Asymmetric Capture of AI-Driven Productivity Gains in Medical Triage: Market Power, Quantum Potential, and the Distribution of Economic Surplus

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Abstract

This paper examines the asymmetric distribution of productivity gains generated by artificial intelligence systems in medical triage, with particular attention to the emerging role of quantum-enhanced computational capabilities. While AI-driven triage systems promise substantial cost reductions and efficiency improvements, the economic surplus generated is unlikely to be distributed equitably among stakeholders. Drawing on theories of market power, rent-seeking behavior, and labor economics, we analyze how hospitals, insurance companies, healthcare professionals, and patients each capture different portions of these gains. The analysis reveals that institutional actors with greater market power tend to appropriate disproportionate shares of the productivity surplus, while vulnerable populations and displaced workers may experience net welfare losses. We discuss the governance structures and policy interventions necessary to ensure more equitable distribution of technological benefits in healthcare markets.

Keywords: Artificial Intelligence, Medical Triage, Productivity Gains, Economic Surplus Distribution, Healthcare Economics

JEL Codes: I11, I18, J24, O33, L13

1 Introduction

The integration of artificial intelligence into medical triage systems represents one of the most significant technological transformations in healthcare delivery. These systems, designed to prioritize patient care based on urgency and medical need, increasingly rely on machine learning algorithms capable of processing vast amounts of clinical data with remarkable speed and accuracy. The recent emergence of quantum computing capabilities promises to further accelerate these algorithms through enhanced optimization and pattern recognition, though practical implementations remain largely experimental (Herman et al., 2022; Quantum Technology and Application Consortium – QUTAC, 2021).

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From an economic perspective, AI-driven triage generates substantial productivity gains by reducing diagnostic errors, minimizing wait times, and optimizing resource allocation within healthcare facilities. However, the distribution of these gains among various stakeholders raises fundamental questions of equity and efficiency (Wheatley Research Consultancy, 2024). Who ultimately benefits from these technological improvements? Do cost savings translate into lower prices for patients, higher wages for healthcare workers, increased profits for hospitals, or premium reductions from insurance companies?

This paper addresses these questions through a theoretical examination of how market structures, bargaining power, and institutional arrangements shape the allocation of AI-generated economic surplus. We focus specifically on triage applications because they represent a critical juncture where technology directly interfaces with patient outcomes and resource allocation decisions (**?**). Unlike purely administrative AI applications, triage systems have immediate implications for clinical care quality, making the distribution question particularly salient from both efficiency and equity perspectives.

The analysis proceeds from the recognition that healthcare markets are characterized by significant imperfections, including information asymmetries, concentrated market power, regulatory constraints, and the presence of third-party payers (Dubbink, 2003). These features fundamentally alter how productivity gains are distributed compared to competitive market benchmarks. Moreover, the introduction of AI technology may itself reshape market dynamics by reducing demand for certain types of labor, altering the relative bargaining positions of different actors, and creating new forms of rent-seeking behavior (Holahan and Lubell, 2016).

While quantum computing remains largely experimental in medical applications, its potential to dramatically enhance AI capabilities warrants consideration in any forward-looking analysis (de Jong, 2022). Quantum algorithms designed for optimization problems could significantly improve triage accuracy and speed, potentially multiplying the productivity gains already observed with classical AI systems (Ajagekar and You, 2019). However, the capital intensity of quantum technology may also concentrate its benefits among well-resourced institutions, exacerbating existing inequalities in healthcare access and outcomes (Wolbring, 2022).

Our theoretical framework builds on established models of economic surplus distribution under imperfect competition, adapting them to the specific institutional context of healthcare markets (Gilles, 2010). We examine how different stakeholders interact in what is essentially a multi-sided bargaining problem, where the total surplus generated by AI must be allocated among hospitals, insurers, physicians, nurses, and patients. The outcome of this allocation process depends critically on each party's bargaining power, outside options, and ability to capture rents through various mechanisms.

