Provider Payment Models for Transformative Technologies in Healthcare

Elodie Adida* Tinglong Dai†

*University of California, Riverside, School of Business, Riverside, California 92521, elodieg@ucr.edu

†Carey Business School, Johns Hopkins University, Baltimore, Maryland 21202; Hopkins Business of Health Initiative, Johns Hopkins University, Washington, District of Columbia 20001, dai@jhu.edu

Abstract. Transformative health technologies, such as robotic surgery, create substantial value but raise new challenges for provider payment design. We study how payment models affect both the quality and adoption of such technologies. In our framework, a developer determines quality—through customization, training, and maintenance—whereas a healthcare provider chooses adoption intensity based on reimbursement and expected net benefits. We first show that under the status quo of no reimbursement, the provider restricts usage to sufficiently complex cases, leading to suboptimal quality and limited uptake. Fee-for-service models encourage broader use but incentivize the developer to reduce quality at higher reimbursement rates, whereas lower rates induce higher quality but limit adoption. We then propose a hybrid payment model that combines fee-for-service and value-based payments. We show that aligning incentives requires value metrics focused on technology *quality* rather than on downstream benefits. Notably, as the marginal cost of achieving higher quality rises, the minimum fee-for-service amount required for incentive alignment decreases. Our analytical framework informs the design of provider payment models that spur the development and deployment of transformative technologies, improving both quality and patient access.

Key words: Provider payment models, incentive design, healthcare operations, new technology.

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1. Introduction

Transformative health technologies are innovations that deliver step-change improvements in outcomes, safety, efficiency, or access relative to prevailing standards of care. Because they are novel and expensive, they often launch without dedicated reimbursement, creating misaligned incentives for adoption (National Institutes of Health 2024). Consider the *da Vinci* robotic surgical system, which enables minimally invasive procedures to be performed with greater precision and control, reducing length of stay, complication rates, and postoperative rehabilitation needs compared with open surgery. However, realizing these benefits requires a significant investment, including \$1–\$2 million in upfront capital, as well as ongoing costs for staff training, preventive maintenance, and product upgrades. These investments are necessary to ensure uptime and maintain high performance standards (Feldstein et al. 2019).

In the U.S., expenses related to new technologies generally fall on healthcare providers. Payers, including both the Centers for Medicare and Medicaid Services (CMS) and private insurers, do not offer higher reimbursement for robotic procedures. Hospital payments follow Diagnosis-Related Groups (DRGs), whereas physician payments rely on Current Procedural Terminology (CPT) codes; neither accounts explicitly for robotic assistance. Attempts to classify robotic procedures as more complex for additional reimbursement are generally denied, and although certain private insurers allow modifiers indicating robotic usage (Healthcare Common Procedure Coding System code S2900), such modifiers do not normally lead to increased payments. Consequently, hospitals usually absorb these extra costs, limiting robotic surgery to sufficiently complex cases (Intuitive Surgical Operations 2023b).

To lower adoption barriers, Intuitive introduced a *pay-per-use* model, whereby hospitals pay the developer per robotic procedure, with total payments capped at the outright purchase price in the case of high utilization (Intuitive Surgical Operations 2023a). This arrangement shifts part of the financial risk from hospitals to the developer: if usage is low, the developer recovers little revenue. In principle, such exposure would encourage investment in workflow integration, comprehensive training, and system reliability to promote provider uptake. In practice, however, pay-per-use contracts only partially mitigate adoption frictions. Because reimbursement does not typically increase when robotic assistance is used, hospitals remain reluctant to use these technologies, particularly for less complex cases where benefits are less pronounced. Consequently, developers face limited demand at prevailing reimbursement levels, which dampens incentives to invest aggressively in quality. This interaction creates a feedback loop of underinvestment and limited uptake.

Recent policy shifts across health systems reflect growing recognition of this structural gap. In 2023, Ontario's public system began reimbursing three robotic-assisted procedures (St. Joseph's Healthcare Hamilton 2023); the United Kingdom increased reimbursement rates for certain robotic surgeries (Beacon One 2024); Japan's national insurance extended limited coverage to robotic procedures (Yoshida et al. 2022); and several Chinese provinces launched pilot reimbursement programs for domestically produced surgical robots (State Council 2024). In the United States, the Medicare Payment Advisory Commission (MedPAC) has long considered alternative payment schemes for emerging technologies (MedPAC 2003). Motivated by these developments, this paper examines transformative innovations—such as surgical robots and AI-based diagnostic tools—that involve high upfront costs yet remain largely unreimbursed under prevailing provider payment models.

Designing appropriate provider payment models for these technologies is not straightforward. Realized effectiveness is tied to quality, which depends on developer effort, including integrating the technology into workflows, training clinicians, maintaining systems, and providing updates. Reimbursement policy must navigate these complexities to align incentives across stakeholders. Design is further complicated by heterogeneity in cost-effectiveness: many technologies do not deliver the same benefit across patient populations. Fee-for-service models risk overuse, whereas value-based reimbursement has been advocated to balance access and cost-effectiveness (Lopez et al. 2020), yet "value" is often challenging to define and attribute. How payment structures shape not only provider behavior but also developers' incentives to invest in quality remains poorly understood.

Despite the need for payer reimbursement to align incentives at both the provider and developer levels, prior work has not modeled how payment can jointly coordinate provider adoption and developer quality. We fill this gap by developing a theoretical model in which a developer sets a per-use price and chooses quality via costly effort, and a provider decides whether to use the technology for a given case. We focus on high-cost, transformative technologies marketed through pay-per-use arrangements.

We begin by analyzing the status quo, where the provider receives no reimbursement for using the technology. The developer chooses the tool's quality and sets a per-use price; the provider decides whether to use it based on case complexity, costs, and expected benefits. Without reimbursement, the provider limits use to high-complexity cases, and the developer under-invests in quality. The developer optimizes price and quality for profit, but equilibrium quality falls below the socially optimal level, leaving many patients unserved. The core mechanism is simple: when bearing the full cost of using a technology, the provider has limited incentive to adopt it broadly; the developer, in turn, is not motivated to invest in high quality for a product with constrained demand.

Next, we examine fee-for-service (FFS) reimbursement, where the provider receives a fixed rate per use. Naturally, the provider's usage decision depends on the reimbursement rate: higher rates encourage broader use, and lower rates limit adoption to complex cases. The developer adjusts pricing and quality accordingly. At high reimbursement rates, the developer may lower quality and price to drive volume; at lower rates, the developer increases quality, but usage remains limited. Fee-for-service thus promotes broader adoption at high reimbursement rates but can lead to suboptimal quality and inefficient usage.

We then turn to value-based payment systems, which raise the question of how "value" should be defined. One approach ties payment to the net *benefit* generated by the technology; another ties it to the *quality* of the technology itself, such as training, support, reliability, and integration. While benefit-based payment seems natural, it tends to skew adoption toward high-complexity patients, thereby leaving less complex patients—who may also gain from the technology—underserved. It is also more difficult to implement in practice, since it requires tracking each individual patient's benefit from the technology. Quality-based payment, by contrast, is simpler to operationalize, because it relies on verifiable features under the developer's control. It also directly rewards the upstream attributes that determine realized effectiveness and can better align incentives—though its performance depends on how providers respond to financial rewards.

Our model captures this responsiveness through a parameter that reflects the weight providers place on patient benefit relative to financial incentives. Although it might seem intuitive that a higher weight on patient benefits would lead to better outcomes, we show that it makes providers less responsive to financial incentives, leading to selective rather than broad use of the technology. As a result, quality-based payments are most effective when this weight is lower, since providers' decisions are more strongly influenced by reimbursement, encouraging adoption across all patients.

Finally, when a purely quality-based system proves insufficient under a high weight on patient benefit, we propose a hybrid model that combines fee-for-service payments with quality-based incentives. The fee-for-service component promotes broad adoption, whereas the quality component restores the developer's incentive to invest in performance. We show that, as long as the fee-for-service payment is sufficiently high, this hybrid model induces providers to choose the first-best quality level and to adopt the technology across the socially optimal patient population. Interestingly, we also observe that as the cost of quality increases, the minimum required fee-for-service payment *decreases*. While counterintuitive, the logic is clear: higher quality costs lower the optimal quality level in the first-best solution, reducing the strength of incentives needed to align outcomes.

Whereas robotic surgery serves as our key motivating example, the implication of our model extends beyond this context. Consider Viz.ai, whose AI-driven stroke triage software became the first artificial intelligence–based medical tool to receive a New Technology Add-on Payment (NTAP) from Medicare in 2020. The NTAP provided hospitals with up to $1,040 in reimbursement per use, catalyzing rapid adoption and enabling further investment in product reliability, workflow integration, and feature development (Viz.ai 2020). By contrast, Pear Therapeutics, despite securing FDA approval in 2017 for its prescription digital therapy targeting substance use disorder, failed to obtain broad insurance coverage. The absence of reimbursement significantly limited uptake and culminated in the firm's bankruptcy in 2023 (Jennings 2023). Similarly, Proton Beam Therapy (PBT)—a highly targeted form of radiation associated with reduced toxicity—has faced inconsistent reimbursement, resulting in underutilization even in well-equipped centers (CMS 2022). These cases underscore the central role of reimbursement in shaping the diffusion trajectory of medical technologies. When reimbursement is absent or misaligned, even promising innovations may fail to scale; when it is present and generous, adoption often follows. Accordingly, the structure of reimbursement is not merely a financing tool but a determinant of innovation outcomes in healthcare.

Our paper provides a theoretical foundation for understanding how reimbursement models shape the tension between upstream developer effort and downstream provider adoption for new healthcare technologies. CMS does not currently reimburse for many such innovations but has shown a willingness to experiment with payment models, especially as generative AI continues to reshape healthcare (Zink et al. 2024). Our model offers guidance for policymakers navigating the trade-offs inherent in payment design and its interplay with both developer investment decisions and provider adoption. The proposed hybrid model, combining fee-for-service with quality-based payments, aligns with emerging policy efforts to facilitate the integration of advanced technologies into clinical care.

2. Literature

Our study contributes to several streams of literature at the intersection of healthcare operations management and the economics of new health technologies.

First, we add to the literature on healthcare provider payment models. A rich body of work in healthcare operations management has examined how various reimbursement schemes influence provider behavior and healthcare outcomes (e.g., Adida et al. 2017; Andritsos and Tang 2018; Guo et al. 2019; Dai and Tayur 2020; Keskinocak and Savva 2020; Betcheva et al. 2021; Vlachy et al. 2023). Prior studies have investigated prospective payment systems, bundled payments, pay-for-performance and outcomes-based reimbursement, reference pricing, and other innovative payment mechanisms (Dada and White 1999; Zhang et al. 2016; Dai et al. 2017; Andritsos and Tang 2018; Savva et al. 2019; Adida and Bravo 2019; Adida 2021; Xu et al. 2022; Nassiri et al. 2022; Adida and Dai 2024). To our knowledge, however, no prior work has examined provider payment design in the specific context of new medical technologies where upstream and downstream decisions are intertwined, and the downstream provider's actions benefit patients as well as the provider itself.

Second, our work relates to the literature on incentive alignment in health technology innovation. There is broad recognition that misaligned incentives between technology developers (upstream firms) and healthcare providers (downstream adopters) can hinder the diffusion of valuable innovations. For example, Chick et al. (2008), Taylor and Xiao (2014), Zhang et al. (2020), and Xu et al. (2022) examine settings in which an upstream innovator or manufacturer and a downstream provider have misaligned objectives and explore mechanisms to improve efficiency (such as outcome-based contracts or risk-sharing arrangements). Outside healthcare, the broader operations management literature shows incentive misalignment and financing frictions can suppress downstream uptake of products and services (e.g., Berman et al. 2019; Escamilla et al. 2021; Lu and Tomlin 2022; Villa et al. 2024). We depart from this line of work by considering a triadic interaction involving a *third-party payer*. In our model, the upstream decisions—the technology's quality and price—shape the downstream decision, namely the provider's technology adoption. Adoption yields benefits to patients and may generate operational cost savings for providers; yet the provider may incur additional costs that are not reimbursed. This creates an incentive misalignment, and our focus on a reimbursement contract set by a third-party payer adds a new dimension to the misalignment problem. The resultant insights are distinctive. For example, we show that higher fee-for-service payments to the provider can, counterintuitively, induce lower technology quality.

