to reach about 1.3 billion by 2040, up from roughly 850 million in 2025 — an increase of about 40%. By 2040, older adults will account for close to 14% of the global population, compared with approximately 11% in 2025.

Exhibit 03

Forecast old-age dependency ratios

By 2030, the United Nations forecasts that there will be 35 people age 65 or older for every 100 people of working age, creating a dependency ratio of 35% globally

Dependency ratio in Europe by 2030 (on par with global)

35%

Dependency ratio in China by 2030

30%

Dependency ratio in Japan by 2030

60%

Source: Census.gov,[41] Eurostat,[42] Bid Data China,[43] Organisation for Economic Co-operation and Development,[44] Oliver Wyman analysis

> “This demographic shift fundamentally alters healthcare economics by increasing per capita demand, while simultaneously shrinking the pool of working-age contributors who finance healthcare through taxes and insurance premiums

In advanced economies, the shift is even more pronounced, with the share of people age 65 and over projected to approach 25% by 2040,[45] intensifying pressure on already labor-constrained and fiscally mature health systems, where public spending is already high and fiscal headroom is limited.

This shift fundamentally alters healthcare economics by increasing per capita demand — particularly for chronic disease management, long-term care, and end-of-life services — while simultaneously shrinking the pool of working-age contributors who finance healthcare systems through taxes and insurance premiums. The result is a structural squeeze on affordability that cannot be resolved through demand management alone.

Rising service costs in labor-intensive systems

Healthcare remains one of the most labor-intensive sectors of the global economy. Unlike manufacturing or logistics, where automation has historically reduced service costs over time, healthcare delivery has struggled to translate technological progress into sustained productivity gains.

Baumol’s “cost disease” remains highly relevant: In labor-intensive service sectors such as healthcare,[46] wages tend to rise in line with economy-wide productivity growth, causing service costs to increase rather than decline over time.

Administrative complexity in healthcare compounds this challenge. In the United States, administrative costs are estimated to account for 25% to 30% of total healthcare spending,[47] a substantially higher share than in most other high-income countries. While precise comparisons vary by methodology, there is broad agreement across OECD and academic studies that administrative functions have expanded faster than patient-facing care delivery capacity, often without commensurate gains in patient outcomes or experience. Without structural change, expect rising wages, regulatory compliance costs, and administrative overhead to continue to push unit costs upward, even before accounting for additional demand from aging populations.

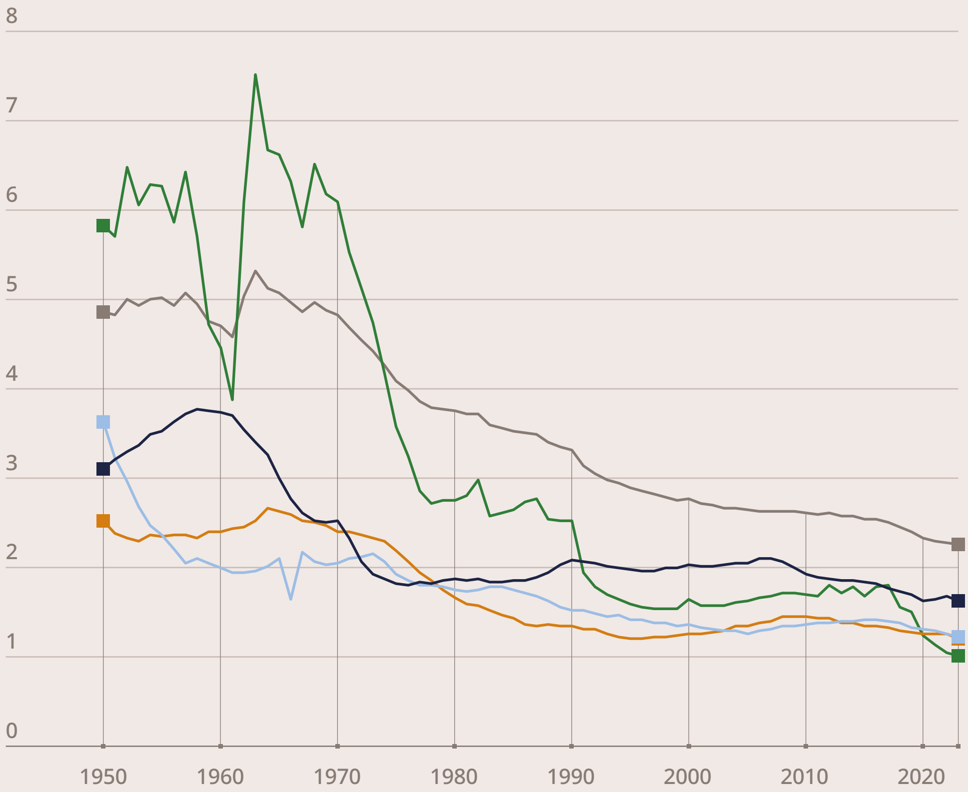
Workforce shortages constrain system capacity

Workforce constraints now represent one of the most pervasive limits on healthcare system capacity. In many regions, demographic aging is simultaneously increasing demand for care while shrinking the pool of working-age adults and healthcare professionals available to deliver it. While the demographic pressures affect other industries, few are as labor-centric as healthcare. The shortfalls also were made worse by the COVID-19 pandemic, which prompted many to leave health professions.

Exhibit 04

The global decline of the fertility rate

Fertility rate
Children per woman, 1950-2023



Source: Human Fertility Database[47], Our World in Data[48], Oliver Wyman analysis

> “Productivity gains per clinician — and per administrative worker — will only be achievable through the effective deployment of technology and redesigned care models

In the US, the ratio of working-age adults to older adults is deteriorating rapidly. That alone would cause worker shortfalls, but in healthcare it is compounded by accelerating clinical burnout, early retirement, and attrition from clinical roles. Europe and the UK face similarly acute pressures, with persistent shortages in primary care, nursing, geriatrics, home health, and long-term care — the very services most critical to supporting expansion in older populations. Besides the aging workforces, the shortfalls also reflect insufficient training pipelines and burnout. In a note dated June 11, 2025, the European Parliament warned that “without immediate actions, healthcare staff shortages in the EU, assessed at 1.2 million doctors, nursing professionals and midwives, could have disastrous consequences.” WHO refers to the situation as a “ticking bomb.”[50]

China faces a different but equally formidable challenge. Despite rapid expansion of medical education over the past two decades, China is projected to experience deficits of about one million to three million physicians and three million to six million nurses by the mid- to late 2030s.[51] These gaps will be created by a combination of a rapidly aging population, a record low birth rate, uneven workforce distribution, and rising demand for higher-acuity care. Like other countries that faced the worst of COVID, China also lost health workers in the years following the pandemic from burnout.

Across regions, the implication is the same: Healthcare systems cannot staff their way out of future demand pressures. Productivity gains per clinician — and per administrative worker — will be essential and ultimately only achievable through the effective deployment of technology and redesigned care models.

1.3 How healthcare's five sectors will contribute to rising costs

Despite the scale of projected growth, global healthcare spending remains highly concentrated in a small number of sectors, with no fundamental shift in the overall spending mix through 2040. Understanding where healthcare spending is structurally anchored will prove critical to identifying where productivity and cost containment efforts can have the greatest impact.

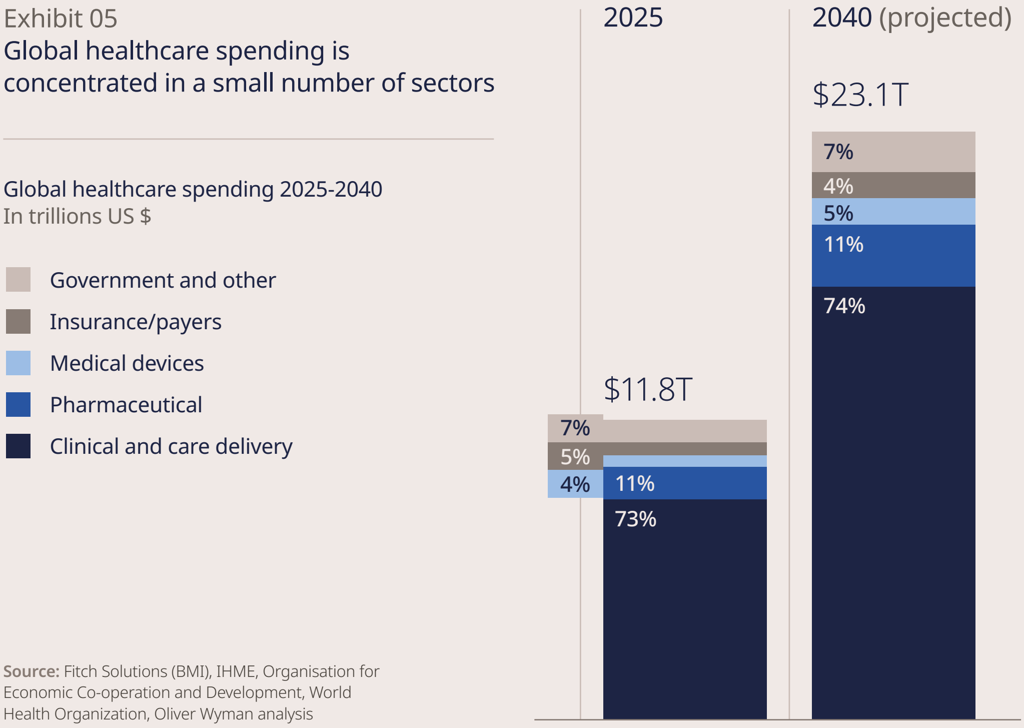


Exhibit 05

Global healthcare spending is concentrated in a small number of sectors

Global healthcare spending 2025-2040

In trillions US $

Source: Fitch Solutions (BMI), IHME, Organisation for Economic Co-operation and Development, World Health Organization, Oliver Wyman analysis

> Clinical care is the largest and most labor-intensive category and the primary driver of systemwide spending growth

By 2040, global healthcare spending is projected to reach about $23.1 trillion, up from $11.8 trillion in 2025. As illustrated in the breakdown by sector, clinical and care delivery accounts for three-quarters of total spending, both today and in projections, underscoring where cost pressures — and therefore productivity opportunities — are most acute. Pharmaceuticals, medical devices and diagnostics, insurance administration, and government and other health services together make up the remaining share. The relative stability of this composition highlights that the healthcare cost challenge is not driven by a shift toward new categories of spending, but by intensifying pressures within existing ones.

Healthcare sector definitions and cost dynamics

Together, these sectors account for nearly all healthcare spending globally.

- **Clinical and care delivery:** Hospitals, inpatient and outpatient physician services, long-term and residential care, dental services, and home health. This is the largest and most labor-intensive category and the primary driver of systemwide expenditure growth.
- **Pharmaceuticals and biotechnology:** Drug discovery, manufacturing, and distribution, with ongoing cost pressure driven by expanded access, increased utilization, and the growing share of specialty and biologic therapies.
- **Medical devices, diagnostics, and equipment:** Devices, imaging, diagnostics, and capital equipment, increasingly embedding software, AI, data, and digital capabilities alongside traditional hardware.
- **Insurance administration:** Health insurance operations, including claims processing, utilization management, customer service, and care management.
- **Government and other health services:** Public health functions, government health programs and ancillary services.

Understanding regional variation in spending

Across health systems, healthcare spending is heavily concentrated in clinical care delivery, which accounts for the majority of total expenditures across regions. This reflects the sector's high labor intensity and shortages, rising unit costs, and care models still organized around specialist- and hospital-centric delivery.

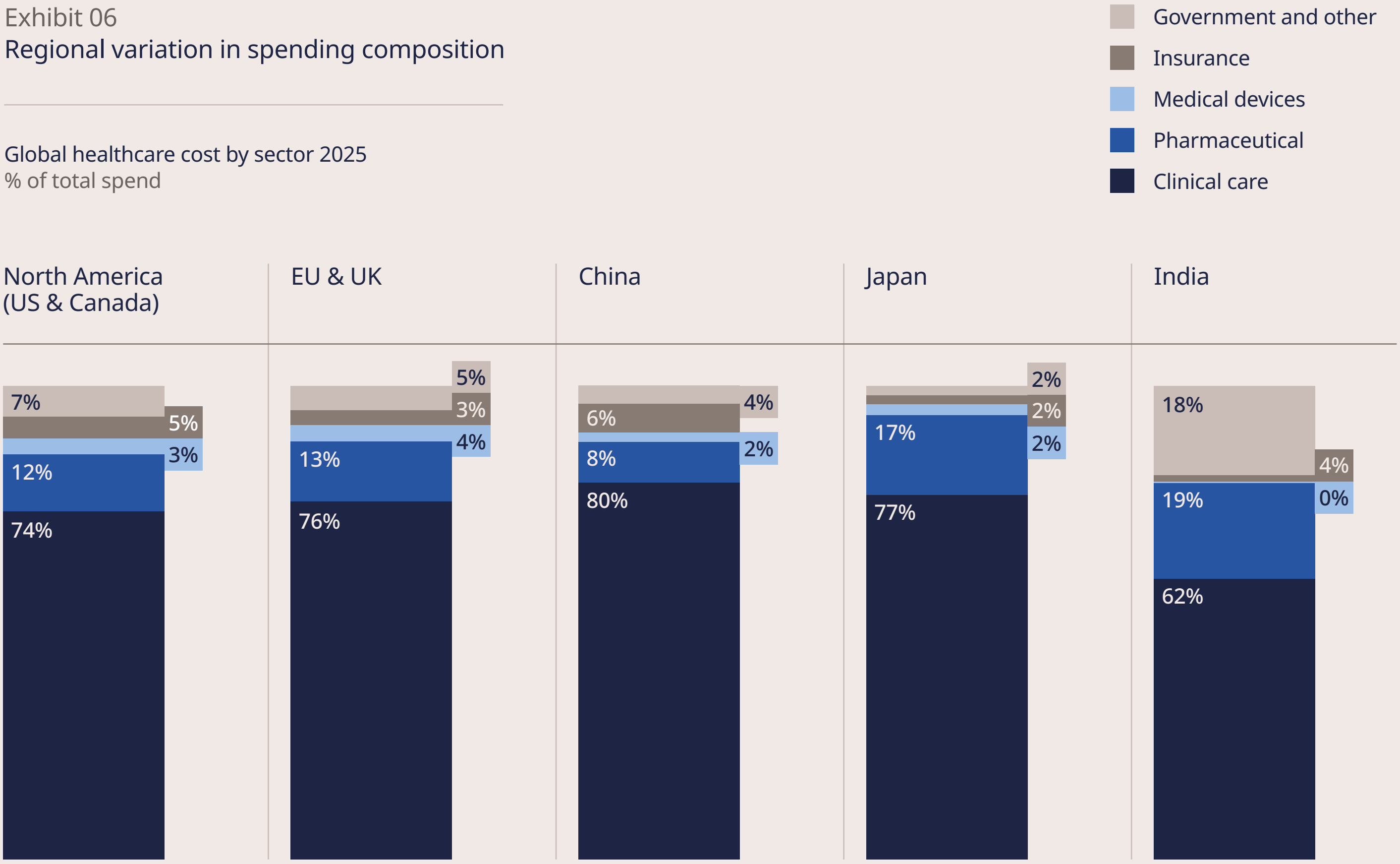
The composition of nonclinical spending, however, varies materially by system design. Multipayer systems — most notably in North America — exhibit a higher relative share of insurance and administrative expenditure, driven by complex claims processing, utilization management, and network controls. More centralized systems in Europe and Japan show lower administrative intensity but still face comparable cost pressure from workforce constraints, utilization growth, and service complexity.

Exhibit 06

Regional variation in spending composition

Global healthcare cost by sector 2025

% of total spend



Source: CDC,[52] Eurostat,[53] India National Health Accounts (NHA) Estimates[54], India National Health Systems Resource Centre, China National Health Accounts (NHA), Hong Kong National Health Accounts,[55] International Trade Administration,[56] Oliver Wyman analysis

> Multipayer systems have higher shares of insurance and admin spending, driven by claims processing, network controls, and utilization management

Europe and the UK show a similar dominance of clinical care in overall spending, but with a lower relative share of insurance administration, reflecting more centralized financing models and tighter administrative cost containment.

Japan stands out with the highest share of spending allocated to direct care delivery, consistent with its aging population, high service utilization, and relatively lean insurance administration.

In contrast, low- and middle-income countries summarized in other developing markets category display a distinct spending pattern. While clinical care is still the largest component, pharmaceutical and medical devices account for a significantly higher share of total healthcare spending than in advanced economies. This reflects rapid expansion of access to medicines, higher out-of-pocket purchasing costs, and the scaling of treatment coverage in systems where insurance penetration and risk pooling are still evolving. In these settings, insurance and administrative costs remain comparatively low, but higher relative spending on pharmaceuticals underscores the importance of drug affordability, supply chains, and industrial policy as central cost drivers.

Despite wide differences in health system design and spending composition, healthcare cost growth is similar across most advanced economies.

North America, Europe, and Japan all exhibit compound annual growth rates of about 4% through 2040, indicating that aging populations, rising unit costs, and workforce constraints exert similar upward pressure across mature systems.

China's higher growth rate reflects ongoing system expansion and rising utilization, while slower growth in other developing markets reflects lower starting spend levels and persistent capacity constraints rather than structural cost containment.

Across regions, the comparison reinforces a critical insight: Healthcare cost pressures stem from different structural sources depending on system design, not simply from the level of total spending. Administrative complexity dominates in some systems, labor intensity and workforce shortages in others, and pharmaceutical reliance in emerging systems.

> “Healthcare cost growth is similar across most advanced economies, despite wide differences in health systems

1.4 Focusing on productivity is key to solving the spending crisis

Taken together, these dynamics point to a clear conclusion: Incremental reforms will not sufficiently curb rising healthcare costs or expand capacity in line with demand. Aging populations, rising unit costs, and skilled labor shortages are converging, creating a once-in-a-generation imperative to rethink how healthcare is delivered, organized, and administered.

In most health systems, the volume and quality of care delivered are not discretionary choices. Coverage expectations, clinical standards, and access commitments are shaped by demographic need, regulation, medical norms, and social contracts. As a result, cost containment cannot realistically be achieved by reducing services or lowering standards without undermining outcomes, equity, and public trust.

Using productivity as a metric is generally defined as the ratio of outputs to an input. The “output” is the amount and quality of services delivered, which must be regarded as a fixed part of the equation, based on our assumptions above. The inputs are primarily labor (clinical and administrative time), capital (facilities, equipment, and IT infrastructure), and intermediate resources (supplies, energy, and rework driven by inefficiency). Thus, the central challenge is to cut the input and deliver the same output. To fully accommodate $8.6 trillion in higher spending, the productivity of our healthcare systems would need to improve by 37% by 2040, or about 2.5% per year.

> “To accommodate $8.6 trillion in higher spending, the productivity of our healthcare system would need to improve 37% by 2040, or about 2.5% per year

Where productivity improvements succeed, they expand effective capacity under current workforce limitations, thus freeing clinical time for patient care, reducing avoidable rework and delays, and improving system resilience. Such improvements allow healthcare systems to absorb rising demand without relying on workforce expansion, which is increasingly difficult to achieve in many labor markets.

The answer to the sector's dilemma could be found in recent advances in artificial intelligence, automation, and robotics that have now reached a level of maturity where they can be embedded at scale into real operating models. When applied to workflows rather than isolated tasks, these technologies can bend the input cost curve, while preserving — and in many cases, improving — quality, access, and patient experience across both advanced and developing economies.

Absent such productivity gains, healthcare systems face an increasingly constrained set of alternatives: longer wait times, workforce burnout, uneven access, and even implicit rationing of care. Productivity cannot be regarded as an optional efficiency agenda, but rather the primary lever for sustaining affordability, resilience, and access in healthcare systems worldwide.

02

The Productivity Opportunity for Healthcare: AI, Robotics, and Quantum Technologies

Artificial Intelligence, robotics, and quantum technologies are converging to reshape the productivity frontier of healthcare. While these technologies differ in maturity and time horizon, together they form a coherent capability stack that can address healthcare's most persistent constraints: labor intensity, fragmentation of workflows, and rising unit costs.

The relevance of this convergence lies not in any single breakthrough, but in how advances across computation, automation, sensing, and coordination reinforce each other and multiply their impact. When deployed in isolation, these technologies deliver incremental efficiency gains; when integrated, they enable structural improvements in system capacity, resilience, and affordability.

2.1 **Artificial intelligence** is ready to become healthcare's productivity engine

> “This moment is noteworthy because performance, cost, and deployability are improving simultaneously

Artificial intelligence (AI) has moved from an experimental decision-support technology to a foundational capability for productivity improvement across healthcare. Unlike earlier digital health technologies, AI can now reshape work end-to-end — across clinical, administrative, and operational domains — at a time when healthcare systems face persistent labor scarcity and rising unit costs.

This moment is noteworthy, not simply because AI capabilities have advanced, but because performance, cost and deployability are improving simultaneously. AI systems are moving beyond narrow task automation toward workflow orchestration, while increasingly interacting with both human and physical systems. Together, these shifts create the conditions for productivity gains at scales that have historically been difficult to achieve in labor-intensive healthcare environments.

The productivity impact of AI can be understood as a progression across three overlapping and reinforcing waves, rather than discrete, sequential phases.

Wave 1:
Task-level analytics and pattern recognition – 2000 to 2018

Early healthcare AI applications focused on machine learning and deep learning models trained on structured, image-based, and signal data. These systems delivered incremental but tangible gains in areas such as medical imaging interpretation, risk prediction, and diagnostic classification — improving speed and consistency but typically requiring substantial human oversight and operating in silos.[57]

While this first wave has contributed meaningfully to improved clinical outcomes and decision quality, its impact on productivity and costs is thus far more limited. Most applications improved individual task productivity rather than reconfiguring workflows. This left labor intensity, handoffs, and end-to-end cycle times largely unchanged.

Wave 2:
Generative and workflow AI – 2019 to 2025

The emergence of large language models and generative AI marked a step change that extended AI from prediction into content generation, summarization, and interaction. In healthcare, this enabled automated documentation, clinical coding, prior authorization support, and patient communication. The primary impact from productivity has been a reduction in the administrative workload, freeing clinician time without altering clinical decision authority.

This wave marks the first point at which AI begins to deliver measurable productivity gains at scale, particularly in administrative and support functions. But adoption remains uneven, and the impact is restricted to discrete workflows rather than systemwide capacity expansion.[58]

Wave 3:
Agentic and system-level AI – 2026 and after

The current frontier shifts AI from a passive tool to an active participant in workflows. Agentic AI systems can plan, sequence, and execute tasks across systems, coordinating with humans, software, and machines. This enables optimization not just of individual steps, but also of entire processes — including hospital operations, laboratory throughput, and clinical trial execution — creating the potential for system-level capacity gains rather than isolated efficiency improvements.[59]

The significance of this wave lies in its potential to increase structural capacity productivity without adding workforce, moving beyond efficiency improvements toward system-level coordination. While still early, agentic systems marks a transition toward AI-enabled operating models capable of addressing healthcare's most persistent productivity challenges with significantly faster adoption compared to previous AI uses. A good indicator for this acceleration in the third wave of AI is the enormous scale-up in use of the only recently launched Model Context Protocol (MCP) that is providing an open-source, standardized interface between AI agents and enterprise software systems. Much like USB-C unified hardware connectivity, MCP transforms what was previously an “N-times-M” integration problem — customer interfaces between each AI model and each enterprise system — into a scalable, reusable architecture. By allowing AI agents to securely access capabilities, data, and workflows across ERP, CRM, electronic health records (EHR), supply chain, and other core platforms through a common protocol, MCP lowers integration friction and dramatically shortens time to deployment.

This is strategically significant for healthcare: Agentic AI can only deliver step changes in productivity if it operates across system boundaries rather than within isolated tools. Open, interoperable interfaces such as MCP therefore act as force multipliers – enabling orchestration at scale, reducing duplication of integration effort, and accelerating the transition from localized automation to true system-level impact.

> “
> The largest economic upside from AI lies in deliberately advancing into workflow and system-level use cases in which productivity gains translate into expanded capacity

How productivity compounds

As AI progresses along this maturity curve, its productivity impact compounds across three levels.

1. **Task efficiency:** Faster execution of individual activities such as documentation, image review, and scheduling
2. **Workflow efficiency:** Fewer handoffs, reduced delays, and less rework across end-to-end processes
3. **System capacity:** Structural gains through better coordination of people, assets, and decision making across the system

Most healthcare organizations currently concentrate on task-level applications. The largest economic upside, however, lies in deliberately advancing into workflow and system-level use cases in which productivity gains translate into expanded capacity under fixed labor constraints.

> “
> In life sciences, AI accelerates trial design, protocol drafting, site selection, and monitoring,while agentic systems coordinating these activities can shorten cycle times

Where AI productivity is already material

There are several domains where AI is already delivering measurable productivity gains at scale.

- **Clinical decision support and diagnostics:** AI-driven tools improve speed, accuracy, and prioritization across imaging, pathology, and laboratory medicine by prescreening cases and flagging high-risk patients — augmenting clinicians rather than replacing them.[60]
- **Administrative and operational automation:** Generative AI automated documentation, scheduling, claims processing, and revenue-cycle management. At the task level, these applications often reduce administrative effort 20% to 40%, translating into reclaimed clinician time and faster patient throughput when deployed systematically.[61]
- **Research, development, and clinical trials:** In life sciences, AI accelerates trial design, protocol drafting, site selection, and monitoring. Agentic systems coordinating these activities can shorten cycle times and improve downstream productivity by bringing therapies to patients faster.[62]
- **Population health and system management:** Predictive analytics and AI-driven forecasting support proactive capacity planning, workforce allocation, and supply-chain resilience by reducing avoidable admissions and smoothing demand peaks that strain already constrained systems.[63]

Machine learning and deep learning:	Large language models:	Multimodal AI:	Federated/ privacy-preserving:	Agentic AI:
Perception tasks (imaging, signal analysis, anomaly detection)	Natural-language interactions, documentation, summarization, knowledge retrieval	Combines text, images, signals and sensor data for clinical and robotic applications	Enables learning across institutions without centralizing sensitive data	Goal-driven systems that divide workflows into tasks and coordinate across systems

Early deployments (described in detail in Chapter 5) already demonstrate that these technologies can deliver material productivity gains when embedded into real workflows.

- In care delivery, predictive risk models paired with structured follow-up and case management can help focus scarce care management capacity on patients most likely to deteriorate after discharge. An evaluation of Kaiser Permanente Northern California's Transitions Program reported that supporting high-risk patients for 30 days after discharge reduced readmission risk by 20%,[64] without increasing mortality — illustrating how analytics can improve targeting and throughput when embedded into operational workflows.

- In pharmaceutical R&D, AI-enabled trial feasibility analysis and protocol optimization directly targeted one of the largest drivers of productivity loss. Industry benchmarks show that over 50% of clinical trials undergo at least one protocol amendment, with each amendment estimated to increase trial costs 20% to 30% and extend timelines by several months. By shifting learning earlier, AI improves development speed and capital efficiency across portfolios.

- In medtech, AI-enabled predictive monitoring and digital-twin analytics applied to connected imaging and diagnostic equipment have been associated with double-digit reductions in unplanned downtime — often as much as 30% to 40% — improving asset utilization, stabilizing clinical throughput, and supporting more reliable operations at scale.

Strategic implications for healthcare leaders:

Treat AI as a core operating infrastructure, not a portfolio of pilots.

Start with measurable workflow wins (documentation, triage, throughput) to fund and legitimize deeper transformation.

Invest in data foundations, integration, and governance, which determine whether AI scales from tools to system capacity.

2.2 Specialist robotics will scale faster in the coming decades

> Specialist robots are effective because they are task-specific, clinically validated, and designed to operate reliably in constrained settings, augmenting clinicians and technicians not replacing them

Robotics in healthcare is already delivering measurable productivity gains, primarily through specialist robots designed for clearly defined, high-value tasks in structured environments. These systems represent the most mature and scalable form of automation in healthcare today, mirroring their current role enhancing industrial productivity. To date, most value creation has come from specialist robotic systems deployed in surgery, sterilization, rehabilitation, and selected industrial activities outside healthcare.

Crucially, specialist robotics spans two distinct modes of automation. In some domains, robots mimic human movements through tightly coupled, in-the-loop systems – systems, such as surgical robots and endoscopic platforms. These augment precision and consistency without removing the clinician from the activity. In others, advances in sensing, safety, and control now enable automated task execution in environments where humans and robots operate side by side. This shift has expanded the use of robotics beyond assistive applications into autonomous cleaning, materials handling, and logistics in hospitals and care facilities — unlocking productivity gains comparable to those realized in industrial settings.

> Behind-the-scenes transport robots, automated sterile goods reprocessing, and disinfection robotic systems deliver some of the highest yet least visible productivity gains

Specialist robots are effective because they are task-specific, clinically validated, and designed to operate reliably in constrained settings. These systems augment clinicians and technicians rather than replacing them, improving precision, endurance, consistency, and throughput, while relieving acute workforce shortages. As a result, specialist robotics are anticipated to remain the primary drivers of robotics-enabled productivity in healthcare over the coming decade, while also establishing the data, workflow, and trust foundations for broader automation.

Where specialist robotics deliver productivity today

Specialist robotics is already delivering productivity gains across the healthcare value chain — from upstream production and distribution to hospital operations, diagnostics, and direct patient care.

- **Production (pharmaceutical and medical devices):** Specialized industrial robots are widely deployed in manufacturing, assembly, packaging, and picking operations — driving productivity, quality, and compliance in regulated environments.[65]
- **Logistics (pharmaceutical and medical devices):** Robotics is increasingly deployed across pharmaceutical and medical device distribution, including warehouse automation, picking and packing, cold-chain handling, and last-mile preparation. These systems improve throughput, accuracy of inventories, and compliance while reducing labor intensity in environments facing chronic workforce shortages and rising service-level expectations.[66]
- **Hospital logistics, sterilization, and utilities:** Behind-the-scenes robotics (transport robots, automated sterile goods reprocessing, and disinfection systems) deliver some of the highest yet least visible productivity gains. By automating transport of medicines, samples, and instruments, hospitals can free scarce clinical staff for patient-facing tasks and compress cycle times across surgical value chains.[67]
- **Diagnostics and laboratories:** Laboratory robotics automate pre-analytics, analysis, and post-analytics, enabling 24/7 operation with consistent quality despite severe staffing shortages. These systems expand diagnostic capacity without proportional labor increases while reducing error rates and reworks.[68]
- **Surgery and interventional medicine:** Robotic-assisted systems improve precision and consistency, reduce variability between operators, and shorten operating times. These gains translate into higher operating room utilization, fewer complications, and shorter lengths of stay — benefiting insurance companies and hospitals — surgeons, nurses, anesthesiology teams, and perioperative workflows.[69,70]
- **Rehabilitation and physical assistance:** Rehabilitation robots and exoskeletons enable more intensive, standardized therapy with the same or fewer therapists, increasing patient throughput and improving outcomes. In patient care settings, robotic lifting and mobility assistance reduce the physical strain on staff and extend workforce longevity.[71]

Across these domains, specialist robots have already delivered time savings of 15% to 30% in targeted workflows — such as surgery duration, with a downstream effect including shorter patient lengths of stay – and throughput increases of 20% to 50% in bottlenecked functions, such as sterile processing, alongside quality and safety improvements that reduce downstream costs.[72]

Why specialist robotics will scale faster in the future

> Most reimbursement systems globally still are tied to human labor and activity and not automated throughput and value created

Despite strong productivity gains in targeted applications, the deployment of specialist robotics has been uneven across healthcare systems, reflecting a set of structural and economic constraints rather than a lack of technical maturity:

1. **Workforce training and workflow changes:** Many specialist robotic systems require extensive clinical training, workflow redesign, and ongoing supervision, slowing adoption outside high-volume centers.
2. **Capital intensity and infrastructure requirements:** Deployment often depends on dedicated physical space and integration with existing facilities. It also requires supporting digital infrastructure. These raise the upfront investment and limit the number of facilities where the costs are justified.
3. **Limited autonomy by design:** Most specialist robots today are optimized for narrowly defined tasks and constrained environments, relying on human oversight and lacking the generalized self-driving capabilities required to automate entire care pathways.

Advances driven by new AI-powered specialist robots — often referred to as “physical AI” — can help overcome these three points, with lower costs for installation and training as well as less training required when implementing them. Chapter 4 provides further detail on this convergence.

A vexing downside involves misaligned incentives and reimbursement models. Most reimbursement systems globally still are tied to human labor and activity rather than automated throughput or value created, limiting the ability of systems to pass on the costs and justify the investment.

2.3 The disruptive potential of **humanoid robots**

> The value of humanoid robots is in their ability to adjust to different tasks, environments, and demand peaks, similar to how human labor negotiates changing workplace demands

Humanoid robotics represents a longer-term — but potentially transformative — lever for healthcare productivity across labor-intensive sectors. Unlike specialist robots, which automate narrowly defined tasks in structured environments, humanoids are designed as general purpose, reprogrammable labor platforms capable of operating across multiple tasks and settings built for humans.