The technological transformation driven by AI and potential quantum enhancement also raises broader questions about innovation governance and societal preparedness (de Jong, 2022). As Wolbring (2022) demonstrates through comprehensive analysis of quantum technology literature, social considerations remain remarkably absent from technical discussions, with equity, diversity, and inclusion frameworks completely overlooked in the vast majority of research outputs. This absence extends to healthcare applications, where distributional questions receive insufficient attention despite their profound implications for access and outcomes.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework for analyzing productivity gains and surplus distribution. Section 3 examines the technological capabilities of AI triage systems and the potential enhancement from quantum computing. Section 4 analyzes how market power shapes the distribution of economic gains among institutional actors. Section 5 considers labor market implications for healthcare professionals. Section 6 evaluates patient welfare and access to care. Section 7 concludes with policy implications.

2 Theoretical Framework: Productivity Gains and Economic Surplus

The economic analysis of technological productivity gains begins with the concept of total surplus, defined as the aggregate welfare generated by an economic activity minus the costs of production. When AI reduces the cost of providing medical triage services, it creates additional surplus that can potentially be distributed among all market participants. The central analytical question concerns how this surplus is divided (Zilberman et al., 2018).

In a perfectly competitive market, economic theory predicts that productivity improvements flow primarily to consumers through lower prices, as firms compete away supranormal profits. However, healthcare markets deviate substantially from competitive ideals (Dubbink, 2003). On the supply side, hospitals often operate in oligopolistic or monopolistic environments, particularly in rural areas or specialized service lines. On the demand side, patients rarely pay full costs directly, with insurance companies serving as intermediaries that negotiate prices and coverage terms.

Consider a stylized model of the triage market before AI adoption. Let the cost of providing triage services be represented by C_0, which includes labor costs for nurses and physicians, administrative overhead, and capital expenses for traditional diagnostic equipment. The value to patients of receiving appropriate triage can be denoted V, which encompasses both the direct health benefits of correct prioritization and the opportunity cost of time spent waiting.

The total surplus in this initial state is $S_0 = V - C_0$. This surplus is divided among stakeholders according to their relative bargaining power and the structure of payment arrangements. Hospitals capture a portion through operating margins, insurers through premium revenues exceeding claims, healthcare workers through wages above their reservation levels, and patients through consumer surplus when the value exceeds their out-of-pocket costs.

Introduction of AI technology reduces triage costs to $C_1 < C_0$, creating additional surplus denoted as:

$$\Delta S = C_0 - C_1$$

The distribution of this increment depends on several factors. First, the degree of competition among hospitals determines whether cost savings are passed through to insurers and patients via lower prices, or retained as increased profits. Second, the bargaining power of insurers relative to hospitals affects how savings are split between premium reductions and insurer margins. Third, the labor market conditions for healthcare professionals influence whether displaced workers find comparable employment or experience wage losses.

Market power plays a decisive role in this allocation process (Gilles, 2010). When hospitals possess significant pricing power, they can retain cost savings without reducing charges for services. This is particularly likely in markets with high concentration or regulatory barriers to entry. Conversely, when insurers have strong negotiating positions, they may extract concessions that force hospitals to share savings through reduced reimbursement rates.

The asymmetry of information further complicates the distribution. Patients typically lack detailed knowledge about the cost structure of triage services, making it difficult to verify whether AI-generated savings are reflected in lower prices. Similarly, insurers may struggle to observe hospital cost reductions directly, though they can infer changes from utilization patterns and outcomes data. This informational opacity creates opportunities for rent extraction by better-informed parties.

Another critical consideration is the public good nature of certain productivity gains. Improvements in triage accuracy benefit not only individual patients but also the broader healthcare system through better resource allocation and reduced emergency department crowding. These positive externalities suggest that social welfare maximization may require different allocation mechanisms than pure market-based distribution would produce (Holahan and Lubell, 2016).

