Aligning Incentives in Health Care: A Multiscale Decision Theory Approach

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Hui Zhang[a], Christian Wernz[a], Anthony D. Slonim[b]

[a]Grado Department of Industrial and Systems Engineering,
Virginia Tech, Blacksburg, VA 24061

[b]Renown Health, Reno, NV 89502

Abstract

Financial incentives offered by insurers to health care providers have been identified as a key mechanism to lower costs while improving quality of care. How to effectively design incentive programs that can align the varying objectives of health care stakeholders, as well as predict program performance and stakeholders' decision response is an unresolved research challenge. The objective of this paper is to establish the foundation for a novel approach based on multiscale decision theory (MSDT) that can effectively model and efficiently analyze such incentive programs, and the complex health care system in general. The MSDT model captures the interdependencies of stakeholders, their decision processes, uncertainties, and how incentives impact decisions and outcomes at the payer, hospital, physician and patient level. We illustrate the modeling approach by applying it to a specific incentive program, the Medicare Shared Savings Program (MSSP) for Accountable Care Organizations (ACOs), which was introduced by the Centers for Medicare and Medicaid Services (CMS) in the United States in 2012. We focus our analysis on computed tomography (CT) use by physicians, and CT scanner investment decisions by hospitals. We determine the conditions under which the incentive program leads to the desired outcomes of cost reduction and quality of care improvements. The results have policy and managerial implications for CMS, ACOs and their members, specifically hospitals, and physicians.

Keywords: Multiscale decision theory, incentives, medical technology, Accountable Care Organizations, Medicare Shared Savings Program, U.S. health care system.

1. Introduction

U.S. health care costs have been rising on average 6.0% per year over the past 20 years and now constitute 17.4% of the nation's Gross Domestic Product (Centers for Medicare and Medicaid Services, 2014a). Medical technologies have been identified as one of the main cost drivers (Farrell et al., 2008). Technology-related expenses are estimated to account for 50% to 67% of the growth in U.S. health care spending (Newhouse, 1992; Kaiser Family Foundation, 2007).

Medical technologies, such as surgical robots and CT scanners, have become indispensable treatment and diagnostic tools in modern patient care (Brenner and Hall, 2007; Turchetti et al., 2012). However, advanced technologies are too frequently administered in cases where alternative and less expensive treatments and tests exist. For example, CT scans are frequently administered to diagnose appendicitis, even though an abdominal exam, blood work, and/or an ultrasound scan are similarly effective and cost less (Lee et al., 2001; Patrick et al., 2003; Smith-Bindman, 2010). Other areas of CT scan overuse include chronic back pain and kidney cancer screening (Dunnick et al., 2005).

The availability and utilization of medical technologies is largely determined by hospitals and physicians. Their investment and usage decisions are influenced by the reimbursement modalities and associated incentives (Boadway et al., 2004; Rauner et al., 2011). In traditional fee-for-service (FFS) systems, physicians are paid for each test or procedure they perform and are thus incentivized to do more, and more cost-intensive tests and treatments than if they were paid based on patient diagnoses or health outcomes (Ma, 1994). In addition, hospitals may invest in technologies that are profitable to them, but not necessarily health or cost effective for patients and payers (Bach, 2010).

The Centers for Medicare and Medicaid Services (CMS), along with private insurers has been exploring and field-testing various payment innovations to reduce unnecessary and uneconomical care with the goal to lower health care cost while improving quality (de Brantes, 2013). A recently introduced and promising program by CMS is the Medicare Shared Savings

Program (MSSP) under which Accountable Care Organizations (ACOs) receive financial incentives for cost reduction and meeting quality standards. Initiated by the Patient Protection and Affordable Care Act of 2010, the first MSSP ACOs were launched in 2012. As of May 2014, 338 MSSP ACOs are serving 4.9 million patients and have achieved net savings of $417 million at improved levels of care quality (Centers for Medicare and Medicaid Services, 2014b; 2014c).

An ACO is formed by a group of health care providers, typically hospitals and physicians, who jointly coordinate the care of their patient population. In MSSP ACOs, physicians continue to receive FFS and hospitals continue to receive DRG (diagnosis-related group) reimbursements for their patients. However, if the reimbursed cost of all ACO members together is below a benchmark set by CMS, and if quality standards are met, the ACO will receive 50-60% of the cost savings (Centers for Medicare & Medicaid Services, 2011a).

CMS has not provided any rules or guidelines for ACOs on how they should distribute the bundled incentives among ACO members (Centers for Medicare & Medicaid Services, 2011b). In conversations with ACO executives, we learned that hospitals – who are typically the ACO leaders – propose and negotiate the incentive distribution mechanisms with their ACO partners. Each ACO is burdened with designing and negotiating their own internal incentive distribution program. Few guidelines exist and are mostly qualitative in nature. For example, DeCamp et al. (2014) advocate for a “fair and equitable” approach, but specific insights or best practices have not yet been published. With this paper, we aim to address this need by introducing a quantitative analysis approach.

The key contribution of this paper is the introduction of an analytical modeling framework based on multiscale decision theory (MSDT) (Wernz, 2008; Wernz and Deshmukh, 2010; 2012) that can capture the interactions and interdependencies between health care stakeholders. We illustrate the model by applying it to the challenge problem of incentive mechanism design and medical technology overuse. In particular, we consider the effect of payer incentives on CT scan use by physicians, CT scanner investments by hospitals, and the ACO-internal incentive distribution mechanisms among ACO members.

This paper will answer the following questions: (1) How can the multi-level interactions and interdependencies between health care stakeholders be effectively modeled and efficiently analyzed? (2) What is the effect of shared savings incentives on stakeholders' decisions and outcomes? (3) How should ACO-internal incentive distribution mechanisms be designed?