In this area, healthcare is unlikely to be the lead market for humanoid adoption, with progress already starting to be made in the industrial, logistics, and service environments that will determine cost curves, reliability, and trust. But downstream, as these systems mature, healthcare is very apt to be one of the biggest beneficiaries, given its labor-intensive nature. Hence, understanding the humanoid impact on healthcare will require visualizing and evaluating it within broader, cross-industry industrialization.

The future of humanoid robots extends far beyond healthcare

Finding a good fit for a new general-purpose labor platform

Humanoid robots differ fundamentally from specialist robotics in both economics and adoption logic. Their value does not lie in optimizing a single task, but in their ability to adjust to different tasks, environments, and demand peaks. Their profile is much more similar to how human labor negotiates changing workplace demands than the way traditional automation operates.

As a result, humanoid adoption is expected to scale first in industries with high labor intensity, acute workforce shortages, and lower regulatory friction — sectors such as manufacturing, warehousing, logistics and industrial services. In these, economic value can be gauged through shorter cycles, more observable economic payback mechanisms such as reduced vacancy exposure, injury avoidance, fewer interruptions in operations and less downtime, and improved output under fixed staffing constraints. In these settings, cost declines and reliability improvements can be incorporated without requiring full end-to-end pathway redesign.

Progress in these early markets will shape the feasibility of later deployment in more regulated and complex environments such as healthcare. Healthcare systems should therefore view humanoid robots not as near-term clinical automation tools, but as longer-term extensions of system capacity. Their readiness for healthcare deployment will depend primarily on demonstrated reliability, safety, and scalability in adjacent sectors before their transfer into clinical settings.

Humanoid robotics represents a longer-term — but potentially transformative — lever for healthcare productivity. Unlike specialist robots, humanoids are designed to perform multiple, potentially unrelated tasks while operating in environments built for humans. Their role is not to replace clinicians, but to assume responsibility for physically demanding, low-complexity tasks that are difficult to automate end-to-end as well as inefficient uses of the time of highly trained staff. Examples include internal logistics, materials transport, waste handling, and repetitive supply movement within hospitals and adjacent facilities.

Over the next 15 years, humanoid robots are likely to evolve from being experimental pilot tests into industrial assets in selected healthcare-adjacent settings. Early adoption is expected to focus on nonclinical and supervised support tasks, particularly in areas with acute labor shortages, such as logistic support, materials handling, environment services and internal transport functions.[73]

Navigating a phased industrialization path

The path to scale is best understood as a phased industrialization process, with adoption expanding as capabilities mature, costs decline, and integration challenges are addressed:

> “As costs decline and reliability improves, humanoids will extend into more complex service roles spanning multiple tasks within care-adjacent settings, under continuous human supervision

Phase 1

Pilots and industrial adjacencies (now through 2030)[74]

Early deployments concentrate on non-clinical, tightly supervised tasks in industrial and healthcare-adjacent environments, where workflows are structured and risk tolerance is low.

In practice, early use cases center on ergonomically challenging or hazardous activities, such as waste handling, supply transport, linen movement, night shift logistics, and repetitive lifting in hospitals and adjacent facilities.

Uptake at this stage is driven primarily by acute labor shortages, worker injury risk, and persistent difficulty staffing physically demanding or unattractive roles rather than pure cost reduction.

Phase 2

Expanded service integration (2030-2035)[75,76]

As costs decline and reliability improves, humanoids extend into more complex service roles that span multiple tasks within care-adjacent settings, under continuous human supervision.

Typical activities at this stage include multi-task logistics across wards, supervised support in pharmacies and laboratories, assistance with mobility and transfers in rehabilitation or elder care, and routine room-to-room service tasks.

Adoption in this phase is enabled by the flexibility of humanoids over task-specific automation, allowing a single system to support multiple workflows and reduce operational fragmentation.

Phase 3:

Scaled deployment and system effects (2035-2040)[77]

At scale, humanoids function as flexible capacity assets across sites, integrated with digital twins and hospital operating systems to support dynamic workload balancing.

At the system level, this could translate into cross-facility logistics, surge support during demand peaks, and coordinated execution of basic support and facilities operations.

At this stage, adoption is driven by system-level resilience and capacity smoothing, enabling providers to flex resources without proportional increases in human labor.

What shapes adoption and scale

In productivity terms, specialist robots optimize peaks; humanoids raise the baseline. While this creates a powerful alignment, the pace and pattern of humanoid adoption will be shaped by a small number of structural boundary conditions:

- **Safety and regulatory requirements** remain paramount, particularly in patient-facing or semi-clinical contexts. Healthcare systems tolerate little operational failure, which constrains where and how humanoids can be deployed without close supervision.
- **Reliability and uptime expectations** in healthcare environments are substantially higher than in many industrial settings.

Exhibit 07

Current humanoid robot models

Figure AI

Figure 02

Height: 168 cm

Load: 20 kg

Boston Dynamics

Atlas

Height: 188 cm

Load: 30 kg

Tesla

Optimus Gen-2

Height: 178 cm

Load: 20.4 kg

Unitree Robotics

H2

Height: 182 cm

Load: 15 kg

Neura Robotics

4NE1 Mini

Height: 180 cm

Load: 15 kg

> For humanoid robots, acceptance and trust by staff and patients are as critical as technical capability

Systems must operate consistently across shifts, sites, and demand surges, limiting tolerance for early stage performance variability.

- **Acceptance and trust by staff and patients** are as critical as technical capability. Adoption depends not only on functional performance, but on how well robots integrate into human workflows and support — rather than disrupt — clinical and operational teams.

- **Mastering more complex environments** will be key to the adoption of humanoids into a wide array of tasks from home care to broad usage in clinics, all parts of the pharma and medical device value chain and of governmental/academic labs and institutions.

What determines humanoid economics and return on investment

Across analysts and investor research, humanoid economics are shaped less by task-level efficiency and more by a small number of structural drivers:

- **Utilization across tasks**, not peak performance on a single activity
- **Reliability and up-time thresholds** suitable for continuous operations
- **Supervision ratios**, which determine whether humanoids are substitutes or additions to the workforce
- **The decline in capital expenditures** driven by scale manufacturing and component commoditization
- **Labor scarcity**, rather than wage arbitrage, as the primary adoption catalyst

These dynamics explain why early humanoids are most valuable in environments with persistent, acute labor shortages and predictable workflows, and why healthcare adoption, particularly in clinical care, will most likely lag behind other industries until reliability, trust and economics converge.

The economics point to rapid scaling once the structural factors are solved

> “The key advantage of relying on a robot: its ability to work continuously with a theoretical yearly time on the job of up to 8,552 hours (assuming weekly maintenance windows of four hours) versus 1,840 for a European working 40-hour days, 46 weeks of the year

Expected unit cost by 2035 could reach levels as low as $15,000 to $30,000 per robot, a value some households in advanced economies could afford, given how much it costs to buy a car.[78,79]

The key advantage of relying on a robot over a human lies in its ability to work continuously with a theoretical yearly worktime of up to 8,552 hours per year (assuming weekly maintenance windows of four hours). By contrast, a typical human worker in Europe with a weekly 40-hour shift and 46 yearly work weeks, including vacation and public holidays, is on the job only 1,840 hours. That said, the vast majority of workers in other parts of the world do not standardly get six weeks off annually. The delta is a factor of above 4.5, with the economic case for using humanoids gaining even though the productivity of a robot will not reach that of a human worker for some time.

Assuming a life span of 10 years and yearly maintenance cost of 5% of a $30,000 acquisition cost, the yearly operating budget could be as low as $4,500 and hourly cost below 52 cents in fully continuous mode.

Taken together, these factors point to a gradual adoption path that first, focuses on structured environments like those in production or logistics. However, we see a strong potential for adoption to accelerate and expand to new activities once humanoids master the structural hurdles.

The economics of humanoid robots are fundamentally driven by modularity. Unlike bespoke automation, humanoids are composed of repeatable, swappable subsystems — actuators, joints, hands, sensors, computers, and power, with costs expected to decline as volumes scale. No single component dominates total costs, which allows a robot’s value to be distributed across standardized modules that can be reused, improved, and competitively sourced across generations.

This structure mirrors the early industrialization of the automotive sector, where cost reductions were unlocked through parts standardization, platform reuse, supplier competition, and cumulative learning at the component level — not a single breakthrough. As humanoid platforms mature, improvements in individual modules — such as hands, vision, or battery systems — propagate rapidly across manufacturers and uses, compressing unit costs and accelerating scale. Exhibit 8 illustrates how humanoid robot costs are distributed across modular components. This reinforces why scale, standardization, and supplier learning — rather than task-specific optimization — drive long-term cost decline.

Exhibit 08
Estimated costs of the Tesla’s Gen-2 humanoid robot by major part

Source: Morgan Stanley Research Blue Paper “Humanoids: Investment Implications of Embodied AI”, 2024

2.4 How the convergence of AI and robotics accelerates the productivity potential

AI becomes a true productivity multiplier when it is coupled with robotics and automation. While AI alone can improve decision making and administrative efficiency, its impact expands materially when digital intelligence is embedded into physical systems that can sense, act, and coordinate work in real environments. Three linkages are particularly important in enabling this shift:

1. Perception and control

AI enables robots to interpret and operate within complex, semi-structured environments through advances in computer vision, sensor fusion, and real-time decision-making. In healthcare, these capabilities allow robots to function safely alongside humans in settings such as laboratories, operating rooms, pharmacies, and hospital corridors — where variability, human presence, and safety constraints are significant.

> Through imitation, robots can learn tasks directly from human demonstrations captured via video, sensors, and digital twins, dramatically reducing programming efforts and accelerating deployment

Recent progress in perception models and cutting-edge AI has significantly improved robots' ability to recognize objects, navigate dynamic spaces, and adjust actions in real time, reducing the need for rigid, pre-programmed workflows and expanding the range of tasks that can be automated reliably.[80]

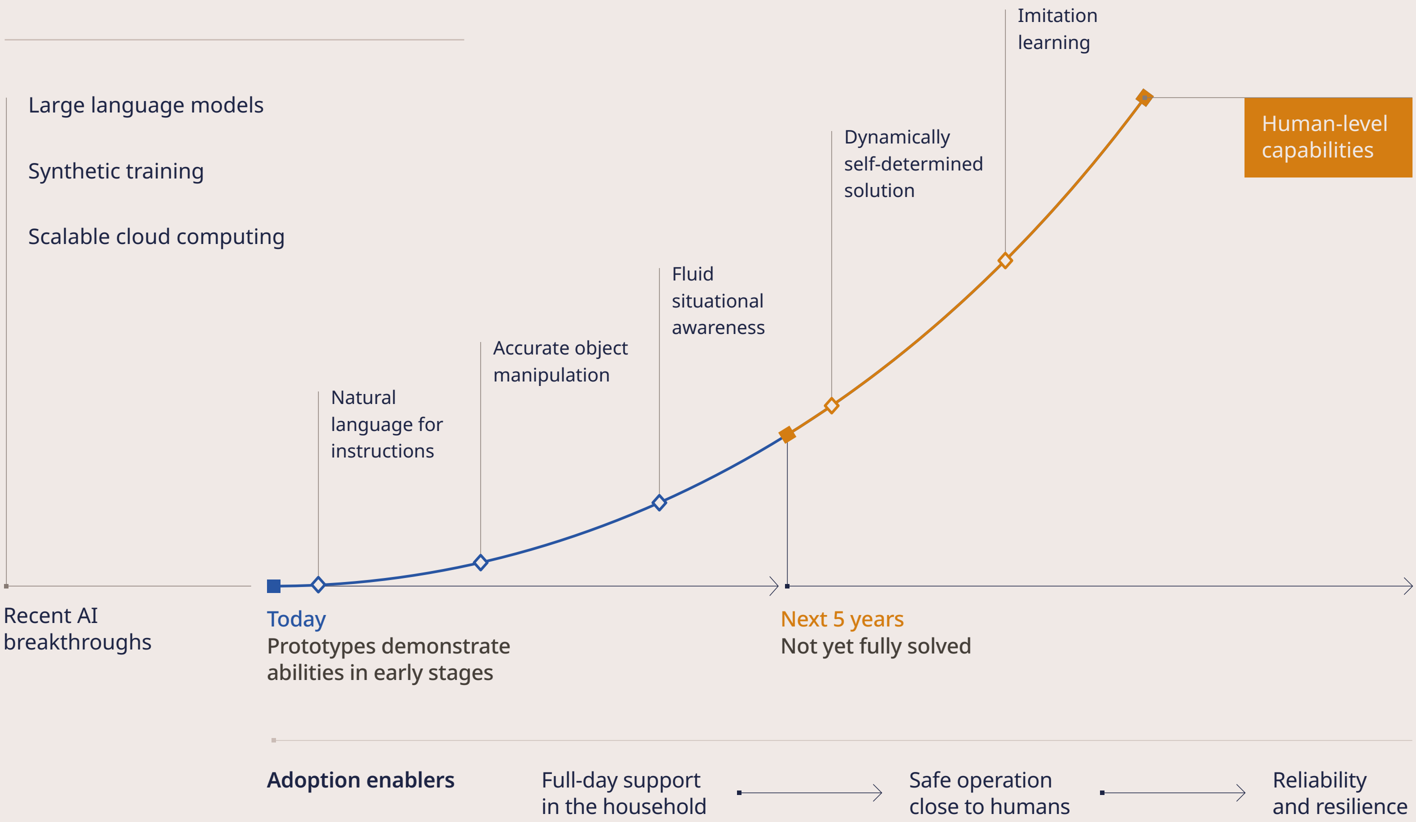
2. Imitation and reinforcement learning

Through imitation learning, robots can learn tasks directly from human demonstrations captured via video, sensors, and digital twins, dramatically reducing programming efforts and accelerating deployment. Reinforcement learning further allows systems to optimize performance over time, improving speed, consistency, and robustness as they accumulate experience.[81]

These learning-based approaches are particularly important for healthcare environments, where tasks are often repetitive but context-dependent and where manual reprogramming for every variation is impractical. Together, imitation and reinforcement learning are lowering the cost and complexity of scaling both specialist robots and, eventually, humanoid robots across multiple workflows.[82]

Exhibit 09

Robot imitation learning maturity curve



Source: Oliver Wyman analysis

> “Agentic AI acts as the coordination layer between humans, robots, and software systems., scheduling tasks, allocating resources, and dynamically adjusting workflows

Exhibit 9 shows how recent advances in AI — particularly large language models, synthetic training, and scalable cloud computing — are progressively expanding robotic capabilities from task-specific execution toward more adaptive, human-level performance. Early-stage systems already demonstrate such capabilities as language-based instruction, object manipulation, and situational awareness, while more advanced learning-based behaviors are expected to mature over the next several years. Together, these advances reduce deployment friction and enable robots to operate more flexibly alongside humans across diverse environments.[83]

3. Orchestration of hybrid workforces

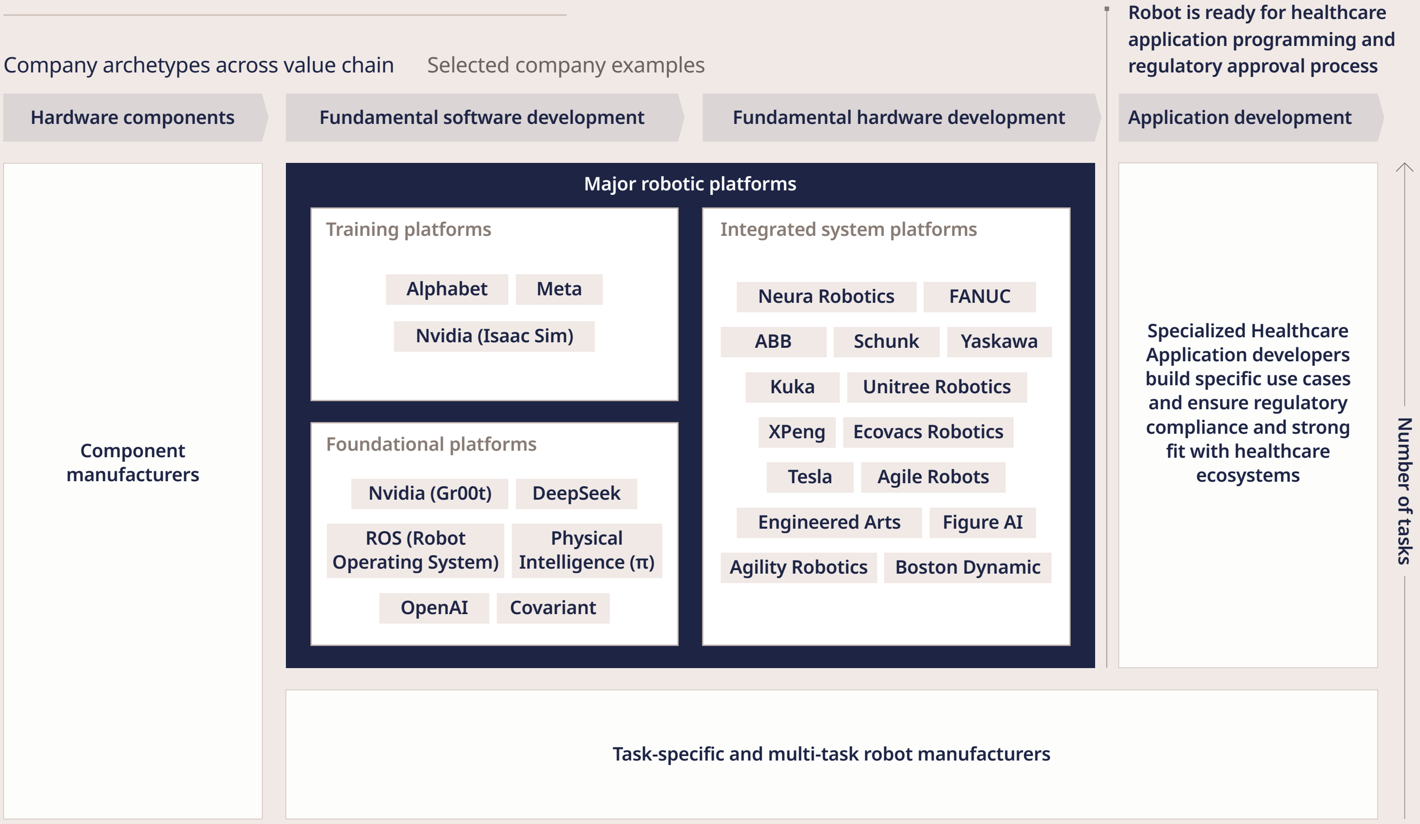
Agentic AI acts as the coordination layer between humans, robots, and software systems. It schedules tasks, allocates resources, and dynamically adjusts workflows — ensuring that robots, digital agents, and clinical staff operate as a coordinated system rather than as isolated components.[84]

In this context, AI reduces the cost and friction that can accompany innovation. By simplifying integration, enabling adaptive behavior, and coordinating across systems, AI shortens the time to market and lowers implementation barriers for robotics. This accelerates diffusion and makes it feasible to deploy automation across broader, multi-step workflows rather than isolated tasks.[85]

How modular components now drive platform ecosystems

As humanoid robots industrialize, value creation is shifting from stand-alone machines toward platform ecosystems that integrate foundational software, standardized hardware modules, and application-specific development. Similar to smartphones and cloud AI, scale advantages accrue to platforms that combine core operating systems, developer tooling, simulation and training environments, and interoperable hardware architectures. This ecosystem logic matters for investment and innovation: Capital increasingly concentrates upstream in foundational platforms (software, computers, control, training) and midstream in standardized hardware modules, while downstream value is unlocked through domain-specific applications, integration, and services. The result is not a single “winning robot,” but a small number of scalable platforms that lower unit costs, accelerate learning, and enable rapid diffusion across industries — including healthcare over time.

Exhibit 10
Key platforms for omni-task robots are emerging



Source: Robotics expert interviews, Oliver Wyman research, Oliver Wyman analysis

How leaders are moving from economics to reality

To ground the economics in reality, the following examples illustrate how robotics is moving from abstract economics to tangible, comparable platforms. Across leading players, designs are converging around similar form factors, payloads, and modular architectures — reflecting a shift from bespoke prototypes toward commercial systems. These specifications matter not because any single robot is "ready" for healthcare today, but because they reveal the underlying cost structure, performance envelope, and scalability logic that will shape adoption over time.

> “Standardization of components and platforms — not one breakthrough design — will ultimately determine how quickly humanoid robots scale, costs fall, and new use cases become economically viable

Case example: AI-enabled and robotic assistance in long-term and elder care (Japan)

The interaction between AI-driven coordination and task-specific robotics is already visible in real-world settings. Long-term care facilities and home care face some of the most severe workforce gaps in healthcare, and Japan has emerged as an early testing ground for both specialist and humanoid robots in nursing homes.

Large observational studies of Japanese long-term care facilities show that task-specific care robots – such as monitoring and communication systems, mobility assistance devices, and transfer robots — can reduce physical strain on caregivers, lower staff turnover, and stabilize service levels under tight labor conditions. Importantly, these systems are most effective when integrated into care routines under human supervision, with AI-enabled coordination supporting task allocation and workflow continuity rather than autonomous caregiving.[86]

Taken together, the convergence of AI and robotics elevates healthcare productivity from isolated task automation toward coordinated, system-level performance. By enabling perception, learning, and orchestration across human and machine workforces, AI allows robotics to scale beyond isolated tasks and into integrated operating models. The result is not autonomous healthcare, but more resilient, flexible systems capable of delivering greater capacity and consistency under persistent labor and cost constraints.

Exhibit 11

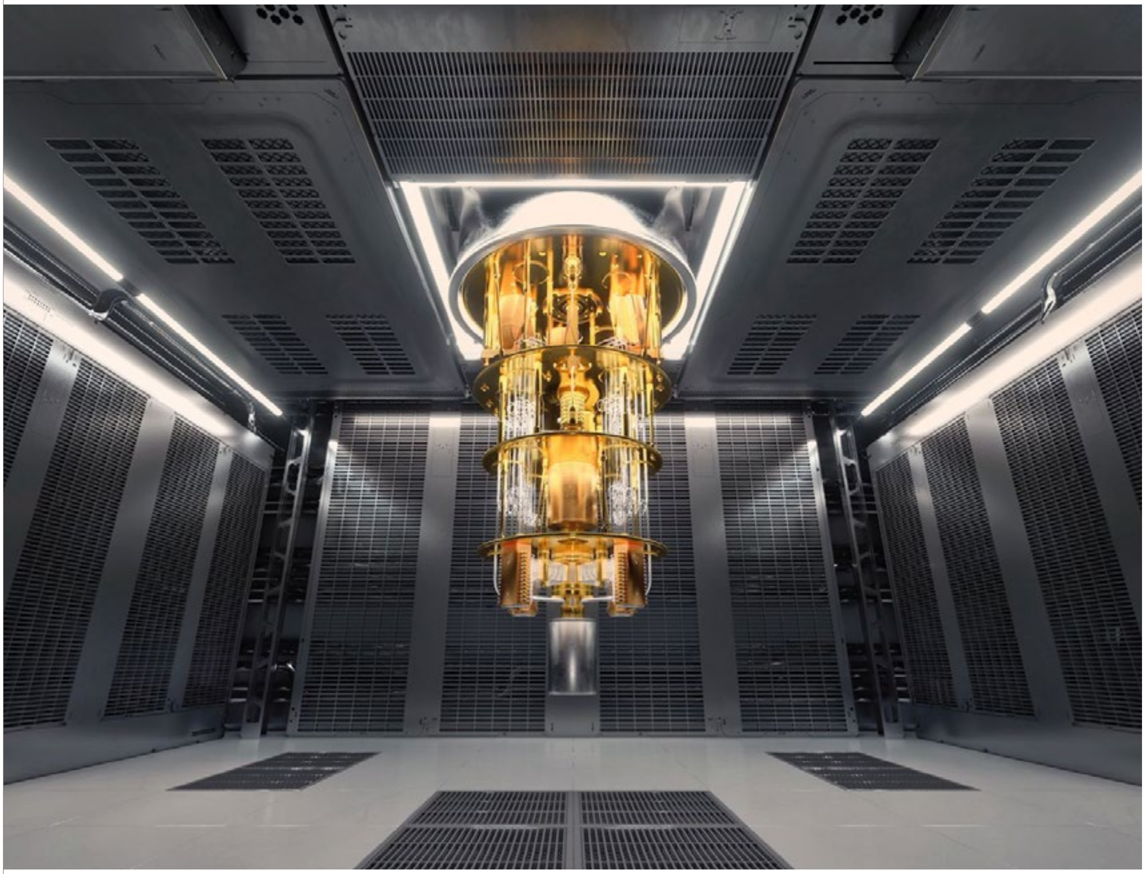
Strategic implications for healthcare systems

Today	Over time
Specialist robotics are the productivity backbone and should be scaled aggressively	Humanoids should be treated as a strategic option, piloted in logistics, support, and industrial adjacencies
Data, workflows, and governance built for specialist robots	These foundations determine readiness for humanoid deployment
Immediate gains come from task-specific automation	Long-term gains come from hybrid models combining specialist precision with humanoid flexibility

2.5

Quantum technology: The accelerator on the horizon

While AI and robotics will drive the bulk of healthcare productivity gains over the next decade, quantum technologies have the potential to act as a powerful, longer-term accelerator by expanding the performance frontier of these systems over time. Rather than functioning as an independent productivity lever in the near term, quantum computing, sensing, and communication should be understood as enabling technologies that amplify the effectiveness, scale, and resilience of AI-driven healthcare transformation.



IBM Quantum Computer

> In healthcare, quantum computing is most relevant for accelerating drug discovery, improving treatment design, and optimizing care delivery networks under uncertainty and complexity

Quantum computing: Expanding the frontier of complex optimization

Quantum computing addresses classes of problems that remain computationally prohibitive for classical systems, including molecular simulation, complex biological modeling, and large-scale optimization.[87] In healthcare, this capability is most relevant for accelerating drug discovery, improving treatment design, and optimizing care delivery networks under high uncertainty and complexity.

As hybrids of quantum and classical start to mature, quantum computing could materially shorten development timelines and unlock efficiency gains that compound those delivered by AI alone.[88]

Quantum sensing: Nearer-term impact on diagnostics and prevention

Quantum sensing represents a nearer-term accelerator with more direct relevance to care delivery. Ultra-sensitive, non-invasive quantum sensors leverage quantum phenomena such as superposition and coherence to detect extremely small changes in physical signals, enabling earlier and more precise diagnostics than conventional sensors can perform.[89]

For example, optically pumped magnetometers are being used to advance wearable, motion-tolerant magnetoencephalography, allowing brain activity to be measured while patients move naturally.[90] Nitrogen-vacancy center sensors can detect molecular-level changes at subcellular resolution.

These capabilities have significant implications for earlier detection of neurological conditions, cardiovascular abnormalities, and other diseases associated with subtle physiological signals.

Speeding up detection to reduce downstream costs

Diagnostics are a critical gateway to lowering healthcare costs and improving outcomes. Earlier detection of disease typically translates into lower downstream treatment costs, reduced acute-care utilization, and improved patient outcomes. By enabling detection of pathological changes before symptoms appear, quantum sensing could support a structural shift from reactive to preventive care.

Research programs at institutions, such as the University of Oxford and the Copenhagen Centre for Biomedical Quantum Sensing, are exploring how quantum sensors can push detection sensitivity beyond classical limits, with the explicit goal of enabling earlier, more precise diagnoses across a range of conditions.[91]

Quantum communication and security: Enabling trusted scale

> “
> Targeted early adoption of quantum can act as a force multiplier, raising the durability and long-term ceiling of healthcare productivity

Quantum communications and post-quantum cryptography play a complementary role by protecting the data infrastructure required for large-scale AI deployment.[92] As healthcare systems become increasingly data-driven and automated, lack of trust in data integrity, model security, and long-term confidentiality can become a constraint.

Quantum-safe communications reduce systemic risk and enable more confident scaling of AI, robotics, and digital workflows across healthcare ecosystems.

Quantum's limits and outlook

Taken together, quantum technologies are unlikely to deliver broad, stand-alone productivity impact before the mid- to late 2030s. Rather than functioning as an independent productivity engine in the near term, their contribution to healthcare productivity can be understood as unfolding across a set of overlapping waves that progressively raise the ceiling for AI-enabled transformation.

In the first wave, unfolding today and into the early 2030s, quantum technologies act primarily as enablers rather than direct productivity drivers. Early applications — particularly in quantum sensing, quantum-safe communication, and hybrid quantum-AI workflows — help reduce systemic risk, strengthen data integrity, and support secure scaling of AI, robotics, and digital workflows across healthcare ecosystems. The productivity impact at this stage is indirect, achieved through improved resilience, trust, and system stability rather than through measurable efficiency gains.

A second wave, emerging in the early to mid-2030s, is expected as the hybrid quantum-classical approaches mature. In this phase, quantum capabilities begin to augment AI in select high-complexity domains, such as optimization problems, molecular simulation, and advanced logistics and scheduling. While still targeted, these applications can act as force multipliers, accelerating learning cycles and improving performance in areas that remain computationally constrained today.

A third wave, extending into the late 2030s and beyond, holds the potential for more direct productivity contributions as quantum computing capabilities mature further. However, this wave remains uncertain and should not be assumed in baseline productivity scenarios. Its role is best understood as expanding the long-term frontier of what is possible, rather than as a prerequisite for near- or medium-term productivity gains.

Across all waves, the central implication is consistent: Quantum technologies are most relevant as complements to — not substitutes for — AI-driven productivity transformation. Targeted early adoption can act as a force multiplier, raising the durability and long-term ceiling of healthcare productivity, while the core productivity reset over the coming decade remains driven by institutional choices, integration, and execution of technologies already available today.

03

Productivity Pathways: How Adoption Choices Will Shape Healthcare System Outcomes

The convergence of artificial intelligence, robotics, and automation has created a credible opportunity to reset healthcare productivity over the coming decades. These technologies have reached sufficient maturity to deliver meaningful gains across clinical, administrative, and operational domains.

However, technology availability alone does not determine outcomes. The pace, scale, and durability of productivity gains depend on how decisively healthcare systems integrate these capabilities into workflows, institutions, and operating models.

In practice, the same underlying technologies can produce very different system-level results — from incremental efficiency improvements that stabilize pressure points to structural capacity expansion that bends long-term cost and workforce trajectories.

For this reason, the productivity reset should not be understood as a single forecasted outcome, but as a set of plausible pathways shaped by adoption choices. These choices determine whether productivity gains remain localized and transient or compound into sustained, systemwide transformation.

This chapter therefore examines how different technology adoption pathways translate into materially different cost, capacity, and affordability outcomes for healthcare systems through 2040.

3.1 Productivity outcomes are a function of choice

The three scenarios presented in this chapter are not forecasts. They do not assume different underlying technologies, nor do they reflect exogenous shocks or speculative breakthroughs. Instead, they represent choice-driven adoption paths that emerge from how healthcare systems act across four dimensions:

- **Speed of adoption** – how rapidly AI and robotics move from pilots to scaled deployment
- **Depth of integration** – whether technology is applied at task, workflow, or system level
- **Institutional alignment** – coordination across regulation, reimbursement, data, and governance
- **Execution discipline** – the ability to standardize platforms, retire legacy processes, and reinvest gains

Across all scenarios, the same set of AI and robotics use cases is assumed to be technically available. What differs is how fully these capabilities are embedded into care delivery and system operations and how fast learnings compound.

Why the scenarios diverge: Reinvestment, integration, and execution

While all scenarios are built on the same underlying set of AI and robotics use cases, they differ materially in the timing, scale, and coordination of investment in technology, integration, workforce transition, and supporting infrastructure. Productivity gains compound only when early efficiencies are reinvested to standardize platforms, redesign workflows, and build system-level capabilities. As a result, scaling productivity requires upfront and parallel investment in digital infrastructure, data integration, cybersecurity, workforce capabilities, and operating model redesign.

Throughout this section, a distinction is made between gross productivity savings — the theoretical efficiency gains before investment — and net savings, which account for the costs of technology acquisition, integration, cybersecurity, workforce reskilling, and organizational transition. Net savings therefore reflect the realistic economic impact of productivity transformation, not just technical potential.

In practice, the scenarios diverge less because of different technologies and more because of different reinvestment choices — whether early gains are absorbed locally, partially reinvested, or redeployed to accelerate systemwide transformation. Scaling AI, robotics, and emerging technologies requires phased investment across foundations, integration, and system redesign — with early costs incurred well before full value is realized.[93]

These dynamics play out differently across health system sectors, shaping where productivity can scale fastest — and where early investment provides the greatest systemwide leverage.

Defining the investment waves

To make these adoption choices explicit over time, this sectionorganizes the analysis into three broad investment waves. These waves are not forecasts of discrete technological breakthroughs, but rather pragmatic phases that reflect how healthcare systems typically sequence investment as capabilities mature, integration solidifies, and operating models evolve. The timing and coordination of investment across these waves differ materially by scenario, shaping both transition costs and the durability of productivity gains.