We can represent the allocation of productivity gains through a simple partitioning framework. Let α denote the share of cost savings captured by hospitals as increased profits, β the share appropriated by insurers through maintained premium levels despite lower claims, γ the portion absorbed by healthcare workers through wage adjustments or employment losses, and δ the fraction passed to patients through lower out-of-pocket costs or improved access. These shares must sum to unity:

$$\alpha + \beta + \gamma + \delta = 1$$

The magnitude of each share depends on the specific institutional and market conditions. In highly concentrated hospital markets with weak insurance negotiating power, we expect α to be large. In markets with powerful insurers and fragmented hospital systems, β may dominate. The labor share γ tends to be negative when workers bear adjustment costs through displacement or wage cuts, effectively redistributing surplus from labor to capital.

This framework helps clarify why technological progress does not automatically improve welfare for all stakeholders, even when it generates clear efficiency gains. The distribution mechanism matters as much as the total magnitude of productivity improvements. Without appropriate policy interventions or governance structures, market power asymmetries can lead to highly skewed outcomes where the benefits of innovation accrue narrowly while costs are borne broadly.

3 The Triage AI Revolution and Quantum-Enhanced Potential

Medical triage represents an ideal application domain for artificial intelligence due to its pattern recognition requirements, the availability of large training datasets, and the potential for significant outcome improvements through faster and more accurate decision-making. Modern AI triage systems employ deep learning architectures trained on millions of patient encounters, enabling them to predict severity, recommend care pathways, and optimize resource allocation with accuracy often exceeding human performance on specific tasks.

The productivity gains from AI triage manifest through multiple channels. First, these systems reduce the time required to assess patients, allowing healthcare facilities to process higher volumes without proportional increases in staffing. Second, improved accuracy in prioritization leads to better matching of patients to appropriate care levels, reducing costly misallocations where urgent cases receive delayed treatment while non-urgent cases consume scarce emergency resources. Third, AI systems can operate continuously without fatigue, providing consistent quality across all hours of operation.

Quantifying these gains requires consideration of both direct cost reductions and quality improvements. On the cost side, AI can partially substitute for skilled labor in initial assessment tasks, reducing personnel expenses. Facilities implementing AI triage have reported labor cost savings ranging from modest to substantial, depending on the baseline staffing model and the degree of automation achieved. Additionally, more accurate triage reduces waste from unnecessary testing and treatment, generating further economies.

Quality improvements translate to economic value through several mechanisms. Patients receiving more appropriate care experience better health outcomes, which have calculable economic worth through quality-adjusted life years and reduced long-term treatment costs. Reduced waiting times create time savings for patients that should be valued at opportunity cost of time. Moreover, better triage accuracy may reduce malpractice liability exposure for providers, lowering insurance premiums and defensive medicine costs.

The emergence of quantum computing introduces a new dimension to this analysis, though one still largely theoretical in practical deployment (Herman et al., 2022; Ajagekar and You, 2019). Quantum algorithms excel at certain optimization problems and pattern recognition tasks that are computationally intensive for classical computers. In the triage context, quantum-enhanced AI could potentially process vastly more complex decision trees, incorporate larger sets of biomarkers and patient history variables, and update models more rapidly as new clinical evidence emerges (Morstyn and Wang, 2024).

Recent developments in quantum optimization demonstrate the technology's potential for complex scheduling and resource allocation problems (Takeori et al., 2024; Borysiuk and Michuta, 2025). Industry consortia have identified numerous practical applications where quantum computing may provide competitive advantages, though healthcare-specific implementations remain nascent (Quantum Technology and Application Consortium – QUTAC, 2021). The integration of quantum capabilities into business analytics frameworks suggests pathways for eventual healthcare adoption (**?**).