Recent policy research has begun to explore how novel payment schemes can incentivize innovation: for instance, Lopez et al. (2020) propose a value-based payment framework for expensive medical technologies, and Yapar et al. (2025) study how regulators might use conditional approvals and value-based pricing for new health technologies to balance access with uncertainty. Our paper complements these papers by providing a formal analysis of how a payer can design provider-facing payments (as opposed to prices for manufacturers) to drive both high-quality innovation and appropriate technology usage.

Third, we contribute to the literature on the diffusion and adoption of healthcare technologies. Empirical studies have investigated factors influencing the adoption of innovations such as robotic surgery. Horn et al. (2022), for example, analyze the diffusion of robotic surgical systems across hospitals and the resulting market allocation effects, whereas Sundaresan et al. (2023) examine how hospitals respond to competitors' adoption of robotic technology. These works highlight economic and competitive forces in technology diffusion. Our model offers a novel theoretical lens by analyzing how reimbursement incentives can shape the adoption trajectory and performance of new technologies. By endogenizing the provider's usage decision and the developer's quality investment, our results speak to how policy levers might accelerate or hinder the diffusion of beneficial innovations in healthcare.

Finally, our paper is conceptually related to the analytical literature on new technology adoption and supplier-buyer coordination (outside the healthcare context). Prior studies have examined how a technology supplier's quality or price decisions interact with a buyer's adoption decisions and the resulting market dynamics (e.g., Cho and McCardle 2009; Cohen et al. 2016; Uppari et al. 2019; Kundu and Ramdas 2022; Zhang and Lee 2022). We extend this line of inquiry by incorporating a third-party payer that reimburses the buyer (provider) for usage and the technology supplier's quality and price decisions that drive uptake; this addition structurally changes the payoff structure and requires a different approach to achieving coordination. By doing so, our model advances understanding of incentive design in settings where usage benefits accrue across stakeholders, and we bridge several streams of literature on healthcare payment design, technology adoption, and innovation incentives.

3. Model

In this section, we present our model setup and notation. The model captures the interaction between an upstream technology developer and a downstream healthcare provider (e.g., a hospital or clinical practice) serving patients.

We consider two intertwined decisions: (1) the upstream, which entails the developer choosing the quality level of the technology; and (2) the downstream, which entails the provider deciding when to use the technology in patient care. Below, we describe each phase in more detail.

Upstream (Stage 1): The developer (e.g., the manufacturer of a surgical robotic system) chooses the quality and price of the technology.[1] Formally, the developer selects a quality level $q > 0$ and sets a usage price $p > 0$ per patient (i.e., per use of the technology). Charging a per-use fee is consistent with real-world pricing strategies for high-cost medical innovations: it lowers the upfront burden on providers and aligns the developer's revenue with actual usage. For instance, the manufacturer of the da Vinci surgical robot offers a pricing model in which hospitals pay a fee per surgery performed with the robot, as described in Section 1. The quality q represents the performance or effectiveness of the technology that results from documentable developer effort (for example, provider training programs, maintenance and timely upgrades, customization, and degree of integration in the provider's workflow). A higher q implies more reliable, effective performance and better integration into the provider's workflow, thereby enhancing patient outcomes when the tool is used. By contrast, a low-quality implementation might yield negligible improvements or even cause inefficiencies. In our context, quality can also encompass the support services the developer provides (such as training and maintenance): for instance, adequate training on a surgical robot can shorten the learning curve for surgeons and improve outcomes. We incorporate all such factors into the single parameter q for simplicity.

We model the cost to the developer of providing quality q as $C(q) = c \cdot q^2$, where $c > 0$ is a cost coefficient. This quadratic cost captures increasing marginal costs of improving quality, a standard assumption in economics of technology design. The developer's profit comes from selling usage of the technology to the provider at price p per use. The developer chooses quality level q and price p to maximize expected profit, taking into account how the provider will respond in the deployment phase. (If no positive profit is attainable, the developer opts not to enter the market; we assume the developer will not participate in a zero-profit scenario.)

Downstream (Stage 2): The healthcare provider treats a continuum of patients (normalized to total mass 1) who are heterogeneous in the complexity or acuity of their condition (for example, a

[1] We study a scenario where the price of the new tool is *endogenous* and set by the developer. This endogenous pricing assumption allows us to analyze the strategic behavior of the developer in setting the optimal price that balances potential revenues and costs. However, scenarios exist in which prices may be exogenously determined due to factors such as the market power of the provider or budget constraints. Nevertheless, our core findings are robust and applicable even under such exogenous pricing conditions. We can show the qualitative nature of our results remains unchanged when prices are externally imposed, as the fundamental trade-offs between cost, quality, and adoption persist.

given type of surgery). Let $x \in [0,1]$ denote a patient's complexity level, with higher x indicating a more complex case, e.g., a sicker patient or more challenging procedure (without loss of generality, we normalize $x = 0$ to represent the least complex procedure for which the new technology yields a non-negative net benefit). We assume x is distributed uniformly on $[0,1]$ for analytical tractability. The provider decides which patients to treat using the new technology. Specifically, the provider will adopt the technology for patients in some subset $[x_1, x_2]$ of the interval $[0,1]$. This choice will depend on the technology's quality q and the usage fee p set by the developer, as well as any potential reimbursement structure. As explained in the next section, due to the structure of the provider's objective function, in equilibrium we indeed establish a threshold policy for the subset of treated patients: there is a critical complexity such that all patients with complexity above the critical value are selected to receive the technology.

The provider's objective reflects a mix of financial and patient welfare considerations. Each time the provider uses the technology, they incur the cost of the developer's fee, p. In return, both the patient and the provider receive a benefit from the use of the technology. Specifically, we denote by $B_1(x,q)$ and $B_2(x,q)$ the incremental benefit respectively to the patient and to the provider of using the technology for a patient of complexity x when the technology quality is q, compared to care without use of the technology. In the case of robotic surgery, the patient benefit $B_1(x,q)$ refers for example to the shorter recovery time due to the less invasive nature of the surgery, reduced blood loss, smaller incision, reduced time spent in the hospital, reduced rehabilitation needs, and reduced chance of complications (Wu et al. 2021; Labban et al. 2022). The provider net benefit $B_2(x,q)$ refers to the benefit of lower operational costs due to having the patient occupy a bed for a shorter amount of time and reduced chance of complications, less the costs of disposable instruments. In addition to the direct net benefit $B_2(x,q)$ to the provider upon using the technology, the provider also derives indirect utility stemming from the patient benefit due to altruism or professional obligation, even if those benefits are not fully monetized. We incorporate this effect by assigning a weight $\delta_1 > 0$ to patient welfare $B_1(x,q)$ in the provider's utility function, representing the provider's altruism or mission-driven weight on patient welfare. Hence, we conceptualize the physician's goal as maximizing a weighted sum of her direct payoff (net direct benefit plus financial compensation from the payer—if any—minus the fee paid to the developer) and patient welfare. Accounting for financial incentives in physician decision-making is prevalent in both the health economics (e.g., Bester and Dahm 2017; Jelovac 2001) and healthcare operations management (e.g., Adida and Dai 2024; Guo et al. 2019) literature. This formulation is in line with the physician agency literature, which models providers as balancing their own financial incentives against patients' health outcomes. Our model incorporates this consideration by including a term proportional to the patient's utility in the physician's objective function. This approach internalizes the physician's concern for the patient's welfare. A purely self-interested provider would correspond to the case of $\delta_1 = 0$. Note that δ_1 may take values greater than 1 when the provider values the patient benefit more than its own bottom line. Thus, if a patient with complexity x is treated with the technology, the provider's utility increase (net of any payment) is

$$B_2(x,q) + \delta_1 B_1(x,q) - p.$$

We assume the provider maximizes utility and, when indifferent, opts not to use the technology; that is, the provider behaves conservatively when the net benefit is zero.

For concreteness, we use a simple functional form for the benefits:

$$B_1(x,q) = b_1 \cdot q \cdot x, \qquad B_2(x,q) = b_2 \cdot q \cdot x$$

where $b_1, b_2 > 0$ are parameters scaling the value of improved care. This specification implies that the benefit (to patients and to the provider) of using the technology increases linearly with the patient's complexity x and with the quality q of the technology.[2] In other words, the technology is most valuable for difficult or severe cases (high x), and a higher-quality technology yields proportionally greater benefit for any given case. This model captures the idea that high-quality tools provide the greatest marginal improvement in challenging situations. For example, a robotic surgical system can enable finer precision and better outcomes in a highly complex surgery (such as a delicate cancer resection), whereas in a simple procedure (low x) the incremental advantage of the robot is minimal because a traditional approach can handle it nearly as well. The benefit function is increasing in both x and q, reflecting that more complex cases and higher technical quality each amplify the value of the technology. We note that $B_i(x,q)$, for $i = 1,2$, is zero if either $q = 0$ (i.e., the technology is inoperative) or $x = 0$ (the minimally eligible case in which the net benefit is always zero), as expected.

We define

$$b \equiv b_1 + b_2 \text{ and } \delta \equiv \frac{\delta_1 b_1 + b_2}{b_1 + b_2},$$

where b is the total benefit scaling factor and $\delta > 0$ is a measure of how much of the total benefit the provider internalizes. We refer to δ as the effective weight of total benefit. Note that when $\delta_1 = 1$, then $\delta = 1$, which corresponds to the case where the provider values the patient benefit and its own benefit equally. However, δ may be greater than 1, whenever $\delta_1 > 1$. In addition, we define the total net benefit as

$$B(x,q) \equiv B_1(x,q) + B_2(x,q) = b \cdot q \cdot x,$$

[2] This linear assumption is made primarily for tractability. In real-world scenarios, the benefits of new technology may exhibit non-linear characteristics due to various factors, such as diminishing returns to quality improvements. Nevertheless, we expect our main results to remain robust as long as the relationship between utility, quality, and patient complexity is monotonic and concave.

so the provider's utility when using the technology can be written as

$$\delta B(x,q) - p.$$

Essentially, $B(x,q)$ represents a measure of the overall system benefit from using the new technology, and δ is the effective weight that the provider assigns to this benefit in its objective function in comparison to its payment to the developer. This leads the provider to adopt the technology selectively for certain patients, when using the technology is worthwhile, but for others the provider prefers conventional practice.

Our model captures the strategic interaction between the developer and the provider in bringing a new healthcare technology into use. The developer's choice of quality and pricing in Stage 1 influences the provider's utilization decision in Stage 2. In addition, we introduce a third party: a payer (e.g., an insurer or government health system) who determines the reimbursement policy for the provider's use of the technology. In the current U.S. healthcare environment, one extreme is the no-reimbursement scenario (the status quo for many new technologies like robotic surgery), in which the provider receives no additional payment for using the technology. Another common scheme is fee-for-service (FFS) reimbursement, wherein the provider would be paid a certain amount per use of the technology (for example, a supplement for each surgery performed with the robotic system). We first analyze these two payment models—(1) no reimbursement and (2) per-use FFS reimbursement—and study their impact on the equilibrium quality q, price p, and usage of the technology. We compare these outcomes to the first-best (socially optimal) benchmark where a planner maximizes total welfare. This comparison will highlight the inefficiencies that arise under each payment regime. We then examine whether an alternative payment design could achieve first-best outcomes by better aligning the incentives of the developer and the provider. In particular, we explore a hybrid reimbursement model and other incentive schemes that share features of both FFS and value-based payments, and we characterize conditions under which such schemes can coordinate the system to attain the socially optimal solution.

3.1. Benchmark Equilibrium: First-Best Scenario

In the first-best scenario, the goal of a social planner is to select both the quality level of the new technology and the set of patients on whom the tool is used to maximize total welfare. This welfare is defined as the combination of patient benefits, provider net benefits, and quality costs (the price represents an internal cash-flow exchange and does not affect the first-best outcome).

The social planner has the option of either not participating (resulting in an objective value of zero) or participating if a positive objective value can be achieved by selecting an optimal quality level and identifying the appropriate set of patients who should receive the new technology. If the social planner chooses to participate, the goal is to maximize the following objective function:

$$-C(q)+\int_{x_1}^{x_2} B(x,q)dx = -cq^2 + bq\int_{x_1}^{x_2} x\ dx = -cq^2 + bq\cdot\frac{x_2^2-x_1^2}{2},$$

where q represents the quality level of the new technology, c is the cost coefficient associated with quality, b is the benefit scaling parameter, and x_1 and x_2 denote the range of patient complexity levels. The integral term $\int_{x_1}^{x_2} x\ dx$ reflects the aggregate complexity of the patient population treated with the new technology, indicating the social planner prioritizes using the new technology on higher-complexity patients due to their greater potential benefit from assistance of the novel tool.