- **Wave 1 (2025-2030):** Digital foundations and early scale, including AI platforms, data integration, cybersecurity and initial — mostly specialist — robotics deployment.
- **Wave 2 (2030-2035):** System integration and capacity expansion, with broader specialist and humanoid robotics deployment, workflow redesign, and early frontier pilots.
- **Wave 3 (2035-2040s):** System redesign and frontier impact, with AI as system orchestrator, flexible and fast-scaling robotic coverage across all robotic forms, and emerging quantum-enabled applications.

3.2 Sectors where productivity can scale fastest

> “Across the five major health system sectors, differences in task standardization, labor intensity, regulatory exposure, and reimbursement models create materially different productivity ceilings and environments

Productivity gains from AI, robotics, and automation will not accrue evenly across the healthcare system. While all sectors benefit from incremental efficiency improvements, the magnitude, speed, and durability of productivity gains vary structurally by function, economics, and operating model.

Across the five major health system sectors, differences in task standardization, labor intensity, regulatory exposure, and reimbursement models create materially different productivity ceilings and environments. Understanding these differences is critical for prioritizing investment and sequencing adoption.

Clinical care delivery (medium to high impact)

Clinical care delivery offers substantial productivity upside, primarily through capacity expansion rather than labor substitution. Specialist robots, AI-assisted diagnostics, and workflow automation can materially improve care coordination, diagnostic throughput, logistics, and clinician efficiency by absorbing repetitive, administrative, and physically demanding tasks.

Rather than replacing clinicians, these technologies expand skilled labor’s capacity, allowing clinicians to focus on complex decision making and patient interaction. The productivity impact is strongest in hospital operations, diagnostics, perioperative workflows, and care coordination, where bottlenecks constrain system throughput.

While full automation is neither feasible nor desirable in most care settings, targeted deployment can unlock meaningful capacity gains, particularly in environments facing persistent workforce shortages. Over time, learning effects and workflow integration can shift care delivery from episodic efficiency gains toward structural throughput improvements and redefined workflows.

Pharmaceuticals (medium impact, compounding over time)

In pharmaceuticals, productivity gains are less immediate but potentially compounding. AI and advanced analytics can accelerate drug discovery, optimize trial design, improve site selection, and reduce cycle times across R&D. This would slow the growth of development costs and increase R&D productivity.

In parallel, automation and robotics in manufacturing and supply chains can improve yield, quality, and reliability while reducing labor intensity. While these gains do not immediately translate into lower drug prices, they reshape the economics of innovation, enabling more assets to be developed within fixed R&D budgets.

Over time, these effects can materially influence system-level affordability by changing the cost curve of therapeutic innovation, particularly when combined with precision medicine and better patient stratification.

Medical devices (high productivity leverage, large expansion as key enabler for all sectors)

Medical devices and diagnostics are positioned to become core productivity enablers across the healthcare system. As value increasingly shifts from stand-alone hardware toward integrated hardware-software platforms, devices become engines of continuous learning, automation, and workflow integration.

AI-enabled imaging systems, robotic platforms that expand from single procedures to multipurpose operational roles, and sensor-rich devices generating longitudinal data all contribute to productivity beyond the device itself — improving diagnostics, reducing rework, and enabling preventive and predictive care models.

As healthcare systems invest in interoperable data platforms and automation, demand will increasingly favor scalable, software-driven device ecosystems, accelerating learning curves and reducing unit costs. In practice, much of the AI, robotics, and automation deployed across care delivery, diagnostics, and operations will be embodied within regulated medical devices — integrating hardware, software, sensing, and connectivity rather than existing as stand-alone tools.

This positions the medical device and diagnostics sector as a central driver of healthcare productivity growth, not just a peripheral supplier, with productivity-enhancing technologies increasingly realized through device-based platforms as they scale across the system.

Health insurance and payer operations (high impact)

Insurance and payer functions represent one of the highest and fastest productivity opportunities in healthcare. Administrative workflows — including claims processing, utilization management, prior authorization, customer service, and care management — are highly digitizable, data-rich, and rule-based, making them well-suited to AI-driven automation.

Unlike clinical care, payer productivity gains will face fewer safety constraints and can scale rapidly with less organizational friction. AI-enabled automation can significantly reduce administrative cost per member, while improving service quality, speed, and the ability to target high-risk populations.

Payer-side productivity gains can also enable downstream system efficiency by reducing the administrative burden on providers and accelerating care pathways. This sector is likely to deliver early, outsized returns and act as a financing engine for broader system transformation.

Other health services (selective, context-dependent impact)

Productivity gains in other health services — including public health, community care, and ancillary services — are highly context-dependent. While variability in funding, regulation, and infrastructure will limit uniform impact, targeted use such as population health analytics, logistics automation, and remote monitoring can deliver meaningful gains in specific settings.

The productivity upside here is less universal but still strategically important, particularly where digital maturity and integration with broader care systems are strong.

Key insight across sectors

The critical insight is not whether productivity gains are possible — they are — but primarily where they scale fastest and compound over time. Sectors with high administrative intensity, repeatable workflows, and strong data foundations will lead early gains, while clinically intensive domains realize productivity primarily through capacity extension and system redesign rather than labor substitution.

These sector-level differences shape not only the size of productivity gains, but also the pace at which scenarios diverge, and where leaders should concentrate early investment to unlock systemwide transformation.

3.3
Scenario overview and outcomes

Exhibit 12

Productivity scenarios at a glance

Incremental adoption	Accelerated adoption	Breakthrough adoption
Risk-averse, fragmented	AI and robotics treated as productivity infrastructure	Deep integration and system redesign
Technology used as point solutions	Selective regulatory evolution	Strong learning effects
Gains stabilize pressure points but do not bend the cost curve	Early gains partially reinvested	Early efficiencies aggressively redeployed

Overview of the three scenarios

Three distinct scenarios were modeled to illustrate how different adoption choices lead to divergent outcomes:

1. Incremental adoption

Technology is deployed cautiously and unevenly, largely as a response to short-term cost pressure. AI and robotics are applied to narrow use cases, with limited workflow redesign and minimal institutional reform. Learning effects are weak, and productivity gains stabilize isolated bottlenecks without altering the long-term cost trajectory.

2. Accelerated adoption

Healthcare leaders treat AI and robotics as core productivity infrastructure, supported by selective regulatory evolution, targeted capability buildup, and reinvestment of early gains. Technology shifts from isolated tools toward integrated workflows, generating meaningful — but not maximal — system-level impact.

3. Breakthrough adoption

Healthcare systems respond decisively to demographic and workforce pressures, pairing rapid technology deployment with deep workflow redesign and institutional modernization. AI and robotics are embedded end-to-end across care delivery and operation, unlocking transformational productivity and capacity gains.

Exhibit 13

Illustrative, scenario-agnostic investment evolution reflects relative emphasis, not spending levels

Scenario-agnostic investment evolution (illustrative)

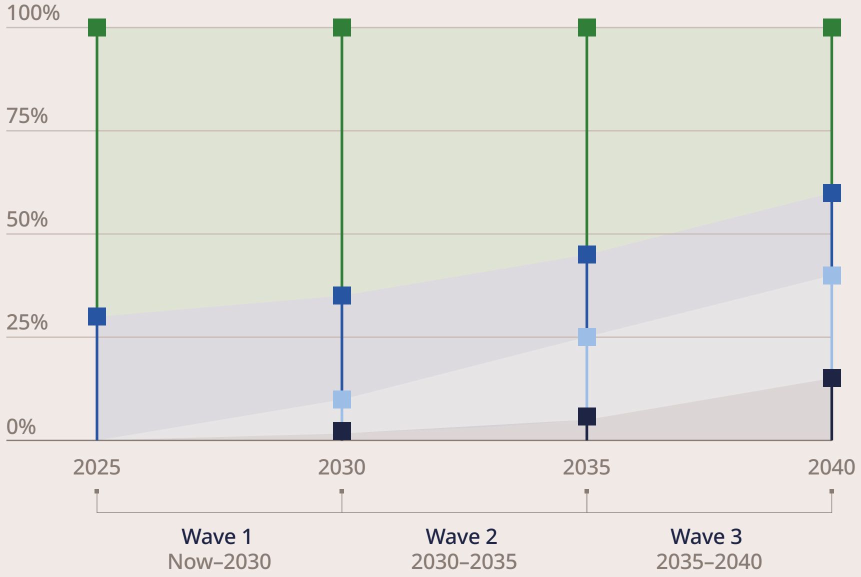
Relative investment emphasis, 2025-2040

🟩 Artificial intelligence

🟦 Specialist robotics

🟦 Humanoid robotics

⬛ Quantum



Source: Oliver Wyman analysis

How the investment focus is evolving across technology domains

Across scenarios and adoption pathways, the focal point for investment will shift markedly over time as system constraints change. Early waves concentrate on digital foundations and proven automation to remove bottlenecks and enable scale.

As integration improves and learnings effects compound, investment progressively reallocates toward more capital-intensive physical systems and, later, toward frontier technologies with higher transformational potential. This evolution reflects sequencing and readiness considerations rather than technology promise alone, with later-stage investments building on capabilities, governance, and infrastructure established earlier.

Technology-specific evolution and investment trajectories

While the pace and scale of adoption vary across scenarios, the underlying investment trajectories of key technologies follow a consistent pattern driven by system readiness, integration complexity, and governance maturity.

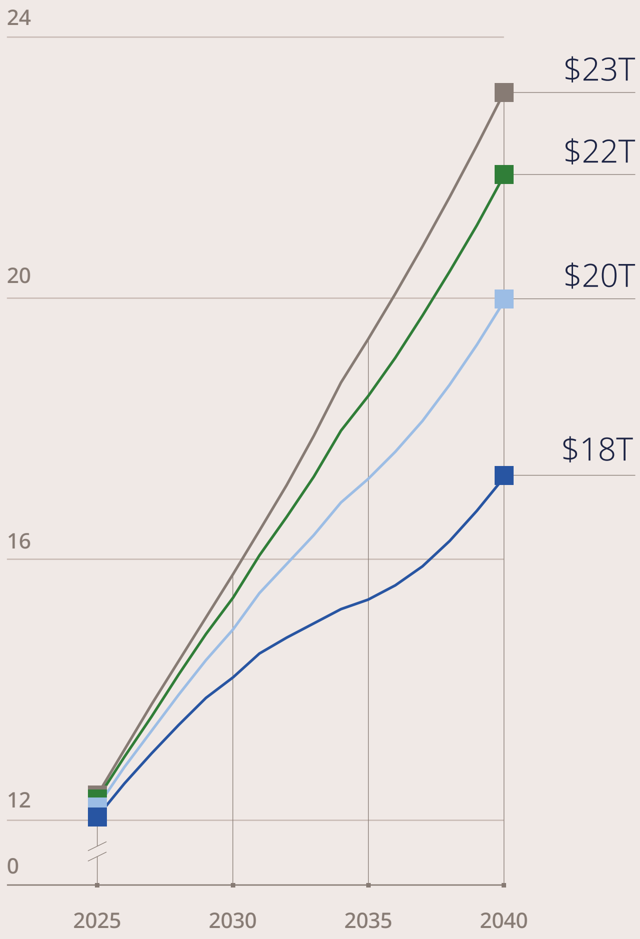
- **Artificial intelligence:** Commands the largest share of early investment as the primary enabler of data integration, workflow automation, and decision support; over time, it becomes embedded infrastructure rather than a distinct marginal investment focus.
- **Specialist robotics:** Scales earlier in targeted clinical and operational settings where safety, return on investment, and integration are well understood, before gradually tapering as deployments mature and become part of the routine capital cycles.
- **Humanoid robotics:** Remains limited in its early waves but accelerates sharply once safety, liability frameworks, workforce acceptance, and system integration reach sufficient maturity, driving a growing share of investment from the early 2030s onward.
- **Quantum technologies:** Attracts modest early investment focused on readiness and targeted pilots, with material investment emerging later as hybrid quantum-classical applications become operationally relevant and capable of amplifying systemwide performance.

Exhibit 14

Overview of scenario results (high-level estimates)

Productivity uplift scenario savings
In trillions US $, 2025-2040

Scenario	2040 savings	Key assumptions
■ Baseline	—	No change from current state
🟩 Incremental adoption	$1.1T	Slow adoption and limited scale benefits. Technology applied as effective point solution only
🟦 Accelerated adoption	$2.8T	Steady expansion and gradual evolution of regulatory frameworks to drive moderate savings
🟦 Break-through adoption	$5.1T	Rapid adoption and strong learning effects drive system redesign and unlock transformative growth



Source: Oliver Wyman analysis

The modeled productivity outcomes diverge sharply across scenarios:

- **In the incremental adoption scenario**, cumulative gross productivity gains reach about $12 trillion by 2040. However, high transition costs, duplicated systems, and limited scale effects will reduce net savings to around $8 trillion.
- **In the accelerated scenario**, coordinated adoption delivers cumulative gross gains of roughly $24 trillion, with net savings of about $20 trillion after accounting for investment and transition costs.
- **In the breakthrough adoption scenario**, strong learning effects, platform scale, and system redesign unlock cumulative gross gains exceeding $40 trillion, with net savings of about $36 trillion.

These differences underscore a central insight: Most of the productivity opportunity is missed not because technologies fail, but because systems fail to scale them correctly.

Productivity gains diverge across regions as adoption accelerates, reflecting differences in system scale, regulatory coherence, capital deployment capacity, and execution discipline rather than technology access alone.

In the incremental adoption scenarios, outcomes remain broadly similar across advanced economies, as limited integration and fragmented deployment constrain scale effects. As adoption deepens, divergence becomes more pronounced: Regions with larger systems, more centralized decision making, and greater capacity to mobilize and coordinate capital at scale capture a disproportionate share of productivity gains, while more fragmented systems realize slower, partial benefits.

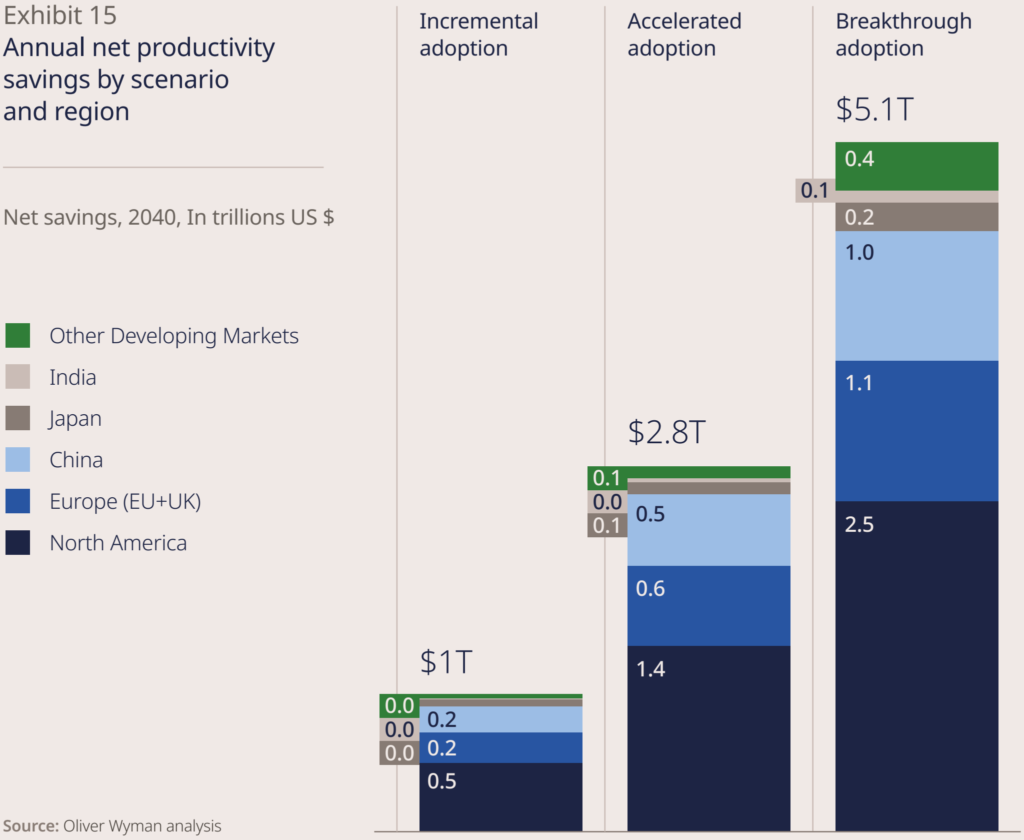
These patterns underscore that regional outcomes are shaped less by baseline spending levels and more by institutional readiness to integrate, standardize, and reinvest productivity gains at scale.

Annual net productivity savings increase sharply as adoption accelerates, reflecting the compounding effects of scale, learning, and system integration. In the slow adoption scenario, annual savings remain modest across all regions, as fragmented deployment and the high costs of transition limit net impact.

Under coordinated, accelerated adoption, annual savings roughly double, driven by broader workflow integration, partial reinvestment of early gains, and declining technology costs.

Exhibit 15
Annual net productivity savings by scenario and region

Net savings, 2040, In trillions US $



Source: Oliver Wyman analysis

The largest step-change occurs in the rapid adoption scenario, where systemwide redesign, strong learning effects, and disciplined reinvestment unlock substantially greater annual savings by 2040.

Across scenarios, regional differences widen as adoption increases, underscoring that sustained annual savings depend not only on technology uptake, but on the ability to scale platforms, retire legacy processes, and convert gross productivity gains into durable net impact.

3.4 How the three scenarios might play out

1. Incremental adoption: Stabilizing pressure without structural reset

In the incremental adoption scenario, healthcare systems adopt AI and robotics cautiously, prioritizing risk avoidance and local efficiency over transformation.

By 2030, AI deployment remains limited to administrative automation and narrow clinical decision-support tools, reaching roughly 20% of applicable organizations. By 2040, adoption expands modestly but remains fragmented, with poor integration into core workflows and limited data interoperability.

Robotics adoption remains concentrated in large, well-capitalized hospitals, focused on established use cases in areas such as surgical and pharmacy automation. Smaller hospitals, outpatient clinics, long-term care facilities, and home settings see minimal penetration. Generalist or humanoid robotics are still confined to pilot projects without operational scale.

Transition costs are high relative to benefits. Repeated pilots, bespoke integrations, and parallel legacy systems dilute learning effects and prevent cost curves from bending. Productivity gains stabilize specific pressure points but do not materially alter healthcare affordability.

System outcome: Incremental efficiency improvements, limited net savings, and continued structural pressure on labor and costs.

2. Accelerated adoption: Bending the cost curve through coordination

In the accelerated scenario, healthcare systems pursue a more deliberate, coordinated adoption strategy.

By 2030, about 50% of healthcare organizations across advanced economies deploy AI across administrative and clinical domains, with growing integration into care coordination, diagnostics, utilization management, and revenue-cycle workflows. By 2040, AI assistants are embedded across most workflows, enabling real-time support and decision augmentation.

Robotics adoption expands across high-return use cases, including logistics, sterilization, diagnostics, and selected care settings. In long-term care, assistive robotics are scaling in controlled environments where workforce shortages are most acute.

Investment is sustained but disciplined. Some early productivity gains are reinvested into IT modernization, cybersecurity, workforce reskilling, and platform integration. Standardization and shared infrastructure allow learning effects to compound through the 2030s.

System outcome: Productivity gains are sufficient to materially slow healthcare cost growth while preserving quality and access.

3. Breakthrough adoption: Productivity as a strategic imperative

In the breakthrough adoption scenario, healthcare systems treat productivity improvement as a strategic necessity, not an efficiency initiative.

By 2030, AI is embedded across core workflows in most high-income healthcare systems, with broader diffusion enabled through platform reuse and international collaboration. By 2040, AI agents coordinate administrative processes, clinical support, and operational planning in near real time.

Robotics adoption becomes pervasive. Autonomous service robots operate across hospitals, nursing homes, and community settings, while assistive devices extend both patient and clinician capabilities. Governments actively support deployment as part of workforce stabilization strategies.

Technology and transition costs decline sharply due to scale, competition, and reuse. Legacy systems are retired rather than duplicated, and organizational redesign enables end-to-end automation. Only 15-20% of gross savings are absorbed by transition costs.

System outcome: Structural productivity improvement enables sustained cost containment, expanded capacity, and system resilience, even in the face of labor shortages.

3.5

Investment required to unlock productivity at scale

The productivity gains described in this report do not emerge automatically from technology adoption. They require substantial, front-loaded investment in digital infrastructure, system integration, workforce capability, and operating model redesign before savings can be realized at scale. Across all scenarios, costs are incurred early — while benefits compound later.

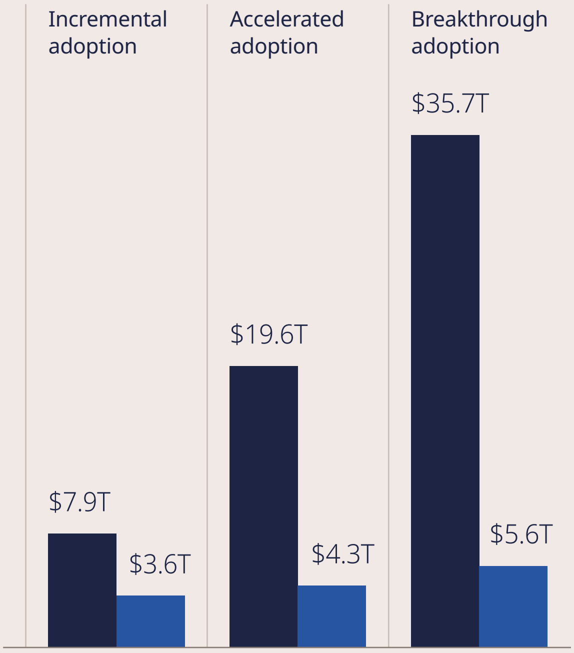
The differences in the three scenarios — incremental, accelerated, and breakthrough — is therefore driven less by access to technology than by the willingness and capacity to absorb near-term investment to unlock long-term systemwide gains.

Exhibit 16

Upfront investment determines long-term productivity outcomes (high-level estimates)

Cumulative net savings and investment required across scenarios
2025-2040, In trillions US $

■ Cumulative net savings 2025-40
■ Cumulative technology investment 2025-40



As illustrated in the graph above, systems that stick with incremental adoption are likely to generate limited net savings by 2040, despite meaningful efficiency potential. High transition costs, duplicated systems, fragmented pilots, and delayed reinvestment prevent early gains from compounding. By contrast, accelerated and breakthrough adoption scenarios assume deliberate, coordinated investment in shared infrastructure, standardized platforms, cybersecurity, data integration, and workforce reskilling — enabling productivity improvements to scale across functions rather than remain localized.

What healthcare systems must invest in to realize savings

The most critical investment that needs to be made early in the transition is to modernize the core digital infrastructure and integrate data across clinical, administrative, and operational domains. In robotics, systems also need to deploy secure, interoperable platforms, retrain clinical and technical staff, and redesign workflows to support automation and learning at scale. Most of the innovation investments will have to be made before savings are realized.

Where early savings are partially reinvested into platforms, integration, and capability buildup, learning effects accelerate and transition costs decline over time. When they are not reinvested, productivity gains remain episodic, fragile, and difficult to sustain.

Exhibit 16 highlights a central insight: There is a massive gap between the $8 trillion in savings possible under an incremental scenario and the more than $35 trillion under the breakthrough outlook. Breakthrough adoption requires healthcare leaders to treat AI, robotics, and automation as long-term productivity infrastructure — analogous to prior investments in hospital capacity, pharmaceutical manufacturing, and national health IT systems.

In this sense, productivity is constrained mostly by the institutional willingness of healthcare executives to invest ahead of realized returns. Systems that commit to disciplined, upfront investment — and protect those investments through governance, regulation, and reinvestment of early gains — are the ones able to bend the cost curve while expanding capacity. Systems that fail to make these investments risk locking in a structurally higher-cost trajectory – even as technology offers a clear mechanism to bend that curve.

3.6 Regional divergence and spending rebalancing productivity outcomes diverge

Productivity gains from AI, robotics, and automation do not accrue evenly across regions. While all health systems have access to broadly similar technologies, outcomes diverge sharply based on institutional readiness — including system scale, regulatory coherence, capital deployment capacity, and execution discipline. As adoption accelerates, these structural differences increasingly shape where productivity compounds fastest and where gains remain localized.

Regional divergence is driven less by baseline spending levels than by how effectively systems integrate technology into workflows, coordinate institutions, and reinvest early efficiency gains. Regions with greater coherence and scale convert productivity improvements into sustained capacity expansion and cost containment; more fragmented systems experience slower diffusion but often retain greater absolute headroom for improvement.

North America's high headroom, high execution complexity

North America enters the productivity transition with the highest per capita healthcare spending and some of the most fragmented delivery, financing, and administrative structures globally. This fragmentation increases execution complexity — but it also creates substantial headroom for productivity gains. As a result, improvements in care coordination, administrative automation, and workflow standardization translate into outsized absolute gains, particularly in accelerated and breakthrough adoption scenarios.

In practice, productivity improvements in North America are most visible where automation reduces administrative burden, improves utilization management, and standardizes high-volume workflows. However, realizing system-level impact requires coordinated execution across payers, providers, and regulators. Where fragmentation persists, productivity gains remain uneven and slower to compound.

Europe and Japan may face diminishing returns without system redesign

Many European and Japanese systems operate with more centralized financing, standardized payment flows, and long-standing cost containment mechanisms. These systems have already captured many first-order efficiency gains, resulting in lower marginal returns from task-level automation alone.

Future productivity gains in these regions depend both on deploying new tools and more on deep system redesign — including end-to-end workflow integration, platform standardization, and reinvestment of early gains into capacity expansion. As a result, productivity improvements are harder to unlock but potentially more durable once achieved.[94]

China and India enjoy speed, scale, and leapfrogging potential

China and several low- and middle-income health systems follow a different trajectory than advanced economies. Lower legacy burden, centralized decision making, and rapid infrastructure build-out enable faster diffusion of AI-enabled capabilities, particularly in diagnostics, population health, and operational management.

While baseline spending levels are lower, deployment speed and scale allow productivity gains to materialize earlier in the adoption curve. At the same time, execution risks remain elevated, particularly where governance, data quality, or workforce capabilities lag behind deployment ambition.[95]

A structural rebalancing of healthcare spending

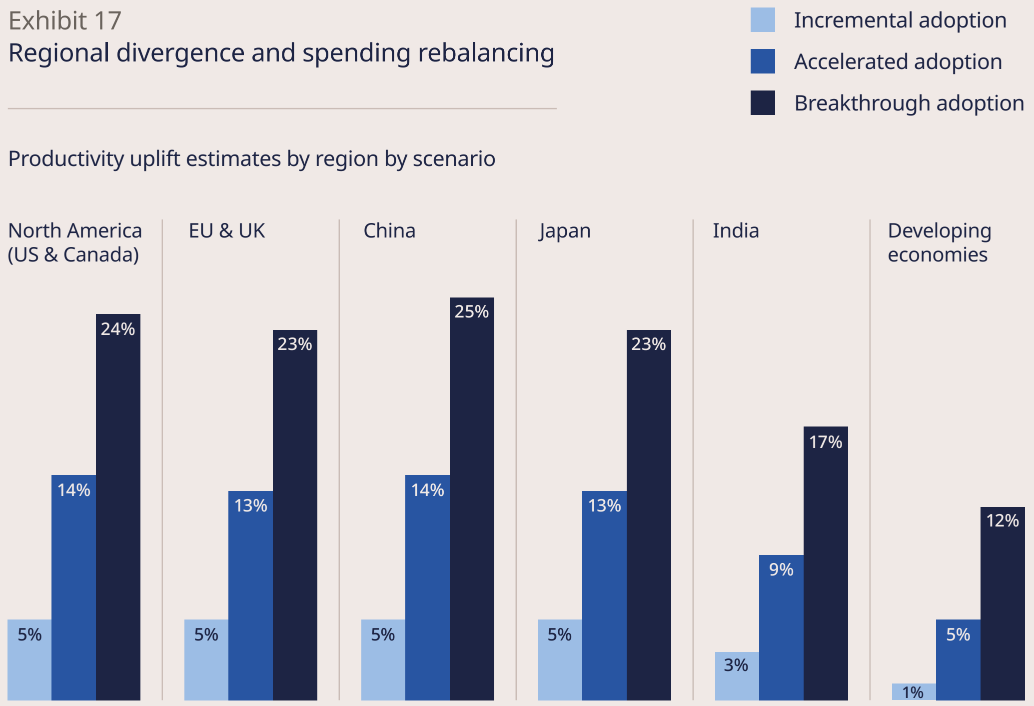
Across all scenarios, higher productivity enables a structural rebalancing of healthcare spending. That means less spending on manual administration, redundant processes, and avoidable acute events and more spending on technology, prevention, and targeted effective care.

The pace and magnitude of this rebalancing vary by region, but the direction is consistent. Regions that combine scale, institutional coordination, and disciplined reinvestment convert productivity gains into sustained improvements in affordability, capacity, and resilience.

The central insight is not whether productivity gains are possible — they are — but where they scale fastest and compound over time. Regional outcomes are shaped less by technology access than by institutional readiness to integrate, standardize, and reinvest. As adoption deepens, these differences widen, reinforcing that productivity is ultimately a function of execution choices rather than technical potential.

Exhibit 17
Regional divergence and spending rebalancing

Productivity uplift estimates by region by scenario



Source: Oliver Wyman analysis

3.7 Bottom line: Productivity is a choice

How we embrace scale and use AI, robotics, and quantum technologies for productivity will define the productivity that healthcare systems take over the next decade, and that will shape outcomes for decades to come. The decisive variables are speed of adoption, openness to innovation, depth of integration, regulatory alignment, and execution discipline. Incrementalism can preserve short-term stability, but it may compromise long-term opportunity. Coordinated action — across technology, institutions, and incentives — can unlock system-level transformation.

Moving from pilots to sustained, systemwide impact hinges on a limited set of system-level conditions, including foundational digital infrastructure, workforce and operating model adaptation, platform standardization, disciplined reinvestment of early gains, and governance frameworks that support learning and trust at scale.

Absent these conditions, productivity gains tend to remain localized and transient. Where they begin to align, learning effects can compound and technology adoption can translate into more durable improvements in capacity, resilience, and affordability. How these conditions are established, sequenced, and sustained in practice — and why they so often prove difficult to align — is the focus of the next chapter.

04

The Five Critical Enablers Needed to Make the Productivity Reset Happen

The productivity reset described in this report is no longer constrained by technological capability. Core technologies — artificial intelligence, advanced analytics, specialist robotics, and early humanoid robots — already exist in deployable form. What determines whether healthcare realizes incremental improvements or more substantial structural productivity gains is how effectively systems address the institutional enablers that sit outside technology itself. These include modern infrastructure, cross cutting capabilities, aligned incentives and regulation, and an innovation mindset tuned to systemic transformation.

Progress in any one domain without the others will limit impact. Sustained productivity gains require coordinated action across four interdependent enablers.

Together, these form the foundation on which productivity can scale beyond point solutions toward systemwide capacity improvement.

The five enablers:

1	2	3	4	5
Technology investment: Building the foundation for scale	**Capability and talent investment: The missing link between technology and impact**	**Changing reimbursement systems and liability rules to scale automation**	**Modernizing regulatory frameworks to enable automation innovation**	**Moving from labor-centric to technology-enabled health systems**

4.1 Technology investment: Building the foundation for scale

AI and robotics can only scale when supported by modern, interoperable infrastructure. Today, data fragmentation, brittle legacy systems, and isolated workflows rank among healthcare's largest productivity drains. Many organizations still attempt to deploy advanced tools on older systems that were not designed for real-time data exchange, automation, or continuous learning — yielding brittle solutions that stall at organizational boundaries.

Without deliberate investments in core digital infrastructure, AI and robotics will remain siloed productivity tools rather than systemwide enablers. A critical challenge is that many of the most important productivity-enabling investments are front-loaded, while their benefits materialize only over time. Upgrading core digital infrastructure, standardizing data, modernizing legacy systems, and building secure, interoperable platforms often require multiyear investment before measurable productivity gains can be realized. This timing mismatch creates adoption friction, particularly in systems facing near-term budget constraints or political pressure for immediate results.

As a result, organizations may delay or fragment investment, even where the long-term productivity case is compelling. This reinforces incremental adoption paths unless early gains are deliberately reinvested to sustain momentum. For systems willing to commit to these front-loaded investments despite delayed returns, several infrastructure priorities are especially critical to achieving structural productivity outcomes.[96]

- **Interoperability and data standards.** Broad adoption of consistent, machine-readable standards — such as Fast Healthcare Interoperability Resources data exchange — is foundational. Without normalized data flows across electronic health records, laboratory systems, imaging, payer platforms, and devices, AI systems remain siloed and limited in scope.

> “
> A critical challenge: Many of the most important productivity-enabling investments are front-loaded

- **Application Programming interfaces (APIs) and cloud-native architectures.** Modular, API-driven integration and cloud infrastructure expand the ability to assemble reusable components across clinical, administrative, and operational domains, enabling automation and learning at scale rather than isolated pilots.
- **Connectivity and edge infrastructure.** Robotics and real-time AI applications increasingly depend on reliable, low-latency connectivity — such as Wi-Fi 6, 5G, and edge computing — particularly in hospitals, long-term care, and home care settings. These networks support collaboration, safety, and responsiveness.
- **Cyber-physical security.** As physical devices become software-driven, cybersecurity risks extend beyond data breaches to operational disruption and patient safety. Investment in operational technology security, historically underdeveloped in healthcare, becomes non-negotiable to protect scaled automation.