However, quantum technology also presents significant challenges that affect the distribution of its benefits. The capital requirements for quantum computing infrastructure are enormous, likely restricting access to large academic medical centers and well-capitalized hospital systems. This could create a two-tier healthcare structure where wealthy institutions offer quantum-enhanced triage while resource-constrained facilities continue using classical AI or even traditional methods. Such stratification would exacerbate existing inequalities in healthcare access and outcomes (Wolbring, 2022).

From a productivity perspective, quantum computing represents a potential multiplier effect on AI capabilities. If quantum algorithms can achieve order-of-magnitude improvements in triage accuracy or speed, the economic surplus generated would increase correspondingly. Yet the distribution question becomes even more acute. The high fixed costs of quantum technology create natural monopoly characteristics, where economies of scale strongly favor concentration. This market structure inherently favors capital owners over other stakeholders.

It is important to distinguish between the productivity gains achievable with current AI technology and the speculative future gains from quantum enhancement. Present-day classical AI already demonstrates substantial performance in triage applications, and the incremental benefit from quantum computing remains uncertain. Focusing policy discussions exclusively on quantum potential risks neglecting the immediate distributional challenges posed by existing AI deployments.

4 Market Power and the Distribution of Economic Gains

The structure of healthcare markets fundamentally shapes how AI-generated productivity gains are distributed among stakeholders. Unlike competitive markets where efficiency improvements rapidly translate into consumer benefits through price competition, concentrated healthcare markets enable providers and insurers to retain substantial portions of the surplus as economic rents. Understanding these dynamics requires careful analysis of bargaining relationships and market power asymmetries (Gilles, 2010).

Hospital market concentration has increased substantially over recent decades through mergers and acquisitions, particularly in systems where significant share of metropolitan areas are now served by dominant hospital networks. This consolidation grants providers considerable pricing power in negotiations with insurers and the ability to resist pass-through of cost savings to patients. When a hospital system faces limited competition, it can maintain price levels even after AI reduces its production costs, capturing the full productivity gain as increased operating margins.

The economic logic is straightforward. If a hospital's costs fall from C_0 to C_1 due to AI implementation, but the hospital maintains its price at level P set under the previous cost structure, then profit per unit increases by exactly:

$$\pi = P - C_1 - (P - C_0) = C_0 - C_1 = \Delta S$$

In competitive markets, rival hospitals would undercut this price to capture market share, but in concentrated markets such competitive pressure is weak or absent. Regulatory price controls can potentially limit this rent extraction, but many healthcare services operate in largely unregulated pricing environments.

Insurance companies represent a countervailing force to hospital market power. Large national insurers often possess significant bargaining leverage due to their ability to direct patient flows through network design and benefit structures. When insurers negotiate reimbursement rates with hospitals, they may demand price concessions that reflect the productivity improvements from AI. However, the outcome depends on the relative bargaining strength of each party.

In markets where a dominant hospital system faces fragmented insurers, the hospital typically prevails in extracting favorable terms. Conversely, in markets with powerful insurers and multiple competing hospitals, insurers can push for lower rates that pass through some or all of the AI-generated cost savings. The bilateral monopoly problem that often characterizes these negotiations means that no unique equilibrium exists; the actual division of surplus depends on bargaining protocols, outside options, and strategic considerations.

Even when insurers successfully negotiate lower hospital reimbursement rates, this does not automatically benefit patients. Insurers may retain these savings as increased underwriting profits rather than reducing premiums. The competitive structure of insurance markets determines whether savings flow through to consumers. In highly competitive insurance markets, premium competition should drive pass-through. However, insurance markets often exhibit significant concentration and product differentiation that insulate carriers from full competitive pressure.

The multi-payer structure prevalent in many healthcare systems complicates surplus distribution further. When hospitals negotiate separately with numerous insurers, each with different beneficiary populations and bargaining power, the allocation of productivity gains becomes highly fragmented. Some insurers may extract favorable terms while others do not, leading to cross-subsidization and inefficient price discrimination across patient populations.