Lemma 1. *In the first-best scenario, the social planner chooses to participate, and the socially optimal quality level is given by* $q^{FB}=\frac{b}{4c}$*. Under this optimal quality level, the social planner uses the new technology for all eligible patients within the specified complexity range.*

Lemma 1 shows that the socially optimal quality level equates the marginal benefit of quality improvement with its marginal cost. Recall that $x\in[0,1]$ denotes case complexity among *eligible* patients, where $x=0$ corresponds to the least-complex case for which the technology yields non-negative net benefit. The resulting first-best quality level, $q^{FB}=\frac{b}{4c}$, induces usage across the entire eligible population and maximizes total surplus. This benchmark serves as a point of comparison for the reimbursement-driven equilibria analyzed in subsequent sections.

4. Analysis of Provider Payment Models

In this section, we examine two payment models for providers using the new technology. The first model represents the status quo in the U.S., where the provider receives no reimbursement for using the technology. The second model aligns with the fee-for-service system, where the provider is reimbursed on a per-use basis for using the new technology.

4.1. Status Quo: No Reimbursement

Under the current reimbursement framework, CMS does not provide separate reimbursement for the use of transformative health technologies such as robotic surgical systems. For example, Healthcare Common Procedure Coding System (HCPCS) code S2900, which designates "surgical techniques requiring use of robotic surgical system," is not currently processed by Medicare and does not trigger additional payment (Intuitive Surgical Operations 2024b). As a result, providers do not receive reimbursement for using new technologies such as robotic surgery. To analyze this scenario, we investigate the provider's decision to use the technology and the developer's decision regarding its quality in the absence of reimbursement.

In the first stage, the technology developer aims to maximize its profit by solving:

$$\max_{p,q>0} \quad -cq^2 + p(x_2 - x_1),$$

where the parameters x_1 and x_2 are determined in the second stage and may depend on the selected price p and quality q.

In the second stage, given the price p and quality q decisions made by the developer, the provider solves:

$$\begin{aligned}\max_{x_1,x_2} \quad & -p(x_2 - x_1) + \delta bq \int_{x_1}^{x_2} x\,dx \\ & = -p(x_2 - x_1) + \delta bq \frac{x_2^2 - x_1^2}{2}.\end{aligned}$$

Before determining the developer's decisions, we first derive the provider's optimal decision in response to the developer's given price and quality choices:

LEMMA 2. *In the second stage, given the price $p > 0$ and quality $q > 0$ selected by the developer, the provider uses the new technology on some patients if and only if $p < \delta bq$. In this case, the provider uses the technology for patients with complexity $x \in \left[\frac{p}{\delta bq}, 1\right]$.*

The intuition behind this result is that the new technology is used only when its quality is sufficiently high or its price is low relative to the benefits derived from its use. Because the benefits of using the new technology are greater for more complex patients, whereas the costs remain uniform across patients, the technology is used for the most complex cases.

PROPOSITION 1. *In the first stage, the developer opts to participate and selects a price $p^* = \frac{(\delta b)^2}{16c}$ and quality $q^* = \frac{\delta b}{8c}$. In the second stage, the provider uses the new technology on half of all patients, specifically those with complexity $x \in \left[\frac{1}{2}, 1\right]$.*

Proposition 1 has several implications regarding the equilibrium outcome without any reimbursement. First, as long as the effective weight δ is less than 2, the equilibrium quality of the new technology is lower than the socially optimal quality level. This result reveals a source of inefficiency in the absence of reimbursement, where the quality of the technology does not reach its potential socially optimal value, due to insufficient financial incentives for the developer under the status quo.

Second, the proposition means that, regardless of the parameter values, only half of the eligible patients receive treatment with the new technology in the equilibrium scenario, in contrast to the first-best scenario (see Lemma 1) where all eligible patients would benefit from it. This disparity highlights a gap between the equilibrium and the socially optimal outcome.

Third, efforts aimed at influencing the provider's weight δ_1 for the technology benefits to patients or modifying the quality cost (c) are insufficient to fully align the equilibrium outcome with the first-best scenario. Although increasing the weight parameter to a high level (so δ reaches 2) would align the quality level with the first-best, this would not address the discrepancy in the proportion of patients receiving treatment with the new technology.

In sum, the absence of reimbursement for the new technology under the status quo hinders the attainment of socially optimal outcomes due to under-investment in quality and under-adoption. This realization motivates the need to explore alternative reimbursement models that better align the incentives of the technology developer and the healthcare provider.

4.2. Fee-for-Service Reimbursement

We next consider the fee-for-service payment system, the predominant method of reimbursing providers for both clinical services and medical devices. Its simplicity and widespread use make fee-for-service a natural mechanism for compensating providers for adopting new technologies (MedPAC 2003).

Under a fee-for-service payment system, the provider receives a fixed reimbursement f for each patient on whom the new technology is used. This payment may represent, for example, an added per-case CPT code or an increase in the DRG rate associated with the technology's use. In our model, we treat f as a parameter that captures a fixed per-use payment to the provider.

In the second stage, given the quality decision q and the price decision p chosen by the developer in the first stage, the provider aims to maximize the net benefit from using the new technology. The provider's problem can be formulated as

$$\begin{aligned}\max_{x_1,x_2} \quad & (f-p)(x_2-x_1)+\delta bq\int_{x_1}^{x_2} x\,dx \\ & = (f-p)(x_2-x_1)+\delta bq\frac{x_2^2-x_1^2}{2},\end{aligned}$$

where x_1 and x_2 denote the range of complexity of patients receiving the technology, while δ and b are as defined in Section 3.

In essence, the provider's problem under the fee-for-service model mirrors the problem without reimbursement, but with one key modification: the price p is adjusted by the reimbursement f. Specifically, the effective price considered by the provider is $p-f$. This adjusted price can be positive or negative, depending on the magnitude of f. If f is large enough to exceed p, the effective price becomes negative, indicating a net gain to the provider per use of the technology.

This adjustment reflects the economic rationale that higher reimbursements may foster broader adoption of new technology because they reduce the net-cost burden on providers. Conversely, if reimbursement is inadequate, the net cost may still deter providers from using the technology, particularly for less complex patients for whom the perceived benefit may not outweigh the cost. The provider's decision is thus influenced by the balance between the reimbursement received and the price paid, which ultimately affects the range of patient complexity x for which the technology is used. We characterize the provider's decision in the following lemma.

LEMMA 3. *In the second stage, given the quality decision $q>0$ and price decision $p>0$ selected by the developer in the first stage,*

(i) if $f \geq p$, the provider uses the new technology on all patients;

(ii) if $p-\delta bq \leq f < p$, the provider uses the new technology on patients with complexity $x \in \left[\frac{p-f}{\delta bq}, 1\right]$;

(iii) else, the provider does not use the new technology.

The intuition behind Lemma 3 is clear: a high reimbursement motivates the provider to use the new technology for all patients. At intermediate reimbursements, the provider limits technology use to more complex cases, with usage increasing as the reimbursement increases. When the reimbursement is too low, the provider avoids using the new technology entirely.

This lemma aligns with intuitive economic reasoning: improved coverage of a healthcare tool is directly linked to increased utilization. In 2018, Japan significantly expanded insurance coverage to include certain robotic gastrointestinal surgeries; the monthly volume of robotic GI procedures doubled immediately following the introduction of reimbursement (Nishigori et al. 2022). Zink et al. (2024) caution that full cost coverage of new technologies may lead to overutilization and excessive healthcare spending, as providers have little incentive to limit use when the financial burden is entirely borne by the payer. A similar logic may underlie the reluctance of payers to reimburse for robotic surgeries. This argument, however, implicitly assumes that the quality of the technology is exogenous to the reimbursement model. Our analysis enriches this perspective by highlighting that full cost coverage can also distort the incentive structure facing the developer. Specifically, as we show next, when the payer fully reimburses the cost of new technologies, the developer has weaker incentives to invest in quality improvements. Guaranteed reimbursement creates a financial cushion that reduces the pressure to enhance the performance of the product.

The proposition below characterizes the developer's decision in the first stage. For ease of presentation, we define

$$\varphi(q,f) = 8\delta bcq^3 - \delta^2 b^2 q^2 + f^2.$$

PROPOSITION 2. *In the first stage, the developer's optimal decisions are as follows:*

(i) If $f \geq \frac{\delta^2 b^2}{27c}$, the developer sets the quality at $q=\epsilon$ (i.e., as small as possible) and the price at $p=f$. In this scenario, the provider uses the new technology on all patients.

(ii) If $f < \frac{\delta^2 b^2}{27c}$, the optimal decisions are to set the quality at $\bar{q}_2$, the unique solution in q of $\varphi(q,f)=0$ on $[\delta b/(12c), \infty)$, and the price at $\bar{p}_2 \equiv (\delta b\bar{q}_2 + f)/2$. In this case, the provider uses the new technology on patients with complexity $[1/2 - f/(2\delta b\bar{q}_2), 1]$.

Proposition 2 can be interpreted as follows. When the reimbursement f is sufficiently high, the developer expects the technology to be used for all patients. In response, it selects a lower quality level to minimize costs, since high utilization ensures profitability even with a lower-quality product. The developer sets the price equal to the reimbursement to maximize revenue while guaranteeing adoption. When the reimbursement is lower, the developer chooses an intermediate quality level, and the technology is used selectively—specifically, for a subset of more complex patients comprising more than half the population.

Note $\partial\varphi(q,f)/\partial q = 2\delta bq(12cq - \delta b)$ is positive on $[\delta b/(12c), \infty)$. It follows that the quality level $\bar{q}_2$, which is the unique root in q of $\varphi(q,f)$ on $[\delta b/(12c), \infty)$, must increase as f decreases to maintain $\varphi(q,f) = 0$. This property indicates an inverse relationship between the reimbursement and the quality: lower reimbursements necessitate higher quality to ensure equilibrium conditions are met. Hence, we have the following corollary, illustrated in Figure 1:

COROLLARY 1. *When* $f < \frac{\delta^2 b^2}{27c}$,

(i) The quality of the new technology weakly decreases as the reimbursement f *increases.*

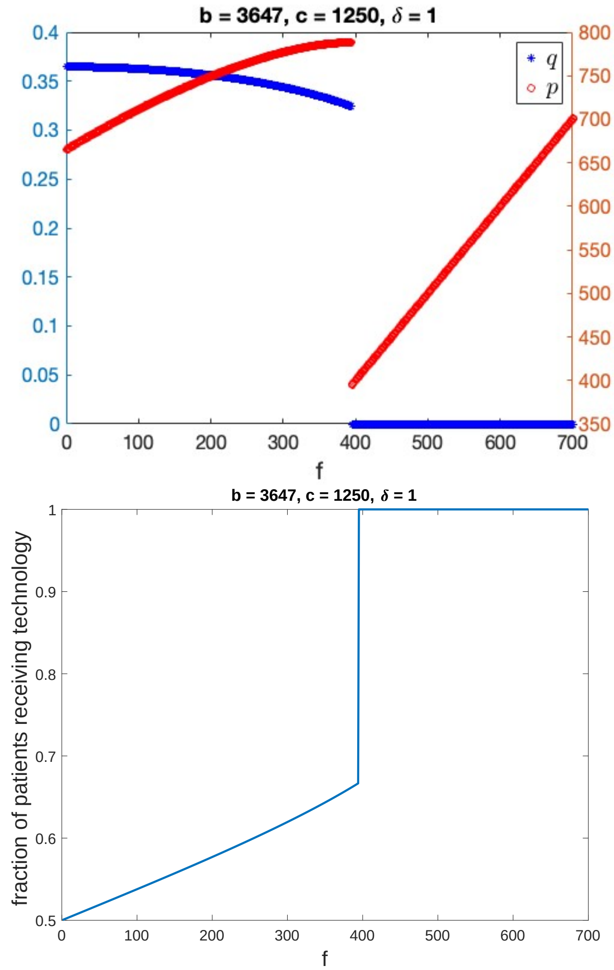
(ii) The price of the new technology increases with the reimbursement f.

Conventional health-policy discourse contends that low reimbursement rates are responsible for poor quality in medications (Hernandez 2023) and limited access to healthcare services (Alexander and Schnell 2024). However, Corollary 1(i) reveals this intuition may not apply to the provider's use of new technologies in the presence of a strategic developer: higher reimbursement rates can, seemingly paradoxically, lead to *lower* quality. The mechanism driving this result lies in the developer's behavior. Increased reimbursement expands the provider's use of the new technology across a broader range of patients. Anticipating this wider market, the developer may strategically reduce the quality of their tools to minimize costs while maintaining substantial demand.