This paper is the first to apply MSDT to health care systems. The new application domain required advances in MSDT modeling and solution techniques. In particular, we needed to model new types of interactions between agents that previous MSDT models had not yet explored. Moreover, we analyzed a game-theoretic problem with sequential decision-making – previous MSDT models are based on simultaneous decisions.

Lastly, this paper contributes to agency theory and the study of incentive problems involving three or more agents. Prior work has been focusing mostly on two-player principal-agent problems. Models of three or more agents exist (Holmstrom and Milgrom, 1991; Itoh, 1992; Henry and Wernz, 2014), but are rare, in part because they are difficult to analyze and solve. However, merely studying the two-agent problem would not account for the complex effects that incentives, or other changes, have on the multi-agent, multi-level health care system. Our three-agent model is an important step towards a comprehensive and complete health care system representation. Future research may build upon this initial MSDT model and incorporate additional key stakeholders, in particular patients and radiologists.

2. Core Concepts and Literature Review

2.1 Multiscale Decision Theory

The theoretical foundations of multiscale decision theory were developed by Wernz (2008). MSDT builds upon concepts from distributed decision making (Schneeweiß, 2003), the theory of hierarchical, multi-level systems (Mesarović et al., 1970), and dependency graphs (Dolgov and Durfee, 2004). It applies modeling and solution techniques from Markov decision processes

(Puterman, 2009) and stochastic game theory (Filar and Vrieze, 1997).

MSDT models analyze dynamic, multi-level systems with interdependent agents. Interdependencies between agents, uncertainties between decisions and outcomes, and agents' strategic thinking are explicitly modeled. Effective and efficient solution algorithms, e.g., Wernz and Deshmukh (2012), have been developed. Results can often be derived analytically.

MSDT has been applied to production planning (Wernz and Deshmukh, 2007a; 2009; 2010), organizational design (Wernz and Deshmukh, 2007b), service operations (Wernz, 2013; Wernz and Deshmukh, 2012; Wernz and Henry, 2009), and supply chain management (Henry and Wernz, 2014), but not yet to health care.

2.2 Models for Payer-Provider Interactions

The health care payer and provider relationship can be formulated as a principal-agent problem. In effective incentive mechanism design, the payer (principal) – typically an insurance company or the government, in case of a single payer system – seeks to identify a reimbursement agreement with the provider (agent), e.g., physician or hospital, that motivates high-quality and cost-effective patient care.

Fuloria and Zenios (2001) developed a dynamic principal-agent model with which they evaluated an outcome-adjusted reimbursement system consisting of prospective payments and quality-based retrospective adjustments. Yaesoubi (2010) formulated a principal-agent model for preventive medical care. Payers and providers design and choose contracts that optimize their objectives, while also maximizing the welfare of patients. Boadway et al. (2004) considered a problem setting where managers and physicians are responsible for different decisions within the hospital under the effect of DRG and FFS reimbursements. Pope et al. (2014) proposed multilateral contracts between payers, providers and patients and showed under which conditions these are superior to bilateral agreements in terms of cost and quality of care.

2.3 Research on ACOs and MSSP

Early discussions on the concept of MSSP and ACO can be found in Fisher et al. (2007), followed by work from Lowell and Bertko (2010), Greaney (2011), Shortell et al. (2010), Shields et al. (2011), and Fisher and Shortell (2010). These studies qualitatively analyzed ACO concepts and their key features, including local accountability, shared savings and performance measurement. Only a few quantitative studies and mathematical models have been developed to analyze the effects of ACOs or MSSP on agents' decision processes. Pope and Kautter (2012), for example, developed a mathematical model and applied simulated data to determine minimum savings requirements in shared savings payment structures. The paper considered the interaction between payer and ACO, but did not model the interactions among ACO members, which we incorporate in this paper.

2.4 Diagnostic Imaging Decisions

To model physicians' imaging decision process, we build upon the concept of diagnostic testing thresholds (Pauker and Kassirer, 1980; Sox, 1986), while incorporating additional probabilistic factors. Pauker and Kassirer (1975, 1980) were the first to derive mathematical expressions for testing and test-treatment threshold to guide clinical decision-making. With a focus on clinical practice, Swets et al. (1979) proposed a general protocol for diagnostic technology evaluation by measuring diagnostic sensitivity and specificity and by generating a relative operating characteristic (ROC) curve for each technology. Based on that, Sox (1986) incorporated Bayes' theorem into modeling diagnostic uncertainty, and provided equations for sensitivity, specificity, and treatment threshold probability. Phelps and Mushlin (1991) extended the scope of analysis beyond the characterization of ROC curves by considering costs of therapy and testing. A cost-effective analysis in combination with a decision tree was used to evaluate new diagnostic medical technologies. Cipriano et al. (2012) developed a Markov model to simulate and analyze the effect of clinical decisions on patients and cost when two diagnostic imaging technologies are available. Other work considered the clinical decision process as a group judgment, and proposed the use of the Delphi method, meta-analyses and case studies to assess medical technology use (Institute of Medicine, 1985).

2.5 Technology Investment Decisions

In this paper, we model a hospital's decision regarding the purchase of a new and more advanced CT scanner. Hospitals have multiple organizational objectives when making these types of capital investment decisions. Wernz et al. (2014) conducted an international study and found that financial, quality and strategic considerations inform the decision process in most hospitals. Prior studies have similarly identified technology leadership, profitability, and value for patient and community as the main investment criteria (Greenberg et al., 2005; Li and Collier, 2000; Teplensky et al., 1995). In our model, we consider financials and hospital reputation, with the latter being a proxy for quality and technology leadership.