Why open fundamental software and hardware platforms are crucial for fast healthcare application development

Beyond individual tools, productivity at scale increasingly depends on the underlying technology platforms on which AI, robotics, and automation are built. Beyond individual tools, productivity at scale increasingly depends on the underlying technology platforms on which AI, robotics, and automation are built. Modular and interoperable platform architectures — spanning AI development, simulation and virtualization, robotics control, and healthcare-specific application layers — enable reuse, faster iteration, and safer scaling across institutions.

Enabling such modular innovation systems will require open (potentially even open source) and fully accessible platforms across core software, such as AI models and digital twins for training and hardware like robots, fundamentals as well as clear APIs and standards for application developers to create workable solutions in the complex highly local healthcare environments.

Open and standards-aligned platforms are particularly important in healthcare, where productivity depends on continuous learning, regulatory traceability, and cross-system coordination. That's why platform choices shape not only integration cost and speed, but whether productivity gains compound over time or remain fragmented.

This is especially important since healthcare systems that rely on closed, tightly connected solutions often struggle to reuse models, integrate workflows, or propagate learning across sites, limiting productivity gains to isolated deployments.

Case study: Implications for the medical device and diagnostics sector

These infrastructure investments represent not only a prerequisite for productivity, but also a significant growth and value-creation opportunity for the medical device and diagnostics sector. As healthcare systems invest in interoperable data platforms, AI-enabled workflows, and robotic automation, value increasingly shifts from stand-alone hardware toward integrated hardware-software systems that improve continuously through data and learning.

Historically, medical devices generated value primarily through physical performance — implants, imaging systems, surgical tools, and capital equipment. The next wave of growth sits at the intersection of devices, AI, and robotics, where software increasingly determines differentiation. Examples include AI-enabled imaging platforms that improve diagnostic accuracy over time, robotic systems that expand from single-procedure tools into multipurpose operational assets, and sensor-rich devices that generate longitudinal data for predictive and preventive care.[97]

As automation scales, demand will increasingly favor platforms that combine sensing, analytics, and actuation, rather than discrete devices. Scale effects accelerate learning curves, improve performance, and reduce unit costs of both computer and robotic hardware – mirroring dynamics previously observed in semiconductors and cloud computing. Over time, this shift could materially expand both the size and strategic importance of the medical device and diagnostics sector, positioning it as a core productivity engine rather than a peripheral supplier to care delivery.[98]

4.2 Capability and talent investment: The missing link between technology and impact

> Without deliberate investment in talent and organizational capability, healthcare systems risk underutilizing advanced tech, remaining dependent on vendors and failing to convert technical potential into durable productivity gains

Technology does not deploy itself. As AI and robotics move from pilots to systemwide deployment, the most significant constraint on productivity is no longer technical feasibility, but the availability of specialized capabilities required to put into operation, govern, and continuously improve these systems in real-world healthcare environments.[99]

Without deliberate investment in talent and organizational capability, healthcare systems risk underutilizing advanced technologies, remaining dependent on vendors and failing to convert technical potential into durable productivity gains.

The critical capability gaps

Several capability gaps are emerging as structural bottlenecks to scale:

- **AI operations and monitoring.** Healthcare organizations require dedicated teams to continuously monitor model performance, detect drift, manage updates, and intervene when systems underperform.[100] These functions resemble DevOps in other industries, but with materially higher clinical, regulatory, and patient-safety stakes
- **Clinical informatics and validation.** Translating AI outputs into clinical action depends on professionals fluent in both medicine and data science. Validation, auditing, and workflow integration are labor-intensive but essential to building trust and enabling adoption at scale.
- **Robotics technicians and systems engineers.** As robotics expands beyond operating rooms into logistics, long-term care, and home settings, new technical roles focused on maintenance, calibration, integration, and safety become indispensable. These skills are scarce and not yet systematically embedded in healthcare workforce planning.[101]

These gaps are not transient. They compound over time, limiting learning effects, slowing diffusion, and constraining the ability of systems to move beyond isolated use cases.

From internal capability build-up to ecosystem advantage

Capability buildup cannot occur in isolation. Leading healthcare systems are increasingly pairing internal investment with ecosystem collaboration — establishing centers of excellence, partnering with device manufacturers on co-development rather than procurement, and building shared platforms across clinical, administrative, and operational domains.

Collaboration models that link traditional medical innovators with AI-native software firms and robotics developers — rather than relying on single vendors — are more likely to deliver scalable productivity outcomes. Over time, these ecosystems become a source of competitive advantage, enabling faster iteration, lower integration costs, and broader diffusion of innovation.

Absent this shift, organizations risk a persistent gap between what technology makes possible and what healthcare systems are able to deliver.

4.3 Changing reimbursement systems and liability rules to scale automation

> When payment is tied to specific credentialed clinicians carrying out tasks, rather than to the task itself or the value it creates, automation and productivity improvements are undervalued

Current reimbursement models — particularly fee-for-service — are largely anchored to human labor rather than to the underlying work performed or the outcomes achieved. When payment is tied to specific credentialed clinicians carrying out tasks, rather than to the task itself or the value it creates, automation and productivity improvements are systematically undervalued.

As a result, replacing manual effort with AI- or robot-enabled execution can reduce billable activity, even when it improves quality, efficiency, or system-level performance. This misalignment means that automation can paradoxically penalize providers financially, slowing adoption despite clear benefits for patients and the broader health system.

A productivity-oriented care model requires continued movement toward value- and outcome-based reimbursement as an entry point for decoupling payment from task execution. In such models, the focus shifts from *who* performs the work to *what* outcomes are achieved, creating space for AI, robotics, and automation to contribute without eroding provider economics. Importantly, this shift does not eliminate the role of clinicians or staff but instead recognizes that productivity gains increasingly come from coordination, prevention, and system-level efficiency rather than additional human activity.

In practice, this implies reimbursement approaches that explicitly recognize value created through automation and coordination, including:

- Payment for avoided utilization, such as reduced admissions, complications, and length of stay, rather than only for delivered services.
- Recognition of administrative automation and care coordination as legitimate sources of value, even when they reduce billable human activity.
- Incentives for AI-enabled preventive and population-health interventions that reduce downstream utilization and improve long-term outcomes.

While elements of this shift are already underway in several systems, progress remains uneven and incomplete, with value and outcome-based reimbursement models still not widespread in key markets such as the United States. When reimbursement continues to value manual effort over outcomes, the economic case for productivity-enhancing technologies will be fragile, limiting reinvestment and slowing systemwide adoption.[102]

Clarifying liability for AI and robotics

One of the most persistent barriers to adoption is uncertainty around liability. When AI or robotic systems contribute to clinical or operational decisions, responsibility may be distributed across multiple actors:

The technology developer.

The healthcare provider deploying the system.

The payer or system that incentivizes its use.

Without clarity, healthcare organizations tend to restrict AI to low-impact use cases, regardless of technical capability. Progress will depend on shared-liability frameworks that reflect real-world, team-based rather than placing all residual risk on individual clinicians or institutions.[103]

4.4 Modernizing regulatory frameworks to enable automation innovation

> A sustained productivity reset requires regulatory frameworks that both protect patients and enable system-level learning

Even when AI and robotic systems are technically mature, ambiguity around approval pathways, and data use can materially slow adoption and limit impact. A sustained productivity reset therefore requires regulatory frameworks that both protect patients and enable system-level learning, diffusion, and scale. Regulatory initiatives in multiple jurisdictions are beginning to recognize this need, particularly for adaptive and continuous learning systems.

Achieving approvals at scale across regulators

Healthcare productivity gains from AI and robotics depend on the ability to deploy solutions across markets. Today, approval processes are still fragmented across major regulators, including the US Federal Drug Administration, European Medicines Agency (EMA), the UK's Medicines and Healthcare products Regulatory Agency,[104] and Japan's Pharmaceuticals and Medical Devices Agency, with timelines that often lag innovation cycles.

> Scope-of-practice rules, staffing ratios, and care delivery standards often fail to account for the support AI and automation can safely provide

In practice, moving from fragmented, jurisdiction-specific approvals to scalable deployment requires regulatory approaches that recognize the adaptive nature of AI systems and the realities of cross-market healthcare delivery. Scaling AI and robotics therefore depends on a small set of structural regulatory shifts that enable continuous learning, coordinated oversight, and post-deployment evolution:

- Agile development standards enabling early testing with low hurdles in low patient risk areas.
- Life cycle-based approval models for adaptive AI systems.
- Greater regulatory convergence or mutual recognition across jurisdictions.
- Expanded use of real-world evidence post-deployment to support continuous learning and updates.

While progress is visible, particularly for AI as software, regulatory processes are still a drag on the pace of technological advancement.

Data privacy, consent, and interoperability

Data governance frameworks such as HIPAA, GDPR, and national privacy laws were designed to protect patients in largely static, siloed data environments. While they are crucial to keep private data safe and avoid private and governmental misuse, they will need to be further advanced to support AI-driven, longitudinal, multisource data use at scale. One example: using federated data access concepts to ensure that fragmentation across regimes does not limit performance, equity, and system-level learning at scale.

To unlock productivity gains while preserving trust, the regulatory framework must evolve along several dimensions:

- Dynamic consent models that reflect fast and secure data access, leveraging federated data models.
- Clearer rules for secondary use of de-identified health data, enabling learning without compromising privacy.
- Explicit interoperability mandates, including adoption of data exchange standards from Fast Healthcare Interoperability Resources,[105] to enable responsible data sharing across systems.

Updating workforce and care regulations

Some regulatory constraints reflect assumptions about manual, human-only workflows that no longer align with technology-enabled care delivery. Scope-of-practice rules, staffing ratios, and care delivery standards often fail to account for the support that AI and automation can safely provide.

Updating these standards, while preserving safety and accountability, could unlock meaningful productivity gains without increasing clinical risk, particularly in care settings facing acute workforce shortages.

4.5 Moving from labor-centric to technology-enabled health systems

> Our enablers require capital, coordination, regulatory courage, and sustained leadership attention

Perhaps the most difficult enabler of productivity transformation is cultural rather than technical. Healthcare systems are deeply labor-centric by design and necessity. As a result, technology is often framed primarily as a risk to jobs, rather than as a structural response to persistent labor shortages and capacity constraints.

A successful productivity reset requires a deliberate shift in mindset away from seeing technology as a replacement strategy and instead treating it as a workforce preservation and capacity-extension strategy. Systems that make progress tend to build confidence through early, visible wins. They encourage experimentation and co-creation across clinical, administrative, and technical teams and explicitly position automation as a tool to stabilize service levels rather than displace staff.

Equally important is adopting risk-proportionate governance and operating models. Not every use case warrants the same level of scrutiny or approval. Non-safety-critical automation — particularly in administrative, operational, and logistics functions — can and should move faster. Creating space for lower-risk use cases to scale builds organizational trust, frees capacity, and lays the groundwork for more complex clinical applications over time.

Balancing opportunity and constraint

The enablers described above are demanding. They require capital, coordination, regulatory courage, and sustained leadership attention. But the alternative — incremental steps in the face of accelerating demographic and workforce pressures — is not viable.

The difference between conservative and aggressive productivity trajectories does not depend upon access to better algorithms. It hinges on whether healthcare systems are willing to invest in the infrastructure, capabilities, operating models, and institutional trust required to let technology do what it is already capable of doing.

Bottom line: From tools to systems

Taken together, the enablers described in this chapter underscore a central insight: The constraint on healthcare productivity is no longer technological capability, but institutional readiness. Artificial intelligence, robotics, and automation are already mature enough to deliver meaningful gains. What determines whether systems realize incremental improvements or structural capacity expansion is how effectively infrastructure, capabilities, incentives, regulation, and operating models evolve in concert.

Progress in any single domain — technology investment without skills, automation without reimbursement alignment, or innovation without trust — will remain self-limiting. Fragmented adoption risks locking healthcare systems into a pattern of localized efficiency gains that fail to translate into systemwide impact.

The productivity reset therefore hinges on coordinated action. Regulatory modernization, capability buildup, interoperable infrastructure, and cultural reframing are not optional complements to innovation; they are its preconditions. The choice facing healthcare leaders is not whether technology is ready, but whether institutions are prepared to adapt fast enough to keep pace with what is already possible.

05

Select High-Impact Examples from the Oliver Wyman Health Technology Use Case Database

From Exhibit 18: High-impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

See the full table →

This chapter highlights a curated set of 200 high-impact use cases from **Exhibit 18**, drawn from Oliver Wyman's proprietary Healthcare Technology Use Case Database. Spanning artificial intelligence, specialized and humanoid robotics, and quantum technologies, these use cases form the practical foundation of the productivity scenarios modeled in this report.

They translate technological potential into operational reality. For each use case, we have captured a clear description, the primary impact mechanism, and estimated adoption rates under the breakthrough scenario through 2040. Together, they quantify how scaled deployment across workflows can bend cost curves and expand system capacity.

The use cases span the full healthcare ecosystem — clinical care, pharmaceuticals, medical devices, insurance, and government and public health — underscoring that productivity transformation is a systemwide opportunity, not a sector-specific initiative.

The sections that follow provide selected deep dives by sector, illustrating how these technologies move from point solutions to embedded, scalable operating capabilities capable of driving durable impact.

5.1

Clinical care delivery: Productivity under labor and capacity constraints

Productivity growth in healthcare has lagged other sectors for more than two decades. OECD analyses show that health-sector productivity has improved at a significantly slower pace than in the broader economy, contributing to rising unit costs and sustained budget pressure. Against this backdrop, care delivery represents the largest and most visible source of productivity strain across healthcare systems.

Rising demand driven by aging populations and the consequent rising prevalence of chronic disease is colliding with persistent workforce shortages, increasing clinical complexity, and care models still organized around manual, labor-intensive workflows. In many systems, productivity challenges manifest less as inefficiency than as capacity constraints that limit access, lengthen wait times, and strain clinical staff – particularly in hospital operations, perioperative settings, diagnostics, and care coordination.[106]

A defining feature of clinical care delivery is its labor intensity. Clinical and administrative personnel account for the majority of operating costs, yet a substantial percentage of their time is absorbed by activities that do not directly contribute to clinical decision making or patient interaction. Documentation, fragmented coordination across care pathways, discharge planning, and internal logistics consume growing shares of clinician and nursing capacity, while reimbursement and regulatory models are still largely anchored to face-to-face activity rather than outcomes.

As a result, productivity gains in clinical care delivery have historically been episodic and localized, with incremental efficiency improvements often absorbed by rising demand or offset by complexity. They fail to compound into durable, systemwide capacity expansion. This dynamic contributes to cost inflation, access constraints, and clinician burnout, reinforcing a cycle in which more resources are required simply to sustain current service.

Consequently, productivity improvement in care delivery is less about labor substitution and more about capacity extension, enabling scarce clinical resources to serve more patients, earlier and more effectively, while preserving safety and quality. Technologies that reduce administrative burden,[107] improve coordination, smooth patient flow, and support earlier intervention can unlock meaningful throughput and quality gains, particularly when embedded into redesigned workflows rather than layered ono existing ones.

Critically, the objective is not to replace the human dimensions of care, but to amplify them. By taking on routine, fragmented, and nonclinical tasks, productivity-enhancing technologies can enable the reallocation of clinician time to direct patient interaction, complex decision making, and relational care – areas where human judgment, empathy, and trust remain irreplaceable. A patient-centered approach therefore sits at the core of effective productivity strategies: Productivity gains are most durable when operational efficiency translates into improved access, experience, and outcomes, and materialize as tangible systemwide capacity relief.

Deep dives: How productivity is unlocked in practice

From Exhibit 18: High-impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

See the full table →

Deep dive 1:

Exception-based remote patient monitoring at scale

Remote patient monitoring (RPM) has expanded rapidly across chronic disease management, post-acute care, and hospital-at-home models. Early deployments often relied on continuous data review and fixed thresholds, generating large volumes of low-signal alerts that created a monitoring burden for already overextended clinical teams, which suggested the technology might face limited scalability.

AI-enabled anomaly detection, however, changes the operating model by learning patient-specific baselines and flagging only clinically meaningful deviations. Instead of reviewing all incoming data streams, clinicians intervene selectively when deterioration signals emerge, enabling exception-based oversight rather than continuous surveillance.

Systematic evidence indicates that RPM interventions can reduce acute care utilization in multiple settings. A 2024 systematic review concludes that RPM is associated with reduced risk of hospital admission/readmission and shorter hospital length of stay across multiple conditions, with effects varying by implementation design and escalation pathways. Within the same review, studies focused on digital sensor alerting systems — a close analogue to anomaly-driven RPM — found a mean reduction in hospitalization risk of approximately 9.6% in randomized trials relative to controls.[108]

A separate systematic review in JMIR mHealth and uHealth (2025) similarly finds that RPM possibly leads to fewer hospitalizations and shorter lengths of stay compared with more conventional care.[109] From a productivity perspective, these effects translate into capacity extension rather than labor substitution. Fewer admissions and avoided escalation help free inpatient capacity, while exception-based alerting reduces cognitive load and allows the same clinical teams to supervise larger patient panels without proportional staffing increases. This operating model also underpins hospital-at-home pathways: CMS' Acute Hospital Care at Home initiative allows participating hospitals to deliver inpatient-level care in patients' homes under waived requirements, reflecting a policy shift to extend capacity beyond traditional inpatient settings.[110]

Deep dive 2:

AI-assisted diagnostic imaging triage at scale

Radiology faces sustained demand growth alongside workforce shortages, making reporting backlogs and turnaround times a capacity constraint. AI tools deployed in diagnostic imaging have therefore focused less on autonomous diagnosis and more on triage, prioritization, and workflow support, enabling specialists to concentrate on the most clinically urgent cases.

Evidence from breast screening provides a clear productivity signal. A workflow-oriented analysis in the *British Journal of Radiology: Artificial Intelligence* reports that workforce modeling showed up to 40% workload reduction with AI as a supporting reader in breast screening, alongside improved turnaround time.[111] The productivity mechanism here is queue management — filtering low-risk studies and prioritizing suspicious cases — rather than replacing clinical judgment.

At the system level, national evaluation programs, such as NHS England's AI in Health and Care Award, emphasize operational endpoints (workflow integration, turnaround time, and backlog reduction) and reinforce that the largest gains occur when AI is embedded into live reporting workflows with clear governance rather than deployed as a stand-alone tool.

Deep dive 3:

Robotic assistance in long-term and elder care

Long-term and elder care face acute workforce constraints driven by physically demanding work, injury risk, and staff attrition. Task-specific robotics — particularly for transfer assistance and repositioning — targets a key driver of productivity loss: the high physical burden of routine care activities and the need to allocate scarce staff time to non-relational tasks.

Evidence from Japan, where care robots have been deployed in nursing homes, indicates measurable operational effects. A facility-level panel study in labor economics finds that robot adoption is associated with an increase in the number of residents receiving care and improvements in indicators linked to productivity and quality (including shifts in task allocation toward "human touch" tasks).[112] Complementing this, a clinical study on long-term use of the Resyone Plus transfer-support robot reports reductions in the need for multiple caregivers for transfers (i.e., fewer transfers requiring assistance from more than one caregiver), consistent with lower physical strain and more efficient allocation of staff time.[113]

The productivity gain is therefore best framed as workforce preservation and task reallocation rather than replacement: reducing physical burden and multi-person dependency helps stabilize staffing and frees caregiver capacity for supervision and relational care.

Deep dive 4:

Autonomous internal logistics in hospitals

Hospitals depend on continuous internal transport of sterile instruments, supplies, specimens, and waste. These logistics tasks consume staff time and introduce variability into care workflows. Autonomous mobile robots (AMRs) are increasingly deployed to automate routine transport in structured hospital environments.

A widely cited study of five AMR applications in hospital logistics concludes that AMRs can increase value-added time for patient care by reducing manual material handling.[114] Importantly, the paper contains concrete operational metrics from case implementations: In one sterile-instrument logistics case, an AMR delivered about 60 wagons daily and substituted for one full-time employee, demonstrating a direct labor-capacity release for internal transport tasks.

Operationally, these gains translate into smoother flow. By removing routine transport from human workflows, hospitals reduce interruptions to nursing and support staff and improve downstream processes such as specimen turnaround and instrument availability — freeing capacity that can be redirected toward patient care.

5.2 Pharmaceuticals: Bringing productivity to R&D, manufacturing, and regulation

Productivity challenges in the pharmaceutical sector are less visible to patients than in care delivery, but no less consequential for system sustainability, affordability, and innovation pace. Over the past two decades, the cost and complexity of bringing new therapies to market have increased materially, even as R&D productivity — measured in approvals per dollar invested — has declined across much of the industry. At the same time, manufacturing, quality, and regulatory requirements have grown more stringent, raising fixed costs and extending cycle times across product life cycles.

A defining feature of declining pharmaceutical productivity has been a general slowdown across multiple stages of the value chain rather than a single constraint. In clinical development, protocol complexity, protracted site activation, and clinical trial recruitment challenges lengthen timelines and increase failure risk. In manufacturing, especially with biologics and advanced modalities, yield variability, deviations, and unplanned downtime constrain output and reliability. In regulatory and quality functions, documentation-heavy processes and jurisdictional variation absorb significant expert time without directly advancing scientific or patient value.

Unlike care delivery, pharmaceutical productivity is not primarily limited by frontline labor availability, but by cycle time, the need for rework, and risk. Incremental inefficiencies compound across long development horizons and global supply networks, driving up unit costs and delaying patient access. As a result, productivity gains that are local — for example, within a single trial, plant, or function — often fail to scale unless they are embedded into standardized, end-to-end operating models.

Thus the highest-impact opportunities for AI, automation, and advanced analytics focus on accelerating learning cycles, reducing manual rework, improving predictability, and strengthening decision making — from trial design and site selection to deviation management, quality release, and post-market surveillance. The key to their success lies in their integration into validated workflows and governed operating models.

Critically, productivity improvement in pharmaceuticals is about augmenting scientific judgment and regulatory rigor, not limiting them. By automating documentation, pattern recognition, and routine decision support, technology can free scarce scientific, engineering, and quality expertise to focus on hypothesis generation, root cause analysis, and risk management. In this capacity, productivity is a prerequisite for sustaining innovation at scale: Gains are most durable when operational efficiency translates into faster development, more reliable supply, and earlier patient access without compromising safety or compliance.

Deep dives: How productivity is unlocked in practice

From Exhibit 18: High-impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

See the full table →

Deep dive 1:

Rewiring clinical development for speed, not certainty

For decades, pharmaceutical clinical development has been organized around a sequential, risk-averse logic designed to maximize certainty at each step before moving forward. While this approach has reduced late-stage failure risk, it has also contributed to steadily rising development timelines, increasing protocol complexity, and declining R&D productivity.[115] Today, the median time from first-in-human trial to approval often exceeds a decade, even as unmet medical need and competitive pressure demand faster innovation.

The constraint lies less in scientific capability than in how development decisions are made and revisited. Trial protocols are often locked in detailed specifications early in development, with site selection relying heavily on historical patterns and prior trial experience, and patient recruitment remaining slow and uneven. When assumptions prove wrong, amendments are costly and delays cascade. Learning cycles are long, and capital becomes locked into designs that are difficult to adapt once trials are underway.

AI and advanced analytics are enabling a shift from this sequential model toward learning-driven clinical development. Rather than optimizing for certainty upfront, leading organizations are using data and simulation to iterate faster, test assumptions earlier, and adapt protocols dynamically. AI-supported trial design tools can simulate enrollment scenarios, operational feasibility, and endpoint sensitivity before studies launch, reducing the likelihood of midtrial amendments. Real-world data and electronic health records are increasingly used to identify high-performing sites and eligible patient populations with greater precision, accelerating feasibility assessment and recruitment.

This shift is already visible in practice. Several large biopharma companies are integrating AI into site selection, protocol optimization, and patient identification to shorten cycle times without increasing risk. Roche[116] and Novartis[117] have publicly described the use of real-world data and advanced analytics to improve trial feasibility and recruitment, while Pfizer[118] has expanded decentralized and digitally enabled trial models to improve speed and patient reach. Contract research organizations such as IQVIA[119] are scaling AI-enabled feasibility and recruitment platforms across portfolios, embedding these tools into standard operating models rather than treating them as pilot technologies.

Critically, productivity gains come from changing the development operating model rather than automation alone. Faster trials require tighter integration between data science, clinical operations, and decision governance. Human judgment remains central, particularly in balancing speed, safety, and scientific validity, but is increasingly augmented by continuous data feedback rather than static plans. Organizations that succeed treat AI as an engine for faster learning across portfolios, not as a point solution.

The implications are significant. Shorter and more adaptive trials reduce development cost, bring therapies to patients sooner, and allow capital to be redeployed more efficiently across pipelines. At system level, this model also supports broader patient inclusion and more representative evidence generation, particularly when real-world data is used to complement traditional trial designs. Over time, clinical development productivity becomes less about avoiding failure at all costs and more about failing faster, learning earlier, and scaling what works.

This transition raises scientific or regulatory standards by making evidence generation more responsive, data-driven, and adaptive. As therapeutic complexity increases, learning-driven development is likely to become a prerequisite for sustaining innovation and affordability at scale.

Deep dive 2:

From batch reliability to predictive biomanufacturing at scale

Pharmaceutical manufacturing productivity has long been optimized for batch reliability rather than predictability. That model is increasingly under strain. As biologics and advanced modalities proliferate, small process deviations can cascade into batch failures, extended investigations, and supply disruptions. Manufacturing becomes a binding constraint on innovation because it remains insufficiently anticipatory.

This challenge is most acute in biologics and advanced therapies, where process variability is high, lead times are long, and buffering capacity is limited. Traditional approaches — standardization, documentation, and post-hoc root cause analysis — remain essential but struggle to keep pace with rising complexity. Investigations are labor-intensive, and learnings are often localized. This means improvements rarely compound across sites or products.

AI and advanced analytics enable a shift toward predictive biomanufacturing – using real-time process data, multivariate analytics, and digital twins to detect early process drift, anticipate variability, and intervene before deviations become failures. Predictive models support dynamic control strategies, more confident release decisions, and improved asset utilization. This shifts manufacturing from exception management to continuous optimization.

This new approach is already being applied. For instance, Roche has described how digitization and real-time data use are being embedded across operations to improve quality and efficiency.[120] Sanofi has outlined how AI, automation, and advanced analytics are being integrated across manufacturing and supply to move beyond siloed processes toward a connected ecosystem.[121,122] These examples reinforce the key point: Productivity gains come from changing how decisions are made and acted upon across engineering, quality, and operations, not isolated tools.

Regulators are also strengthening the enabling environment. The FDA has formalized support for advanced manufacturing through such programs as the Advanced Manufacturing Technologies Designation Program that are aimed at accelerating adoption of innovative approaches without compromising quality.[123,124] Predictive approaches still depend on high-quality data, robust validation, and transparent governance, with poor integration or weak change management eroding trust and limiting impact.

Deep dive 3:

From episodic submissions to continuous regulatory readiness

Pharmaceutical regulation has historically been organized around episodic submission cycles: Evidence is compiled, submitted, reviewed, and then updated through discrete variations. That model is still fit-for-purpose for many products, but it is increasingly misaligned with modern development and life cycle realities — particularly where evidence is continuously generated across trials, real-world use, safety surveillance, and manufacturing.

A growing share of regulatory and quality burden now sits in life cycle management: managing label updates, post-market commitments, periodic reporting, and cross-market consistency. Much of this work remains document-centric and manually intensive, absorbing scarce expert capacity and slowing iteration even when the underlying evidence is available.

AI and improved data integration enable a shift toward continuous regulatory readiness — building modular, living evidence bases that can be updated constantly and automatically as data emerge, rather than assembled as static dossiers. In practice, this means structured content reuse, automated consistency checks, and analytics-supported evidence compilation, with expert review focused on judgment-intensive decisions rather than repetitive document assembly and updating. Industry reporting indicates major drugmakers are already using AI to compress operational timelines for regulatory documentation and trial operations, signaling that this capability is moving from experimentation to scale.[125]

This shift represents an operating model change rather than a mere technology upgrade. Continuous readiness requires tighter integration between regulatory, safety, quality, development, and manufacturing teams, with clear accountability for data stewardship and decision governance. The prize is material: faster lifecycle updates, stronger cross-market consistency, and more timely alignment between evidence and patient access — without weakening standards. Roche's own framing on regulatory "speed and agility" reflects this broader direction of travel toward faster, more responsive pathways under sustained rigor.[126]

Deep dive 4:

From supply-chain efficiency to anticipatory access and resilience

Pharmaceutical supply chains have traditionally been optimized for efficiency under stable demand assumptions. Recent disruptions — from pandemics to geopolitical shocks — have exposed the fragility of this model. Drug shortages, uneven geographic availability, and delayed launches have underscored that supply reliability is now a strategic and reputational issue, not merely an operational one. The FDA's analysis of drug shortages highlights how quality and manufacturing issues create access constraints and impair patient care.[127]

The disruption generates a disconnect between upstream decisions and downstream realities. Manufacturing plans, release schedules, and distribution strategies are often set with limited visibility into real-time demand signals, epidemiological trends, or access bottlenecks. When conditions change, responses are reactive, slow, and costly — driving both shortages and waste.

AI and advanced analytics enable a shift toward anticipatory access management: integrating signals from clinical development, manufacturing, epidemiology, and commercial channels to simulate demand scenarios, identify supply risks earlier, and adjust production and distribution proactively. The productivity gain here is measured not only in cost, but in avoided emergency interventions, fewer stock-outs and write-offs, and improved ability to align supply with public health priorities — especially when new therapies are complex and supply-constrained.

This is also increasingly aligned with the broader global context: The World Economic Forum's recent work on global value chains emphasizes a "new operating reality" of persistent volatility and embedded disruption, reinforcing the need to treat resilience as a core operating requirement rather than an exception plan.[128] For pharmaceuticals, that translates into planning and access models designed to operate under uncertainty — strengthening reliability, trust, and equity in the delivery of medicines.

5.3 Medical devices: Productivity across innovation, manufacturing, and installed base performance

Productivity challenges in the medical technology sector sit at the intersection of innovation intensity, manufacturing precision, and long-lived installed bases operating in regulated clinical environments. Medtech companies face sustained pressure to accelerate product innovation while maintaining high standards of safety, reliability, and regulatory compliance — all within increasingly competitive and cost-constrained healthcare markets.

A defining feature of medtech productivity pressure is the need to iterate rapidly under regulatory constraint. Product development cycles are lengthening as devices become more software-enabled, interconnected, and data-intensive, while regulatory expectations around validation, traceability, and post-market monitoring continue to rise. Incremental delays or rework in design verification, clinical evidence generation, or submission preparation can materially affect time to market and life cycle value, particularly in fast-moving device categories.

At the same time, manufacturing and quality operations face growing complexity. High mix-low volume production, tight tolerances, and increasing customization limit the applicability of traditional scale efficiencies. Quality deviations, inspection bottlenecks, and unplanned downtime not only affect yield and cost, but can disrupt supply to care providers and erode trust. Unlike pharmaceuticals, where batch scale dominates, medtech productivity is often constrained by consistency, reliability, and speed of iteration across many product variants.

Beyond development and manufacturing, a substantial share of medtech value — and productivity opportunity — sits in the installed base. Devices operate for years in clinical settings, requiring service, maintenance, upgrades, and user support. Inefficient field service, reactive maintenance, and fragmented data flows between devices, manufacturers, and providers can drive avoidable cost while limiting uptime and clinical value. Productivity gains therefore depend on shifting from reactive to predictive service models and improving lifecycle visibility.

AI, automation, and advanced analytics are increasingly being deployed across medtech R&D, manufacturing, quality, and service operations to address these constraints. The highest-impact opportunities focus on accelerating design and validation cycles, improving inspection and yield, reducing rework, and increasing installed-base uptime through predictive monitoring. As with other sectors, impact depends less on individual technologies than on their integration into validated, end-to-end operating models that span engineering, quality, regulatory, and service functions.

By automating documentation, inspection, and routine decision support, technology can free engineering, quality, and service expertise to focus on complex problem-solving, innovation, and customer support. Durable productivity gains are achieved when operational efficiency translates into faster innovation cycles, more reliable supply, higher device uptime, and sustained clinical trust.

Deep dives: How productivity is unlocked in practice

From Exhibit 18: High-impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

See the full table →

Deep dive 1:

From sequential development to continuous device iteration

For medtech innovation, the biggest constraint is not engineering capability, but the gap between learning and implementation. Design assumptions are often validated late, human-factor issues surface after prototypes are locked, and verification activities remain heavily document-centric. When issues emerge, rework cascades across engineering, quality, and regulatory functions, delaying a product's market introduction.

AI-enabled simulation, digital twins, and advanced analytics are enabling a shift toward continuous device iteration. Rather than relying on physical prototypes and sequential testing, leading medtech companies are using virtual models to evaluate design options earlier, stress-test performance across use conditions, and identify failure modes before builds are finalized. This shortens iteration loops while improving confidence in safety and performance.