Professional associations and labor unions represent additional actors with potential influence over surplus distribution. Physician groups may negotiate compensation arrangements that preserve their income levels despite AI-driven productivity improvements, effectively extracting a share of the gains through bargaining. Nursing unions may similarly push for wage protections or employment guarantees. The strength of these professional organizations varies widely across jurisdictions and institutional settings, creating further heterogeneity in distributional outcomes.

Rent-seeking behavior can also dissipate productivity gains through socially wasteful activities. Hospitals and insurers may invest substantial resources in lobbying for favorable regulatory treatment, litigation over contract terms, or strategic positioning to enhance bargaining power. While these activities redistribute surplus among private parties, they generate no social value and represent deadweight losses that reduce the net welfare benefit of technological progress.

5 Labor Market Implications for Healthcare Professionals

The impact of AI-driven triage on healthcare labor markets represents one of the most significant distributional channels through which productivity gains are allocated. While aggregate employment effects remain uncertain, the technology clearly shifts demand across different skill categories and may reduce total labor requirements for triage functions (Raja and Christiaensen, 2017). Healthcare workers who bear adjustment costs through displacement, wage reductions, or skill obsolescence effectively contribute a portion of the productivity surplus through foregone earnings.

Triage has traditionally been a labor-intensive function requiring skilled nursing staff and physician oversight. AI systems automate significant portions of this work, particularly the initial assessment and prioritization tasks that consume substantial nursing time in emergency departments and urgent care facilities. As these routine components become computerized, demand for labor performing these specific functions declines, creating displacement pressure.

The magnitude of labor market effects depends critically on the substitutability between AI and human workers. If AI can perform triage tasks with minimal human supervision, the technology represents a close substitute for existing labor, likely leading to significant displacement. Conversely, if effective triage requires substantial human judgment working in conjunction with algorithmic outputs, AI and labor may be complements, potentially increasing demand for skilled professionals even as it reduces demand for routine assessors.

Empirical evidence from early AI triage deployments suggests a mixed pattern. Some facilities have reduced triage nursing staff while others have redeployed workers to other functions rather than eliminating positions. The heterogeneity in responses reflects differences in institutional constraints, labor market conditions, and strategic choices about service quality. Unionized facilities may face contractual obligations that limit workforce reductions, while non-union facilities enjoy greater adjustment flexibility.

Wage effects operate through both direct and indirect channels. Directly, workers displaced from triage roles who seek alternative healthcare employment may accept lower wages to secure positions, exerting downward pressure on wages across the broader nursing labor market. Indirectly, the demonstration that AI can substitute for certain nursing functions may weaken the bargaining position of healthcare workers more generally, as employers gain credible outside options to human labor.

The skill-biased nature of technological change in healthcare means that AI impacts different worker categories asymmetrically (Saleem and Higuchi, 2014). Highly skilled physicians capable of complex diagnostic reasoning may experience increased demand for their expertise in managing difficult cases and overseeing AI systems. Less specialized nurses performing routine assessments face greater substitution risk. This skill bias exacerbates wage inequality within healthcare professions and may require policy interventions to support workers adversely affected.

Transition costs represent an important component of the labor share of productivity gains. Workers who invest in retraining to acquire AI-complementary skills bear direct costs of education and foregone earnings during transition periods. Those unable or unwilling to retrain may exit healthcare employment entirely, suffering permanent income losses if alternative opportunities offer lower compensation. These adjustment costs should be counted as part of the economic burden borne by labor.

The geographic mobility of healthcare workers creates additional complications. In regions with declining demand for traditional triage nurses but growth in other healthcare occupations, workers may need to relocate to find suitable employment. Migration costs and family ties often make such moves difficult, trapping workers in shrinking labor markets. The resulting geographic mismatch between labor supply and demand generates frictional unemployment that represents a real cost of technological transition.