Importantly, this finding does not negate the idea that higher reimbursement enhances patient access. Instead, it highlights the trade-off between access and quality in designing provider payment models. To achieve both goals, policymakers must carefully consider how reimbursement structures influence developer incentives.

In light of Proposition 2, Corollary 1 implies that although lower reimbursement rates may encourage higher quality by limiting the financial pressures on the developer to reduce costs, they also restrict the provider's use of the new technology to a narrower subset of patients (because $-f/q$ increases). This finding reflects a constrained market environment where both quality and price are adjusted downward. Consequently, setting reimbursement rates too low risks undermining the broader uptake of new technologies, reducing their potential societal benefits. Policymakers, therefore, face the challenge of striking a balance between ensuring quality and accessibility in the reimbursement design, aiming to achieve both in tandem.

Figure 1 **Price, quality, and usage vs. f under fee-for-service**



Corollary 2. *The fee-for-service payment model does not achieve coordination with the first-best outcome. Moreover, when $\delta < 1.5$, the quality level under fee-for-service is strictly lower than the first-best quality.*

Corollary 2 builds on Corollary 1 by highlighting the consequence of the tension between accessibility and quality of new technologies inherent within the fee-for-service payment system. Specifically, setting the reimbursement f high enough may align the coverage of the new technology with the first-best scenario, ensuring all patients have access to the new tool. However, this full coverage comes at the cost of significantly diminished quality—the quality level would approach zero, far below the first-best benchmark. Conversely, reducing the fee could lead to improvements in quality, but these improvements would still fall short of the first-best standard, and the reduced fee would simultaneously decrease the number of patients who receive the new technology. This trade-off reveals the fee-for-service model's limitations in balancing quality and accessibility, calling for a better-designed payment scheme, which we examine in the next section.

5. Value-Based Provider Payment: Benefit Versus Quality

Given the inefficiencies inherent in both the no-reimbursement status quo and the traditional fee-for-service system, we now explore alternative payment models that can more effectively align the incentives of the provider and the developer.

One potential remedy is value-based payment models, which have gained traction as alternatives to traditional fee-for-service systems by aiming to reward providers based on the value they deliver, rather than the volume of services provided (Adida and Bravo 2019). However, despite its popularity, value-based payment is not without challenges—chief among them is the difficulty in precisely defining what "value" means in the context of healthcare (Reinhardt 2016).

In this section, we examine two potential definitions of value in the context of new technologies in healthcare: (1) value as the *benefit* derived from the use of the new technology, and (2) value as the *quality* of the new technology itself. These definitions guide our analysis of how different payment models can impact the adoption and quality of new technologies. From an implementation perspective, benefit-based payment is harder to operationalize, since it requires tracking each individual patient's outcomes attributable to the technology, whereas quality-based payment can rely on verifiable features under the developer's control.

5.1. Benefit-Based Payment

We start with considering a payment structure whereby reimbursement is tied directly to the benefit provided by the new technology in improving patient outcomes, formalized as $f + \gamma B$, where f and γ are constants, and B, as defined in Section 3, represents the total net value delivered from the use of the new technology.

Given the developer's quality decision q and price decision p in the first stage, the provider solves:

$$\max_{x_1, x_2} \int_{x_1}^{x_2} (f + \gamma bqx - p)\, dx + \delta bq \int_{x_1}^{x_2} x\, dx = (f - p)(x_2 - x_1) + (\gamma + \delta)\, bq \frac{x_2^2 - x_1^2}{2}.$$

This formulation shows the benefit-based payment model intensifies the provider's incentives to deliver value, as captured by $\delta + \gamma$. However, this model is inherently biased toward more complex cases, because these cases generate higher measurable benefits, as the next result demonstrates.

Lemma 4. *No benefit-based payment can achieve the first-best outcome.*

The intuition behind Lemma 4 is that although the benefit-based payment model strengthens incentives for high-quality care by tying reimbursement to the benefit generated by the use of the new technology, it incentivizes usage of the new technology on complex patients who yield greater measurable value. Hence, this payment model creates misalignment with the first-best scenario, where care would be optimally distributed across all patient types.

Lemma 4 means paying providers based on the benefits delivered, although theoretically more appealing than the status quo or the fee-for-service model, can end up *widening* disparities in access to new technologies, leaving less complex cases underserved.

5.2. Quality-Based Payment

Given the limitations of the benefit-based model, we next explore a payment structure that aligns provider incentives with the intrinsic quality of the new technology. Specifically, we consider a reimbursement scheme of the form γq, where q denotes the quality of the new technology and γ is a constant.

This approach is designed to align both upstream and downstream incentives by encouraging the developer to invest in quality while ensuring the provider is motivated to use the technology appropriately. Under this payment model, the provider's decision as to whether to use the technology, given the quality decision q and price decision p by the developer, is captured by:

$$\max_{x_1,x_2} \int_{x_1}^{x_2} (\gamma q - p)\, dx + \delta b q \int_{x_1}^{x_2} x\, dx = (\gamma q - p)(x_2 - x_1) + \delta b q \frac{x_2^2 - x_1^2}{2}.$$

Here, the provider's use of the new technology is contingent on the following conditions:

- If $p - \gamma q \le 0$, the provider uses the new technology for all patients.
- If $p - (\gamma + \delta b) q \le 0 < p - \gamma q$, the provider uses the new technology for patients with complexity $x \in \left[\frac{p-\gamma q}{\delta b q}, 1\right]$.
- Otherwise, the provider does not use the new technology.

To determine the quality, q, and the price, p, the developer compares two potential settings: one that results in full coverage and another that leads to partial coverage. Coordination to the first-best requires that the full-coverage case dominate the partial-coverage case. The following proposition investigates conditions for the quality-based payment system to coordinate the system:

PROPOSITION 3. *Setting $\gamma = \frac{b}{2}$ enables the quality-based payment scheme to align decisions with the first-best outcome when $\delta \le \frac{1}{2}$. However, when $\delta > \frac{1}{2}$, the provider uses the new technology on only a subset of patients, thereby making coordination unattainable.*

Proposition 3 shows that, under appropriate conditions, a quality-based payment model can align the incentives of the developer and healthcare provider, achieving the first-best outcome. The conditions reveal a counterintuitive relationship between the effective weight δ and the effectiveness of quality-based payment systems in achieving the social optimum. Conventional wisdom in health policy suggests inefficiencies arise primarily from providers valuing their profits too much compared to patient welfare (i.e., δ_1 is too low). This perspective is behind many policy reforms aimed at fostering patient-centered care by increasing the emphasis on patient welfare (i.e., increasing δ_1 and thus δ), thereby potentially reducing the role of financial incentives in shaping provider behavior. However, the above proposition brings to light a paradoxical effect of the intrinsic motivation: for a quality-based payment system to align provider actions with the first-best outcome, δ must be sufficiently small. Specifically, when $\delta \le \frac{1}{2}$, setting the quality coefficient γ at $b/2$ optimally balances the trade-offs between quality care and cost efficiency, incentivizing providers to make decisions that align with the socially optimal outcome. Interestingly, if providers strongly value patient welfare (high δ), the provider's intrinsic motivation to prioritize patient outcomes renders a purely quality-based reimbursement ineffective. In the case in which $\delta > \frac{1}{2}$, the setting with partial coverage becomes dominant, inducing the provider to use the new technology on only a subset of patients, thereby making coordination unattainable. When the effective weight δ is high, providers are already inclined to value patients—especially the high-complexity patients; extra quality-based incentives don't correct the bias in favor of high-complexity patients.

This result aligns with recent literature highlighting the complexities of designing payment systems in healthcare. Studies suggest that although patient-centered motivations are desirable, they can weaken the influence of incentive structures designed to improve efficiency and quality outcomes. For instance, Prendergast (2007) argues high intrinsic motivation may limit the ability of external rewards to influence behavior. Echoing these findings, Proposition 3 reveals the nuanced role of δ in shaping healthcare efficiency, meaning policies solely focused on increasing patient-centeredness may overlook the role of financial incentives and interaction with upstream agents' decisions in shaping provider behavior.

Taken together, our analysis reveals a sharp contrast between benefit-based and quality-based definitions of value. Benefit-based payment strengthens incentives where measured gains are largest, but it skews usage toward complex patients and cannot implement the first-best. Quality-based payment, by contrast, rewards upstream attributes—training, support, reliability, and integration—that determine realized effectiveness and, under appropriate conditions, can align provider and developer decisions. From an implementability perspective, benefit-based payment requires tracking each individual patient's outcomes attributable to the technology, whereas quality-based payment can rely on verifiable features under the developer's control. This comparison motivates the hybrid design in the next section, which combines a per-use fee to secure appropriate adoption with a quality-contingent component to sustain high performance.

6. A Hybrid Payment System

We have shown in the preceding section that the quality-based payment system proves ineffective when the provider heavily weighs the benefits from treatment. We now shift our focus to a hybrid payment system that merges aspects of both fee-for-service and quality-based payment mechanisms. In this payment scheme, the provider is compensated with a fixed per-use reimbursement of f in addition to the quality-based proportional payment (γq). In practical terms, the fixed fee encourages treating more patients, while the quality-based term rewards the developer for maintaining high quality. Because coordination is achievable using a quality-based payment when $\delta \leq 1/2$ (see Section 5.2), we focus in this section on the case of $\delta > 1/2$.

6.1. Coordinating Hybrid Model

Under this hybrid payment model, the provider's decision-making process in the second stage, given the quality decision q and price decision p by the developer, is captured by:

$$\max_{x_1,x_2} \int_{x_1}^{x_2} (f+\gamma q-p)\,dx + \delta bq \int_{x_1}^{x_2} x\,dx = (f+\gamma q-p)(x_2-x_1) + \delta bq \frac{x_2^2-x_1^2}{2}.$$

The provider's use of the new technology is contingent on the following conditions:

- If $p-\gamma q \le f$, the provider uses the new technology for all patients.
- If $p-(\gamma+\delta b)q \le f < p-\gamma q$, the provider uses the new technology for patients with complexity $x \in \left[\frac{p-f-\gamma q}{\delta bq}, 1\right]$.
- Otherwise, the provider does not use the new technology.

Similarly to the quality-based payment, to determine the quality, q, and the price, p, the developer compares two potential settings: one that results in full coverage and another that leads to partial coverage. Coordination to the first-best requires that the full-coverage case dominate the partial-coverage case.

The comparison of optimal developer profit between full and partial coverage settings gives rise to the existence of a threshold payment $\bar{f}$ above which the provider's and developer's incentives are aligned to the first-best under a hybrid model. A reimbursement amount f above this threshold level guarantees the provider's financial incentives are sufficient for full usage, whereas the developer commits to a quality level that aligns with first-best outcomes. The following proposition provides the conditions for the hybrid payment scheme to coordinate the developer's and the provider's incentives:

Proposition 4. *Suppose $\delta > 1/2$, and let*

$$\tilde{f} = \begin{cases} \frac{\left(\delta+\frac{1}{2}\right)^3 b^2}{12\delta c\sqrt{3}} & \text{if } \delta > 1+\sqrt{3}/2 \\ \frac{b^2\left(\delta+\frac{1}{2}\right)^2\left(\delta-\frac{1}{2}\right)}{12\delta c} & \text{else.} \end{cases}$$

- *If $f \ge \tilde{f}$, setting $\gamma = \frac{b}{2}$ enables the hybrid payment scheme to align decisions with the first-best outcome.*
- *$f^* \in (0, \tilde{f}]$ exists such that coordination is achieved if and only if $\gamma = \frac{b}{2}$ and $f \ge f^*$.*

Proposition 4 first provides a sufficient condition leading to a coordinating payment scheme. Namely, it obtains a closed-form expression for $\tilde{f}$, the minimum fee-for-service amount to the provider that ensures the first-best outcome arises. As long as the payment meets this minimum value, the provider has sufficient incentives to use the new technology on all eligible patients, and the quality level the developer selects matches the first-best as well as long as the quality-based payment parameter γ is set adequately.

Proposition 4 also gives a necessary and sufficient condition for coordination, in the form of a proof of the existence of a threshold f^* such that for any $f \geq f^*$ and an appropriate γ, the first-best is achieved (all patients treated, optimal quality). Due to a lack of tractability, we do not have a closed-form expression on this threshold. However, we can show through extensive numerical experiments that f^* is well approximated by $\tilde{f}$, and has the same monotonicity properties (as an illustration, see Figure 3 in Section 6.2).