This shift is already visible in practice. GE HealthCare has deployed AI-enabled predictive services, such as OnWatch Predict, which use continuous equipment monitoring and digital-twin-based models to predict component wear and failure across imaging systems. This enables earlier intervention and reduce unplanned downtime by approximately 36%, saving over 18 hours of downtime per device annually.[129] The technology creates near-continuous uptime across imaging fleets.[130] Beyond service productivity gains, these capabilities reveal real-world performance patterns at scale.

Similarly, Siemens Healthineers applies digital-twin simulation to medical device manufacturing and production planning, allowing virtual testing of process changes, earlier identification of bottlenecks, and faster iteration under regulatory constraints.[131] By shifting validation and learning upstream into virtual environments, manufacturers can shorten development cycles while maintaining traceability and quality.

Productivity gains come from operating model changes. Continuous iteration requires tighter integration between engineering, quality, regulatory, and manufacturing teams, with clear governance over model use and decision authority. While human judgment remains central — particularly in balancing innovation speed with safety and compliance — it is increasingly augmented by earlier, richer, and more actionable information.

Regulatory frameworks are evolving in parallel. The US FDA's principles on Good Machine Learning Practice (GMLP) explicitly recognize the role of modeling, simulation, and continuous learning in medical-device development, emphasizing lifecycle oversight rather than static validation.[132] When implemented with appropriate controls, continuous device iteration improves speed and learning without compromising regulatory trust.

Over time, this shift enables medtech companies to move from episodic innovation to learning-driven product lifecycles, where insights from design, manufacturing, and real-world use are continuously reintegrated. Productivity gains materialize not simply as faster launches, but as more reliable products, fewer late-stage failures, and sustained clinical trust — allowing innovation to scale without increasing risk.

Deep dive 2:

Quality at the speed of innovation

Ensuring quality is the guiding principle for medtech manufacturing. Many medtech environments – particularly for capital equipment, implantables, and software-enabled devices — operate in high-mix, low-volume environments with tight tolerances and growing customization. Manual inspection, deviation handling, and corrective actions consume significant capacity and slow throughput — particularly as product variants proliferate.

Traditional quality models rely heavily on end-of-line inspection and retrospective investigation. While effective for compliance, these approaches do not scale with innovation speed. Quality teams spend disproportionate time reviewing routine issues, while early signals of systemic problems are often missed.

AI-enabled visual inspection and real-time quality analytics enable a shift from inspection to prevention. Computer vision systems can detect defects with greater consistency than manual inspection, while analytics identify process drift before non-conformances occur. This allows quality functions to focus on exception management and root-cause prevention rather than volume review, improving both throughput and reliability.

At scale, the productivity opportunity is inseparable from disciplined quality systems. Medtronic's supplier quality expectations emphasize process capability, production controls, and systems that maintain conformance to specifications — underscoring how quality performance is governed end-to-end, not simply checked at the end.[133] FDA inspection guidance on design controls similarly emphasizes traceability from user needs through design verification and validation — highlighting why quality has to be engineered into the lifecycle rather than added after the fact.[134]

Regulatory frameworks support this shift when controls are robust. FDA's Quality System Regulation (Part 820) sets expectations for design and production controls, documentation, and corrective/preventive action — requirements that advanced inspection and analytics must satisfy through validation, traceability, and appropriate oversight.[135] Productivity gains are therefore achieved not by weakening standards, but by making quality systems more scalable, proactive, and data driven.

Deep dive 3:

From reactive service to self-monitoring devices

For many medtech companies, the installed base represents the largest share of lifecycle value — and a major source of hidden productivity loss. Reactive service models rely on failure reporting, manual diagnostics, and on-site interventions, driving high cost, device downtime, and disruption for providers.

As devices become connected, telemetry data enables a shift toward self-monitoring devices and predictive service. Sensors and analytics detect performance degradation early, trigger remote diagnostics, and schedule service proactively before failure occurs. This improves uptime, reduces emergency interventions, and optimizes field-service utilization.

This model is already operating at scale. GE HealthCare uses predictive analytics to monitor imaging equipment and reduce unplanned downtime.[136] Philips has similarly highlighted remote monitoring and predictive service as core to improving device reliability and provider experience.[137]

Peer-reviewed evidence shows that AI can materially improve the predictability of critical medical equipment failure, anticipating certain failure mode one to two days in advance, based on real-time device sensor data.[138]

Productivity gains extend beyond service cost. Higher uptime improves clinical throughput, reduces rescheduling, and strengthens trust with providers. Over time, self-monitoring devices also enable software updates, performance optimization, and outcome-linked service models — shifting medtech economics from break-fix to continuous value delivery.

Deep dive 4:

Regulation as a learning loop

Medtech regulation has traditionally emphasized pre-market assurance, with post-market surveillance focused on adverse event reporting and corrective action. As devices become software-driven and continuously updated, this static model is under strain. Learning increasingly happens after deployment, but regulatory processes are not always designed to absorb and act on that learning efficiently.

AI-enabled post-market surveillance and real-world performance analytics are enabling a shift toward regulation as a learning loop. Continuous monitoring of device performance, usage patterns, and outcomes allows earlier detection of issues and faster, safer iteration. Evidence generation becomes ongoing rather than episodic, supporting timely updates without compromising safety.

Regulatory frameworks are evolving accordingly. FDA guidance on Predetermined Change Control Plans (PCCPs) explicitly recognizes controlled, continuous updates to AI-enabled device software functions, creating a pathway for iteration under predefined conditions and oversight.[139] Internationally, IMDRF's Good machine learning practice for medical device development: Guiding principles emphasizes lifecycle monitoring, transparency, and governance as foundations for safe iteration.[140]

When regulatory frameworks support continuous feedback from real-world performance, manufacturers can align quality and safety with measurable operational benefits, such as 30-36% reductions in downtime attributed to predictive analytics, underscoring regulation's role as an accelerator, not a barrier to productivity.[141]

For manufacturers, this shift improves productivity by reducing friction in updates, strengthening regulatory confidence, and aligning innovation with real-world performance. For regulators and providers, it improves transparency and safety. Regulation, in this model, becomes an enabler of faster learning rather than a brake on iteration — allowing medtech innovation to scale responsibly.

5.4 Health insurance: Productivity across administration, risk management, and care coordination

A defining feature of insurance productivity pressure is the sheer scale of transaction-intensive processes. Claims volumes continue to rise with utilization, benefit designs have grown more complex, and regulatory requirements have expanded, increasing manual review, exception handling, and rework. As a result, administrative costs and cycle times remain high, and friction at payer–provider interfaces contributes materially to delays, dissatisfaction, and avoidable systemwide cost.

Unlike care delivery or life sciences, insurance productivity is not primarily constrained by scientific uncertainty or manufacturing precision, but by process fragmentation, information asymmetry, and risk management under regulatory scrutiny. Incremental automation within individual functions — such as claims intake or customer service — has delivered local efficiency gains, but these gains often fail to compound when workflows remain siloed and decision logic is duplicated across functions.

At the same time, insurers play a critical role in shaping downstream system productivity. Inefficient authorization processes, slow claims resolution, and opaque benefit interpretation can drive avoidable provider burden and consumer care provider resources and also dilute incentives for efficient care delivery. Productivity challenges in insurance therefore have systemwide implications, extending beyond the payer balance sheet to provider capacity, access, and total cost of care.

AI, automation, and advanced analytics are increasingly being applied across insurance operations to address these constraints. The highest-impact opportunities focus on reducing manual processing, accelerating decision cycles, improving anomaly detection, and coordinating actions across claims, utilization management, care management, and service operations. As in other sectors, productivity gains usually depend on end-to-end workflow redesign, data integration, and clear governance over automated decisions.

By automating routine decisions and prioritizing human review where judgment is required, insurers can reduce friction for providers and members while strengthening program integrity. Durable productivity gains are achieved when operational efficiency translates into faster access decisions, lower administrative burden, and more effective coordination of care — supporting affordability and access across the system.

Deep dives: How productivity is unlocked in practice

From Exhibit 18: High-impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

See the full table →

Deep dive 1:

Prior authorization modernization as a productivity lever

While prior authorization is most visible — and most extensively documented — in the United States, similar utilization review and pre-approval processes exist across many health systems under different institutional forms. The underlying productivity challenge — manual, fragmented decision workflows at the payer–provider interface — is therefore broadly applicable beyond the US context.

Prior authorization is one of the largest sources of avoidable administrative workload at the payer–provider interface, and a key reason productivity gains in healthcare fail to translate into frontline capacity. The operational burden is substantial: the American Medical Association reports that practices complete an average of 39 prior authorization requests per physician per week and spend 13 hours per week on the process. Forty percent of physicians report staff who work exclusively on prior authorization and 89% report PA contributes to burnout.[142] This is time not spent on patient care, and it creates cycle-time friction across the system.

The productivity opportunity lies in increasing automation, moving PA from fragmented, manual workflows to standardized digital exchange with predictable decision timelines. The Centers for Medicare and Medicard Services (CMS) have already pushed in this direction with the Interoperability and Prior Authorization Final Rule

(CMS-0057-F), which aims to improve electronic data exchange and streamline PA processes.[143] CMS estimates these policies will generate approximately $15 billion in savings over 10 years through reduced administrative burden and improved process efficiency.[144]

Productivity gains come from reducing rework, shortening decision cycles, and standardizing data exchange so exceptions are reviewed by humans while routine requests flow through faster and more transparently. In practice, this is one of the few payer-side levers that directly releases provider-side capacity at scale.

Deep dive 2:

Claims automation and straight-through processing at scale

While the most granular benchmarking on claims automation comes from the United States, where transaction standards and reporting are relatively mature, similar claims adjudication and reimbursement workflows exist across most multi-payer health systems. The underlying productivity opportunity — reducing manual handling through standardized, electronic transactions — is therefore broadly applicable beyond the US context.

Claims operations remain highly transaction-intensive, with manual handling concentrated in intake, document review, exception routing, and follow-up. Even modest improvements in straight-through processing can release large volumes of administrative capacity because claims throughput scales exponentially with automation coverage.

Independent benchmarking reinforces the magnitude of the administrative opportunity. In the US, the CAQH Index estimates that $89 billion is spent on the administrative transactions it tracks (eligibility, claims, prior auth, etc.), and that the industry could save $18.3 billion annually by transitioning to fully electronic transactions in the areas assessed.[145] The 2025 CAQH update also frames a $20 billion opportunity to reduce administrative waste and improve access as electronic automation adoption rises.[146]

The productivity mechanism is clear: document ingestion and rule-based adjudication are automated for routine claims, while AI/NLP supports rapid classification and exception handling so human work focuses on edge cases. This is most effective when paired with interoperability standards and disciplined claim-edit governance rather than piecemeal automation.

Deep dive 3:

Payment integrity and fraud/waste/abuse analytics

Payment integrity is a major productivity and affordability lever because it reduces leakage while concentrating human investigation on the highest-yield anomalies. The scale is non-trivial: a 2024 systematic review notes that estimates of healthcare expenditure lost to fraud range from 3% to 10% of total spending, highlighting why detection and prevention remain core to system sustainability.[147,148]

At national scale, Korea's Health Insurance Review and Assessment Service (HIRA) provides a model of centralized claims review and assessment. Peer-reviewed descriptions of the HIRA data ecosystem note that claims data in Korea cover 46 million patients per year (approximately 90% of the population) and include submissions from 80,000 healthcare service providers (as of 2011), illustrating the scale at which analytics can be applied when data are centralized. OECD analysis of Korea's integrated health information architecture highlights HIRA's role in claims review and data infrastructure, reinforcing the feasibility of data-driven program integrity at population scale.[149]

The productivity gain is twofold: Fewer improper payments reduce downstream rework and disputes, while analytics-driven case prioritization increases investigator yield by focusing human review where it is most likely to recover funds or prevent recurrence.

Deep dive 4:

Precision risk stratification and proactive care management

A large share of payer value creation depends on identifying members at high risk of avoidable utilization and intervening early through care management, navigation, and adherence support. The constraint: Without high-precision stratification, care management can become broad outreach with weak yield.

Digital risk stratification combines claims history, utilization patterns, and clinical proxies to prioritize outreach and tailor interventions. The productivity mechanism is that care managers spend less time on low-yield outreach and more time on high-risk members with actionable gaps, improving avoided utilization per care-manager hour.

This logic is closely linked to the administrative modernization agenda as well: In the US, CMS policy direction emphasizes improved data exchange and interoperability across payers and providers to reduce burden and improve coordination, which is a prerequisite for targeting and scaling proactive care management.[150]

In systems where payer–provider data exchange is mature, risk stratification enables a shift from reactive utilization management to proactive prevention, improving both affordability and access while reducing administrative load created by avoidable escalations.

5.5 Government and public health: Productivity as system stewardship and resilience

Productivity challenges in government and public health differ fundamentally from those in care delivery, insurance, or life sciences. Public-sector health functions are responsible not only for service delivery and financing, but for system stewardship: ensuring access, affordability, preparedness, and resilience across entire populations. These responsibilities are carried out under tight fiscal constraints, high public accountability, and complex governance structures that span national, regional, and local institutions.

A defining feature of productivity pressure in the public sector is the scale and heterogeneity of administrative and coordination tasks. Public payers and health agencies manage large volumes of eligibility determinations, claims oversight, program integrity activities, reporting obligations, and inter-agency data exchanges — often across fragmented legacy systems and inconsistent standards. Manual processing, duplication of effort, and limited interoperability consume significant administrative capacity without directly improving health outcomes.

At the same time, governments face rising expectations around preparedness and responsiveness. Recent shocks — from pandemics to supply disruptions — have exposed the limitations of traditional public health surveillance, early warning systems, and emergency coordination. Delayed signal detection, slow data aggregation, and rigid operational models reduce the ability of public institutions to anticipate and respond to emerging risks, increasing downstream human and economic costs.

Unlike private-sector actors, public health productivity is not measured primarily in margin or throughput, but in timeliness, coverage, and reliability at population scale. Incremental efficiency gains within individual agencies often fail to translate into system-wide impact when coordination across ministries, payers, providers, and international bodies remains weak. As a result, productivity improvements must address not only internal operations, but also the interfaces between public institutions and the broader health ecosystem.

AI, automation, and advanced analytics are increasingly being explored to address these constraints across public health surveillance, program administration, fraud and waste detection, and data interoperability. The highest-impact opportunities focus on accelerating information flows, reducing manual processing, improving anomaly detection, and enabling earlier intervention — particularly in settings where delays and fragmentation have disproportionate consequences. As in other sectors, impact depends less on isolated tools than on integration into governed, accountable operating models.

In government and public health, productivity improvement is not about reducing oversight or public accountability, but about strengthening state capacity. By automating routine administrative tasks, improving data integration, and supporting decision making under uncertainty, technology can allow public institutions to focus scarce expertise on policy design, risk management, and crisis response. Durable productivity gains are achieved when operational efficiency translates into faster service delivery, stronger preparedness, and greater trust in public health systems — reinforcing their ability to act as effective stewards of population health.

Deep dives: How productivity is unlocked in practice

From Exhibit 18: High-impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

See the full table →

Deep dive 1:

Public health epidemic intelligence at scale

Public health agencies face an increasingly complex surveillance challenge: potential outbreaks and health threats emerge faster and across more channels than traditional indicator-based systems can capture. Manual monitoring of reports, media, and informal signals is labor-intensive and difficult to scale, particularly when early signals are weak, ambiguous, or geographically dispersed.

Epidemic intelligence systems address this constraint by automating the collection, filtering, and triage of large volumes of open-source information, allowing human analysts to focus on verification and response rather than exhaustive scanning. The productivity gain comes from shifting public health surveillance from manual review to prioritized signal assessment.

The Epidemic Intelligence from Open Sources (EIOS) initiative, led by the World Health Organization, illustrates the scale at which this model is now operating. According to WHO, EIOS is currently used by 120 countries and 30 partner organizations and networks, supporting early detection and assessment of public health threats without proportional increases in surveillance staffing.[151] This reflects a transition from isolated national monitoring efforts to a shared global intelligence infrastructure.

WHO's EIOS Strategy 2024–2026 further clarifies the productivity logic of this approach, positioning EIOS as a core system for strengthening early warning, improving collaboration across countries, and accelerating the identification of signals that require public health action.[152] By centralizing signal detection and standardizing triage processes, EIOS allows national and regional teams to expand situational awareness while concentrating expert capacity on the most credible risks.

From a productivity perspective, epidemic intelligence platforms extend the effective reach of public health surveillance. Automated scanning and prioritization increase the number of potential signals assessed, while human expertise is reserved for validation, risk assessment, and response coordination. This enables earlier intervention and improves preparedness without requiring linear growth in public health workforce capacity.

As health threats become more frequent and interconnected, epidemic intelligence systems such as EIOS demonstrate how governments can increase early-warning capacity and response readiness through workflow redesign and shared digital infrastructure, rather than through additional staffing alone.

Deep dive 2:

National AI deployment for time-critical diagnostics

Government-backed national deployments of AI can generate productivity gains when they target the most time-sensitive pathways — where minutes translate into outcomes — and when rollout is standardized across networks rather than confined to pilots. Stroke care is a high-salience example because capacity and outcomes depend heavily on speed of diagnosis and referral.

In England, the Government reported that the Brainomix e-Stroke system – an AI system revolutionising NHS stroke care – reduced "door in and out" time from 140 minutes to 79 minutes. Government funding enabled more than 111,000 suspected stroke patients to benefit from the system across five stroke networks.[153] More recently, NHS England reported that an AI tool has been rolled out to a network of over 70 hospitals, helping clinicians identify clots faster and supporting timelier thrombectomy access, which NHS England states can double chances of regaining independence after a major stroke.[154]

The productivity gain comes through system-level time compression: faster triage reduces avoidable delays, improves routing to specialist centers, and increases throughput in time-critical pathways without proportional expansion in specialist workforce.

Deep dive 3:

National health data platforms as an enabling infrastructure

Public programs and ancillary health services depend on digital data infrastructure that supports continuity of care, program administration, population analytics, and system learning. When records and transactions are fragmented across providers and administrative silos, productivity losses accumulate through duplicate data entry, manual record transfer, and delayed decision making. National health data platforms address this constraint by standardizing repositories and enabling secure access across providers, payers, and citizens.

Finland's Kanta Services uses a platform considered among the most mature national digital health platforms globally. The platform comprises shared services including the national Patient Data Repository and the MyKanta patient portal, which stores electronic medical records, prescriptions, laboratory results, and other clinical information in a central system accessible to both providers and patients. According to peer-reviewed evidence, 92% of Finnish adults ages 18 to 65 had used the national My Kanta patient portal by 2021, reflecting widespread adoption of the infrastructure across the population.[155]

All public and private healthcare providers and pharmacies in Finland are connected to the Kanta data services, ensuring that clinical data are transferred securely and centrally upon capture in electronic systems, rather than residing in separate local silos.[156]

Once a common data platform is in place, downstream processes shift from bespoke data chasing to standardized reuse. This reduces administrative friction — eliminating separate requests for records for instance — and accelerates referrals and care coordination. It also supports public health reporting and research. Over the long term, national platforms like Kanta multiply productivity by enabling routine interoperability, reducing duplicate documentation work, and supporting analytics that drive better resource allocation.

Finland's experience illustrates how investment in digital infrastructure can unlock systemwide productivity gains: When data flow reliably between organizations and end users, administrative overhead shrinks and capacity is freed for higher-value tasks across the health system.

Deep dive 4:

Regulatory sandboxes to accelerate safe adoption

A central constraint on deploying novel AI-enabled health technologies is not only technical performance but also regulatory uncertainty: how to validate, monitor, and update systems safely under real-world conditions. Regulatory sandboxes provide a controlled environment to resolve novel questions faster, reducing friction for innovators while strengthening oversight.

The UK Medicines and Healthcare products Regulatory Agency (MHRA) launched AI Airlock as its first regulatory sandbox for AI as a Medical Device, aimed at accelerating solutions to novel regulatory challenges.[157] Regulatory reporting indicates that the pilot is expected to include four to six projects to test a range of issues, including real-world deployment and governance.[158]

The productivity gain is twofold: Innovators reduce time lost to uncertainty and rework, while regulators build reusable frameworks that speed subsequent evaluations. Over time, this shifts adoption from ad hoc negotiations to standardized pathways — supporting scale without weakening public trust.

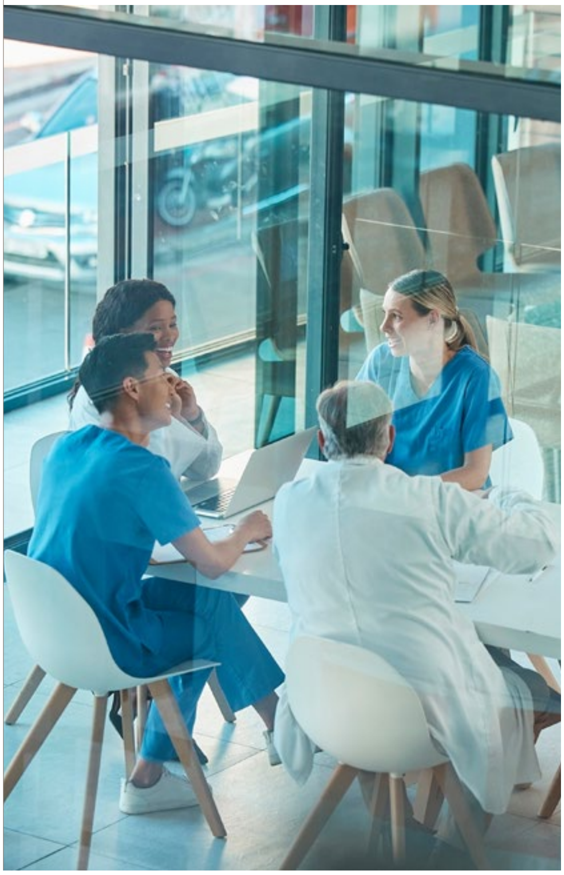


Exhibit 18

Selected High-Impact use cases from the Oliver Wyman Healthcare Technology Use Case Database

1.1 Research

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%): 2030	Est adoption magnitude (%): 2035	Est adoption magnitude (%): 2040
OWR00103	AI literature/patent mining & hypothesis generation		✓	✓			LLMs mine publications, patents, and internal reports to surface evidence, contradictions, and novel hypotheses.	Cuts researcher time spent on search/synthesis and improves decision quality in target and portfolio reviews.	25 – 49%	50 – 74%	75 – 100%
OWR00102	AI IP landscaping & freedom-to-operate scouting		✓	✓			AI scans patents, filings, and publications to map IP landscapes, detect infringement risks, and guide filing strategy.	Reduces manual search cost and accelerates IP decisions during discovery and device design.	50 – 74%	75 – 100%	75 – 100%
OWR00099	AI-driven biomarker discovery for stratified therapies		✓	✓			AI discovers predictive and pharmacodynamic biomarkers from omics, imaging, and real-world outcomes to enable precision therapies and devices.	Improves trial success and label differentiation by identifying responsive subpopulations and monitoring markers earlier.	25 – 49%	50 – 74%	75 – 100%
OWR00100	AI-enabled target identification & prioritization		✓	✓			ML integrates multi-omics, real-world data, and literature to identify and prioritize novel disease targets.	Raises probability of technical success and reduces early discovery cycle time by focusing experiments on high-confidence targets and pathways.	25 – 49%	50 – 74%	75 – 100%
OWR00107	AI-enabled small-molecule design & lead optimization		✓				Generative AI proposes novel small molecules optimized for potency, selectivity, and developability constraints.	Cuts design-make-test cycles and increases hit/lead quality, reducing cost per candidate and accelerating portfolio throughput.	25 – 49%	50 – 74%	75 – 100%
OWR00106	AI-enabled protein/antibody design & lead optimization		✓	✓			AI designs proteins/antibodies/enzymes (sequence and structure) to meet functional and manufacturability targets.	Accelerates biologics discovery and improves developability, reducing attrition and time to IND.	25 – 49%	50 – 74%	75 – 100%
OWR00108	AI-assisted synthesis planning and retrosynthesis		✓				AI suggests synthesis routes and retrosynthesis plans, optimizing for cost, safety, and supply availability.	Reduces time spent on route scouting, improves yield and scalability decisions, and speeds up make-cycles for medicinal chemistry.	25 – 49%	50 – 74%	75 – 100%
OWR00109	AI-driven phenotypic screening and image-based assay interpretation		✓	✓			Computer vision analyzes high-content imaging and phenotypic screening to quantify cellular responses and identify novel mechanisms.	Increases throughput and consistency of phenotypic screens, improving hit discovery for complex biology and reducing manual annotation.	50 – 74%	75 – 100%	75 – 100%
OWR00113	AI-assisted Evidence Synthesis & Living Guidelines		✓	✓		✓	LLM-enabled tooling accelerates literature search, screening, data extraction, and drafting to keep evidence reviews continuously updated.	Cuts time-to-guideline updates and improves policy/HTA responsiveness with lower analyst burden.	25 – 49%	50 – 74%	50 – 74%
OWR00251	AI knowledge-graph drug repurposing (indication expansion)		✓				Use AI over biomedical knowledge graphs to predict new drug–disease links for approved or clinical-stage compounds and prioritize repurposing candidates.	Cuts hypothesis-generation time, improves hit rates for repurposing candidates, and reduces early discovery spend by focusing wet-lab and clinical validation on high-probability mechanisms.	50 – 74%	75 – 100%	75 – 100%
OWR00253	AI transcriptomic signature matching for drug repurposing (CMap/LINCS-style)		✓				Match disease gene-expression signatures to drug-induced signatures to identify compounds that may reverse disease biology and support repurposing hypotheses.	Improves repurposing target selection and shortlists candidates faster by using scalable 'signature reversal' screens before committing to expensive in vivo studies.	50 – 74%	50 – 74%	75 – 100%
OWR00267	AI real-world evidence mining for repurposing signals		✓				Apply causal ML and pharmacoepidemiology on EHR/claims/registry data to detect off-label effectiveness signals and prioritize repurposing/label expansion opportunities.	Reduces cost and cycle time to identify promising indications, improves trial prioritization, and supports faster go/no-go decisions for repurposed assets.	25 – 49%	50 – 74%	75 – 100%
OWR00268	AI evidence triage of clinician-reported off-label outcomes		✓				AI repurposing using clinician-reported off-label outcomes (crowdsourced evidence triage)	Use AI to mine structured clinician reports of novel drug uses and triage signals into prioritized repurposing hypotheses and validation studies.	0 – 24%	25 – 49%	50 – 74%
OWR00111	In-silico ADMET/toxicity prediction & early de-risking		✓				Predictive models estimate ADMET, tox, and DMPK properties early to de-risk candidates before expensive studies.	Reduces late-stage attrition and animal study burden, improving portfolio economics and speed.	50 – 74%	75 – 100%	75 – 100%
OWR00110	Robotic high-throughput screening with AI-guided active learning		✓				Robotic high-throughput screening (HTS) runs and analyzes millions of assays with AI-guided active learning.	Boosts screening capacity and improves hit rates while reducing manual labor and error/rework.	50 – 74%	75 – 100%	75 – 100%
OWR00101	Robotic biobanking and sample management		✓	✓			Robots automate biobank intake, labeling, storage, retrieval, and chain-of-custody for biological samples and device components.	Improves sample integrity and throughput while reducing errors and enabling larger-scale translational research.	50 – 74%	50 – 74%	75 – 100%
OWR00105	Robotic automated Wet Labs		✓	✓			Robots execute repeatable wet-lab experiments guided by AI for high-throughput screening.	Boosts experimental velocity and reproducibility with fewer human errors.	25 – 49%	25 – 49%	50 – 74%
OWR00098	Self-driving / autonomous laboratories (closed-loop experimentation)		✓	✓			Self-driving labs combine robotics and AI to design, run, and iterate experiments with minimal human intervention.	Enables 24/7 experimentation, higher reproducibility, and faster learning cycles—dramatically increasing R&D throughput.	0 – 24%	25 – 49%	50 – 74%

0 – 24% | 25 – 49% | 50 – 74% | 75 – 100%

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%): 2030	Est adoption magnitude (%): 2035	Est adoption magnitude (%): 2040
OWR00097	Quantum sensing for ultra-sensitive assay and instrumentation monitoring		✓	✓			Quantum sensors enable ultra-sensitive measurement (magnetic, gravimetric, optical) to improve assay instrumentation and biosignal detection in R&D.	Improves sensitivity and reproducibility of measurements, enabling earlier detection of weak signals and reducing experimental noise and rework.	░	░	░
OWR00104	Quantum-enabled molecular simulation for hard chemistry problems		✓				Hybrid quantum–classical simulations improve modeling of molecular energies and interactions for drug design.	Could reduce synthesis iterations and improve prediction of binding/selectivity for hard chemistry problems by late 2030s.	░	░	░
OWR00112	Quantum-enhanced Formulation and Polymorph Prediction for Solid-State Drugs		✓				Use quantum chemistry and hybrid quantum-classical simulation to predict polymorph stability and excipient interactions to accelerate formulation.	Reduces late-stage formulation failures, shortens time to stable dosage forms, and improves manufacturability for complex molecules.	░	░	░
OWR00271	Quantum-accelerated virtual screening for repurposing		✓				Quantum-accelerated virtual screening for repurposing (late-2030s frontier)	Use hybrid quantum–classical workflows to accelerate virtual screening and binding/optimization for repurposing large libraries against complex targets.	░	░	░

1.2 Development

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%): 2030	Est adoption magnitude (%): 2035	Est adoption magnitude (%): 2040
OWD00119	AI-agentic clinical operations planning		✓				Agentic AI orchestrates study startup tasks (budgets, contracts, ethics packages, document routing) across CTMS and partners.	Shortens startup timelines and reduces coordination overhead between sponsor, CRO, and sites.	░	▒	▓
OWD00125	AI-driven site selection and feasibility forecasting		✓	✓			AI ranks sites and investigators using performance, patient availability, and operational constraints to improve feasibility.	Reduces start-up delays and improves enrollment rates, cutting overall clinical timelines and CRO cost.	▓	█	█
OWD00122	AI-enabled patient recruitment, prescreening & eConsent support		✓	✓			AI prescreens and matches patients to trials using EHR/RWE, including multilingual outreach and eConsent support.	Improves enrollment speed and diversity while lowering recruitment cost per patient.	▒	▓	█
OWD00121	AI-optimized clinical trial protocol & statistical plan generation		✓	✓			AI designs protocols and statistical plans, optimizing endpoints, inclusion criteria, and sample size using prior data.	Shortens study start-up, improves feasibility, and increases probability of success while reducing amendments.	▒	▓	█
OWD00120	AI pharmacometrics & dose optimization (PK/PD, exposure-response)		✓				AI augments pharmacometrics with faster model selection, covariate discovery, and simulation for dose and regimen optimization.	Improves dose decisions and may reduce number of cohorts/amendments, increasing success rates and speed.	▒	▓	█
OWD00126	AI-powered risk-based monitoring and centralized oversight		✓	✓			AI enables risk-based monitoring by predicting site/data issues and focusing monitoring effort where it matters most.	Cuts monitoring cost and reduces quality issues by shifting from blanket SDV to targeted oversight.	▓	█	█
OWD00123	AI-assisted clinical data cleaning, query management & SDV automation		✓	✓			AI automates query generation, source data verification, and data cleaning to reduce manual effort in EDC/SDTM pipelines.	Cuts database lock timelines and reduces errors, enabling faster analyses and submissions.	▒	▓	█
OWD00124	GenAI medical writing for protocols, CSRs, CTDs and IBs		✓	✓			GenAI drafts clinical and regulatory documents (protocols, CSRs, IB, CTD modules) with traceable source citations.	Reduces cycle time and cost of documentation, enabling faster submissions and more consistent quality.	▒	▓	█
OWD00116	Digital endpoints with wearables + AI anomaly detection		✓	✓			AI derives validated digital endpoints from wearable and sensor data for decentralized trials and device studies.	Enables remote measurement, reduces site visits, improves patient retention, and generates richer longitudinal data.	▒	▓	█
OWD00128	AI-assisted Design Controls Traceability & Risk Management for Medical Devices			✓			Use AI to automate requirements traceability, hazard analysis, and design documentation updates across the medical device design-control lifecycle (ISO 13485/14971)	Reduces engineering documentation burden, lowers audit findings, speeds design iterations and submissions, and improves consistency of risk files and DHF/DMR artifacts.	▒	▓	█
OWD00096	AI Clinical Trial Matching at Point of Care		✓	✓		✓	AI screens EHR data against eligibility criteria to identify trial candidates and automate outreach and pre-screening.	Boosts enrollment speed and diversity while reducing coordinator workload and accelerating evidence generation.	░	▒	▓
OWD00118	AI-enabled synthetic control arms and RWE comparators		✓				AI builds synthetic control arms from real-world data to reduce control enrollment and improve feasibility.	Can cut trial cost and accelerate enrollment while maintaining statistical rigor when appropriate.	░	▒	▓
OWD00127	In-silico trials / digital twins to optimize device and combination-product studies		✓	✓			In-silico trials use virtual patients and device/drug models to supplement evidence and optimize design and protocols.	Can reduce physical trial burden and shorten development timelines, especially for medtech and combination products.	░	▒	▓
OWD00114	Quantum sensing-based diagnostic devices for non-invasive diagnostic of patients	✓		✓			Quantum sensors enable ultra-sensitive measurement (magnetic, gravimetric, optical) that can allow for new non-invasive and at distance monitoring of patients in clinical settings	Improves sensitivity and reproducibility of measurements, simplifies diagnostic process and reduces time with patient setup	░	░	░
OWD00115	Quantum-secure collaboration for sensitive trial and IP data (QKD/PQC)		✓	✓			Quantum-safe security (PQC and, later, quantum key distribution) protects clinical, genomic, and IP data shared across ecosystems.	Enables trusted cross-company learning and decentralized research collaborations without raising long-term breach risk.	░	░	░
OWD00117	Quantum/hybrid optimization for trial network scheduling and supply planning		✓				Hybrid quantum optimization explores large design spaces for trial scheduling, patient routing, and trial supply distribution.	May reduce delays and waste in complex multi-country trial networks by late 2030s.	░	░	░