To help hospital executives choose among investment alternatives, various operations research approaches have been proposed and/or applied, e.g., the simple multi-attribute rating technique (Kleinmuntz, 2007), goal programming (Keown and Martin, 1976; Wacht and Whitford, 1976), cost-effectiveness analysis (Birch and Gafni, 1992; Laupacis, 1992), real options analysis (Pertile, 2009, Wernz et al., 2013), game theory (Levaggi et al., 2009), and multi-objective optimization (Focke and Stummer, 2003). However, none of these mathematical approaches has considered how investment and usage decisions affect each other, and how both of these in turn are affected by incentives. In this paper, we analyze these interdependencies.

3. Modeling Approach

3.1 Model Overview

To support the model building process for this and future MSDT problems, we introduce and propose the use of an *agent interdependence diagram*, which can graphically capture and map the interdependencies of decisions and outcomes among agents. The agent interdependence diagram is a novel contribution to MSDT. Figure 1 shows the diagram for the agent interaction analyzed in this paper.

An agent interdependence diagram uses different types of arrows to represent the different interdependencies among agents. A dashed arrow represents a payment or incentive, while a solid arrow represents other influences that affect decisions or outcomes. The letters D (decision) and O (outcome) at the beginning and end of an arrow indicate whether a decision or an outcome is affecting another agent's decision or outcome.

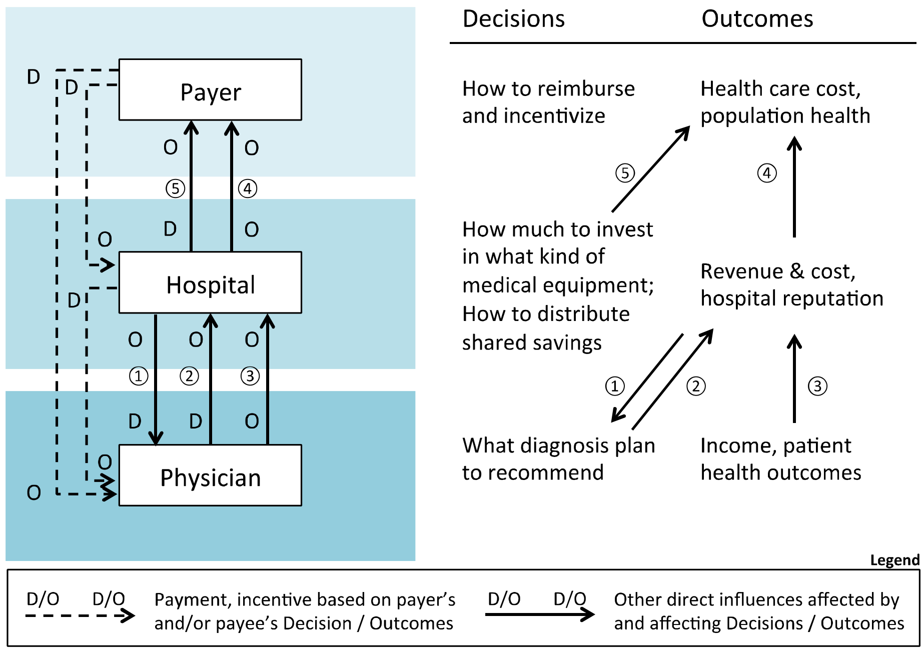


Figure 1. Agent interdependence diagram

At the highest level of the system, the payer (here CMS) decides how to reimburse and incentivize ACOs via MSSP. Under MSSP, physicians are paid on a FFS basis, and hospitals receive payments according to DRGs, a fixed payment determined by the medical diagnosis of the patient. Additionally, ACOs receive a certain share $\mu \in [0,1]$ of the difference between their Medicare billings and cost benchmark $M \in \mathbb{R}_+$, both of which are decided by the payer. Medicare billings above the benchmark result in a penalty (negative incentive); Medicare billings below the benchmark result in a reward (positive incentive).

At the next lower, second level of the system, the hospital, referred to as agent H, makes two types of decisions, taking into account the payer's incentive mechanism: (1) to buy a new, more advanced CT scanner, or not to buy a new device (status quo), and (2) what constant share

$m \in [0,1]$ of the payer's bundled incentive to give to the physicians (retaining share 1-*m* for itself). We assume that agent H, as the ACO leader, can unilaterally decide this sharing percentage.

At the third and lowest level of the system, and after the decisions of the payer and agent H, the physician chooses the diagnostic intervention to recommend to each patient. We assume that a patient follows a physician's recommendation. We represent all physicians as a single agent P and consider their aggregate decision behavior. The aggregate CT scan decisions by physicians results in a CT scan rate $a^P \in [0,1]$. This CT scan rate is the decision variable of agent P in our model.

The sequential decisions of the three agents lead to a game-theoretic situation. We model the interaction as a non-repeated game with a one-time decision by each agent. Figure 2 summarizes the agents' decisions and their sequence. We assume that the overall structure of the payer's incentive program has been set, but that cost benchmark *M* still needs to be decided.