Another implication of the proposition is that the fee-for-service component f of the hybrid payment decreases in c: a higher quality cost reduces the fee-for-service payment required to induce the developer to provide the corresponding quality level. The intuition is that, as shown in Section 3.1, the first-best quality declines with the unit cost of quality. Thus, technologies for which quality is more costly may paradoxically require smaller fee-for-service payments to align incentives at the margin—an insight that runs counter to conventional wisdom.

To implement the proposed hybrid payment system in practice, policymakers could operationalize quality-contingent payments by creating new billing codes or modifiers tied to technology quality metrics. For example, Medicare could introduce a supplemental payment for procedures involving a certified “high-quality” device—defined by meeting specific criteria related to training, support, and performance. This approach would be analogous to existing NTAP programs (Viz.ai 2020), but with an added quality verification component.

6.2. Numerical Illustration

We now illustrate our model and analysis using a numerical example, based on the use of robotic-assisted radical prostatectomy (RARP) versus the traditional open radical prostatectomy (ORP) for localized prostate cancer. Table 2 summarizes the calibrated parameters and the ranges considered. In the base scenario, the total patient-plus-provider benefit parameter is $b_1 + b_2 = \$3{,}647$ (per high-complexity case for full-quality), the cost parameter is $c = \$1{,}250$ per full-quality unit, and the provider’s effective weight on patient benefit is $\delta = 1.0$ (we provide details on how these parameters were calibrated in the remainder of this section).

Using the base values, we compute the equilibrium outcomes under various payment models, summarized in Table 1. The first-best quality is $q = b/(4c) = 0.73$ with full patient coverage. Under no reimbursement, the quality drops to $q = \delta b/(8c) = 0.36$ and only half of the patients receive the technology. Under FFS, if $f < \$394$, the quality and coverage depend on the value of f (illustrated in Figure 1); for example, a fixed reimbursement of $f = \$300$ lowers the quality to $q = 0.34$ but raises the coverage of patients receiving the technology to 62% (if $f \geq \$394$, all patients are covered but the quality is near zero). Under the hybrid payment, the coordinating quality-based payment factor is $\gamma = 1824$ and the minimum fixed fee of $f = \$998$ yields the first-best quality and coverage.

Table 1 Quality and coverage across payment systems

Payment system	Quality	Coverage fraction
First-best	0.73	100%
No reimbursement	0.36	50%
Fee-for-Service; f from 0 to \$394	0.36 to 0.32	50% to 67%
Fee-for-Service; $f > \$394$	0	100%

Table 2 Calibrated Parameter Values and Ranges for RARP vs. ORP Example

Parameter	Base Value	Range	Key Sources
b_1 (patient benefit per case, USD)	847	500–1,000	Labban et al. (2022); Wu et al. (2021) Luciani et al. (2017); Sammon et al. (2014)
b_2 (provider benefit per case, USD)	2,800	2,000–4,000	Labban et al. (2022); Wu et al. (2021); KFF (2023) Luciani et al. (2017); Feldstein et al. (2019)
c (cost coefficient, USD)	1,250	500–3,000	DCFmodeling (2025); Eckhoff et al. (2023)
δ_1 (provider weight on patient utility)	1.0	0.5–3	Adida and Dai (2024)

Below, we describe in detail how we calibrated our model.

Calibration of b_1 and b_2 (RARP vs. ORP). Our model distinguishes two benefit components: b_1 corresponds to the *patient* benefit (lower chance of complications, faster recovery, lower morbidity, regained productivity), whereas b_2 corresponds to the *provider* benefit (reduced resource utilization and complication costs). We calibrate these parameters using clinical evidence comparing robotic-assisted radical prostatectomy (RARP) with open radical prostatectomy (ORP).

Step 1: Gross system benefit. We normalize the highest attainable quality at $q = 1$. Meta-analyses indicate that a full-quality RARP program ($q = 1$) lowers postoperative length-of-stay by 1.6 days and reduces the incidence of blood transfusion and major complications by 12 and 1.5 percentage points, respectively (Labban et al. 2022) for high-complexity cases ($x = 1$). The monetary value of a hospital day is approximately $c_{\text{day}} = \$3{,}000$ to the hospital and $v_{\text{prod}} = \$239$ in patient productivity (U.S. Bureau of Labor Statistics 2025). Hence the benefit from the shorter stay is

$$1.6 \times (c_{\text{day}} + v_{\text{prod}}) = 1.6 \times (3{,}000 + 239) = \$5{,}182.$$

Adverse-event reductions generate an additional

$$0.12 \times c_{\text{tx}} + 0.015 \times c_{\text{comp}} = 0.12 \times \$2{,}000 + 0.015 \times \$15{,}000 = \$240 + \$225 = \$465,$$

where $c_{\text{tx}} = \$2{,}000$ (blood transfusion) and $c_{\text{comp}} = \$15{,}000$ (major complications). The *gross* system benefit of RARP for a high-complexity patient is therefore $b^{\text{gross}} = \$5{,}182 + \$465 = \$5{,}647$.

Step 2: Accounting for disposable-instrument cost. Each RARP procedure entails approximately \$2,000 of disposable instruments and supplies borne by the provider (Feldstein et al. 2019). Denote this cost by $c_{\text{disp}} = \$2{,}000$. Subtracting it from the gross benefit yields the *net* system benefit

$$b \equiv b^{\text{gross}} - c_{\text{disp}} = \$5{,}647 - \$2{,}000 = \$3{,}647.$$

Step 3: Splitting the net benefit. We attribute the entire disposable-instrument cost to the provider, so the provider's net benefit is

$$b_2 = \underbrace{\$4{,}800}_{\text{hospital-day savings}=1.6c_{\text{day}}} - \underbrace{\$2{,}000}_{c_{\text{disp}}} = \$2{,}800.$$

The patient's benefit remains $b_1 = \$847$ (patient productivity gains and adverse-event reduction).

Calibration of cost function $C(q)$. Because the mass of patients is normalized to one, we calibrate the cost of quality on a per–procedure basis. We specify $C(q) = cq^2$ to capture recurring service and support costs. High-end robotic systems (for example, the da Vinci platform) are covered by annual service plans that include preventive maintenance, remote diagnostics, software updates, technical support, and covered parts/labor, and are billed per year (Intuitive Surgical 2025). Public disclosures and industry reports indicate typical annual service fees of roughly \$80,000–\$190,000, with full coverage plans around \$250,000 (DCFmodeling 2025; Eckhoff et al. 2023). At a typical volume of 200 procedures per year (Monk and McKee 2016), these fees imply approximately \$1,250 per case for a full coverage plan. Under per-use arrangements that we focus on, the developer bundles the system cost, service, and financing into a single per–procedure operational fee with an annual or lifetime cap; that is, service is included within the per-use payment (Intuitive Surgical Operations 2023a). These institutional features reinforce our calibration, under which recurring service and support alone yield an implied per–case cost of \$1,250 to achieve full support; we therefore set $c = \$1{,}250$.

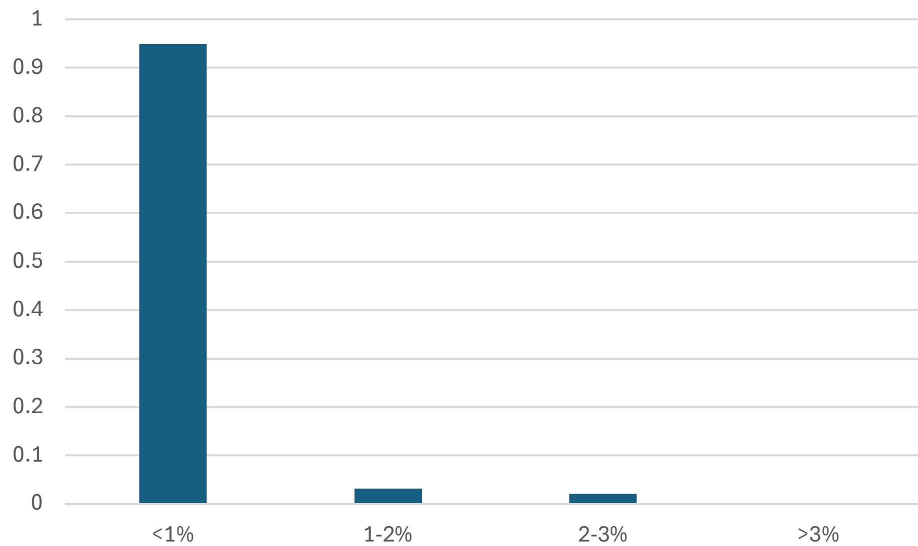
Provider's effective weight of benefit from technology (δ). Finally, we calibrate the provider's weighting of the benefit from the technology. We modeled the provider as valueing a combination of patient and provider benefits, with weight δ_1 on patient welfare in their objective. Empirical studies suggest that, on average, clinicians value patient welfare roughly on par with their own financial incentives. To reflect this, we set $\delta_1 = 1$ in the baseline. Hence, we obtain

$$\delta = \frac{(1) \cdot b_1 + b_2}{b_1 + b_2} = 1.$$

This implies the provider internalizes the full combined benefit $B(x, q)$; that is, values a dollar of patient benefit as much as a dollar of direct gain. In the context of RARP, $\delta = 1$ means the provider (surgeon or hospital) is equally motivated by patient outcomes and operational savings.

To conduct some sensitivity analysis when the key coefficients vary around their base-case values, we consider a wide range of scenarios of parameters as listed in Table 2.

Figure 2 **Histogram of the AS between f^* and $\tilde{f}$ across all scenarios**



- $\delta \in (0.5; 3]$ in increments of 0.05 (50 possible values);
- $b \in (2,500;\ 7,000]$ in increments of 10 (450 possible values);
- $c \in (500;\ 3,000]$ in increments of 10 (250 possible values).

These parameter values result in 5,625,000 parameter scenarios. In each scenario, we evaluate the gap between f^* and $\tilde{f}$, calculated as $(\tilde{f} - f^*)/\tilde{f}$. We also test in each scenario the monotonicity of f^* with respect to, respectively, c, b, and δ within the range described above. Our findings are the following: the maximum gap between f^* and $\tilde{f}$ across all scenarios equals 2.1%, but the average gap is much lower, at 0.22% (see Figure 2). In addition, in 94.86% of cases, the gap is smaller than 1%. This finding confirms $\tilde{f}$ is a very good approximation for f^*. Figure 3 illustrates that unless δ is relatively large, f^* is equal to or extremely close to $\tilde{f}$. Moreover, we obtained that in 100% of scenarios, f^* has the same monotonicity properties as $\tilde{f}$, namely, monotonically decreasing in c, increasing in b and increasing in δ.

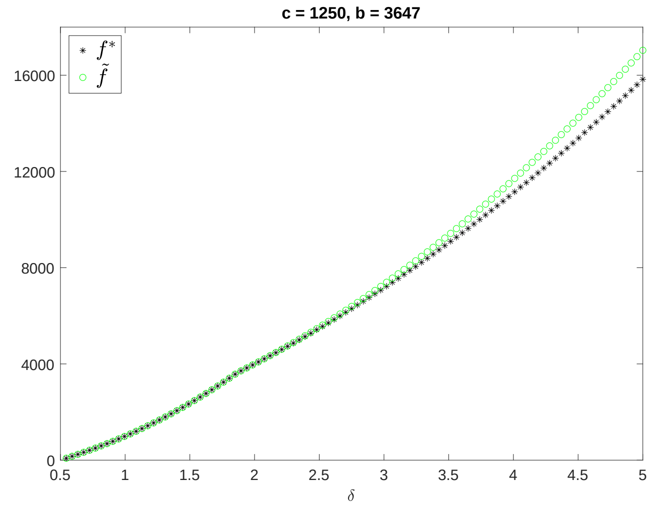
7. Extensions

In this section, we explore some extensions to our main model, each addressing specific dimensions of the problem to test the robustness of our findings and assess the implications of alternative payment mechanisms. Section 7.1 analyzes a subscription-based pricing model, contrasting it with fee-for-service structures. Section 7.2 evaluates the potential for subsidies to address misalignments between private and social incentives.

7.1. Subscription-based Pricing

As an extension, we note that new technologies may also be offered under subscription or lease-like arrangements (Cohen and Toubiana 2024). In such contracts, the developer specifies a flat periodic

Figure 3 **Illustration of f^* and $\tilde{f}$ over a range of values of δ in the base case scenario for b and c**



fee and a quality level q, giving the provider access to the technology for an unlimited number of cases without additional per-use charges. Manufacturers such as Intuitive have introduced subscription-like flexible acquisition models along these lines to broaden hospital access to robotic surgery platforms (Intuitive Surgical Operations 2024a).