From a longer-term perspective, AI adoption may influence career choices of prospective healthcare workers, reducing entry into professions perceived as vulnerable to automation. If nursing school enrollments decline in anticipation of reduced demand for traditional triage skills, healthcare systems may face shortages of workers needed for AI-complementary tasks. This dynamic response of labor supply to technological change can create medium-term imbalances even if long-run demand ultimately stabilizes at higher levels.

6 Patient Welfare and Access to Care

From the patient perspective, AI-driven improvements in triage quality represent potentially substantial welfare gains through better health outcomes, reduced waiting times, and more appropriate care allocation. However, whether patients actually realize these benefits depends on how healthcare delivery systems respond to productivity improvements and how the economic surplus is distributed across stakeholders. Patient welfare effects operate through multiple channels that may work in reinforcing or offsetting directions.

The most direct benefit to patients comes from improved clinical outcomes when AI enhances triage accuracy. More precise initial assessments reduce the likelihood of serious conditions being misclassified as non-urgent, decreasing morbidity and mortality from delayed treatment. Similarly, better identification of truly urgent cases reduces unnecessary emergency department utilization, allowing scarce resources to focus on patients with genuine emergencies. These quality improvements have tangible economic value measurable through health metrics and quality-adjusted life years.

Time savings represent another important dimension of patient welfare. Traditional triage processes often involve substantial waiting periods before patients receive initial assessment and subsequent care. AI systems can reduce these delays significantly, creating utility for patients who value their time. The economic worth of these time savings should be calculated at patients' opportunity cost, which varies by income level, employment status, and urgency of medical need. For serious conditions, reduced diagnostic time may also improve clinical outcomes beyond the direct accuracy effects.

However, these potential benefits may not translate into actual welfare gains if healthcare providers and insurers capture the productivity surplus through higher prices or maintained premiums despite lower costs. If hospitals retain cost savings as increased profits without improving service quality or reducing charges, patients gain nothing from AI implementation despite the technology's productive efficiency. Similarly, if insurers maintain premium levels even as triage costs decline, the surplus flows to shareholders rather than beneficiaries.

Access to care represents a critical distributional dimension. If AI triage enables facilities to process more patients with existing resources, capacity constraints may ease, improving access for previously underserved populations. However, if cost savings primarily flow to affluent facilities while resource-constrained providers lack capital for AI investment, healthcare inequality may worsen. Low-income patients seeking care at underfunded public hospitals would face traditional triage processes while wealthy patients enjoy AI-enhanced services at premium facilities.

The two-tier structure becomes particularly pronounced when considering quantum-enhanced AI capabilities (Wolbring, 2022; Wheatley Research Consultancy, 2024). If only elite academic medical centers can afford quantum computing infrastructure, the quality gap between high-end and basic triage services could widen dramatically. Patients with means would seek care at quantum-enabled institutions, while those dependent on public insurance or geographically isolated facilities would receive inferior assessments. This stratification contradicts principles of equitable healthcare access.

Out-of-pocket costs represent the most direct financial impact on patients. In healthcare systems where patients pay substantial cost-sharing for emergency department visits or urgent care, any reduction in charges directly benefits consumers. However, in systems dominated by insurance coverage with fixed copayments, patients may see no financial benefit even when underlying costs decline. The pass-through of cost savings depends entirely on insurance benefit design and competitive dynamics in insurance markets.

The risk adjustment performed by AI triage also has distributional implications. More accurate identification of patient severity levels enables better risk prediction, which insurers may use to refine coverage decisions and premium structures. While this improves allocative efficiency in insurance markets, it can disadvantage high-risk patients who face higher premiums or reduced coverage. The welfare effects depend on whether risk adjustment is used to improve population health management or to engage in cream-skimming and risk selection.

Patient autonomy and consent represent non-economic dimensions of welfare that warrant consideration. AI triage systems make decisions affecting care priority and resource allocation with limited patient input, potentially conflicting with preferences for human interaction and shared decision-making. Some patients may value human assessment intrinsically, experiencing welfare losses when AI replaces personal contact even if clinical outcomes improve.