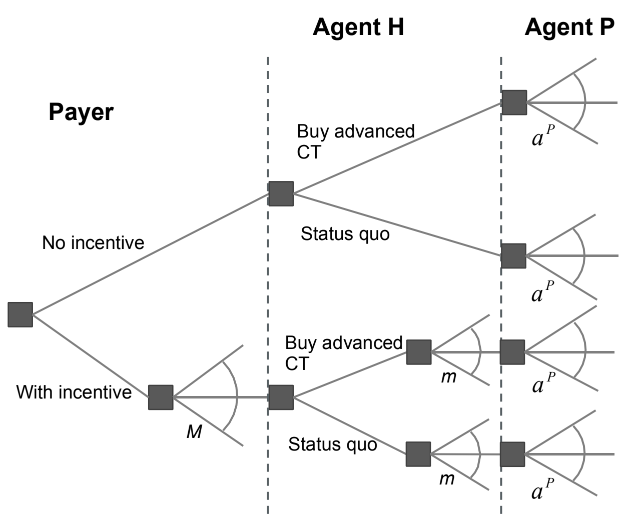


Figure 2. Game structure

3.2 Agents' Decision Processes

We model the agents as risk-neutral and rational, i.e., agents maximize their expected payoffs by calculating their payoffs and the payoffs of other agents, and choose decisions according to the Nash equilibrium concept. The payoffs of agents H and P are multi-attribute objective functions: agent H aims to minimize costs, while maximizing hospital reputation; agent P aims to maximize its income (FFS+incentive), while maximizing health outcomes for patients.

3.2.1 Hospital – Agent H

The decisions (actions) by agent H are notated by a_h^H, with a_1^H signifying *buy advanced CT scanner*, and a_2^H referring to *status quo*. Agent H's action a_h^H has a one-time investment cost $k(a_h^H)$, with cost parameters

$$k(a_h^H) = \begin{cases} k_1, & \text{for } a_1^H \\ k_2, & \text{for } a_2^H \end{cases} . \qquad (1)$$

Additionally, decision a_h^H results in a maintenance cost. We distinguish between a high cost and a low cost outcome, which are represented by states s_1^H and s_2^H, respectively. Maintenance costs depend on the investment decision, but are uncertain. The uncertainty is modeled as a discrete conditional probability $\Pr^H\left(s_a^H \mid a_h^H\right) = \alpha_{a;h}^H$. Each maintenance cost outcome (state) is associated with a payoff for the agent. We use the convention of MSDT and refer to payoffs as rewards. Agent H's reward associated with the maintenance cost is denoted by $r^H\left(s_a^H\right)$. Besides investment costs and maintenance costs, agent H's reward is further affected by operating costs and hospital reputation, which will be discussed in detail in Section 3.3.

3.2.2 Physicians – Agent P

At the physician level, the decision process is modeled structurally similar to the process at the hospital level. For each patient, a physician takes an action a_p^P, with a_1^P denoting the action *CT scan*, and a_2^P referring to an *alternative* diagnostic intervention.

Agent P sees patients with heterogeneous conditions. Based on the observed condition of a patient, the physician assesses the necessity of a CT scan. We use the necessity threshold concept of Pauker and Kassirer (1980) to model agent P's CT scan decision. Patients that fall below the threshold will not receive a CT scan, and an alternative intervention is chosen, such as an ultrasound or a wait-and-see approach. For patients above the threshold, a CT scan is ordered.

We assume that the patient population with respect to CT scan necessity follows a normal distribution, which we approximate with a triangular distribution. The triangular distribution allows us to analytically solve our model. Figure 3 shows the probability density function of the patient distribution and illustrates the CT scan necessity threshold.

The necessity threshold separates the patient population into two regions. The region under the curve to the right of the threshold represents the share of patients that receive a CT scan. This share of patients is the CT scan rate a^P. In other words, the necessity threshold corresponds to the CT scan rate a^P. With a^P specified, the CT scan decision (a_1^P vs. a_2^P) for each patient is also specified.

We chose the CT scan rate a^P as agent P's decision variable, as opposed to the equivalent necessity threshold, since we are interested in the decision response of agent P. Our model does not seek to prescribe to physicians the conditions under which they should administer a CT scan, but rather analyzes and predicts their behavior in response to incentives and changes in CT scanner technology.

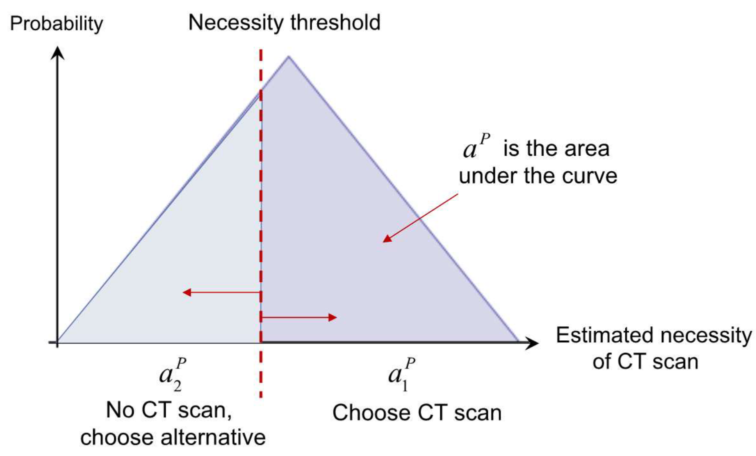
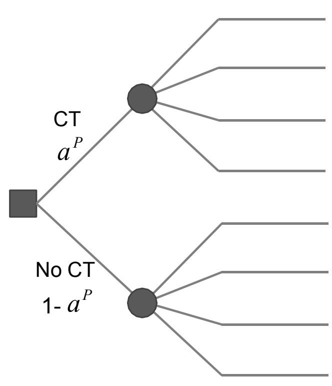


Figure 3. Threshold model for CT scan necessity of patient population

Each action a_p^P leads to an uncertain outcome in *Medicare billings* and *health improvement*. The state space of the physicians' two-dimensional outcomes is denoted by $S^P = \left\{ s_{1,1}^P, \ldots, s_{b,c}^P, \ldots, s_{B,C}^P \right\}$. Subscript b refers to *Medicare billings* and c to *health improvement*. *Medicare billings* can be either high or low, denoted by $s_{1,\cdot}^P$ and $s_{2,\cdot}^P$, respectively. Note that in most cases physicians do not receive payment for CT scans per se, and the Medicare billings here account for downstream diagnosis and treatment payments. The state of *health improvement* is also either high (due to correct diagnosis) or low (due to misdiagnosis) and depends on whether a patient had received a CT scan or not.