We denote p as the present value of the expected time-discounted subscription-fee/lease revenue. In the first stage, the developer solves

$$\max_{p,q>0} \quad -cq^2 + p.$$

In the second stage, given the decisions on price p and quality q made by the developer, if participating, the provider solves

$$\max_{x_1,x_2} \quad -p + \delta bq \int_{x_1}^{x_2} x\,dx.$$

The following proposition describes the equilibrium under a subscription mechanism.

Proposition 5. *Under a subscription model or lease agreement, the developer sets the quality level at $q = \delta b/(4c)$; the provider participates and uses the new technology on all patients.*

Although a subscription-based payment scheme between the provider and the developer addresses a separate issue from how the provider is reimbursed by the payer for new technology usage, it is worth noting that such a model achieves coordination to the first-best outcome if and only if $\delta = 1$. For this effective weight, both the quality level and the range of patients for whom the new technology is used are aligned to the first-best. However, the quality decision is misaligned if $\delta \neq 1$.

7.2. Subsidies

We consider subsidies in two pricing environments: per-use and subscription.

First, under per-use pricing, a provider-side price subsidy that covers a fraction of the per-use fee reduces the effective price from p to $p' \in (0,p)$ and shifts the provider's adoption threshold from $x \geq p/(\delta bq)$ to $x \geq p'/(\delta bq)$, thereby expanding usage. However, unless the effective price is driven to zero and quality is simultaneously aligned, a positive threshold remains and full adoption is not achieved; moreover, the subsidy does not address the developer's quality choice, so misalignment with the first-best persists. A developer-side subsidy that lowers the quality cost from c to $c' \in (0,c)$ raises the chosen quality but leaves the provider's threshold structure intact; in the baseline no-reimbursement environment such a subsidy still yields partial adoption, so coordination fails. In short, under per-use pricing, partial subsidies—whether to the provider or the developer—can expand access or improve quality at the margin but do not jointly induce full adoption and first-best quality.

Next, under subscription-based pricing, the developer sets a flat fee and quality, and the provider uses the technology for all eligible patients. A provider-side subsidy s that increases the provider's willingness to pay is largely passed through into a higher subscription price and leaves the developer's quality choice unchanged, so it does not deliver first-best quality. By contrast, a developer-side cost subsidy that reduces the effective cost coefficient to δc implements the first-best quality when $\delta < 1$ (and quality is already first-best when $\delta = 1$), though such targeted subsidies may be difficult to implement in practice.

Taken together, subsidies can alleviate either the adoption margin (per-use provider subsidy) or the quality margin (developer cost subsidy), but—except for some developer-side subsidies under subscription-based pricing—they do not coordinate both margins simultaneously.

8. Conclusions

As transformative technologies such as robotic surgery become increasingly integrated into healthcare delivery, designing provider payment models that support development, ensure quality, and promote appropriate use is critical. In the United States, however, prevailing provider payment systems offer little or no reimbursement for such technologies, and even pay-per-use contracts that reduce providers' balance-sheet risk do not, on their own, resolve the financial and operational frictions these innovations generate. Without well-structured incentives, both developers and providers face barriers that hinder effective deployment in clinical practice.

This paper develops a theoretical framework to analyze how alternative reimbursement models shape both the development and the use of new healthcare technologies. We show that existing approaches—either no reimbursement or fee-for-service alone—fail to promote high-quality innovation and efficient adoption. Under no reimbursement, providers bear the full cost at the point of care, leading to selective use and weak incentives for developers to invest in quality. Fee-for-service can broaden use as payments rise but, by rewarding volume, may dull developers' incentives to maintain quality and push adoption beyond efficient levels, complementing concerns in the literature (see, e.g., Zink et al. (2024)). Our contribution is to endogenize developer behavior and link reimbursement policy directly to upstream quality investment.

We then compare two value-based approaches that hinge on how "value" is defined. Defining value as *benefit*—paying on realized patient gains—seems natural but skews use toward the most complex cases and is difficult to implement, since it requires attributing outcomes to the technology for each individual patient. Defining value as *quality*—rewarding training, support, integration, and reliability under the developer's control—is more implementable and better aligns incentives by targeting the upstream drivers of effectiveness.

Provider behavior conditions these results. When providers place greater weight on patient benefit for its own sake, they become less responsive to financial incentives, so quality-contingent payments alone may fail to achieve first-best adoption. To address this, we propose a hybrid payment structure that combines a per-use fee with quality-based rewards, restoring incentives for both adoption and quality and implementing socially efficient use across patient populations.

Finally, our comparative statics yield a counterintuitive implication: higher quality costs can *reduce* the per-use fixed reimbursement required to align incentives. As costs rise, the socially optimal quality falls, and weaker payments suffice to coordinate developer investment and provider adoption. Effective payment design therefore depends not only on clinical value but also on the technology's cost structure and on how providers balance patient benefit against financial considerations.

The framework extends beyond robotic surgery to a range of emerging healthcare technologies, including digital therapeutics, AI diagnostic tools, and other high-cost innovations. In each case, widespread adoption depends on aligning developer and provider incentives through appropriate reimbursement design.

As transformative technologies reshape healthcare delivery, payment system design will play a key role in driving their impact on costs, quality, and access. The hybrid model analyzed here illustrates how reimbursement policies can better align incentives, foster innovation, and promote appropriate adoption of transformative technologies.

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Online Appendix to "Provider Payment Models for Transformative Technologies in Healthcare"

PROOF OF LEMMA 1. At the first-best, the social planner decides which patients $[x_1, x_2]$ to use the technology on (where $0 \le x_1 \le x_2 \le 1$), to maximize

$$bq\frac{x_2^2 - x_1^2}{2},$$

hence it is clear that it is socially optimal to use the technology on all patients. The socially optimal quality is obtained by solving

$$\max_{q>0} \quad -cq^2 + \frac{bq}{2},$$

which leads to $q = b/(4c)$. The social planner's objective then equals

$$-\frac{b^2}{16c} + \frac{b^2}{8c} = \frac{b^2}{16c} > 0,$$

so the social planner opts to participate. *Q.E.D.*

PROOF OF LEMMA 2. In stage 2, the provider decides which patients $[x_1, x_2]$ to use the technology on (where $0 \le x_1 \le x_2 \le 1$), to maximize

$$f(x_1, x_2) = -p(x_2 - x_1) + \delta bq\frac{x_2^2 - x_1^2}{2},$$

$$\text{where} \quad \frac{\partial f}{\partial x_1}(x_1, x_2) = p - \delta bq x_1$$

$$\frac{\partial f}{\partial x_2}(x_1, x_2) = -p + \delta bq x_2.$$

If $p > \delta bq$, then $\frac{\partial f}{\partial x_1} > 0$ and $\frac{\partial f}{\partial x_2} < 0$ for all $x_1, x_2 \in [0, 1]$, so $x_1^* = x_2^*$. No patient receives AI.

Otherwise, if $p \le \delta bq$, we have $\frac{\partial f}{\partial x_1} > 0$ if and only if $x_1 < \frac{p}{\delta bq}$ and $\frac{\partial f}{\partial x_2} > 0$ if and only if $x_2 > \frac{p}{\delta bq}$. Hence, f is unimodal in x_1 and reaches its maximum at $\frac{p}{\delta bq}$. Moreover, for $x_2 \ge \frac{p}{\delta bq}$, f is increasing in x_2, so the optimal solution is $(x_1, x_2) = (\frac{p}{\delta bq}, 1)$. *Q.E.D.*

PROOF OF PROPOSITION 1. If $p > \delta bq$, the technology is not used in stage 2, so the developer does not participate as there is no possibility of earning any revenue. In stage 1, the developer solves the following problem (and participates if and only if the optimal objective value is positive):

$$\max_{p,q>0} \quad \varphi(p, q) = -cq^2 + p\left(1 - \frac{p}{\delta bq}\right) = -cq^2 + p - \frac{p^2}{\delta bq}$$

$$\text{s.t.} \quad p \le \delta bq.$$

We have

$$\frac{\partial \varphi}{\partial p}(p, q) = 1 - \frac{2p}{\delta bq}$$

$$\frac{\partial \varphi}{\partial q}(p, q) = -2cq + \frac{p^2}{\delta bq^2}$$

$$\frac{\partial^2 \varphi}{\partial p^2}(p, q) = -\frac{2}{\delta bq} < 0$$

$$\frac{\partial^2 \varphi}{\partial q^2}(p,q) = -2c - 2\frac{p^2}{\delta b q^3} < 0$$
$$\frac{\partial^2 \varphi}{\partial p \partial q}(p,q) = \frac{2p}{\delta b q^2}.$$

The first-order conditions can be written as:

$$2p = \delta b q$$
$$2c\delta b q^3 = p^2,$$

that is,

$$q = \frac{\delta b}{8c}, \qquad p = \frac{\delta^2 b^2}{16c}.$$

Note in particular that, at this stationary point solution, the constraint $p \leq \delta b q$ is valid.

The second-order condition requires that, at the stationary point,

$$\frac{2}{\delta b q}\left(2c + 2\frac{p^2}{\delta b q^3}\right) - \frac{4p^2}{\delta^2 b^2 q^4} > 0,$$
$$\Leftrightarrow \frac{32c^2}{\delta^2 b^2} > 0 \text{ after simplifications.}$$

Hence, the unique stationary point is the optimal solution. Moreover, at this solution, the objective value equals $\delta^2 b^2/(64c) > 0$, so the developer opts to participate. *Q.E.D.*

Proof of Lemma 3. The proof is similar to the proof of Lemma 2. If $p - f > \delta b q$ (i.e., if $f < p - \delta b q$), the technology is not used on any patient. Otherwise, if $f \geq p - \delta b q$, the optimal solution is $(x_1, x_2) = (\frac{p-f}{\delta b q}, 1)$. *Q.E.D.*

Proof of Proposition 2. We start with proving the following lemma:

Lemma A1. *The inequality*

$$\varphi\left(\frac{\delta b + \sqrt{(\delta b)^2 - 24cf}}{12c}, f\right) \leq 0$$

is equivalent to the condition

$$\frac{\delta^2 b^2}{27c} \leq f \leq \frac{\delta^2 b^2}{24c}.$$

Proof of Lemma A1. To establish this equivalence, observe that $f \leq \delta^2 b^2/24c$ is required for the square root to exist, and

$$\varphi\left(\frac{\delta b + \sqrt{(\delta b)^2 - 24cf}}{12c}, f\right) = f^2 + \frac{b^4\delta^4 + b\delta\left(b^2\delta^2 - 24cf\right)^{3/2} - 36b^2 c\delta^2 f}{216c^2}. \tag{A1}$$

This expression equals zero when $f = \delta^2 b^2/(27c)$. Next, we examine the total derivative of (A1) with respect to f:

$$\frac{d}{df}\varphi\left(\frac{\delta b + \sqrt{(\delta b)^2 - 24cf}}{12c}, f\right) = 2\left[f - \frac{b\delta\left(\delta b + \sqrt{(\delta b)^2 - 24cf}\right)}{12c}\right]. \tag{A2}$$

This derivative is always negative because

$$\frac{b\delta\left(\delta b+\sqrt{(\delta b)^2-24cf}\right)}{12c} > \frac{(\delta b)^2}{12c} \geq 2f > f.$$

Because the derivative is negative and φ equals zero at $f = \delta^2 b^2/(27c)$, it follows that

$$\varphi\left(\frac{\delta b+\sqrt{(\delta b)^2-24cf}}{12c}, f\right) \leq 0 \tag{A3}$$

if and only if

$$\frac{\delta^2 b^2}{27c} \leq f \leq \frac{\delta^2 b^2}{24c}. \tag{A4}$$

Q.E.D.

To prove Proposition 2, we need to solve two optimization problems, and select the one leading to the higher objective value (provided it is positive, to ensure participation). The first optimization problem is

$$\begin{aligned} \max_{p,q>0} \quad & -cq^2 + p \\ \text{s.t.} \quad & p \leq f. \end{aligned}$$

The optimal solution is $q = \epsilon$ and $p = f$, with an objective value of $f - c\epsilon^2 \approx f$.