░ 0 – 24%
▒ 25 – 49%
▓ 50 – 74%
█ 75 – 100%

2.1 Care delivery

OWC Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Pharma	Medical Devices	Insurance	Government/ other	Description	Impact	Est adoption magnitude (%) 2030	2035	2040
OWC00188	AI-based Ambient Clinical Documentation	✓					Ambient AI captures clinician-patient dialogs and generates structured notes integrated with the electronic health record (EHR).	Reduces documentation time and burnout while improving note quality and completeness.	25 – 49%	25 – 49%	50 – 74%
OWC00013	AI Personalized Treatment Planning	✓					AI synthesizes clinical, genomic, and social determinants data to recommend individualized care plans.	Improves outcomes and reduces unnecessary utilization through tailored decisions.	0 – 24%	25 – 49%	50 – 74%
OWC00026	AI Diagnostic Imaging & Pathology	✓		✓			AI analyzes imaging and pathology slides to flag findings, quantify disease, and prioritize cases for review.	Speeds diagnosis and increases accuracy, improving outcomes and reducing backlogs.	50 – 74%	50 – 74%	75 – 100%
OWC00002	Agentic Care Coordination	✓			✓		Agentic (autonomous, goal-directed) AI agents orchestrate cross-team tasks, data, and communications to proactively align patients with services, close care gaps, and streamline handoffs.	Reduces delays and fragmentation, improving outcomes and experience while lowering administrative overhead.	25 – 49%	50 – 74%	50 – 74%
OWC00006	Autonomous Disinfection Robots	✓	✓	✓		✓	Robots autonomously disinfect rooms using AI navigation and validated protocols.	Lowers infection risk, standardizes cleaning, and saves labor.	25 – 49%	50 – 74%	75 – 100%
OWC00025	AI-based predictive patient deterioration alerts	✓					AI predicts clinical deterioration (e.g., sepsis, respiratory failure) and triggers early-warning alerts.	Enables earlier intervention, reducing ICU transfers, mortality, and length of stay.	25 – 49%	25 – 49%	50 – 74%
OWC00001	Smart Unit Dose Robotic Cabinets	✓	✓	✓			Smart unit dose/Automated Dispensing Cabinets (ADCs) track medications and control access on nursing units.	Improves medication safety and inventory accuracy, reducing waste/diversions.	25 – 49%	50 – 74%	50 – 74%
OWC00023	AI Sepsis Early Warning & Response Orchestration	✓					ML models predict sepsis risk early and trigger protocolized response workflows and care-team escalation.	Reduces mortality and ICU escalations while improving clinician efficiency and throughput by acting earlier.	25 – 49%	50 – 74%	75 – 100%
OWC00024	AI Therapy Companions	✓					AI chat/voice companions support behavioral health and adherence with evidence-based prompts and monitoring.	Increases engagement and adherence, improving outcomes at lower cost.	25 – 49%	50 – 74%	75 – 100%
OWC00019	AI-based patient screening for abnormalities	✓					AI analyses voice patterns and codify voice biomarkers to non-invasively detect abnormalities for diagnosis	Enables low-friction, non-invasive screening (e.g., voice/digital biomarkers) to identify at-risk patients earlier, prioritize follow-up, and reduce downstream acute events and unnecessary diagnostics.	0 – 24%	25 – 49%	25 – 49%
OWC00021	AI Radiology Workflow Orchestration (Protocoling, Triage, Reporting)	✓		✓			AI automates exam protocol suggestions, triage queues, and report drafting to reduce turnaround time end-to-end.	Increases radiologist throughput and reduces backlogs beyond interpretation-only tools.	25 – 49%	50 – 74%	50 – 74%
OWC00022	AI-assisted Radiation Therapy Planning & QA	✓		✓			AI automates contouring and plan optimization with automated QA checks before physicist approval.	Cuts planning time and expands capacity while reducing rework and errors.	25 – 49%	50 – 74%	75 – 100%
OWC00020	AI-guided Antimicrobial Stewardship	✓				✓	AI recommends antibiotic selection, dosing, and de-escalation using labs, vitals, and local resistance patterns.	Reduces C. diff and resistance-related costs while improving outcomes and shortening length of stay.	0 – 24%	25 – 49%	50 – 74%
OWC00018	Humanoid robots for Meal & Hydration Assistance	✓		✓			Humanoid distributes meals/fluids and retrieves trays while navigating dynamic ward environments.	Sustains patient nutrition/hydration workflows and frees support staff time.	0 – 24%	25 – 49%	25 – 49%
OWC00015	Robotic Phlebotomy & Vascular Access	✓		✓			Autonomous or semi-autonomous robots use imaging guidance to draw blood and place IVs with high first-stick success.	Improves patient experience and reduces phlebotomy bottlenecks, enabling faster diagnostics and fewer repeat sticks.	0 – 24%	25 – 49%	25 – 49%
OWC00003	AI Surgical Assistance & Robotics	✓		✓			AI supports intraoperative guidance, tool selection, and robotic actuation for precision and safety.	Enhances surgical accuracy and consistency, reducing complications and operative time.	0 – 24%	25 – 49%	50 – 74%
OWC00004	Remote Surgical Proctoring	✓		✓			AI/telepresence tools enable remote expert oversight and guidance during procedures.	Expands access to expertise and reduces training barriers.	0 – 24%	25 – 49%	50 – 74%
OWC00005	Surgical Digital Twin	✓		✓			AI builds a patient-specific virtual model (digital twin) to plan and guide surgery.	Improves planning precision and reduces operative risk/time.	0 – 24%	25 – 49%	50 – 74%
OWC00012	AI Medication Reconciliation	✓					AI compares meds across sources (EHR, pharmacy, patient list) to identify discrepancies and suggest corrections.	Reduces adverse drug events and readmissions while saving clinician time.	0 – 24%	25 – 49%	50 – 74%
OWC00014	Humanoid care robots	✓		✓			Humanoid robots assist with lifting, transport, and routine tasks guided by AI, reducing physical strain on staff.	Improves safety and productivity, addressing labor shortages in "dull/dirty/dangerous" work.	0 – 24%	25 – 49%	50 – 74%
OWC00016	AI-powered virtual nursing & RPM	✓					Virtual Nursing augments care via remote teams, while RPM (Remote Patient Monitoring) uses connected devices and AI to track patients at home.	Extends staffing capacity, reduces readmissions, and improves chronic care management.	0 – 24%	25 – 49%	50 – 74%
OWC00017	Humanoid OR Turnover Support	✓		✓			Humanoid helps turn rooms (waste removal, supply restock, instrument runs) between cases under staff supervision.	Shortens turnover, reduces staff fatigue, and stabilizes OR schedules.	0 – 24%	0 – 24%	50 – 74%

0 – 24% | 25 – 49% | 50 – 74% | 75 – 100%

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%) 2030	Est adoption magnitude (%) 2035	Est adoption magnitude (%) 2040
OWC00011	Robotic Ultrasound Acquisition with AI Guidance	✓		✓			Robots and AI guidance enable standardized ultrasound acquisition with remote specialist supervision.	Expands imaging access in low-resource settings and reduces sonographer workload while standardizing quality.	0 – 24%	0 – 24%	25 – 49%
OWC00008	Humanoid patient sitter/companion (Non-clinical)	✓		✓			Humanoid provides observation, reminders, and companionship for low-acuity or eldercare patients, escalating to staff as needed.	Supports patient engagement and safety checks while alleviating staffing constraints.	0 – 24%	0 – 24%	25 – 49%
OWC00009	Humanoid patient transfer & repositioning robot	✓		✓			Humanoid robot assists with safe bed-to-chair transfers, turning, and repositioning to reduce staff musculoskeletal strain.	Improves safety and productivity in nursing workflows while reducing injury-related costs.	0 – 24%	0 – 24%	25 – 49%
OWC00010	Humanoid robot ward runners (Supplies/Specimens)	✓		✓			Humanoid performs ad-hoc runs (fetching medications, supplies, and lab specimens) navigating doors/elevators and cluttered corridors.	Reduces delays and manual transport burden, improving turnaround times and staff availability.	0 – 24%	0 – 24%	25 – 49%
OWC00007	Quantum-assisted EMS Dispatch & Routing Optimization	✓		✓		✓	Hybrid quantum-classical optimization improves ambulance dispatch, routing, and hospital destination decisions under uncertainty.	Reduces response times and ED overcrowding by balancing capacity across a region.	0 – 24%	0 – 24%	0 – 24%
OWC00049	AI-based Provider Network Optimization	✓			✓		AI optimizes network adequacy, access, cost, and quality via supply-demand modeling and referral patterns.	Enhances member access and reduces total cost of care.	25 – 49%	25 – 49%	50 – 74%

2.2 Production

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%) 2030	Est adoption magnitude (%) 2035	Est adoption magnitude (%) 2040
OWS00045	Computer vision for automated QC inspection (drug product & device components)		✓	✓			Computer vision inspects vials, syringes, tablets, and device components to detect defects with consistent quality.	Increases inspection throughput, reduces false rejects, and improves traceability for investigations and recalls.	50 – 74%	75 – 100%	75 – 100%
OWS00043	AI predictive maintenance for GMP equipment		✓	✓			Predictive maintenance models forecast equipment failure and optimize maintenance scheduling for GMP assets.	Reduces unplanned downtime, improves OEE, and lowers maintenance cost while supporting compliance.	50 – 74%	75 – 100%	75 – 100%
OWS00033	Robotics for aseptic fill-finish and sterile handling	✓	✓	✓			Robotics automate aseptic fill-finish, isolator operations, and sterile handling to minimize contamination and increase flexibility.	Reduces contamination risk and operator interventions, improves line flexibility for small batches, and raises throughput.	25 – 49%	50 – 74%	75 – 100%
OWS00042	Autonomous intralogistics (AMRs) for materials, WIP, and sterile goods movement		✓	✓			AMRs automate internal transport of materials, WIP, and finished goods within plants and warehouses, including clean logistics.	Reduces non-value-added travel and improves schedule adherence, especially in multi-floor facilities.	25 – 49%	50 – 74%	75 – 100%
OWS00044	Robotics/cobots for packaging, labeling, line changeover and kitting		✓	✓			Cobots automate secondary packaging, labeling, and kitting while enabling quick changeovers for multi-SKU production.	Improves throughput and reduces ergonomic injuries, with faster changeovers and fewer packaging errors.	25 – 49%	50 – 74%	75 – 100%
OWS00041	AI energy and utilities optimization for plants		✓	✓			AI optimizes HVAC, cleanroom utilities, and energy usage while maintaining GMP environmental specs.	Reduces energy cost and carbon footprint without compromising sterility/temperature/humidity constraints.	25 – 49%	50 – 74%	75 – 100%
OWS00040	AI-driven process control (PAT) and real-time release decision support		✓	✓			AI-driven process control uses PAT/IoT data to optimize bioprocess and small-molecule manufacturing in real time.	Improves yield, reduces deviations, supports real-time release, and lowers COGS while increasing capacity.	25 – 49%	50 – 74%	75 – 100%
OWS00031	Biohazard Sorting Robots	✓	✓	✓			Robots sort and route biohazard waste with AI vision and safe handling protocols.	Improves staff safety and compliance, reducing exposure and fines.	25 – 49%	25 – 49%	50 – 74%
OWS00032	Robotic Sterile Processing Automation	✓	✓	✓			Robotics and AI automate instrument decontamination, inspection, packing, and tracking.	Improves turnaround time and quality, lowering infection risk and OR delays.	25 – 49%	25 – 49%	50 – 74%
OWS00034	Robotic Autonomous Hospital and Lab Logistics	✓		✓			Autonomous mobile robots (AMRs—Autonomous Mobile Robots), move supplies, meds, and specimens across the hospital. Includes last-meter "TUG" units, which perform last-meter delivery to units, labs, and pharmacies.	Increases reliability and speed of logistics while reducing manual transport burden.	25 – 49%	25 – 49%	50 – 74%
OWS00038	AI root-cause analysis and CAPA recommendation for deviations		✓	✓			AI analyzes deviation histories, process data, and maintenance logs to suggest likely root causes and CAPA actions.	Reduces investigation cycle time and recurrence of deviations, improving compliance and uptime.	25 – 49%	50 – 74%	75 – 100%
OWS00039	GenAI batch record review, deviation narrative drafting and release packets		✓	✓			GenAI automates batch record review, drafts deviation summaries, and assembles release packets with traceable evidence.	Cuts QA cycle time and reduces human error in batch review, increasing throughput and reducing inventory hold time.	25 – 49%	50 – 74%	75 – 100%
OWS00048	AI generative design for device components, tooling and fixtures			✓			Generative design proposes device geometries, implants, and manufacturing fixtures optimized for performance and manufacturability.	Accelerates design iterations, reduces material use, and improves performance; pairs with simulation and additive manufacturing.	25 – 49%	50 – 74%	75 – 100%
OWS00047	Robotic additive manufacturing + automated inspection for personalized devices			✓			Robotics and AI automate additive manufacturing (3D printing) and inline inspection for patient-specific device components.	Enables scalable mass customization with higher yield and faster turnaround for patient-matched implants and instruments.	25 – 49%	25 – 49%	50 – 74%
OWS00046	Bioprocess digital twins for scale-up and continued process verification		✓	✓			Digital twins simulate bioprocesses to support scale-up, tech transfer, continuous verification, and what-if optimization.	Reduces scale-up failures, accelerates tech transfer to plants/CDMOs, and improves robustness of continuous manufacturing.	25 – 49%	25 – 49%	50 – 74%
OWS00029	Robotic Exoskeletons for Mobility/Lifting	✓	✓	✓		✓	Powered exoskeletons assist staff/patients with lifting and mobility under AI-controlled support.	Reduces musculoskeletal injuries and improves mobility/rehab outcomes.	0 – 24%	25 – 49%	50 – 74%

0 – 24% 25 – 49% 50 – 74% 75 – 100%

OW Healthcare Use Case ID	Use Case Name	Applied in					Description	Impact	Est adoption magnitude (%)		
		Clinical Care/ Hospitals	Pharma	Medical Devices	Insurance	Government/ other			2030	2035	2040
OWS00037	Humanoid robots for flexible kitting, tool swaps, and exception handling in GMP		✓	✓			Humanoid assists with flexible kitting, tool swaps, and exception handling in Good Manufacturing Practice (GMP) environments.	Increases flexibility for short-run or complex changeovers while maintaining safety and quality.	0 – 24%	25 – 49%	50 – 74%
OWS00030	Humanoid Facility Rounds & Maintenance services	✓	✓	✓		✓	Humanoid conducts rounds (filter checks, bulb changes, signage placement) and reports anomalies via vision AI.	Improves facility responsiveness and safety with reduced manual patrols.	0 – 24%	25 – 49%	25 – 49%
OWS00027	Humanoid robots for flexible shopfloor logistics and changeover support (future)	✓	✓	✓			General-purpose humanoid robots assist with material movement, basic changeover tasks, and night-shift support under supervision.	Could mitigate labor shortages for physically demanding tasks and provide flexible capacity for variable production schedules by late 2030s.	0 – 24%	25 – 49%	25 – 49%
OWS00035	Distributed robotic microfactories for personalized therapies/devices		✓	✓			Containerized robotic microfactories produce small-batch personalized therapies or devices near patients, orchestrated by AI across networks.	Could cut lead times dramatically for personalized products and reduce cold-chain complexity by manufacturing closer to point-of-care.	0 – 24%	0 – 24%	0 – 24%
OWS00036	Quantum/hybrid optimization for production scheduling and campaign planning		✓	✓			Hybrid quantum optimization supports multi-plant production scheduling, campaign planning, and capacity allocation under constraints.	May improve plan quality and reduce changeover/downtime in highly constrained networks as quantum matures.	0 – 24%	0 – 24%	0 – 24%

2.3 Supply Chain & Procurement

OW Healthcare Use Case ID	Use Case Name	Clinical Care/ Hospitals	Pharma	Medical Devices	Insurance	Government/ other	Description	Impact	2030	2035	2040
OWS00071	AI demand forecasting (SKU/location)		✓	✓			AI forecasts demand at SKU/location level using multi-source signals (sales, epidemiology, tenders, seasonality).	Reduces stockouts and excess inventory, improving service levels and working capital for drugs and devices.	50 – 74%	75 – 100%	75 – 100%
OWS00059	AI spend analytics and procurement savings identification	✓	✓	✓	✓	✓	AI identifies procurement savings, supplier consolidation opportunities, and spend anomalies across categories.	Reduces cost and improves compliance with preferred suppliers while lowering manual analysis effort.	50 – 74%	75 – 100%	75 – 100%
OWS00070	AI cold-chain excursion detection & predictive shelf-life	✓	✓	✓		✓	AI detects cold-chain excursions and predicts remaining shelf life using IoT telemetry across transport and storage.	Reduces spoilage and deviations, enables proactive interventions, and improves compliance for temperature-sensitive products.	50 – 74%	75 – 100%	75 – 100%
OWS00069	AI multi-echelon inventory optimization		✓	✓			AI optimizes inventory buffers and replenishment across multi-echelon networks for drugs/devices, balancing service and cost.	Lowers working capital and obsolescence while improving fill rates, particularly for cold-chain and short-shelf-life products.	25 – 49%	50 – 74%	75 – 100%
OWS00062	Warehouse automation with autonomous mobile robots (AMRs) and robotic picking	✓	✓	✓		✓	Autonomous mobile robots (AMRs) and robotic picking automate warehouse fulfillment for pharma and medical device distribution.	Improves throughput, accuracy, and labor productivity while reducing picking errors and overtime costs.	25 – 49%	50 – 74%	75 – 100%
OWS00067	AI supply-risk early warning (supplier, geo, quality)	✓	✓	✓			AI monitors supplier, geopolitical, and quality signals to predict shortages and trigger mitigation actions early.	Reduces disruptions, emergency sourcing, and compliance risks, improving patient supply continuity.	25 – 49%	50 – 74%	75 – 100%
OWS00068	AI-enabled anti-counterfeit and diversion detection	✓	✓	✓	✓	✓	AI detects counterfeit, diversion, and anomalous distribution patterns using serialization, track-and-trace, and marketplace signals.	Reduces revenue loss and patient safety risk while improving compliance with serialization regulations.	25 – 49%	50 – 74%	75 – 100%
OWS00058	AI agent-based Procurement Dynamic Sourcing		✓	✓			Use AI to dynamically run sourcing actions for direct and indirect categories as agent.	Reduces procurement cost, improves supply resilience, and shortens sourcing cycles—especially for constrained APIs, device components, and electronics.	25 – 49%	25 – 49%	50 – 74%
OWS00051	AI Cold Chain Monitoring & Management	✓	✓	✓		✓	Sensors and AI monitor temperature/humidity to protect biologics through transport and storage.	Prevents spoilage and regulatory non-compliance, ensuring product efficacy.	25 – 49%	25 – 49%	50 – 74%
OWS00055	AI Autonomous Scheduling & Intake	✓					AI optimizes appointment scheduling, digital pre-visit intake (forms, consent, benefits verification) with minimal staff intervention.	Improves access, throughput, and patient satisfaction while cutting front-desk workload.	25 – 49%	25 – 49%	50 – 74%
OWS00056	AI Care Scheduling and Throughput Agents	✓					AI agents dynamically optimize bed capacity, and downstream resource utilization.	Raises throughput, reduces cancellations and idle time, and improves access.	25 – 49%	25 – 49%	50 – 74%
OWS00057	Vendor Performance and Risk Analytics	✓	✓	✓	✓	✓	AI monitors supplier KPIs (Key Performance Indicators), quality signals, and financial risk to trigger mitigations.	Reduces supply disruptions and cost variance, improving resilience.	25 – 49%	25 – 49%	50 – 74%
OWS00061	Predictive Procurement/Inventory	✓	✓	✓		✓	AI forecasts demand and optimizes ordering across suppliers, distribution, and hospital supply chains.	Reduces stockouts and waste while lowering working capital and expedite costs.	25 – 49%	25 – 49%	50 – 74%
OWS00066	Supply chain digital twin for disruption simulation and resilient planning	✓	✓	✓		✓	A supply chain digital twin simulates network constraints, disruptions, and capacity to support resilient planning.	Improves disruption response and enables proactive mitigation, reducing shortages, write-offs, and expedited logistics.	25 – 49%	25 – 49%	50 – 74%
OWS00060	Autonomous Inspection Drones for Warehouse and Facility Inventory Audits	✓	✓	✓		✓	Use autonomous drones with computer vision to perform cycle counts, inspect storage conditions, and verify labeling/UDI compliance in warehouses and plants.	Improves inventory accuracy, reduces labor for counting/inspections, and detects storage excursions earlier.	0 – 24%	25 – 49%	50 – 74%
OWS00065	Robotic / autonomous last-mile delivery for critical parts and samples (future)	✓	✓	✓		✓	Autonomous delivery robots/drones handle time-critical delivery of devices, parts, and samples between facilities and hospitals.	Reduces courier cost and cycle time for urgent deliveries and supports distributed service models.	0 – 24%	25 – 49%	25 – 49%
OWS00050	AI Hospital-at-Home Logistics coordination	✓	✓	✓			AI coordinates equipment, meds, staff, and monitoring for acute care at home.	Expands capacity and lowers cost while maintaining quality and safety.	0 – 24%	25 – 49%	50 – 74%

0 – 24% 25 – 49% 50 – 74% 75 – 100%

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%) 2030	Est adoption magnitude (%) 2035	Est adoption magnitude (%) 2040
OWS00052	AI Emergency Triage Optimization	✓					AI prioritizes emergency department (ED) patients using risk scores and resource forecasts.	Shortens wait times, reduces LWBS (Left Without Being Seen), and allocates resources better.	0 – 24%	25 – 49%	50 – 74%
OWS00053	AI OR Scheduling Optimization	✓					AI optimizes Operating Room (OR) block time, case sequencing, OR preference cards, and turnover based on constraints and predictions.	Increases OR utilization and reduces delays and overtime.	0 – 24%	25 – 49%	50 – 74%
OWS00054	AI-based Automated Discharge Planning	✓					AI orchestrates discharge tasks, referrals, and patient instructions, aligning services and follow-ups.	Shortens length of stay and reduces post-discharge complications.	0 – 24%	25 – 49%	50 – 74%
OWS00063	Quantum/hybrid optimization for distribution network design and routing		✓	✓			Hybrid quantum optimization supports distribution network design, routing, and allocation under constraints and disruptions.	May improve near-optimal planning for large networks (global pharma/device) as quantum matures in late 2030s.	0 – 24%	0 – 24%	0 – 24%
OWS00064	Quantum-optimized Supply Chain Network Design and Routing (hybrid quantum-classical)		✓	✓			Apply hybrid quantum optimization to complex network-design and routing problems beyond classical heuristics.	Improves resilience and cost-to-serve in multi-echelon networks and can reduce stockouts/expiry in cold-chain and high-value device distribution as complexity grows.	0 – 24%	0 – 24%	0 – 24%

3.1 Customer Service & Billing

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%) 2030	Est adoption magnitude (%) 2035	Est adoption magnitude (%) 2040
OWM00131	AI medical information assistant for HCPs and patients	✓	✓	✓		✓	AI medical information assistants answer HCP/patient questions using approved sources with escalation for complex inquiries.	Improves response speed and consistency while lowering call center and medical information workload.	50 – 74%	75 – 100%	75 – 100%
OWM00135	AI-based user guidance and issue resolution	✓		✓		✓	AI troubleshooting assistants guide users through device issues using manuals, logs, and known fixes with escalation to experts.	Reduces call time, speeds resolution, and improves uptime for connected medical devices.	25 – 49%	50 – 74%	75 – 100%
OWM00134	AI predictive field service for connected devices (maintenance before failure)	✓		✓		✓	AI uses device telemetry to predict failures and schedule service proactively, reducing downtime and emergency repairs.	Improves device uptime and customer satisfaction while lowering warranty and service costs.	25 – 49%	50 – 74%	75 – 100%
OWM00140	AI-driven Warranty, Complaint and Field Failure Analytics for Connected Medical Devices			✓			Use AI to detect early failure patterns from service tickets, device logs, and complaints to reduce downtime and improve design and supplier quality.	Cuts warranty/service cost, improves uptime for providers, reduces recalls, and strengthens design feedback loops.	25 – 49%	50 – 74%	75 – 100%
OWM00141	Zero-Touch Revenue Cycle Management (incl. Automated Medical Coding & Billing)	✓			✓		End-to-end AI automates registration, eligibility, coding, billing, posting, and denials with minimal human intervention.	Improves clean-claim rates, speeds cash flow, and lowers administrative cost.	25 – 49%	50 – 74%	75 – 100%
OWM00142	AI Fraud/Waste/Abuse Detection				✓		AI flags suspicious billing, upcoding, and phantom claims with explainable risk scoring.	Cuts improper payments and enhances program integrity and compliance.	25 – 49%	50 – 74%	75 – 100%
OWM00143	AI Claims Processing & Audit Agents				✓		AI validates claims against policies and medical necessity to prevent overpayments. AI automates claims intake, adjudication, and audit with rules, models, and anomaly detection.	Reduces leakage and recovery costs, improving payer financial performance.	25 – 49%	50 – 74%	75 – 100%
OWM00137	GenAI Patient Communication & After-Visit Summaries	✓					Generative AI produces patient-friendly after-visit summaries, instructions, and message drafts in multiple languages with clinician review.	Improves comprehension and adherence while reducing clinician inbox burden and call-backs.	25 – 49%	50 – 74%	75 – 100%
OWM00133	Contact Center AI Automation	✓			✓		Conversational AI (artificial intelligence) handles calls, chats, and messages for scheduling, benefits, claims, and care navigation, escalating to agents only when needed.	Increases first-contact resolution, lowers wait times, and reduces call center operating costs.	25 – 49%	25 – 49%	50 – 74%
OWM00132	AI personalization for patient support programs and adherence nudges	✓	✓	✓			AI personalizes patient support journeys (education, reminders, nurse escalation) to improve adherence and outcomes.	Reduces discontinuation and improves real-world effectiveness while lowering support cost per patient.	25 – 49%	50 – 74%	75 – 100%
OWM00138	AI-assisted Appeals, Grievances & Case Resolution				✓		LLMs summarize cases, extract policy evidence, and draft decisions and member communications for human approval.	Shortens cycle times and reduces call-backs while improving consistency and audit trails.	25 – 49%	50 – 74%	75 – 100%
OWM00136	AI Clinical Inbox & Referral Management	✓					Agentic AI triages clinician inbox messages, routes referrals, and drafts responses using patient context and guidelines.	Reduces clinician burnout and speeds referral completion and patient communication.	25 – 49%	50 – 74%	50 – 74%
OWM00129	AI Denials Management Automation	✓			✓		AI classifies denial reasons, recommends fixes, and automates appeals with payer-specific evidence and templates.	Recovers revenue and reduces A/R (Accounts Receivable) cycle time with lower manual rework.	0 – 24%	25 – 49%	50 – 74%
OWM00139	Telepresence robots for remote device setup and field support (future)			✓			Telepresence robots enable remote experts to assist with device setup, inspections, and training when travel is constrained.	Reduces travel cost and speeds support response, especially for global installations.	0 – 24%	25 – 49%	25 – 49%
OWM00130	Quantum-safe communications for connected devices and patient portals	✓	✓	✓			PQC-secured channels protect device telemetry, remote updates, and patient support communications against future quantum threats.	Prevents long-term exposure for long-lived devices and regulated data, reducing risk of recalls due to cybersecurity vulnerabilities.	0 – 24%	0 – 24%	0 – 24%

0 – 24%　25 – 49%　50 – 74%　75 – 100%

3.2 Marketing & Sales

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%) 2030	2035	2040
OWM00148	AI key opinion leader (KOL) identification and network mapping		✓	✓			AI maps KOL networks and emerging experts using publication, guideline, and congress data to prioritize engagement.	Improves efficiency of medical affairs and commercial planning while reducing manual research and missed opportunities.	50 – 74%	75 – 100%	75 – 100%
OWM00149	AI-driven segmentation and next-best-action omnichannel orchestration		✓	✓			AI recommends next-best actions and omnichannel journeys for HCPs and patients, constrained by consent and compliance rules.	Improves commercial efficiency and targeting while reducing wasted outreach and increasing patient adherence support.	50 – 74%	75 – 100%	75 – 100%
OWM00147	GenAI compliant content generation with automated claims checks	✓			✓		GenAI creates compliant HCP/patient content (emails, brochures, scripts) with automated claims and citation checks.	Cuts content cycle times and agency spend while improving consistency and enabling more personalized engagement.	50 – 74%	75 – 100%	75 – 100%
OWM00150	AI competitive intelligence and pipeline monitoring		✓	✓			AI continuously monitors competitor pipelines, trials, patents, and news to deliver early insights and alerts.	Improves strategic decision-making and reduces manual tracking effort across therapeutic areas and device categories.	25 – 49%	50 – 74%	75 – 100%
OWM00145	AI pricing, tenders and contracting optimization		✓	✓			AI models pricing, tender strategy, and contracting scenarios using elasticity, competitor signals, and payer constraints.	Improves net revenue realization and reduces manual contracting cycles, especially for complex global markets.	25 – 49%	50 – 74%	50 – 74%
OWM00146	AI-assisted sales enablement and field coaching		✓	✓	✓		AI coaches analyze call notes and interactions to provide compliant coaching, objection handling, and training for reps.	Improves effectiveness and consistency while reducing manager coaching burden.	25 – 49%	50 – 74%	50 – 74%
OWM00144	AI-driven HEOR / value dossier modeling for market access		✓	✓			AI accelerates HEOR modeling, evidence synthesis, and value dossier generation to support payer negotiations.	Reduces cycle time for submissions and improves scenario testing for access strategies.	25 – 49%	25 – 49%	50 – 74%
OWM00152	XR/AR + AI product training for surgeons and device users	✓		✓			XR training uses AI tutors and simulated digital twins to train clinicians on devices and procedures with objective skill scoring.	Reduces training cost and variability while improving adoption and reducing use errors.	0 – 24%	25 – 49%	50 – 74%
OWM00153	AI Misinformation Detection & Targeted Public Health Communication		✓			✓	AI monitors channels for health misinformation trends and helps craft targeted, evidence-based communication interventions.	Improves vaccine uptake and adherence while reducing costs of ineffective campaigns.	0 – 24%	25 – 49%	50 – 74%
OWM00151	AI-Personalized Insurance Products				✓		AI configures benefit plans and incentives tailored to member risk and preferences.	Raises enrollment, satisfaction, and preventive care uptake while managing risk.	0 – 24%	25 – 49%	50 – 74%