We differentiate between four states: $s_{\cdot,1}^P$ (CT, correct diagnosis), which includes the possibilities of both true positive and true negative testing result, $s_{\cdot,2}^P$ (CT, misdiagnosis), which includes false positive and false negative results, $s_{\cdot,3}^P$ (no CT, correct diagnosis) and state $s_{\cdot,4}^P$ (no CT, misdiagnosis). Since CT scans are a diagnostic tool, and not a treatment, we only want to capture the specificity of the diagnostic test (true vs. false) and do not differentiate between a sick or healthy patient. Figure 4 summarizes agent P's decision and outcomes (states).



State	State description	*Medicare billings*	*Health improvement*
$s_{1,1}^P$	CT, correct diagnosis	high	high
$s_{1,2}^P$	CT, misdiagnosis	high	low
$s_{2,1}^P$	CT, correct diagnosis	low	high
$s_{2,2}^P$	CT, misdiagnosis	low	low
$s_{1,3}^P$	No CT, correct diagnosis	high	high
$s_{1,4}^P$	No CT, misdiagnosis	high	low
$s_{2,3}^P$	No CT, correct diagnosis	low	high
$s_{2,4}^P$	No CT, misdiagnosis	low	low

Figure 4. Agent P's decision tree

The conditional probabilities of outcomes (states) given a decision are $\Pr^P\left(s_{b,c}^P \mid a_p^P\right) = \alpha_{b,c;p}^P$. We assume *Medicare billings* and *health improvement* are independent events, and thus $\Pr^P\left(s_{b,c}^P \mid a_p^P\right) = \Pr^P\left(s_{b,\cdot}^P \mid a_p^P\right) \cdot \Pr^P\left(s_{\cdot,c}^P \mid a_p^P\right) = \alpha_{b,\cdot;p}^P \cdot \alpha_{\cdot,c;p}^P$.

Lastly, each state is associated with a reward function $r^P\left(s_{b,c}^P\right)$. We assume that the rewards of the two dimensions are additive, i.e., $r_{total}^P\left(s_{b,c}^P\right) = r^P\left(s_{b,\cdot}^P\right) + r^P\left(s_{\cdot,c}^P\right)$.

3.3 Interdependencies Between Agent H and Agent P

The decision processes of agents H and P influence each other through two types of interdependencies, ① and ②, as introduced in the agent interdependency diagram (Figure 1). Agent interdependencies are further specified in a *detailed graphical representation* as shown in Figure 5. The detailed graphical representation is an extension of the *action-outcome interdependency* graph introduced by Wernz (2007a). We propose the detailed graphical representation as step 2 in the MSDT modeling approach after the agent interdependency diagram had been created in step 1. Step 3 is the mathematical formulation, discussed next.

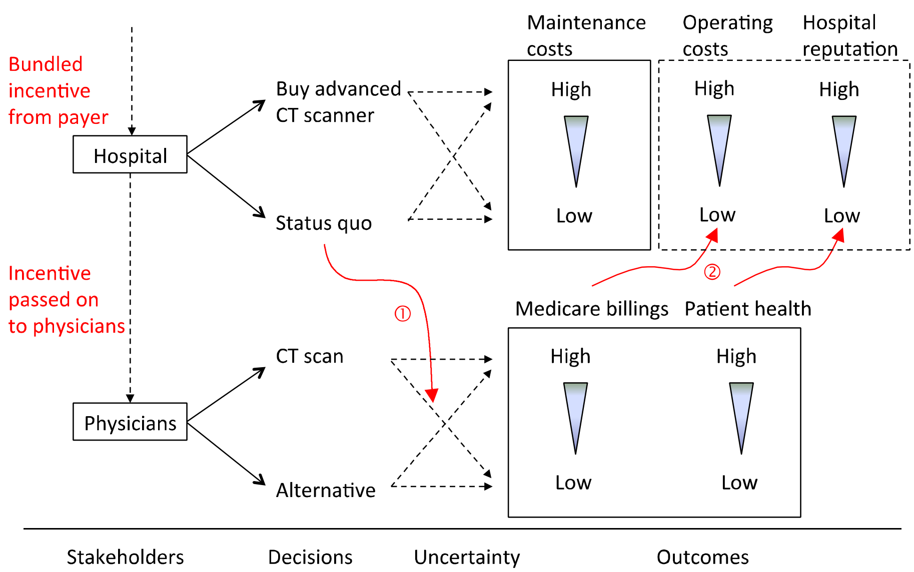


Figure 5. Detailed graphical representation of hospital-physician interdependencies

Interdependency ① is the influence of agent H's decision a_h^H on the conditional probability $\Pr^P\left(s_{b,c}^P \mid a_p^P\right)$ of agent P. Here, the hospital's decision of upgrading its CT scanner affects the CT scan accuracy. To capture this interdependency, the probabilities for a correct diagnosis given a CT scan are modified through an *additive change function* (Wernz & Deshmukh, 2010) with a *change coefficient* Δ such that

$$\Pr_{final}^P\left(s_{\cdot,1}^P \mid a_1^P, a_h^H\right) = \begin{cases} \Pr^P\left(s_{\cdot,1}^P \mid a_1^P\right) + \Delta, & \text{if } h = 1 \\ \Pr^P\left(s_{\cdot,1}^P \mid a_1^P\right), & \text{if } h = 2 \end{cases}, \tag{2}$$

$$\Pr_{final}^P\left(s_{\cdot,2}^P \mid a_1^P, a_h^H\right) = \begin{cases} \Pr^P\left(s_{\cdot,2}^P \mid a_1^P\right) - \Delta, & \text{if } h = 1 \\ \Pr^P\left(s_{\cdot,2}^P \mid a_1^P\right), & \text{if } h = 2 \end{cases}. \tag{3}$$