The second optimization problem is

$$\begin{aligned} \max_{p,q>0} \quad & \psi(p,q) = -cq^2 + p\left(1 - \frac{p-f}{\delta bq}\right) \\ \text{s.t.} \quad & p > f \\ & p - \delta bq \leq f. \end{aligned}$$

We have

$$\begin{aligned} \frac{\partial \psi}{\partial p}(p,q) &= 1 - \frac{2p-f}{\delta bq} \\ \frac{\partial \psi}{\partial q}(p,q) &= -2cq + \frac{p(p-f)}{\delta bq^2}. \end{aligned}$$

The first-order conditions can be written as:

$$\begin{aligned} 2p - f &= \delta bq \\ 2c\delta bq^3 &= p(p-f). \end{aligned}$$

The former implies $p - \delta bq = f - p \leq f$, consistent with the second constraint of the optimization problem. The latter implies in particular $p - f > 0$, consistent with the first constraint of the optimization problem. Hence, at a stationary point, both constraints are satisfied.

We have

$$\begin{aligned} \frac{\partial^2 \psi}{\partial p^2}(p,q) &= -\frac{2}{\delta bq} < 0 \\ \frac{\partial^2 \psi}{\partial q^2}(p,q) &= -2c - 2\frac{p(p-f)}{\delta bq^3} < 0 \\ \frac{\partial^2 \psi}{\partial p \partial q}(p,q) &= \frac{2p-f}{\delta bq^2}, \end{aligned}$$

where the first two inequalities are trivially satisfied at a stationary point. The second-order conditions also require that, at a stationary point,

$$\frac{2}{\delta bq}\left(2c+2\frac{p(p-f)}{\delta bq^3}\right)-\left(\frac{2p-f}{\delta bq^2}\right)^2>0.$$

Using the first-order condition, the above inequality simplifies to $12c/(\delta bq)-1/q^2>0$, or equivalently, $q>\delta b/(12c)$.

Plugging the first first-order condition into the second, we obtain

$$\frac{\delta^2b^2q^2-f^2}{4}=2\delta bcq^3,$$

or equivalently

$$\varphi(q,f)\equiv 8\delta bcq^3-\delta^2b^2q^2+f^2=0.$$

We need to solve this equation for q to find the quality at a stationary point for a given f. We have

$$\frac{\partial\varphi(q,f)}{\partial q}=24\delta bcq^2-2\delta^2b^2q=2q\delta b(12cq-\delta b).$$

Hence, $\varphi(q,f)$ is unimodal in q, reaching a minimum when $q=\delta b/(12c)$. At that minimum, $\varphi(q,f)$ takes the value (after simplifications)

$$\varphi\left(\frac{\delta b}{12c},f\right)=f^2-\frac{\delta^4b^4}{3\times 12^2c^2}.$$

Therefore, the equation $\varphi(q,f)=0$ in q has two solutions $\bar{q}_1,\bar{q}_2$ if and only if $f<\delta^2b^2/(12c\sqrt{3})$. (If $f=\delta^2b^2/(12c\sqrt{3})$, there is a single solution $q=\delta b/(12c)$ and $\varphi(q,f)\geq 0$ for all q, and if f is above the threshold, there is no solution.) In addition, because $\varphi(0,f)>0$, both solutions $\bar{q}_1,\bar{q}_2$ are non-negative; they are equidistant to $\delta b/(12c)$. It follows that a unique stationary point $\bar{q}_2$ exists satisfying the second-order conditions if and only if $f<\delta^2b^2/(12c\sqrt{3})$. Moreover, we have $\delta b/(12c)<\bar{q}_2<\delta b/(6c)$.

It remains to ensure that at this solution (together with the associated price, $\bar{p}_2\equiv(\delta b\bar{q}_2+f)/2$), the objective value is larger than that at the first optimization problem. Namely, we need to ensure that, at this stationary point,

$$-cq^2+p\left(1-\frac{p-f}{\delta bq}\right)=-3cq^2+\frac{\delta bq}{2}+\frac{f}{2}>f,$$
$$\Leftrightarrow -3cq^2+\frac{\delta bq}{2}-\frac{f}{2}>0.$$

This degree-2 polynomial is less than or equal to zero if $(\delta b)^2\leq 24cf$. Otherwise, it has two positive roots that are equidistant to $\delta b/(12c)$. Hence, the objective value is larger than that at the first optimization problem if and only if the stationary point is located in between these two roots, that is, if and only if

$$\bar{q}_2\leq\frac{\delta b+\sqrt{(\delta b)^2-24cf}}{12c},$$

or equivalently, if and only if

$$\varphi\left(\frac{\delta b+\sqrt{(\delta b)^2-24cf}}{12c},f\right)>0.$$

Using Lemma A1, this inequality is equivalent to

$$\frac{\delta^2b^2}{27c}\leq f\leq\frac{\delta^2b^2}{24c}. \tag{A5}$$

Conclusion:

- if $f > \delta^2 b^2/(12c\sqrt{3})$, no stationary point exists in the second optimization problem. At the boundaries/limit, the objective is the same or worse than the first optimization problem;
- else, if $f \geq \delta^2 b^2/(24c)$, the second optimization problem has a worse objective than the first;
- else, if $f \geq \delta^2 b^2/27c$, the second optimization problem has a worse objective than the first.
- else, that is, if $f < \delta^2 b^2/(27c)$, one stationary point exists that is the unique maximizer, given by $\bar{q}_2$ as the larger root in q of $\varphi(q,f)$, and associated price $\bar{p}_2 \equiv (\delta b \bar{q}_2 + f)/2$.

Q.E.D.

Proof of Corollary 1. We start with proving the following lemma:

Lemma A2. *The inequality*

$$\varphi\left(\frac{\delta b + \sqrt{(\delta b)^2 + 48cf}}{24c}, f\right) \leq 0$$

is equivalent to the condition

$$\frac{\delta^2 b^2}{27c} \geq f.$$

Proof of Lemma A2. We start by noting

$$\varphi\left(\frac{\delta b + \sqrt{\delta^2 b^2 + 48cf}}{24c}, f\right) = \frac{b\delta f\sqrt{b^2\delta^2 + 48cf}}{36c} - \frac{b^3\delta^3\left(\sqrt{b^2\delta^2 + 48cf} + b\delta\right)}{864c^2} + f^2,$$

which is equal to zero when $f = \frac{b^2\delta^2}{27c}$. The total derivative of the above quantity with respect to f is given by

$$2f\left(\frac{b\delta}{\sqrt{b^2\delta^2 + 48cf}} + 1\right) > 0.$$

Therefore, it follows that

$$\varphi\left(\frac{\delta b + \sqrt{\delta^2 b^2 + 48cf}}{24c}, f\right) < 0$$

if and only if $f < \frac{b^2\delta^2}{27c}$. *Q.E.D.*

To prove Corollary 1(i), note $\varphi(q^*, f) = 0$ implies

$$\frac{\partial \varphi}{\partial q}\frac{dq^*}{df} + \frac{\partial \varphi}{\partial f} = 0. \tag{A6}$$

Because $\partial\varphi/\partial f = 2f > 0$, it follows that

$$\frac{\partial \varphi}{\partial q}\frac{dq^*}{df} < 0.$$

Moreover, since $\partial\varphi/\partial q > 0$ when $q \in [\delta b/(12c), \infty)$, it follows that $dq^*/df < 0$.

To prove Corollary 1(ii), note

$$\frac{dp^*}{df} = \frac{1}{2}\delta b\frac{dq^*}{df} + \frac{1}{2}.$$

Moreover, from (A6),

$$\frac{dq^*}{df} = -\frac{\partial\varphi/\partial f}{\partial\varphi/\partial q} = -\frac{2f}{2\delta b q^*(12cq^* - \delta b)}.$$

As a result,

$$\frac{dp^*}{df} = \frac{-2f\delta b + 2\delta bq^*(12cq^* - \delta b)}{4\delta bq^*(12cq^* - \delta b)},$$

which has the sign of $12c(q^*)^2 - \delta bq^* - f$. This degree-2 polynomial in q^* has a positive discriminant, a positive root, and a negative root; moreover it grows to infinity as q^* grows large. Hence, on the positive domain, the polynomial is positive if and only if q^* is above the positive root, namely, $(\delta b + \sqrt{(\delta b)^2 + 48cf})/(24c)$. Because φ is increasing in q for $q > \delta b/(12c)$, it follows that $dp^*/df \geq 0$ if and only if

$$\varphi\left(\frac{\delta b + \sqrt{\delta^2 b^2 + 48cf}}{24c}, f\right) \leq 0.$$

By Lemma A2, we have $dp^*/df \geq 0$ if and only if $\delta^2 b^2/27c \geq f$. By part (ii) of Proposition 2, we have $f < \delta^2 b^2/27c$. As a result, $dp^*/df \geq 0$. *Q.E.D.*

Proof of Corollary 2. As noted in the proof of Proposition 2, the quality set with a fee-for-service reimbursement is either $q = \epsilon$ (near zero) with the technology used on all patients, or $q = \bar{q}_2$, where $\delta b/(12c) < \bar{q}_2 < \delta b/(6c)$ with the technology used on a subset of patients. Because at the first-best, the technology is used on all patients with a non-near-zero quality, matching the first-best is impossible.

Furthermore, $\delta b/(6c) < b/(4c)$ when $\delta < 1.5$. Hence, the quality is lower than that at the first-best, given by $b/(4c)$. *Q.E.D.*

Proof of Lemma 4. Coordination would require that the second case of Proposition 2 holds and

$$\frac{1}{2} - \frac{f}{2\delta b\bar{q}_2} = 0,$$

that is, $f = \delta b\bar{q}_2$. Moreover, $\varphi(\bar{q}_2, f) = 0$ implies

$$8\delta bc\bar{q}_2^3 - \delta^2 b^2 \bar{q}_2^2 + \delta^2 b^2 \bar{q}_2^2 = 0,$$

that is, $\delta bc\bar{q}_2^3 = 0$ which contradicts $\delta > 0$ and $\bar{q}_2 > \delta b/(12c)$. *Q.E.D.*

Proof of Proposition 3. We need to solve two optimization problems, and select the one leading to the higher objective value (provided it is positive, to ensure participation). The first optimization problem is

$$\begin{aligned} \max_{p,q>0} \quad & -cq^2 + p \\ \text{s.t.} \quad & p - \gamma q \leq 0. \end{aligned}$$

The optimal solution is $q = \gamma/(2c)$ and $p = \gamma^2/(2c)$, with an objective value of $\gamma^2/(4c)$. With these decisions, the technology is used on all patients, so this coordinates to the first-best if and only if the quality decisions match, that is, $\gamma = b/2$.

The second optimization problem is

$$\begin{aligned} \max_{p,q>0} \quad & \psi(p,q) = -cq^2 + p\left(1 - \frac{p - \gamma q}{\delta bq}\right) \\ \text{s.t.} \quad & p - \gamma q > 0 \\ & p - (\gamma + \delta b)q \leq 0. \end{aligned}$$

If this problem dominates the first, the technology is used for only a fraction of patients, making coordination impossible, regardless of γ. Hence, to focus on whether coordination is possible, we set $\gamma = b/2$ and we seek to determine whether the optimal objective value of the second optimization problem may dominate that of the first.

We have

$$\frac{\partial \psi}{\partial p}(p,q) = 1 - \frac{2p - \gamma q}{\delta b q} = 1 - \frac{2p}{\delta b q} + \frac{\gamma}{\delta b}$$
$$\frac{\partial \psi}{\partial q}(p,q) = -2cq + \frac{p^2}{\delta b q^2}.$$

The first-order conditions can be written as:

$$p = \frac{\delta b + \gamma}{2} q$$
$$2c\delta b q^3 = p^2.$$

Plugging the first condition into the second, we obtain $p = q = 0$ (leading to an objective value of zero, worse than the first problem) or

$$q = \frac{(\delta b + \gamma)^2}{8c\delta b}, \qquad p = \frac{(\delta b + \gamma)^3}{16 c\delta b}.$$

Regarding the constraints, we have (using $\gamma = b/2$)

$$p - \gamma q = (\delta b - \gamma)q/2 = b(\delta - 1/2)q/2 > 0 \text{ if and only if } \delta > 1/2$$
$$p - (\gamma + \delta b)q = -p \le 0.$$

Hence, if $\delta > 1/2$, the stationary point satisfies the constraints; otherwise, no stationary point (other than $(0,0)$) exists in the feasible domain, so the first constraint is tight at the optimum ($p = \gamma q$), and the problem reduces to the first optimization problem. We thus focus on the case $\delta > 1/2$ in the remainder of the proof.