4.1 Quality & Regulatory

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%) 2030	2035	2040
OWM00075	AI complaint intake, coding and triage (device and pharma product quality)	✓	✓	✓			AI automates intake, coding, and triage of product complaints and service tickets for medical devices and pharma with exception-based human review.	Reduces cycle time to investigate/close complaints and improves signal detection for potential quality issues.	25 – 49%	50 – 74%	75 – 100%
OWM00089	AI regulatory intelligence: monitoring guideline changes and impact analysis		✓	✓			AI monitors global regulator updates and standards, mapping changes to impacted products, SOPs, and filings.	Reduces missed changes and speeds updates to dossiers and QMS, lowering compliance risk.	25 – 49%	50 – 74%	75 – 100%
OWM00088	Robotics for QC lab automation (sample prep, assay execution, reporting)		✓	✓			Robots automate QC sample preparation, assay execution, and reporting to increase capacity and reduce errors.	Improves QC throughput and consistency, enabling faster batch release and reducing out-of-spec investigations.	25 – 49%	50 – 74%	75 – 100%
OWM00092	UDI and product master data automation with AI validation		✓	✓			AI automates UDI assignment checks, master data validation, and cross-system synchronization to reduce labeling and reporting errors.	Improves compliance and reduces rework across global product master data processes.	25 – 49%	50 – 74%	75 – 100%
OWM00087	GenAI-enabled regulatory submissions drafting and assembly		✓	✓			GenAI supports regulatory strategy, submission assembly, and response authoring with structured traceability and QC checks.	Shortens submission timelines, reduces rework, and improves consistency across regions and product lines.	25 – 49%	25 – 49%	50 – 74%
OWM00095	Wastewater + AI Forecasting for Respiratory Viruses			✓		✓	Public health agencies combine wastewater signals with AI models to forecast outbreaks and hospitalizations.	Improves preparedness, staffing, and vaccine/antiviral allocation while reducing surge costs.	25 – 49%	50 – 74%	50 – 74%
OWM00085	AI supplier quality monitoring and audit prioritization		✓	✓			AI scores supplier quality risk using audits, deviations, delivery performance, and external signals to prioritize oversight.	Reduces supplier-related deviations and shortages by focusing QA resources on the highest risks.	25 – 49%	50 – 74%	75 – 100%
OWM00086	AI/GenAI for labeling, IFU, and artwork change control		✓	✓			GenAI updates labeling/IFU drafts and artwork while checking consistency with approved claims, UDI, and local requirements.	Reduces cycle time and errors for frequent label changes and reduces recalls due to labeling mistakes.	25 – 49%	50 – 74%	75 – 100%
OWM00077	AI-based Credentialing Automation	✓			✓		AI automates provider credential verification, enrollment, and maintenance across health systems and payer networks.	Shrinks onboarding time and compliance risk, enabling faster provider productivity and reimbursement.	25 – 49%	25 – 49%	50 – 74%
OWM00072	Automated Compliance & Reporting	✓	✓	✓	✓	✓	AI assembles regulated reports, audits logs, and evidence packs across standards (e.g., HIPAA—Health Insurance Portability and Accountability Act; GDPR—General Data Protection Regulation).	Lowers compliance risk and cycle time while increasing reporting accuracy and consistency.	25 – 49%	25 – 49%	50 – 74%

0 – 24% | 25 – 49% | 50 – 74% | 75 – 100%

OW Healthcare Use Case ID	Use Case Name	Applied in					Description	Impact	Est adoption magnitude (%)		
		Clinical Care/ Hospitals	Pharma	Medical Devices	Insurance	Government/ other			2030	2035	2040
OWM00073	Regulatory Reporting Automation	✓	✓	✓	✓	✓	AI compiles mandated submissions (clinical, safety, financial, quality) across agencies and jurisdictions with automated validation.	Decreases submission effort and risk of non-compliance, accelerating approvals and audits.	25 – 49%	25 – 49%	50 – 74%
OWM00078	AI Act/MDR Compliance Tooling for Deployed Clinical AI	✓		✓	✓	✓	Tools automate risk management, monitoring, and documentation required under medical device and AI regulations across the AI lifecycle.	Reduces compliance overhead and accelerates safe scaling of clinical AI across organizations.	25 – 49%	25 – 49%	50 – 74%
OWM00083	AI post-market surveillance and vigilance signal detection (devices & drugs)		✓	✓			AI monitors post-market data (complaints, registries, EHR, literature) to detect emerging quality/safety issues sooner.	Reduces time to detect issues and lowers recall and litigation risk while focusing expert review.	25 – 49%	50 – 74%	75 – 100%
OWM00084	Regulatory Q&A copilots for health authority interactions (drafting responses, tracking commitments)	✓	✓	✓		✓	AI copilots draft responses to regulator questions and track commitments across markets with evidence-linked traceability.	Speeds response cycles and reduces errors in commitment tracking, lowering the risk of delays and post-approval findings.	25 – 49%	50 – 74%	75 – 100%
OWM00081	AI audit readiness: automated evidence capture and continuous compliance monitoring		✓	✓			AI continuously assembles audit evidence from systems and flags missing records, reducing audit prep and findings.	Cuts time spent on audit preparation and improves inspection outcomes via continuous compliance.	25 – 49%	25 – 49%	50 – 74%
OWM00082	AI deviation detection and CAPA automation (predictive quality)		✓	✓			AI predicts deviations from process and quality signals and automates CAPA workflows toward preventive quality.	Shifts quality from reactive to preventive, reducing batch failures and audit findings.	25 – 49%	25 – 49%	50 – 74%
OWM00091	GenAI clinical evaluation report (CER) and technical documentation drafting			✓			GenAI drafts and maintains clinical evaluation reports and technical files by synthesizing evidence with traceable citations.	Cuts authoring time and improves consistency across device families and markets.	25 – 49%	25 – 49%	50 – 74%
OWM00076	AI Copilot for Computer System Validation (CSV) / Computer Software Assurance (CSA) and Change Control	✓	✓	✓		✓	Deploy GenAI assistants to draft validation protocols, test scripts, and change-control packages for GMP systems (MES/LIMS/QMS/ERP) and SaMD tooling.	Cuts validation lead time, reduces documentation effort, improves consistency of test evidence, and enables faster deployment of digital capabilities in GMP environments.	25 – 49%	25 – 49%	50 – 74%
OWM00079	Hospital AI Device Safety Surveillance (Real-time Post-market)	✓		✓		✓	Hospitals mine device logs, EHR outcomes, and incident reports to detect early safety signals for devices and SaMD in use.	Prevents harm and reduces downtime/recalls by detecting issues earlier and improving reporting quality.	0 – 24%	25 – 49%	50 – 74%
OWM00090	GenAI ISO 14971 risk management file and hazard analysis drafting		✓	✓			GenAI accelerates hazard identification, risk analysis, and risk control documentation while maintaining traceability to evidence.	Reduces documentation burden and helps teams keep risk files current as products and software evolve.	0 – 24%	25 – 49%	50 – 74%
OWM00080	System-wide Patient Safety Signal Detection (AI Early Warning)	✓	✓	✓		✓	AI scans near real-time outcome and incident data to flag statistically unusual safety patterns for rapid review and inspection.	Earlier detection of unsafe care reduces harm, litigation risk, and cost of large-scale safety failures.	0 – 24%	50 – 74%	50 – 74%
OWM00094	GenAI-supported Health Technology Assessment (HTA) Automation		✓	✓		✓	Generative AI assists HTA agencies with evidence synthesis, economic model drafting, and dossier review triage.	Reduces assessment cycle time and improves transparency via structured provenance and audit trails.	0 – 24%	25 – 49%	50 – 74%
OWM00093	AI-assisted Regulatory Submission Triage & Review		✓	✓		✓	Regulators use AI to triage submissions, check completeness, and surface risk signals while keeping humans in decision control.	Shortens review queues and improves consistency and post-market learning.	0 – 24%	25 – 49%	25 – 49%
OWM00074	Quantum sensing for early contamination and environmental drift detection	✓	✓	✓		✓	Quantum sensors provide more sensitive monitoring of environmental parameters to detect micro-variations that precede excursions in environmental monitoring in cleanrooms and critical labs	Prevents deviations and batch loss by enabling earlier intervention; becomes more valuable as continuous manufacturing grows. Detect contamination or process drift earlier than classical sensors, preventing batch loss and improving patient safety.	0 – 24%	0 – 24%	0 – 24%

5.1 Finance

OW Healthcare Use Case ID	Use Case Name	Clinical Care/ Hospitals	Pharma	Medical Devices	Insurance	Government/ other	Description	Impact	2030	2035	2040
OWI00156	AI FP&A forecasting and scenario planning	✓	✓	✓	✓	✓	AI automates forecasting and scenario planning for revenue, COGS, and R&D spend with driver-based models.	Shortens planning cycles and improves forecast accuracy, freeing finance teams to focus on decision support.	50 – 74%	75 – 100%	75 – 100%
OWI00155	AI-enabled Back-Office RPA	✓	✓	✓	✓	✓	Robotic Process Automation (RPA) bots execute repetitive enterprise tasks (finance, HR, IT, procurement) across systems and formats.	Cuts operating cost, reduces errors, and frees staff for higher-value work.	50 – 74%	50 – 74%	50 – 74%
OWI00160	AI-enabled Finance Close, Accrual Automation and Continuous Controls Monitoring	✓	✓	✓	✓	✓	Apply AI to automate reconciliations, accrual estimation, and anomaly detection to shorten close cycles and strengthen controls.	Reduces finance operations effort, lowers error rates, and improves decision speed for R&D and manufacturing investments.	25 – 49%	50 – 74%	75 – 100%
OWI00163	AI-based Prior Authorization API Compliance & Automation (CMS-0057-F)				✓		Payers implement standardized prior-authorization APIs and automate decisioning and status updates to meet interoperability rules.	Shortens authorization cycles, reduces manual work, and lowers provider abrasion while improving auditability.	25 – 49%	50 – 74%	75 – 100%
OWI00157	RPA + AI exception handling for AP/ AR and close processes	✓	✓	✓	✓	✓	RPA handles routine AP/AR and close tasks; AI resolves exceptions and drafts explanations for variances and journals.	Shortens close cycles and reduces manual effort while improving controls and transparency.	25 – 49%	50 – 74%	75 – 100%
OWI00158	AI automation of chargebacks/rebates and revenue leakage detection	✓	✓	✓	✓	✓	AI detects anomalies in chargebacks, rebates, and gross-to-net calculations to reduce leakage and disputes.	Improves net revenue realization and reduces reconciliation cycle time.	50 – 74%	50 – 74%	50 – 74%
OWI00162	Risk Adjustment AI Coding Copilots (HCC/DRG Support)				✓		LLMs assist coders and clinicians in capturing complete, compliant diagnoses for risk adjustment and DRG accuracy.	Improves revenue accuracy and reduces retrospective chart chase effort.	25 – 49%	50 – 74%	75 – 100%

0 – 24% 25 – 49% 50 – 74% 75 – 100%

OW Healthcare Use Case ID	Use Case Name	Applied in					Description	Impact	Est adoption magnitude (%)		
		Clinical Care/ Hospitals	Pharma	Medical Devices	Insurance	Government/ other			2030	2035	2040
OWI00159	AI-driven ESG/CSRD Reporting and Product Sustainability Analytics	✓	✓	✓	✓	✓	Use AI to automate ESG data collection, calculate product footprints, and generate audit-ready disclosures with traceability.	Reduces reporting burden, improves data quality for sustainability claims, and enables design-to-sustainability decisions in device materials and pharma supply chains.	▓	▓	█
OWI00161	Graph AI for Fraud Rings & Collusion Detection	✓	✓		✓		Graph analytics detects suspicious provider-member-pharmacy networks to identify organized fraud and abuse earlier.	Reduces improper payments and improves investigation prioritization with fewer false positives.	▒	▓	█
OWI00154	Quantum optimization for R&D portfolio and capital allocation (future)	✓	✓	✓	✓	✓	Hybrid quantum optimization explores complex R&D portfolio tradeoffs, manufacturing capex sequencing, and risk constraints.	Could improve portfolio ROI under uncertainty as quantum matures, complementing classical OR and simulation.	░	░	░
5.2 HR											
OWI00168	AI-personalized learning paths for reskilling (AI, robotics, quality)	✓	✓	✓	✓	✓	AI builds personalized training and certification plans to reskill staff for digital, automation, and quality roles.	Improves training effectiveness and reduces time to competency for new operating models.	▒	▓	█
OWI00167	GenAI-enabled Personalized Learning Content Factory and Simulation Training (GxP, sales, service)	✓	✓	✓	✓	✓	Use generative AI to produce role-based microlearning, SOP explainers, and scenario simulations for GMP, quality, commercial, and field-service training.	Cuts training content development cost, improves training completion and comprehension, and accelerates onboarding for new roles created by AI/robotics adoption.	▒	▓	█
OWI00169	AI talent sourcing and screening for specialized roles (R&D, data, manufacturing)	✓	✓	✓	✓	✓	AI automates candidate sourcing, screening, and skill matching, including internal mobility for scarce roles.	Reduces time-to-hire and improves match quality for high-demand skills (AI, automation, regulatory).	▒	▓	▓
OWI00165	AI workforce planning and capacity forecasting	✓	✓	✓	✓	✓	AI forecasts workforce demand/supply by function and geography to plan hiring, automation, and outsourcing decisions.	Reduces over/understaffing, supports strategic reskilling and automation roadmaps.	▓	▓	█
OWI00166	AI Talent Marketplace & Skills Graph for Workforce Redeployment in Pharma/MedTech	✓	✓	✓	✓	✓	Create an AI-driven skills ontology that matches employees to projects, roles, and training to accelerate redeployment as automation changes job content.	Reduces time-to-staff critical roles, increases retention, and makes productivity gains translate into capacity expansion rather than unmanaged displacement.	▒	▓	█
OWI00170	AI/VR Training Simulators	✓	✓	✓	✓	✓	AI with Virtual Reality (VR) simulates clinical scenarios and procedures for training and assessment.	Improves competency and retention, reducing training time and errors.	▒	▓	▓
OWI00164	Robotics and XR simulation for safety and SOP training		✓	✓			XR/robotics simulators train operators on aseptic technique and device assembly with objective scoring before live work.	Reduces training time and deviations, improving right-first-time performance and safety.	▒	▓	▓
5.3 Legal											
OWI00177	AI contract risk management for suppliers, service providers, and distributors	✓	✓	✓	✓	✓	AI reviews contracts, flags risky clauses, and accelerates renegotiation and approvals.	Cuts legal cycle times and reduces outside counsel spend while improving risk consistency.	▓	█	█
OWI00176	AI IP portfolio management and invention mining		✓	✓		✓	AI monitors invention disclosures, prior art, and patent families to optimize filing strategy and maintenance decisions.	Improves IP quality and reduces manual effort in portfolio analysis.	▒	▓	█
OWI00173	GenAI Contract Lifecycle Management for Clinical, Supplier and Distribution Agreements	✓	✓	✓	✓	✓	Use large language models to draft, review, negotiate, and monitor pharma/medtech contracts with clause playbooks and risk controls.	Cuts contracting cycle time, reduces external legal spend, improves compliance with regulated clauses (e.g., quality, privacy, audit rights), and increases reuse of preferred terms across markets.	▒	▓	█
OWI00172	AI-driven Patent Landscaping & Freedom-to-Operate Analysis for Pharma and Medical Devices	✓	✓	✓	✓	✓	Apply AI to mine patents and scientific literature to map IP landscapes, identify white spaces, and accelerate freedom-to-operate reviews.	Improves R&D prioritization and reduces late-stage IP surprises by identifying crowded art earlier; lowers external search spend and accelerates patent drafting cycles.	▒	▓	▓
OWI00175	AI compliance monitoring for promotional, privacy, and anti-corruption policies		✓	✓			AI monitors communications and transactions for potential compliance issues (off-label risk, privacy, bribery signals).	Reduces compliance risk and manual review burden while enabling proactive remediation.	▒	▓	█
OWI00174	Value-Based Contract Simulation through AI	✓	✓	✓	✓	✓	AI simulates outcomes, cost, and risk for value-based payment models to optimize contract terms and shared-savings arrangements.	Aligns incentives, reduces downside risk, and improves clinical and financial performance.	░	▒	▓
OWI00171	Post-quantum cryptography legal readiness and vendor contracting	✓	✓	✓	✓	✓	Legal programs update contracts, SLAs, and supplier requirements for post-quantum crypto and crypto-agility.	Reduces long-term legal and compliance exposure by ensuring vendors meet evolving cybersecurity expectations.	░	░	░

░ 0 – 24% ▒ 25 – 49% ▓ 50 – 74% █ 75 – 100%

5.4 IT

OW Healthcare Use Case ID	Use Case Name	Applied in: Clinical Care/ Hospitals	Applied in: Pharma	Applied in: Medical Devices	Applied in: Insurance	Applied in: Government/ other	Description	Impact	Est adoption magnitude (%): 2030	Est adoption magnitude (%): 2035	Est adoption magnitude (%): 2040
OWI00195	AI Coding & Test Automation for Regulated Software (SaMD, firmware, and manufacturing systems)	✓	✓	✓	✓	✓	Use AI coding assistants and automated test generation to accelerate development while enforcing documentation, traceability, and cybersecurity controls required for regulated software.	Shortens release cycles for SaMD and digital features, improves test coverage, and reduces defects that can trigger recalls or regulatory findings.	50 – 74%	75 – 100%	75 – 100%
OWI00194	AI-assisted software development and testing for regulated systems	✓	✓	✓	✓	✓	AI accelerates code generation, test-case creation, and documentation for regulated applications (MES/QMS/RIM/SaMD).	Improves developer productivity and reduces defects while maintaining validation evidence.	50 – 74%	75 – 100%	75 – 100%
OWI00182	AI-driven data quality monitoring and anomaly detection	✓	✓	✓	✓	✓	AI monitors data pipelines for drift, missingness, and schema changes to prevent downstream analytics and compliance failures.	Reduces time spent troubleshooting data issues and prevents bad decisions and audit findings.	25 – 49%	50 – 74%	75 – 100%
OWI00193	AIOps for Autonomous IT Operations and Incident Resolution in Regulated Environments	✓	✓	✓	✓	✓	Deploy AI agents to detect incidents, correlate logs/metrics, propose fixes, and automate low-risk remediations across ERP, data platforms, and GxP applications.	Improves uptime of critical digital systems, reduces IT ticket volume, and speeds mean-time-to-repair while maintaining auditability.	25 – 49%	50 – 74%	75 – 100%
OWI00181	GxP-grade MLOps for model lifecycle, validation and change control	✓	✓	✓	✓	✓	GxP-grade MLOps manages model validation, monitoring, and change control for AI used in regulated decisions and manufacturing.	Enables safe scaling of AI by reducing validation effort per model and preventing drift-related compliance issues.	25 – 49%	50 – 74%	75 – 100%
OWI00184	AI-supported Release of Information Automation	✓	✓	✓	✓	✓	AI automates Health Information Management (HIM) requests, verifies authorization, and redacts protected health information (PHI) before release.	Speeds turnaround and reduces privacy breaches and legal exposure.	25 – 49%	25 – 49%	50 – 74%
OWI00191	AI-driven IT/OT Cybersecurity Monitoring for GMP Facilities and Device Manufacturing		✓	✓		✓	AI detects threats and anomalies across IT/OT networks and connected medical devices to reduce breach and downtime risk and downtime risks	Reduces unplanned downtime and avoids quality/regulatory events caused by cyber incidents; improves visibility across legacy OT assets.	25 – 49%	50 – 74%	75 – 100%
OWI00183	Edge AI Model Lifecycle Management for Deployed Medical Devices (secure updates, monitoring, drift)	✓	✓	✓		✓	Create a regulated MLOps capability to deploy, monitor, and update edge AI models on medical devices with auditability and cybersecurity controls.	Enables safer scaling of AI-enabled devices, reduces post-market safety risk, and supports faster improvements without full device replacement cycles.	25 – 49%	50 – 74%	75 – 100%
OWI00189	AI-based digital thread across medical device software lifecycle (SaMD, firmware, updates)			✓			A regulated digital thread links requirements, code, tests, risk files, and post-market signals to manage device software at scale.	Reduces documentation burden and speeds safe software updates while improving traceability and compliance.	25 – 49%	50 – 74%	75 – 100%
OWI00179	AI-enabled enterprise knowledge graph across R&D, clinical, and manufacturing data		✓	✓			Knowledge graphs connect molecules, targets, trials, manufacturing batches, and device components to enable cross-domain insights.	Improves reuse of knowledge, speeds investigations, and enables more powerful AI by providing context and lineage.	25 – 49%	25 – 49%	50 – 74%
OWI00180	AI-based synthetic data generation for privacy-preserving sharing and testing	✓	✓	✓	✓	✓	Generative models create synthetic clinical and manufacturing datasets to enable development/testing without exposing sensitive data.	Speeds analytics and AI development while reducing privacy risk and easing cross-border collaboration.	25 – 49%	25 – 49%	50 – 74%
OWI00185	AI-Powered Diagnostic Devices	✓		✓			Devices integrate AI to analyze signals (e.g., ECG—Electrocardiogram) and produce actionable findings.	Delivers faster, more accurate diagnostics and triage.	0 – 24%	25 – 49%	50 – 74%
OWI00186	Connected Health Devices with AI	✓		✓			Devices stream patient data for AI analysis to inform treatment and self-management.	Improves outcomes and engagement, enabling digital therapeutics.	0 – 24%	25 – 49%	50 – 74%
OWI00178	ML-based federated learning across partners without centralizing data	✓	✓	✓	✓	✓	Federated learning trains models across hospitals, partners, or plants without moving raw data, improving privacy and scale.	Enables larger training cohorts and broader learning while reducing data-sharing friction.	0 – 24%	25 – 49%	50 – 74%
OWI00196	AI-enabled Hospital Digital Twin for Capacity and Flow	✓				✓	A digital twin simulates patient flow, staffing, and asset utilization to optimize bed management, OR scheduling, and throughput.	Reduces bottlenecks and cancellations and increases capacity without adding staff.	0 – 24%	25 – 49%	50 – 74%
OWI00187	AI Multi-Modal Diagnostics	✓		✓			AI fuses signals (text, imaging, labs, sensor data) to improve diagnostic accuracy and triage.	Reduces diagnostic error and time-to-treatment, improving safety and efficiency.	0 – 24%	25 – 49%	50 – 74%
OWI00190	Quantum random number generation for high-assurance security (future)	✓	✓	✓	✓	✓	Quantum random number generators improve cryptographic strength for key generation and device security modules.	Strengthens security for long-lived devices and regulated systems; adoption increases as QRNG hardware commoditizes.	0 – 24%	0 – 24%	0 – 24%
OWI00192	Post-Quantum Cryptography Migration for Connected Medical Devices and Enterprise IT/OT	✓	✓	✓	✓	✓	Migrate to NIST-standard post-quantum cryptography across device firmware, cloud services, and GMP OT to protect long-lived patient and IP data.	Reduces long-term confidentiality and integrity risk ('harvest now, decrypt later') for regulated product data, manufacturing recipes, and patient/device telemetry.	0 – 24%	0 – 24%	0 – 24%

0 – 24% 25 – 49% 50 – 74% 75 – 100%

06

Call to Action

Healthcare is entering a decisive decade. Aging populations, rising chronic disease burdens, workforce shortages, and persistent unit cost inflation are converging to place unprecedented pressure on health systems worldwide. Absent sustained productivity improvement, global healthcare spending could approach $23 trillion by 2040, threatening long-term affordability and access across both public and private systems.

A significant share of this trajectory is not inevitable. As this report has shown, trillions of dollars in future spending growth can be avoided through sustained improvements in healthcare productivity. Artificial intelligence, automation, and robotics are no longer experimental tools: They are increasingly capable of managing complex workflows, supporting and extending scarce labor, and enabling system-level redesign rather than incremental efficiency gains.

What distinguishes this wave of digital health is not only its technological maturity. It comes at a time of great need when technology is ready to start deploying. Declining technology costs, improving integration capabilities, and mounting workforce constraints are making the sector and policymakers more eager to embrace the new technology as soon as it is available. Productivity is no longer optional, but rather a prerequisite for system viability, making many less tempted by a more gradual approach to adoption.

6.1 A productivity reset may mean more people-centered healthcare

But there is a right way and wrong way to begin its adoption. Despite the productivity opportunity inherent in AI and robotics, the core value of healthcare remains irreducibly human. Centering the human experience through people-focused care is also a proven pathway to better outcomes and more efficient use of resources, and it should anchor how the next wave of technology is deployed.

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People-centered care frameworks emphasize the need to organize around the preferences, capabilities, and lifestyles of patients, workers, families, and communities, not around technologies, institutions, or payment flows. Moments of serious illness, birth, disability, and dying are times when patients and families most need presence, touch, and genuine interpersonal connection, not only accurate diagnostics or highly efficient workflows.

Decades of research on patient experience, trust, continuity, and adherence show that empathy, high-quality communication, and longitudinal relationships are strongly associated with better outcomes. These include lower mortality, fewer hospital admissions and readmissions, reduced emergency room visits, improved quality of life, greater treatment adherence, and inevitably lower total costs of care.

> “High-touch” care can be cost-efficient even before any productivity gains from advanced technology are realized

Randomized and quasi-experimental studies of person-centered interventions in chronic disease management and hospital care demonstrate that such models can improve health-related quality of life while reducing or stabilizing overall expenditures. This underscores that “high-touch” care can be cost-efficient even before any productivity gains from advanced technology are realized.[159,160,161,162,163]

This evidence base has two important implications for how AI, robotics, and quantum technologies should be integrated into the future health system. First, healthcare is not manufacturing: Full automation of “end-to-end” encounters is neither realistic nor desirable, particularly in high-stakes, emotionally charged situations such as breaking bad news, engaging in shared decision making about risky procedures, or caring for patients who are frightened, in pain, or cognitively impaired. At these moments, people-centered care requires that patients can see and hear from human clinicians and caregivers who feel accountable to these patients and for their outcomes.

Technology needs to operate in the background to remove administrative friction, surface better information, and augment judgment so that clinicians are given the time and attention span to provide this kind of people-centered care. To achieve this, there must be social acceptance of advanced technology in care settings. Patients, families, and frontline workers must experience these tools as protecting and promoting dignity, autonomy, and human contact. Used well, AI and related tools can reinforce the very mechanisms that already drive better outcomes — with one of the biggest being the additional bandwidth it gives clinicians and caregivers to focus on their patients.[164,165,166]

The choices leaders make now will determine whether this productivity reset strengthens or undermines that human foundation. If systems over-rotate toward visible automation — robots at the bedside, AI agents as the primary interface — without simultaneously investing in workforce support, communication capabilities, and co-design with patients and communities, they risk a backlash. That could lead to slower adoption, regulatory retrenchment, and deepening mistrust.

The test of any technology should be whether it strengthens continuity of relationships, shared decision-making, and a sense of safety and respect among patients and workers. All of these things have been linked to reduced emergency use, lower hospitalization rates, and, in some contexts, lower mortality and total costs.

Cost-cutting cannot be at the heart of productivity agendas. Instead, health systems must frame AI, robotics, and — over time — quantum technologies as strategies to preserve and amplify the human elements of care and extend the reach of scarce clinicians through the reduction of paperwork, physically demanding tasks, and burnout. By doing this, leaders can align the productivity agenda with what patients and health workers say they value most — people-centered care.

The strategic challenge ahead is not to choose between “high-tech” and “high-touch,” but to demonstrate to the patient and worker constituencies that they no longer can have one without the other.

6.2 Changes need to be systemwide to gain enough traction

> “ Health system leaders and policymakers must treat AI, automation, and robotics as core operating infrastructure, not peripheral innovation

Because of the potential pervasiveness of how technology would be used, this opportunity will require coordinated leadership across the healthcare ecosystem. No single actor or segment — whether in healthcare, technology, finance, or government — can deliver the productivity reset alone.

Moving forward, health system leaders and policymakers must treat AI, automation, and robotics as core operating infrastructure of the sector, not peripheral innovation. This requires sustained investment in data foundations, workflow redesign around outcomes, and disciplined scaling of proven solutions. Savings from productivity gains must be reinvested to strengthen capacity, resilience, and financial sustainability — not absorbed as one-off cost relief and bottom-line bonanza.

Payers and insurers are well-positioned to act as accelerators. By modernizing administrative workflows, deploying AI-enabled care management, and evolving reimbursement models to reward avoided utilization and better outcomes, rather than lower utilization, payers can unlock productivity gains within their own operations and across provider networks.

Pharmaceutical and medical device companies also have a critical role. AI-enabled trials, automated laboratories, and advanced manufacturing can materially improve R&D productivity, shorten development timelines, and lower the cost of innovation. In medical devices, the future lies at the intersection of hardware, software, and robotics — enabling continuous learning, automation, and human-machine collaboration across care settings.

Policymakers and regulators are essential enablers. Adaptive regulatory frameworks, clearer liability models, interoperable data standards, and modernized data governance are prerequisites for safe and scalable deployment. Regulation should evolve to support continuous learning systems while preserving trust, safety, and equity.

Investors must be prepared to support this transition with patient capital. Productivity transformation carries execution risk, but investing too little poses greater systemic risk. Capital allocation should favor platforms, interoperability, and scalable operating models rather than isolated point solutions.

6.3 Balancing ambition with realism

> “ The greater risk today is too little ambition rather than overhyping immature technologies or scaling without discipline

This report does not argue that technology is a panacea. AI and robotics have limits, and poorly governed deployment carries real risks — from wasted capital to erosion of trust. Overhyping immature technologies or scaling without discipline can slow progress rather than accelerate it.

Yet the greater risk today is too little ambition. Workforce shortages and demographic pressures are structural and accelerating. The productivity gains outlined in this report are grounded in real-use cases already delivering measurable impact. Incrementalism may preserve short-term stability, but it risks locking healthcare into an unsustainable trajectory.

The choice facing healthcare leaders is no longer whether to push for change to occur, but whether it will be shaped deliberately, at scale, and in time. The tools are ready. The need is clear. What remains unclear is whether there is sufficient willingness to act with coordination, discipline, and resolve.