Interdependency ② describes the influence of agent P's states on agent H's reward. While maintenance costs only depend on agent H's decision, operating costs and hospital reputation are determined solely by the state of agent P. We indicate the sole source of influence by a separate dashed line box in Figure 5. Higher Medicare billings of physicians are linked to higher operating costs for the hospital. Similarly, greater health improvements at the physician level lead to an increase in hospital reputation. In summary, the hospital's reward function is affected by the physician-level Medicare billings and patient health outcomes, which we model via a *reward influence function*

$$r^{P\to H}\left(s_{b,c}^P\right) = \gamma_b \cdot r^P\left(s_{b,\cdot}^P\right) + \gamma_c \cdot r^P\left(s_{\cdot,c}^P\right) \tag{4}$$

with scaling coefficients γ_b and γ_c. Agent H's total reward, before incentives, is thus

$$r_{total}^H(a_h^H, s_a^H, s_{b,c}^P) = k\left(a_h^H\right) + r^H\left(s_a^H\right) + r^{P\to H}\left(s_{b,c}^P\right). \tag{5}$$

<u>3.4 Incentives</u>

The incentive offered by the payer depends on the total costs generated by agents H and P. We assume that agent H's maintenance and operating cost is the basis for the reimbursement by the payer. The hospital-level cost considered by the payer is

$$r_{cost}^{H}\left(s_{a}^{H},s_{b,\cdot}^{P}\right)=r^{H}\left(s_{a}^{H}\right)+\gamma_{b}\cdot r^{P}\left(s_{b,\cdot}^{P}\right). \tag{6}$$

For the physician, *Medicare Billings* are reimbursed, and the physician-level cost is

$$r_{cost}^{P}\left(s_{b,\cdot}^{P}\right)=r^{P}\left(s_{b,\cdot}^{P}\right). \tag{7}$$

The payer's incentive program is specified by the cost benchmark M and the share μ that the ACO receives based on the generated savings. The incentive payment to the ACO is

$$g^{ACO}\left(s_{a}^{H},s_{b,\cdot}^{P}\right)=\mu\cdot\left[M-r_{cost}^{H}\left(s_{a}^{H},s_{b,\cdot}^{P}\right)-r_{cost}^{P}\left(s_{b,\cdot}^{P}\right)\right]. \tag{8}$$

ACO internally, agent H decides how much of this incentive to pass on to agent P by setting the sharing percentage m. The inventive transfer functions are

$$g^{P}\left(s_{a}^{H},s_{b,\cdot}^{P},m\right)=m\cdot g^{ACO}\left(s_{a}^{H},s_{b,\cdot}^{P}\right), \tag{9}$$

$$g^{H}\left(s_{a}^{H},s_{b,\cdot}^{P},m\right)=\left(1-m\right)\cdot g^{ACO}\left(s_{a}^{H},s_{b,\cdot}^{P}\right). \tag{10}$$

4. Analysis Approach

Risk-neutral agents H and P base their decisions on expected rewards. The uncertainties considered in the expected reward calculation can be aggregated in one function:

$$\Pr(s_{a}^{H},s_{b,c}^{P}\mid a^{P},a_{h}^{H})=$$

$$\Pr^{H}(s_{a}^{H}\mid a_{h}^{H})\cdot\left[a^{P}\cdot\Pr^{P}(s_{b,\cdot}^{P}\mid a_{1}^{P})\cdot\Pr_{final}^{P}\left(s_{\cdot,c}^{P}\mid a_{1}^{P},a_{h}^{H}\right)+\left(1-a^{P}\right)\cdot\Pr^{P}(s_{b,\cdot}^{P}\mid a_{2}^{P})\cdot\Pr^{P}(s_{\cdot,c}^{P}\mid a_{2}^{P})\right]. \tag{11}$$

Using this aggregated probability function and the aforementioned reward influence and incentive transfer functions, the expected values of incentives and rewards, given agents' decisions, can be calculated. The expected reward of agent H is:

$$E(r_{total}^{H}\mid a_{h}^{H},a^{P})=\sum_{a}\sum_{b}\sum_{c}r_{total}^{H}(a_{h}^{H},s_{a}^{H},s_{b,c}^{P})\cdot\Pr(s_{a}^{H},s_{b,c}^{P}\mid a^{P},a_{h}^{H}). \tag{12}$$