We have

$$\frac{\partial^2 \psi}{\partial p^2}(p,q) = -\frac{2}{\delta b q} < 0$$
$$\frac{\partial^2 \psi}{\partial q^2}(p,q) = -2c - 2\frac{p^2}{\delta b q^3} < 0$$
$$\frac{\partial^2 \psi}{\partial p \partial q}(p,q) = \frac{2p}{\delta b q^2}.$$

The second-order conditions require that, at a stationary point,

$$\frac{2}{\delta b q}\left(2c + 2\frac{p^2}{\delta b q^3}\right) - \left(\frac{2p}{\delta b q^2}\right)^2 > 0.$$

Using the first-order condition, the above inequality simplifies to $4c/(\delta b q) > 0$, which is trivially satisfied. Hence, the stationary point is the optimal solution.

It remains to compare the objective of the second optimization problem at the optimal solution with that of the first one. After simplifications, the objective of the second problem at the unique stationary point is

$$(\gamma + \delta b)^4 / (64 c \delta^2 b^2),$$

which is larger than the objective of the first problem ($\gamma^2/(4c)$) because

$$\frac{(\gamma+\delta b)^4}{64c\delta^2 b^2} \geq \frac{\gamma^2}{4c} \Leftrightarrow (\gamma+\delta b)^2 \geq 4\delta b\gamma$$
$$\Leftrightarrow (\gamma-\delta b)^2 \geq 0.$$

Hence, coordination is possible if $\delta < 1/2$; otherwise, the second optimization problem dominates. *Q.E.D.*

Proof of Proposition 4. We need to solve two optimization problems, and select the one leading to the higher objective value (provided it is positive, to ensure participation). The first optimization problem is

$$\max_{p,q>0} \quad -cq^2 + p$$
$$\text{s.t.} \quad p - \gamma q \leq f.$$

The optimal solution is $q = \gamma/(2c)$ and $p = f + \gamma^2/(2c)$, with an objective value of $f + \gamma^2/(4c)$. With these decisions, the technology is used on all patients so this coordinates to the first-best if and only if the quality decisions match, that is, $\gamma = b/2$.

The second optimization problem is

$$\max_{p,q>0} \quad \psi(p,q) = -cq^2 + p\left(1 - \frac{p-f-\gamma q}{\delta b q}\right)$$
$$\text{s.t.} \quad p - \gamma q > f$$
$$p - (\gamma+\delta b)q \leq f.$$

If the second optimization problem yields a higher objective value than the first, the technology is used only for a subset of patients, making coordination unattainable irrespective of the value of γ. To obtain the conditions under which coordination is feasible, we fix $\gamma = b/2$ and evaluate whether the optimal objective value of the second optimization problem can exceed that of the first.

We have

$$\frac{\partial\psi}{\partial p}(p,q) = 1 - \frac{2p-f-\gamma q}{\delta b q} = 1 - \frac{2p-f}{\delta b q} + \frac{\gamma}{\delta b}$$
$$\frac{\partial\psi}{\partial q}(p,q) = -2cq + \frac{p(p-f)}{\delta b q^2}.$$

The first-order conditions can be written as:

$$2p - f = (\delta b + \gamma)q$$
$$2c\delta b q^3 = p(p-f).$$

The former implies $p - (\delta b+\gamma)q = f - p \leq f$, consistent with the second constraint of the optimization problem. The first constraint of the optimization problem is $p - \gamma q > f$, i.e., using the first of the FOC, $q > f/(\delta b - \gamma)$. This requires $\delta b > \gamma$, which is valid when $\gamma = b/2$ and $\delta > 1/2$. We still need to check whether this constraint is satisfied at a stationary point. (If not, the constraint is tight, and the second problem reduces to the first optimization problem.)

We have

$$\frac{\partial^2\psi}{\partial p^2}(p,q) = -\frac{2}{\delta b q} < 0$$

$$\frac{\partial^2\psi}{\partial q^2}(p,q) = -2c - 2\frac{p(p-f)}{\delta b q^3} < 0$$
$$\frac{\partial^2\psi}{\partial p \partial q}(p,q) = \frac{2p-f}{\delta b q^2},$$

where the first two inequalities are trivially satisfied at a stationary point. The second-order conditions also require that, at a stationary point,

$$\frac{2}{\delta b q}\left(2c + 2\frac{p(p-f)}{\delta b q^3}\right) - \left(\frac{2p-f}{\delta b q^2}\right)^2 > 0.$$

Using the first-order condition, the above inequality simplifies to $12c\delta bq > (\delta b + \gamma)^2$ or, equivalently, $q > (\delta b + \gamma)^2/(12c\delta b)$.

Plugging the first first-order condition into the second, we obtain

$$\frac{(\delta b + \gamma)^2 q^2 - f^2}{4} = 2\delta bcq^3$$

or, equivalently,

$$\varphi(q) \equiv 8\delta bcq^3 - (\delta b + \gamma)^2 q^2 + f^2 = 0.$$

We need to solve this equation for q to find the quality at a stationary point. We have

$$\varphi'(q) = 24\delta bcq^2 - 2(\delta b + \gamma)^2 q = 2q(12\delta bcq - (\delta b + \gamma)^2).$$

Hence, $\varphi(q)$ is unimodal, reaching a minimum when $q = (\delta b + \gamma)^2/(12\delta bc)$. At that minimum, $\varphi(q)$ takes the value (after simplifications)

$$\varphi\left(\frac{(\delta b + \gamma)^2}{12\delta bc}\right) = f^2 - \frac{(\delta b + \gamma)^6}{3 \times (12\delta bc)^2}.$$

Therefore, the equation $\varphi(q) = 0$ has two solutions $\bar{q}_1, \bar{q}_2$ if and only if $f < (\delta b + \gamma)^3/(12\delta bc\sqrt{3}) = \bar{f}$ (using the fact that $\gamma = b/2$). (If $f = (\delta b + \gamma)^3/(12\delta bc\sqrt{3})$, there is a single solution $q = (\delta b + \gamma)^2/(12\delta bc)$ and $\varphi(q) \geq 0$ for all q, and if f is above the threshold, there is no solution.) In addition, because $\varphi(0) > 0$, both solutions $\bar{q}_1, \bar{q}_2$ are non-negative; they are equidistant to $(\delta b + \gamma)^2/(12\delta bc)$. It follows that a unique stationary point $\bar{q}_2$ exists satisfying the second-order conditions if and only if $f < (\delta b + \gamma)^3/(12\delta bc\sqrt{3})$. Moreover, we have $(\delta b + \gamma)^2/(12\delta bc) < \bar{q}_2 < (\delta b + \gamma)^2/(6\delta bc)$.

Because the first-order condition gives $p = \frac{((\delta b + \gamma)q + f)}{2}$, and because $\gamma = b/2$ with $\delta > 1/2$, the stationary point satisfies the first constraint $p - \gamma q > f$ if and only if $q > \frac{f}{\delta b - \gamma}$. This condition holds if and only if one of the following is true:

$$\varphi\left(\frac{f}{\delta b - \gamma}\right) < 0 \quad \text{or} \quad \bar{q}_1 > \frac{f}{\delta b - \gamma}.$$

Simplifying further, we find that $\varphi\left(\frac{f}{\delta b - \gamma}\right)$ has the same sign as the expression $2cf - \gamma(\delta b - \gamma)$. Thus, the constraint is satisfied if either $2cf - \gamma(\delta b - \gamma) < 0$ or both $2cf - \gamma(\delta b - \gamma) > 0$ and $\frac{f}{\delta b - \gamma} < \frac{(\delta b + \gamma)^2}{12\delta bc}$. Specifically, this implies either:

$$f < \frac{\gamma(\delta b - \gamma)}{2c} \quad \text{or} \quad \frac{\gamma(\delta b - \gamma)}{2c} < f < \frac{(\delta b + \gamma)^2(\delta b - \gamma)}{12\delta bc}.$$

Therefore, the stationary point satisfies the first constraint if and only if:

$$f < \frac{(\delta b + \gamma)^2(\delta b - \gamma)}{12\delta bc} = \frac{b^2(\delta + \frac{1}{2})^2(\delta - \frac{1}{2})}{12\delta c}.$$

If f exceeds this threshold, the stationary point becomes infeasible, leaving the second optimization problem with no interior solution. Observe

$$\frac{b^2(\delta+\frac{1}{2})^2(\delta-\frac{1}{2})}{12\delta c}<\bar{f} \quad \Leftrightarrow \quad \sqrt{3}(\delta-\frac{1}{2})<\delta+\frac{1}{2}$$
$$\Leftrightarrow \quad \delta<1+\frac{\sqrt{3}}{2}\approx 1.87.$$

Provided that the stationary point is feasible, it remains to compare the objective value at this solution (together with the associated price, $\bar{p}_2\equiv((\delta b+\gamma)\bar{q}_2+f)/2)$ verus that at the first optimization problem. Namely, the first optimization problem dominates when, at this stationary point,

$$-cq^2+p\left(1-\frac{p-f-\gamma q}{\delta bq}\right)=-3cq^2+\left(\frac{(\delta b+\gamma)q}{2}+\frac{f}{2}\right)\left(1+\frac{\gamma}{\delta b}\right)<f+\frac{\gamma^2}{4c},$$
$$\Leftrightarrow -3cq^2+\frac{(\delta b+\gamma)^2}{2\delta b}q-\frac{f}{2}+\frac{f\gamma}{2\delta b}-\frac{\gamma^2}{4c}<0.$$

If the optimal solution to the second optimization problem lies on one of the boundaries, two possibilities exist: either the first or the second constraint is tight. If the first constraint in tight, the problem reduces to the first optimization problem. If the second constraint is tight, the optimal solution is $q=0, p=f$ with an objective value of zero, which is worse than the first optimization problem.

Hence,

- if $\delta>1+\sqrt{3}/2$ and $f>b^2(\delta+1/2)^3/(12\delta c\sqrt{3})$, or if $\delta<1+\sqrt{3}/2$ and $f>b^2(\delta+1/2)^2(\delta-1/2)/(12\delta c)$, no feasible stationary point exists in the second optimization problem. The solution is that of the first optimization problem. Hence, setting $\gamma=b/2$ coordinates to the first-best;
- otherwise, a feasible stationary point (solution of the second optimization problem) exists. We need to find it and test whether the resulting objective is worse than the objective of the first problem. We first need to find $\bar{q}_2$ the larger root of the equation

  $$\varphi(q)\equiv 8\delta bcq^3-(\delta b+\gamma)^2q^2+f^2=0.$$

  Set $\bar{p}_2\equiv((\delta b+\gamma)\bar{q}_2+f)/2$. Then, we test whether

  $$-3cq^2+\frac{(\delta b+\gamma)^2}{2\delta b}q-\frac{f}{2}+\frac{f\gamma}{2\delta b}-\frac{\gamma^2}{4c}<0. \tag{A7}$$

  If so, setting $\gamma=b/2$ coordinates to the first-best. If not, the second optimization problem dominates the first, and no coordination is possible, because only a fraction of patients receives the technology at the optimal solution.

Taking the derivative with respect to f of the equation $\varphi(q)=0$, we obtain

$$\frac{\partial\bar{q}_2}{\partial f}=\frac{f}{\bar{q}_2}\frac{1}{(\delta b+\gamma)^2-12\delta bc\bar{q}_2}.$$

Because we have $\bar{q}_2>\frac{(\delta b+\gamma)^2}{12\delta bc}$, it follows that $\frac{\partial\bar{q}_2}{\partial f}<0$. Furthermore, by taking the partial derivative of the left-hand side of (A7) with respect to f and using the expression for $\frac{\partial\bar{q}_2}{\partial f}$, we obtain:

$$\frac{f-(\delta b-\gamma)\bar{q}_2}{2\delta b\bar{q}_2}<0,$$

where the inequality holds due to the first feasibility constraint. As a result, (A7) is equivalent to requiring f to exceed a certain threshold. Given that coordination is possible for f above $\tilde{f}$ and impossible for $f=0$, it follows that the threshold f^* lies within the interval $(0,\tilde{f}]$. *Q.E.D.*

Proof of Proposition 5. If participating, the provider uses the technology on all patients (i.e., $x_1 = 0,\ x_2 = 1$). As a result, the provider participates if and only if $p < \delta bq/2$. Hence, in the first stage, the developer sets $p = \delta bq/2 - \epsilon$ and selects the quality level q to maximize $-cq^2 + \delta bq/2$. It follows that the developer sets $q = \delta b/(4c)$ and its profit is positive; thus, the developer elects to participate. *Q.E.D.*