Endnotes

1 Organisation for Economic Co-operation and Development (OECD). (2024). *Fiscal Sustainability of Health Systems*. https://www.oecd.org/en/publications/fiscal-sustainability-of-health-systems_880f3195-en.html

2 Dieleman, J. L., Campbell, M., Chapin, A., Eldrenkamp, E., Fan, V. Y., Haakenstad, A., ... & Murray, C. J. (2017). Future and potential spending on health 2015–40: Development assistance for health, and government, prepaid private, and out-of-pocket health spending in 184 countries. *The Lancet,* vol. 389, no. 10083, pp. 2005-2030. https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(17)30873-5

3 BMI, a Fitch Solutions Company. (2025). *Healthcare Industry Research*. https://www.fitchsolutions.com/bmi/healthcare

4 IHME. (2025). *Financing Global Health*. https://www.healthdata.org/data-tools-practices/interactive-visuals/financing-global-health

5 Organisation for Economic Co-operation and Development (OECD). (2025). *Health at a Glance 2025*. https://www.oecd.org/en/publications/2025/11/health-at-a-glance-2025_a894f72e.html

6 World Health Organization. (2025). *Current health expenditure (CHE) as percentage of gross domestic product*. https://www.who.int/data/gho/data/indicators/indicator-details/GHO/current-health-expenditure-(che)-as-percentage-of-gross-domestic-product-(gdp)-(-)

7 United Nations. (2024). *World Population Prospects 2024: Dataset.* https://www.un.org/development/desa/pd/content/world-population-prospects-2024-dataset

8 Dzau, V. J., Asch, D. A., Hannaford, B., Aggarwal, R., & Pugh, C. M. (2017). Debate on the cost of innovation in healthcare: is it too costly?. *BMJ Simulation & Technology Enhanced Learning,* vol.3(suppl 1), pp. S33-S36. https://access.portico.org/stable?au=phzpvv45pqg

9 U.S. Census Bureau (2023). *Population projections*. https://www.census.gov

10 Zweig, M., Kimmell, J., Knowles, M. (2026). *2025 year-end digital health funding overview: A tale of two markets*. Rock Health. https://rockhealth.com/insights/2025-year-end-digital-health-funding-overview-a-tale-of-two-markets/

11 Olsen, O. (2026). *Digital health funding increases in 2025, spurred by AI: report*. Biopharma Dive. https://www.biopharmadive.com/news/digital-health-funding-2025-boosted-ai-rock-health/809484/

12 Meade, H. (2026). *Unlocking health care innovation to enhance access and improve outcomes*. Ernst & Young. https://www.ey.com/en_us/insights/health/progress-through-policy-the-digital-health-imperative

13 Gaffney, A., Woolhandler, S., Cai, C., Bor, D., Himmelstein, J., McCormick, D., & Himmelstein, D. U. (2022). Medical documentation burden among US office-based physicians in 2019: a national study. *JAMA internal medicine*, vol. 182, no.5, pp. 564-566. https://jamanetwork.com/journals/jamainternalmedicine/fullarticle/2790396

14 Nauenberg, E., Ng, C., & Zhu, Q. (2023). A Tale of Two Countries: Changes to Canadian and U.S. Senior Population Projections due to the Pandemic-Implications for Health Care Planning in Canada and Other Western Countries. *Journal of population ageing,* vol. 16, pp. 27-41. https://link.springer.com/article/10.1007/s12062-022-09397-z

15 Canadian Institute for Health Information. (2024). *The state of the health workforce in Canada, 2024*. https://www.cihi.ca/en/the-state-of-the-health-workforce-in-canada-2024

16 Eurostat (2023). *Population projections*. https://ec.europa.eu/eurostat

17 Riesser, C. (2025). *US and European Healthcare: An Insider's View*. Medium. https://medium.com/@CRiesser/us-and-european-healthcare-an-insiders-view-c8ca893a7b7e

18 Galen Growth. (2025*). European Digital Health Bucks The Trend*. https://www.galengrowth.com/european-digital-health-bucks-the-trend/

19 Galen Growth. (2025*). Europe Digital Health Funding in Q3 2025: Resilience Amid Rationalisation*. https://www.galengrowth.com/europe-digital-health-funding-in-q3-2025-resilience-amid-rationalisation/

20 World Economic Forum. (2026). *The gap is widening between super-ageing and youthful populations. Experts explain the implications*. https://www.weforum.org/stories/2025/01/super-ageing-and-youthful-populations-global-risks-report/

21 European Parliament. (2020). *Japan's ageing society*. https://www.europarl.europa.eu/RegData/etudes/BRIE/2020/659419/EPRS_BRI(2020)659419_EN.pdf

22 Statistics Japan (2023). *Statistical Handbook of Japan*. https://www.stat.go.jp

23 World Economic Forum. (2019). *Japan's workforce will be 20% smaller by 2040*. https://www.weforum.org/stories/2019/02/japan-s-workforce-will-shrink-20-by-2040/

24 Asao, K., Seitani, H., Stepanyan, A., & Xu, T. (2025). The Impact of Aging and AI on Japan's Labor Market: Challenges and Opportunities. *IMF Working Papers*, no. 2025/184. https://ssrn.com/abstract=5558898

25 Kushida, K. (2024). *Japan's Aging Society as a Technological Opportunity*. Carnegie Endowment for International Peace. https://carnegieendowment.org/research/2024/10/japans-aging-society-as-a-technological-opportunity

26 Cabinet Office. (2020), *Moonshot Goals for the Moonshot Research and Development Program*. Bureau of Science, Technology and Innovation. https://www8.cao.go.jp/cstp/english/moonshot/outline_en.pdf

27 Ken Research. (2024). Japan AI in Elderly Care Robotics Platforms Market. https://www.kenresearch.com/japan-ai-in-elderly-care-robotics-platforms-market

28 Vogt, G., & König, A. S. L. (2023). Robotic devices and ICT in long-term care in Japan: Their potential and limitations from a workplace perspective. *Contemporary Japan,* vol. 35, pp. 270-290. https://www.tandfonline.com/doi/full/10.1080/18692729.2021.2015846

29 Florek, K. (2023). 'Carebots' and the care crisis. European Public Service Union. https://www.epsu.org/article/human-touch-can-carebots-replace-human-empathy-and-compassion

30 State Council The People's Republic of China. (2024). *Over one-fifth of Chinese population older than 60, says official report*. https://english.www.gov.cn/news/202410/12/content_WS6709cb9ac6d0868f4e8ebbda.html

31 World Economic Forum. (2023). *Here's how China is dealing with its rapidly ageing population*. https://www.weforum.org/stories/2023/03/heres-how-china-is-dealing-with-its-ageing-population/

32 Zhao, P., Li, J., & Zhang, M. (2025). Unequal roles of cities in the intercity healthcare system. *Nature Cities*, vol. 2, pp. 198-209. https://www.nature.com/articles/s44284-024-00185

33 Reuters. (2025). *China's population falls for a third consecutive year*. https://www.reuters.com/world/china/chinas-population-falls-third-consecutive-year-2025-01-17/

34 Time. (2024). *China Unveils Extensive 'Silver Economy' Plan to Adapt to Aging Population*. https://time.com/6555949/china-silver-economy-aging-population-plan/

35 Reuters. (2025). *China rolls out plan to tackle growing issue of dementia*. https://www.reuters.com/world/china/china-rolls-out-plan-tackle-growing-issue-dementia-2025-01-06/

36 Word Bank Group. (2020). Physicians (per 1,000 people) – India. https://data.worldbank.org/indicator/SH.MED.PHYS.ZS

37 World Health Organization (WHO). (2024). Global strategy on human resources for health: workforce 2030. https://apps.who.int/gb/ebwha/pdf_files/EB156/B156_15-en.pdf

38 Campbell, J., Buchan, J., Cometto, G., David, B., Dussault, G., Fogstad, H., ... & Tangcharoensathien, V. (2013). Human resources for health and universal health coverage: fostering equity and effective coverage. *Bulletin of the World Health Organization*, vol. 91, pp. 853-863. https://pmc.ncbi.nlm.nih.gov/articles/PMC3853950/

39 HealthIT.gov. (2024). *Fast Healthcare Interoperability Resources (FHIR)*. U.S. Department of Health and Human Services. https://www.healthit.gov/topic/standards-technology/standards/fhir

40 United Nations (2022). *World Population Prospects 2022*. https://www.un.org/development/desa/pd

41 Vespa, J. E., Armstrong, D. M., & Medina, L. (2018*). Demographic turning points for the United States: Population projections for 2020 to 2060*. US Census Bureau. https://www.census.gov/content/dam/Census/library/publications/2020/demo/p25-1144.pdf

42 Eurostat. (2025). *Population structure and ageing*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_structure_and_ageing

43 Mei, Q., Kennedy, S., & Mazzocco, I. (2023). *China Is Growing Old Before It Becomes Rich: Does It Matter?*. Big Data China. https://bigdatachina.csis.org/china-is-growing-old-before-it-becomes-rich-does-it-matter/

44 Jones, R. S. (2024). Addressing demographic headwinds in Japan: A long-term perspective. *OECD Economics Department Working Papers*. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/addressing-demographic-headwinds-in-japan-a-long-term-perspective_85b9a67f/96648955-en.pdf

45 Organization for Economic Co-operation and Development (OECD). (2023). *Health at a Glance*. https://www.oecd.org/health/health-at-a-glance/

46 van Ark, B., Hoskins, J., & Jörden, N. (2023). Public Sector Productivity–managing the Baumol cost disease. *Productivity Insights Paper*, no. 25. https://www.productivity.ac.uk/research/public-sector-productivity-managing-the-baumol-cost-disease/

47 Himmelstein, D. U., Campbell, T., & Woolhandler, S. (2020). Health care administrative costs in the United States and Canada, 2017. *Annals of internal medicine*, vol. 172, no. 2, pp. 134-142. https://www.acpjournals.org/doi/abs/10.7326/m19-2818

48 Human Fertility Database (2025). *HFD summary indicators*. https://www.humanfertility.org/

49 Roser, M. (2025). *The global decline of the fertility rate*. Our World in Data. https://ourworldindata.org/global-decline-fertility-rate

50 European Parliament. (2025). *Disastrous shortage of healthcare workers in the EU.* https://www.europarl.europa.eu/doceo/document/E-10-2025-002331_EN.html

51 Wang, Q., Liu, S., Yang, X., Gong, C., Zhang, W., Yang, L., ... & Tangcharoensathien, V. (2025). *Anticipated need, demand, and supply of doctors and beds in China: approaching a turning point. Discover Health Systems, vol. 4.* https://link.springer.com/article/10.1007/s44250-025-00178-x

52 CDC National Center for Health Statistics. (2025). *National Health Expenditure Accounts*. https://www.cdc.gov/nchs/hus/sources-definitions/nhea.htm

53 Eurostat. (2025). *Healthcare expenditure statistics by function, provider and financing scheme*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Healthcare_expenditure_statistics_by_function,_provider_and_financing_scheme#Key_data_and_overview_of_healthcare_financing.2C_functions_and_providers

54 National Health Mission. (2024). *National Health Accounts Estimates for India.* https://nhsrcindia.org/sites/default/files/2024-09/NHA%202021-22.pdf

55 Health Bureau. (2024). *Hong Kong's Domestic Health Accounts*. https://www.healthbureau.gov.hk/statistics/en/dha.htm

56 International Trade Administration. (2025). *Healthcare Japan Country Stats*. https://www.trade.gov/healthcare-resource-guide-japan

57 Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical image analysis*, vol. 42, pp. 20-88. https://www.sciencedirect.com/science/article/abs/pii/S1361841517301135

58 Gorenshtein, A., Omar, M., Glicksberg, B. S., Nadkarni, G. N., & Klang, E. (2025). AI agents in clinical medicine: a systematic review. *medRxiv*. https://pmc.ncbi.nlm.nih.gov/articles/PMC12407621/

59 Karunanayake, N. (2025). Next-generation agentic AI for transforming healthcare. *Informatics and Health*, vol. 2, issue 2, pp. 73-83. https://www.sciencedirect.com/science/article/pii/S2949953425000141

60 Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). Artificial intelligence in healthcare: transforming the practice of medicine. *Future healthcare journal*, vol. 8, issue 2, pp. e188-e194. https://www.sciencedirect.com/science/article/pii/S2514664524005277

61 Butt, J. S. (2023). The Impact of Artificial Intelligence (AI) on the Efficiency of Administrative Decision Making Including Ethical & Legal Considerations and Comparative Study about Countries Already Incorporated AI for Administrative Decisions. *Acta Universitatis Danubius. Juridica,* no. 3, pp. 7-25. https://www.ceeol.com/search/article-detail?id=1216576

62 Taherdoost, H., & Madanchian, M. (2024). The Impact of Artificial Intelligence on Research Efficiency. *Results in Eng.*, vol. 26. https://www.sciencedirect.com/science/article/pii/S2590123025008205

63 Organization for Economic Co-operation and Development (OECD). (2024). *Artificial Intelligence and the health workforce*. https://www.oecd.org/en/publications/artificial-intelligence-and-the-health-workforce_9a31d8af-en.html

64 Permanente Medicine. (2017). *Leveraging Predictive Analytics to Transform Health*. https://permanente.org/wp-content/uploads/2017/11/Fact-Sheet_Predictive-Analytics-with-Hyperlinks.pdf

65 Interpharma Ph. (2025). *Roadmap for a futureproof production site. Advanced pharma manufacturing: a success factor*. https://www.interpharma.ch/wp-content/uploads/2025/06/20250626_iph_hightech_phramaproduktion_broschuere_a4_web_EN_cu02.pdf

66 Pharmaceutical Technology. (2025). *Engineering the future: how robotics and automation are transforming pharmaceutical logistics*. https://www.pharmaceutical-technology.com/sponsored/engineering-the-future-how-robotics-and-automation-are-transforming-pharmaceutical-logistics/

67 Hintze, M., Hoose, M. (2025). *A Game-Changer for Hospital Logistics*. Fraunhofer Institute for Material Flow and Logistics IML. https://www.iml.fraunhofer.de/en/press-and-media/discover-logistics/discover-logistics-25/a-game-changer-for-hospital-logistics.html

68 eERNI. (2025). Lab automation technologies: Revolutionising the future of research and development. https://www.betterask.erni/ch-en/lab-automation-technologies-revolutionising-the-future-of-research-and-development/

69 Eitelwein, O., Mishra, A., Forss, M., & Eleftheriadou, D. (2023). *Positioning the industry for growth in robotic surgery*. Oliver Wyman. https://www.oliverwyman.com/our-expertise/perspectives/health/2023/august/positioning-the-industry-for-growth-in-robotic-surgery.html

70 Riad, A., Hadid, M., Elomri, A., Al-Ansari, A., Rejeb, M. A., Qaraqe, M., ... & Omri, A. E. (2025). Advancements and Challenges in Robotic Surgery: A Holistic Examination of Operational Dynamics and Future Directions. *Surgery in Practice and Science*, vol. 22. https://www.sciencedirect.com/science/article/pii/S2666262025000233

71 Aprile, I. G., Quaglini, S., Turchetti, G., Pecchia, L., Comandè, G., Gramatica, F. (2025). Rehabilitation robotics and allied digital technologies: opportunities, barriers and solutions for improving their clinical implementation. A position paper from the Fit for Medical Robotics Initiative. *Frontiers in Robotics and AI,* vol. 12: 1531067. https://www.frontiersin.org/journals/robotics-and-ai/articles/10.3389/frobt.2025.1531067/full

72 Maynou, L., McGuire, A., & Serra-Sastre, V. (2024). Efficiency and productivity gains of robotic surgery: The case of the English National Health Service. *Health Economics*, vol. 33, no. 8, pp. 1831-1856. https://onlinelibrary.wiley.com/doi/10.1002/hec.4838

73 World Economic Forum. (2025). *Humanoid robots offer both disruption and promise. Here's why*. https://www.weforum.org/stories/2025/06/humanoid-robots-offer-disruption-and-promise/

74 British Broadcasting Corporation (BBC). (2026). *Car giant Hyundai to use human-like robots in factories*. https://www.bbc.co.uk/news/articles/cvgjm5x54ldo

75 Arm. (2026). *The next platform shift: Physical and edge AI, powered by Arm*. https://newsroom.arm.com/blog/the-next-platform-shift-physical-and-edge-ai-powered-by-arm

76 Evans, S. (2026). *Arm Launches Physical AI Unit*. AI Business. https://aibusiness.com/robotics/arm-launches-physical-ai-unit

77 Whalesbot. (2025). *Humanoid Robots: Abilities, Challenges, and the Road Ahead*. https://www.whalesbot.ai/blog/humanoid-robots-abilities-challenges-and-the-road-ahead

78 Insikt Group. (2025). *The Future of Humanoid Robots*. https://assets.recordedfuture.com/Executive-Insights/eir-2025-1120.pdf

79 Bank of America. (2025). *Humanoid Robots 101*. https://institute.bankofamerica.com/content/dam/transformation/humanoid-robots.pdf

80 Cao, L. (2025). Humanoid Robots and Humanoid AI: Review, Perspectives and Directions. *ACM Computing Surveys*, vol. 58, issue 4, pp. 1-37. https://dl.acm.org/doi/full/10.1145/3770574

81 Welte, E., & Rayyes, R. (2025). Interactive imitation learning for dexterous robotic manipulation: challenges and perspectives—a survey. *Frontiers in Robotics and AI*, vol. 12, pp. 1682437. https://www.frontiersin.org/journals/robotics-and-ai/articles/10.3389/frobt.2025.1682437/full

82 Al-Hamadani, M. N., Fadhel, M. A., Alzubaidi, L., & Harangi, B. (2024). Reinforcement learning algorithms and applications in healthcare and robotics: A comprehensive and systematic review. *Sensors*, vol. *24*, issue 8, pp. 2461-2503. https://www.mdpi.com/1424-8220/24/8/2461

83 Cao, L. (2025). Humanoid Robots and Humanoid AI: Review, Perspectives and Directions. *ACM Computing Surveys*, vol. *58*, no. 4, pp. 1-37. https://dl.acm.org/doi/full/10.1145/3770574

84 Nama, P. (2022). Optimizing automation systems with AI: A study on enhancing workflow efficiency through intelligent decision making algorithms. *World Journal of Advanced Engineering Technology and Sciences*, vol. *7*, no. 2, pp. 296-307. https://wjaets.com/node/1678

85 Costanzo, M., Smeriglio, R., & Di Nuovo, S. (2024). New technologies and assistive robotics for elderly: A review on psychological variables. *Archives of Gerontology and Geriatrics plus*, vol. 1, issue 4. https://www.sciencedirect.com/science/article/pii/S2950307824000535

86 Wright, J. (2023). *Inside Japan's long experiment in automating elder care*. MIT Technology review. https://www.technologyreview.com/2023/01/09/1065135/japan-automating-eldercare-robots/

87 World Economic Forum. (2025). *Quantum Technologies: Key Strategies and Opportunities for ICT Leaders*. https://www.weforum.org/publications/quantum-technologies-key-strategies-and-opportunities-for-ict-leaders/

88 Maskara, N., Ostermann, S., Shee, J., Kalinowski, M., McClain Gomez, A., Araiza Bravo, R., ... & Yelin, S. F. (2025). Programmable simulations of molecules and materials with reconfigurable quantum processors. *Nature Physics*, vol. 21, issue 2, pp. 289-297. https://www.nature.com/articles/s41567-024-02738-z

89 Aslam, N., Zhou, H., Urbach, E. K., Turner, M. J., Walsworth, R. L., Lukin, M. D., & Park, H. (2023). Quantum sensors for biomedical applications. *Nature Reviews Physics*, vol. 5, issue 3, pp. 157-169. https://www.nature.com/articles/s42254-023-00558-3

90 Schofield, H., Boto, E., Shah, V., Hill, R. M., Osborne, J., Rea, M., ... & Brookes, M. J. (2022). Quantum enabled functional neuroimaging: the why and how of magnetoencephalography using optically pumped magnetometers. *Contemporary Physics*, vol. 63, issue 3, pp. 161-179. https://www.tandfonline.com/doi/full/10.1080/00107514.2023.2182950

91 Novo Nordisk Foundation. (2024). *Researchers aim to advance quantum sensing to transform disease diagnosis and prevention*. https://novonordiskfonden.dk/en/news/researchers-aim-to-advance-quantum-sensing-to-transform-disease-diagnosis-and-prevention

92 World Economic Forum. (2025). *Quantum Technologies: Strategic Imperatives for Health and Healthcare Leaders*. https://www.weforum.org/publications/quantum-technologies-strategic-imperatives-for-health-and-healthcare-leaders/

93 World Economic Forum. (2025). *The Future of AI-Enabled Health: Leading the Way*. https://reports.weforum.org/docs/WEF_The_Future_of_AI_Enabled_Health_2025.pdf

94 P4H Social Health Projection Network. (2025). *Containing costs and nudging doctors and hospitals towards policy goals in Japan*. https://p4h.world/en/containing-costs-and-nudging-doctors-and-hospitals-towards-policy-goals-in-japan/

95 Precedence Research. (2025). *China Sets Ambitious Goal with Its Nationwide AI Healthcare Vision*. https://www.precedenceresearch.com/news/china-ai-healthcare-vision

96 World Health Organization (WHO). (2021). *Global strategy on digital health 2020-2025*. https://www.who.int/publications/i/item/9789240020924

97 Pinto-Coelho, L. (2023). How artificial intelligence is shaping medical imaging technology: a survey of innovations and applications. *Bioengineering*, vol. 10, issue 2. https://www.mdpi.com/2306-5354/10/12/1435

98 U.S. Food & Drug Administration. (2025). *Artificial Intelligence in Software as a Medical Device*. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-software-medical-device

99 Organization for Economic Co-operation and Development (OECD). (2025). *Digital and AI skills in health occupations*. https://www.oecd.org/en/publications/digital-and-ai-skills-in-health-occupations_5fbd42ab-en.html

100 Chatzichristos, C., Chatzichristos, G., Borremans, I., Gruyaert, S., De Vos, I., De Vos, M., & De Backere, F. (2025). Bridging the AI-Literacy Gap in Health Care: Qualitative Analysis of the Flanders Case Study. *Journal of Medical Internet Research*, vol. 27, pp. e76709. https://www.jmir.org/2025/1/e76709

101 Joseph, J. (2025). Enabling Responsible, Secure and Sustainable Healthcare AI-A Strategic Framework for Clinical and Operational Impact. *arXiv preprint*. https://arxiv.org/abs/2510.15943

102 van Kessel, R., Srivastava, D., Kyriopoulos, I., Monti, G., Novillo-Ortiz, D., Milman, R., ... & Mossialos, E. (2023). Digital health reimbursement strategies of 8 European countries and Israel: scoping review and policy mapping. *JMIR mHealth and uHealth*, vol. 11, e49003. https://mhealth.jmir.org/2023/1/e49003/

103 European Commission. (2021). *Excellence and trust in artificial intelligence*. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/excellence-and-trust-artificial-intelligence_en

104 Gov UK. (2023). *Software and AI as a Medical Device Change Programme roadmap*. https://www.gov.uk/government/publications/software-and-ai-as-a-medical-device-change-programme/software-and-ai-as-a-medical-device-change-programme-roadmap

105 Fast Healthcare Interoperability Resources (FHIR). (2025). *FHIR Overview*. https://www.hl7.org/fhir/overview.html

106 Organization for Economic Co-operation and Development (OECD). (2016). *Health Workforce Policies in OECD Countries: Right Jobs, Right Skills, Right Places*. https://doi.org/10.1787/9789264239517-en.

107 Organization for Economic Co-operation and Development (OECD). (2025). *Health at a Glance 2025: OECD Indicators.* https://doi.org/10.1787/8f9e3f98-en.

108 Tan, S. Y., Sumner, J., Wang, Y., & Wenjun Yip, A. (2024). A systematic review of the impacts of remote patient monitoring (RPM) interventions on safety, adherence, quality-of-life and cost-related outcomes. *NPJ Digital Medicine*, vol. 7, number 192. https://www.nature.com/articles/s41746-024-01182-w

109 Smedslund, G., Østerås, N., & Hestevik, C. H. (2025). Effects of remote patient monitoring on health care utilization in patients with noncommunicable diseases: Systematic review and meta-analysis. *JMIR mHealth and uHealth*, vol. 13, e68464. https://mhealth.jmir.org/2025/1/e68464

110 Centers for Medicare & Medicaid Services. (2024). Lessons from CMS' Acute Hospital Care at Home Initiative. https://www.cms.gov/blog/lessons-cms-acute-hospital-care-home-initiative

111 Lip, G., Novak, A., Goyen, M., Boylan, K., & Kumar, A. (2024). Adoption, orchestration, and deployment of artificial intelligence within the National Health Service—facilitators and barriers: an expert roundtable discussion. *BJR| Artificial Intelligence*, vol. 1, issue 1, ubae009. https://academic.oup.com/bjrai/article/1/1/ubae009/7687959

112 Eggleston, K., Lee, Y. S., & Iizuka, T. (2021). *Robots and labor in the service sector: Evidence from nursing homes* (No. w28322). National Bureau of Economic Research. https://www.nber.org/papers/w28322

113 Kato, K., Yoshimi, T., Aimoto, K., Sato, K., Itoh, N., & Kondo, I. (2023). Reduction of multiple-caregiver assistance through the long-term use of a transfer support robot in a nursing facility. *Assistive Technology*, vol. 35, issue 3, pp. 271-278. https://www.tandfonline.com/doi/10.1080/10400435.2022.2039324

114 Fragapane, G., Hvolby, H. H., Sgarbossa, F., & Strandhagen, J. O. (2020, August). Autonomous mobile robots in hospital logistics. In *IFIP international conference on advances in production management systems* (pp. 672-679). https://vbn.aau.dk/ws/files/458075934/Autonomous_mobile_robots_in_hospital_logistics_31052020.pdf

115 Roland, A., Fox, W., & Baker, A. (2024). Efficiency, effectiveness and productivity in pharmaceutical R&D. *Nat Rev Drug Discov*, vol. 23, pp. 656-657. https://www.nature.com/articles/d41573-024-00068-6

116 Roche. (2024). *Roche innovations in the use of health data*. https://www.roche.ch/en/stories/roche-innovations-in-the-use-of-health-data

117 Novartis. (2025). *Build in increments that are individually valuable & collectively transformative.* https://faculty.ai/lesson-08-novartis

118 Alsunidale, M., Zalzala, M. (2025). *Pfizer's AI-Powered Feasibility and Cost Efficiency: The Future of Clinical Trial Recruitment. The Clinical Trial Vanguard*. https://www.clinicaltrialvanguard.com/conference-coverage/pfizers-ai-powered-feasibility-and-cost-efficiency-the-future-of-clinical-trial-recruitment/nt/

119 Shankar, R. (2025). *How Emerging AI Capabilities are Reshaping Life Sciences*. IQVIA. https://www.iqvia.com/blogs/2025/10/how-emerging-ai-capabilities-are-reshaping-life-sciences

120 Roche. (2023). *Delivering value through digital manufacturing*. https://www.roche.com/stories/diagnostics-operations-digitalisation

121 O'Callaghan, B. (2023). *AI Goes Industrial*. Sanofi. https://www.sanofi.com/en/magazine/our-science/ai-goes-industrial

122 Duhamel, S., and Lecomte, M. (2025). *Digital and AI Powered Manufacturing & Supply: Delivering Faster and Safer for Patients*. Sanofi. https://www.sanofi.com/en/magazine/our-science/digital-and-ai-powered-manufacturing-and-supply-delivering-faster-and-safer-for-patients

123 U.S. Food & Drug Administration (FDA). (2025). *Advancing Product Quality*. https://www.fda.gov/drugs/pharmaceutical-quality-resources/advancing-product-quality

124 U.S. Food & Drug Administration (FDA). (2024). Advanced Manufacturing Technologies Designation Program. https://www.fda.gov/regulatory-information/search-fda-guidance-documents/advanced-manufacturing-technologies-designation-program

125 Reuters. (2026). *Drugmakers turn to AI to speed trials, regulatory submissions.* https://www.reuters.com/legal/litigation/drugmakers-turn-ai-speed-trials-regulatory-submissions-2026-01-26/

126 Roche. (2023). *Regulatory speed & agility.* https://www.roche.com/stories/regulatory-speed-agility

127 U.S. Food & Drug Administration. (2020). *Drug shortages: Root causes and potential solutions.* https://www.fda.gov/drugs/drug-shortages/report-drug-shortages-root-causes-and-potential-solutions

128 World Economic Forum. (2026). *Global value chains outlook 2026: Orchestrating corporate and national agility.* https://reports.weforum.org/docs/WEF_Global_Value_Chains_Outlook_2026.pdf

129 GE HealthCare. (2026). *Predictive services in healthcare are more important than ever.* https://www.gehealthcare.com/services/predictive-services

130 GE HealthCare. (2026). *OnWatch predict for image guiding solutions. https://www.gehealthcare.com/services/onwatch-predict-for-image-guiding-solutions?srsltid=AfmBOoooOV_dfipLEWGZt3ewikgbSyvSItmUfRSBt6PsdNE6z_DokT_z*

131 Siemens AG. (2026). *Manufacturing simulation for medical devices with the production digital twin.* https://resources.sw.siemens.com/en-US/e-book-manufacturing-simulation-medical-device-production-digital-twin/

132 U.S. Food & Drug Administration (FDA). (2025). *Good machine learning practice for medical device development: Guiding principles*. https://www.fda.gov/medical-devices/software-medical-device-samd/good-machine-learning-practice-medical-device-development-guiding-principles

133 Medtronic. (2026). *Supplier quality. https://www.medtronic.com/en-us/our-company/governance/suppliers/supplier-quality.html*

134 U.S. Food & Drug Administration (FDA). (2023). *Design controls.* https://www.fda.gov/inspections-compliance-enforcement-and-criminal-investigations/inspection-guides/design-controls

135 National Archives and Records Administration (NARA); U.S. government publishing office (GPO). (2024). *Part 820—Quality management system regulation.* https://www.ecfr.gov/current/title-21/chapter-I/subchapter-H/part-820

136 GE HealthCare. (2026). *Predictive services in healthcare are more important than ever.* https://www.gehealthcare.com/services/predictive-services

137 Philips. (2026). *Managed services.* https://www.usa.philips.com/healthcare/service/managed-services

138 Tang, Y., Zhou, Y., Wu, T., Wang, C., Li, Z., & Li, K. (2025). AI-driven predictive maintenance for medical imaging equipment: A deep learning framework based on the IoMT data. *Reliability Engineering & System Safety*, *270*, 112152. https://doi.org/10.1016/j.ress.2025.112152

139 U.S. Food & Drug Administration (FDA). (2025). *Marketing submission recommendations for a predetermined change control plan for artificial intelligence-enabled device software functions.* https://www.fda.gov/regulatory-information/search-fda-guidance-documents/marketing-submission-recommendations-predetermined-change-control-plan-artificial-intelligence

140 International Medical Device Regulators Forum (IMDRF). (2025). *Good machine learning practice for medical device development: Guiding principles.* https://www.imdrf.org/documents/good-machine-learning-practice-medical-device-development-guiding-principles

141 Opentext. (2026). *Customer stories – Philips healthcare.* https://www.opentext.com/customers/philips-healthcare-3

142 American Medical Association (AMA). (2025). *Fixing prior auth: Nearly 40 prior authorizations a week is way too many*. https://www.ama-assn.org/practice-management/prior-authorization/fixing-prior-auth-nearly-40-prior-authorizations-week-way

143 Centers for Medicare & Medicaid Services (CMS), United States Government. (2025). *CMS interoperability and prior authorization final rule (CMS-0057-F).* https://www.cms.gov/cms-interoperability-and-prior-authorization-final-rule-cms-0057-f

144 Centers for Medicare & Medicaid Services (CMS), United States Government. (2024). *Medicare and Medicaid Programs.* https://www.federalregister.gov/documents/2024/02/08/2024-00895/medicare-and-medicaid-programs-patient-protection-and-affordable-care-act-advancing-interoperability

145 CAQH. (2023). *2023 CAQH Index Report – A new normal: How trends from the pandemic are impacting the future of healthcare administration.* https://www.caqh.org/hubfs/43908627/drupal/2024-01/2023_CAQH_Index_Report.pdf

146 CAQH. (2025). *New CAQH index reveals $20b savings opportunity to cut waste, reduce costs, and improve patient access.* https://www.caqh.org/blog/new-caqh-index-reveals-20b-savings-opportunity-to-cut-waste-reduce-costs-and-improve-patient-access

147 du Preez, A., Bhattacharya, S., Beling, P., & Bowen, E. (2024). Fraud detection in healthcare claims using machine learning: A systematic review. *Artificial Intelligence in Medicine*. https://doi.org/10.1016/j.artmed.2024.103061

148 Kumaraswamy, N., Markey, M. K., Ekin, T., Barner, J. C., & Rascati, K. (2022). Healthcare Fraud data mining methods: A look back and look ahead. *Perspectives in health information management*. https://pmc.ncbi.nlm.nih.gov/articles/PMC9013219/

149 Organization for Economic Co-operation and Development (OECD). (2022). *Towards an integrated health information system in Korea.* https://doi.org/10.1787/c4e6c88d-en.

150 Centers for Medicare & Medicaid Services, United States Government. (2024). *CMS interoperability and prior authorization final rule CMS-0057-F.* https://www.cms.gov/newsroom/fact-sheets/cms-interoperability-and-prior-authorization-final-rule-cms-0057-f

151 World Health Organization (WHO). (2026). *Epidemic intelligence from open sources – Zero impact from health threats.* https://www.who.int/initiatives/eios

152 World Health Organization (WHO). (2025). *Epidemic intelligence from open sources (EIOS) strategy 2024—2026.* https://www.who.int/publications/i/item/B09476

153 Department of Health and Social Care; The Rt Hon Steve Barclay MP (Government of United Kingdom). (2022). *Artificial intelligence revolutionising NHS stroke care.* https://www.gov.uk/government/news/artificial-intelligence-revolutionising-nhs-stroke-care

154 The National Health Service (NHS) England. (2025). *'Life-changing' AI support helping stroke patients get a second chance.* https://www.england.nhs.uk/2025/12/life-changing-ai-support-helping-stroke-patients-get-a-second-chance/

155 Kujala, S., Hörhammer, I., Väyrynen, A., Holmroos, M., Nättiaho-Rönnholm, M., Hägglund, M., & Johansen, M. A. (2022). Patients▯ experiences of web-based access to electronic health records in Finland: Cross-sectional survey. Journal of Medical Internet Research, 24(6), e37438. https://doi.org/10.2196/37438

156 Kela's Info Tray. (2026). *Statistics on the Kanta services.* https://tietotarjotin.fi/en/statistic/957560/statistics-on-the-kanta-services

157 Government of UK. (2024). *AI airlock: The regulatory sandbox for AIaMD.* https://www.gov.uk/government/collections/ai-airlock-the-regulatory-sandbox-for-aiamd

158 Regulatory Focus (RAPS.org). (2024). *Euro roundup: MHRA launches AI airlock.* https://www.raps.org/news-and-articles/news-articles/2024/5/euro-roundup-mhra-launches-ai-airlock

159 Nkhoma, K. B., Cook, A., Giusti, A., Farrant, L., Petrus, R., Petersen, I., … & Harding, R. (2022). A systematic review of impact of person-centred interventions for serious physical illness in terms of outcomes and costs. *BMJ open*, vol. 12, no. 7: e054386. https://bmjopen.bmj.com/content/12/7/e054386

160 Pirhonen, L., Gyllensten, H., Olofsson, E. H., Fors, A., Ali, L., Ekman, I., & Bolin, K. (2020). The cost-effectiveness of person-centred care provided to patients with chronic heart failure and/or chronic obstructive pulmonary disease. *Health Policy OPEN*, vol. 1, pp. 100005. https://www.sciencedirect.com/science/article/pii/S2590229620300034

161 Harding, E., Wait, S., & Scrutton, J. (2015). The state of play in person-centred care. The Health Policy Partnership. https://www.healthpolicypartnership.com/app/uploads/The-state-of-play-in-person-centred-care.pdf

162 Sharkiya, S. H. (2023). Quality communication can improve patient-centred health outcomes among older patients: a rapid review. *BMC Health Services Research*, vol.23, no. 886. https://link.springer.com/article/10.1186/s12913-023-09869-8

163 Engström, S. G., André, M., Arvidsson, E., Östgren, C. J., Troein, M., & Borgquist, L. (2025). Personal GP-continuity improves healthcare outcomes in primary care populations–A systematic review. *British Journal of General Practice*, vol. 75, issue 757. https://bjgp.org/content/75/757/e518

164 Baker, R., Freeman, G. K., Haggerty, J. L., Bankart, M. J., & Nockels, K. H. (2020). Primary medical care continuity and patient mortality: a systematic review. *British Journal of General Practice*, vol. 70, issue 698. https://bjgp.org/content/70/698/e600

165 Çakmak, C., & Uğurluoğlu, Ö. (2024). The effects of patient-centered communication on patient engagement, health-related quality of life, service quality perception and patient satisfaction in patients with cancer: a cross-sectional study in Türkiye. *Cancer Control*, vol. 31. https://journals.sagepub.com/doi/full/10.1177/10732748241236327

166 Pirhonen, L., Olofsson, E. H., Fors, A., Ekman, I., & Bolin, K. (2017). Effects of person-centred care on health outcomes—a randomized controlled trial in patients with acute coronary syndrome. *Health Policy*, vol.121, issue 2, pp. 169-179. https://www.sciencedirect.com/science/article/abs/pii/S0168851016303451

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