Applying all parameter values to Eq. (12) results in

$$
\begin{aligned}
&E(r^H_{total} \mid a^H_h, a^P) = r^H\left(s^H_2\right) + k_h + \left[r^H\left(s^H_1\right) - r^H\left(s^H_2\right)\right]\alpha^H_{1;h} \\
&+\gamma_b\left\{r^P\left(s^P_{2,\cdot}\right) + \left[r^P\left(s^P_{1,\cdot}\right) - r^P\left(s^P_{2,\cdot}\right)\right]\alpha^P_{1,\cdot;2}\right\} + \gamma_c\left\{r^P\left(s^P_{\cdot,4}\right) + \left[r^P\left(s^P_{\cdot,3}\right) - r^P\left(s^P_{\cdot,4}\right)\right]\alpha^P_{\cdot,1;2}\right\} \\
&+a^P\left\{\gamma_b\left[r^P\left(s^P_{1,\cdot}\right) - r^P\left(s^P_{2,\cdot}\right)\right]\left(\alpha^P_{1,\cdot;1} - \alpha^P_{1,\cdot;2}\right)\right. \\
&\left.+\gamma_c\left\{\left[r^P\left(s^P_{\cdot,1}\right) - r^P\left(s^P_{\cdot,2}\right)\right](\alpha^P_{\cdot,1;1} + \Delta) + r^P\left(s^P_{\cdot,2}\right) - \left[r^P\left(s^P_{\cdot,3}\right) - r^P\left(s^P_{\cdot,4}\right)\right]\alpha^P_{\cdot,1;2} - r^P\left(s^P_{\cdot,4}\right)\right\}\right\}
\end{aligned} \quad . \qquad (13)
$$

Note that in the expression of the expected reward $E(r^H_{total} \mid a^H_2, a^P)$ for not buying a CT scanner (status quo), the change coefficient is $\Delta = 0$. Additionally, in Eq. (13), $r^P\left(s^P_{\cdot,1}\right)$ is a function of a^P and the triangular patient distribution (the mathematical expression is provided in Table 1 in Section 5).

The expected reward of agent P is

$$
E(r^P_{total} \mid a^H_h, a^P) = \sum_a \sum_b \sum_c r^P_{total}\left(s^P_{b,c}\right) \cdot \Pr(s^H_a, s^P_{b,c} \mid a^P, a^H_h) \,. \qquad (14)
$$

For decision a^H_1 (buy CT scanner), this results in

$$
\begin{aligned}
&E(r^P_{total} \mid a^H_1, a^P) = r^P\left(s^P_{2,\cdot}\right) + \left[r^P\left(s^P_{1,\cdot}\right) - r^P\left(s^P_{2,\cdot}\right)\right]\alpha^P_{1,\cdot;2} + \left[r^P\left(s^P_{\cdot,3}\right) - r^P\left(s^P_{\cdot,4}\right)\right]\alpha^P_{\cdot,1;2} + r^P\left(s^P_{\cdot,4}\right) \\
&+a^P \cdot \left\{\left[r^P\left(s^P_{1,\cdot}\right) - r^P\left(s^P_{2,\cdot}\right)\right](\alpha^P_{1,\cdot;1} - \alpha^P_{1,\cdot;2}) + \left[r^P\left(s^P_{\cdot,1}\right) - r^P\left(s^P_{\cdot,2}\right)\right](\alpha^P_{\cdot,1;1} + \Delta)\right. \\
&\left.+r^P\left(s^P_{\cdot,2}\right) - \left[r^P\left(s^P_{\cdot,3}\right) - r^P\left(s^P_{\cdot,4}\right)\right]\alpha^P_{\cdot,1;2} - r^P\left(s^P_{\cdot,4}\right)\right\}
\end{aligned} \quad . \qquad (15)
$$

The expected reward $E(r^P_{total} \mid a^H_2, a^P)$ for not buying a CT scanner (status quo) is obtained by setting change coefficient $\Delta = 0$ in Eq. (15).

The final rewards for agents H and P consist of the expected rewards (before incentives) and the expected incentives are

$$
E\left(r^H_{final} \mid a^H_h, m, a^P\right) = E(r^H_{total} \mid a^H_h, a^P) + E(g^H \mid a^H_h, m, a^P) \,, \qquad (16)
$$

$$
E\left(r^P_{final} \mid a^H_h, m, a^P\right) = E\left(r^P_{total} \mid a^H_h, a^P\right) + E(g^P \mid a^H_h, m, a^P) \,. \qquad (17)
$$

The expected incentives for agent H is

$$
\begin{aligned}
&E(g^H \mid a_h^H, m, a^P) = \mu \cdot (1-m) \cdot \\
&\Big\{ r^H\left(s_2^H\right) + M - r^P\left(s_{2,\cdot}^P\right) + \left[r^H\left(s_1^H\right) - r^H\left(s_2^H\right)\right]\alpha_{1;h}^H - \left[r^P\left(s_{1,\cdot}^P\right) - r^P\left(s_{2,\cdot}^P\right)\right]\alpha_{1,\cdot;2}^P \\
&+\gamma_b\left\{ r^P\left(s_{2,\cdot}^P\right) + \left[r^P\left(s_{1,\cdot}^P\right) - r^P\left(s_{2,\cdot}^P\right)\right]\alpha_{1,\cdot;2}^P \right\} + a^P(\gamma_b - 1)\left[r^P\left(s_{1,\cdot}^P\right) - r^P\left(s_{2,\cdot}^P\right)\right]\left(\alpha_{1,\cdot;1}^P - \alpha_{1,\cdot;2}^P\right) \Big\}
\end{aligned}
. \tag{18}
$$

By replacing $(1-m)$ with m in Eq. (18), one obtains the expression of $E(g^P \mid a_h^H, m, a^P)$.

Each agent chooses decision(s) to maximize its expected final reward. The decisions are sequential: (1) the payer chooses whether to incentivize, and if so sets cost benchmark *M*, (2) agent H makes an investment decision, and (3) agent P decides the CT scan necessity threshold (expressed as CT scan rate). We derive the subgame perfect Nash equilibrium for the agents' sequential game through backward induction (Myerson, 1997).