Data privacy and algorithmic bias pose additional patient welfare concerns. AI triage systems require access to extensive personal health information, creating privacy risks if data security is inadequate. Moreover, if training data or algorithms contain biases that disadvantage certain demographic groups, AI implementation could exacerbate existing health disparities. Minority populations and vulnerable groups may receive systematically worse triage assessments, leading to discriminatory care allocation that harms welfare and violates equity norms.

7 Conclusion

This analysis demonstrates that the distribution of productivity gains from AI-driven medical triage depends fundamentally on market structures, bargaining power asymmetries, and institutional arrangements rather than following automatically from technological capabilities. While AI triage generates substantial economic surplus through cost reductions and quality improvements, this surplus does not flow equitably to all stakeholders. Instead, market power enables hospitals and insurers to capture disproportionate shares, while healthcare workers may bear adjustment costs through displacement or wage pressure, and patients may see limited benefits despite being the ultimate source of demand.

The emerging potential for quantum-enhanced AI capabilities introduces additional distributional concerns by concentrating advanced technology in well-capitalized institutions, potentially exacerbating existing healthcare inequalities (Wolbring, 2022; Wheatley Research Consultancy, 2024). The capital intensity of quantum computing creates natural monopoly characteristics that favor surplus accumulation by institutional actors over distribution to workers or patients. Without deliberate policy interventions, market forces alone are unlikely to generate socially optimal allocation of technological gains.

Several policy implications emerge from this analysis. First, healthcare price regulation may be necessary to ensure that cost savings from AI adoption translate into lower prices rather than increased provider rents. This could take the form of administered pricing systems, reference pricing, or mandatory pass-through requirements for productivity improvements. Second, stronger antitrust enforcement in healthcare markets could reduce the concentration that enables rent extraction, fostering more competitive dynamics where efficiency gains flow to consumers.

Third, labor market policies should address the adjustment costs borne by displaced healthcare workers (Raja and Christiaensen, 2017). This might include retraining programs specifically designed for healthcare professionals affected by AI automation, wage insurance to buffer income losses during transitions, and potentially tax credits or subsidies for employers who maintain employment levels while implementing new technologies. Fourth, insurance market reforms could mandate that productivity savings be reflected in premium reductions, preventing insurers from capturing the entire surplus.

Fifth, access equity requires attention to ensure that AI benefits reach underserved populations. This could involve subsidies for technology adoption at safety-net hospitals, requirements that public payers receive cost savings, or quality standards ensuring minimum triage capabilities across all facilities. Quantum computing's potential for exacerbating inequality suggests that public investment in shared quantum infrastructure accessible to multiple institutions might be warranted to prevent excessive stratification.

Finally, governance mechanisms that give patients and workers voice in decisions about AI implementation and surplus distribution could improve allocative outcomes. This might include patient representation on hospital boards, collective bargaining rights for affected workers, or participatory technology assessment processes that incorporate stakeholder perspectives beyond capital owners and managers.

The central insight is that technological progress in healthcare does not automatically improve welfare for all participants. The distribution of gains matters as much as their magnitude, and market power asymmetries lead to highly skewed outcomes absent corrective policies. Ensuring that AI-driven productivity improvements benefit patients and workers as well as institutional shareholders requires active governance and policy design rather than reliance on market forces alone. As quantum-enhanced capabilities emerge, these distributional challenges will likely intensify, making proactive policy development increasingly urgent.

Future research should empirically examine the actual distribution of AI-generated surplus in healthcare markets, measuring how much flows to different stakeholder groups under varying market conditions. Case studies of specific AI implementations could provide valuable evidence about the mechanisms through which productivity gains are allocated. Additionally, research on optimal governance structures and policy interventions to promote equitable distribution would inform practical reform efforts. The questions raised here about who captures the gains from technological progress extend beyond medical triage to broader debates about automation, inequality, and economic justice in an era of rapid technological change.

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