We begin the analysis with the payer's decision branch of *no incentives*. Knowing agent H's investment decision a_h^H, agent P chooses the optimal CT scan rate a^{P*} to maximize its expected reward:

$$
a^{P*} = \underset{a^P \in [0,1]}{\arg\max}\, E(r_{total}^P \mid a_h^H, a^P). \tag{19}
$$

Anticipating agent P's best response a^{P*}, agent H chooses the optimal investment decision a_h^{H*} that maximizes its expected reward:

$$
a_h^{H*} = \begin{cases} a_1^H, & \text{if } E(r_{total}^H \mid a_1^H, a^{P*}) > E(r_{total}^H \mid a_2^H, a^{P*}) \\ a_2^H, & \text{if } E(r_{total}^H \mid a_1^H, a^{P*}) < E(r_{total}^H \mid a_2^H, a^{P*}) \\ a_1^H \text{ or } a_2^H, & \text{otherwise} \end{cases}. \tag{20}
$$

For the decision branch *with incentives*, the analysis of agents H and P is the same, expect that they now take the incentive sharing percentage m^* into account:

$$
m^* = \underset{m \in [0,1]}{\arg\max}\, E\left(r_{final}^H \mid a_h^{H*}, m, a^{P*}\right). \tag{21}
$$

The expected reward maximization problems of agents H and P, Eq. (19-21), are solved by taking the derivative of the corresponding analytical expressions (13), (15), and (18). The closedform solutions of the results are large in size and cannot be effectively presented. However, the analytical results enable us to easily determine the optimal decisions for numerical parameter values. Moreover, analytical results allows for a comprehensive sensitivity analysis with low computational cost and in short time (compared to simulation models). The following section illustrates the numerical analysis and discusses specific and general model insights.

5. Numerical Analysis and Results

We start the numerical analysis with a base case where the payer level-cost benchmark *M* and the ACO-level incentive sharing percentage *m* are fixed, before we consider them as decision variables and analyze them in a later section. For all calculations, we used Mathematica®.

5.1 Base Case: Optimal Decisions of Payer, Hospital and Physicians

For the base case, we assume a fixed sharing percentage m=0.5 and the benchmark M=35. All further parameter values are provided in Table 1.

Table 1. Parameter values for numerical analysis

Parameter	Value	Note
Payer		
Incentive share of cost savings from payer	$\mu = 50\%$	
Agent H		
Action cost	$K = \begin{cases} k_1 = -4, & \text{if } a_1^H = 1 \\ k_2 = 0, & \text{if } a_2^H = 1 \end{cases}$	
Reward of direct cost	$r^H\left(s_1^H\right) = -10$, $r^H\left(s_2^H\right) = -8$	
Conditional probability	$\Pr^H\left(s_1^H \mid a_1^H\right) = 0.9$, $\Pr^H\left(s_2^H \mid a_1^H\right) = 0.1$ $\Pr^H\left(s_1^H \mid a_2^H\right) = 0.1$, $\Pr^H\left(s_2^H \mid a_2^H\right) = 0.9$	
Agent P		
Reward of Medicare billings	$r^P\left(s_{1,\cdot}^P\right) = 5$	High billings
	$r^P\left(s_{2,\cdot}^P\right) = 3$	Low billings
Reward of health improvement	$r^P\left(s_{\cdot,1}^P\right) = E\left[X \mid X \ge F^{-1}\left(1 - a^P\right)\right]$, $f_X\left(x \mid min,max,mode\right) = f_X\left(x \mid \text{-}60,100,20\right)$	Correct diagnosis using CT*
	$r^P\left(s_{\cdot,2}^P\right) = -20$	Misdiagnosis using CT
	$r^P\left(s_{\cdot,3}^P\right) = 20$	Correct diagnosis without CT
	$r^P\left(s_{\cdot,4}^P\right) = -20$	Misdiagnosis without CT
Conditional probability	$\Pr^P\left(s_{1,\cdot}^P \mid a_1^P\right) = 0.8$, $\Pr^P\left(s_{2,\cdot}^P \mid a_1^P\right) = 0.2$ $\Pr^P\left(s_{1,\cdot}^P \mid a_2^P\right) = 0.2$, $\Pr^P\left(s_{2,\cdot}^P \mid a_2^P\right) = 0.8$	Medicare billings**
	$\Pr^P\left(s_{\cdot,1}^P \mid a_1^P\right) = 0.8$, $\Pr^P\left(s_{\cdot,2}^P \mid a_1^P\right) = 0.2$ $\Pr^P\left(s_{\cdot,1}^P \mid a_2^P\right) = 0.5$, $\Pr^P\left(s_{\cdot,2}^P \mid a_2^P\right) = 0.5$	Health outcomes
Interdependencies		
Change coefficient	$\Delta = 0.15$	
Reward influence function coefficient	$\gamma_b = -4$, $\gamma_c = 1$	

*The estimated CT necessity of individual patient is denoted by a random variable *X*, which is triangularly distributed (Figure 3). We assume that in the case of correct diagnosis using CT, the CT necessity of individual patient corresponds to the patient's health improvement value. A greater value of necessity implies that a CT scan is more important for physicians to make the correct clinical diagnosis and results in a greater health improvement value. Hence, the reward of health improvement is the expectation of the estimated necessity for the given patient cases.

**We assume the conditional probability of high Medicare billings given a CT scan is higher than that given no CT scan, due to the reasons that (1) following a CT scan, physicians are likely to perform further downstream diagnoses and treatments, thereby receiving additional reimbursements, and (2) patients requiring a CT scan are, on average, sicker than those that do not require the scan, hence the total billings are higher (Duszak et al., 2012).

Following the analysis approach in the previous section, we determine the subgame perfect Nash equilibria, which are the agents' optimal decisions. The optimal decision and the associated agent rewards are shown in Figure 6.

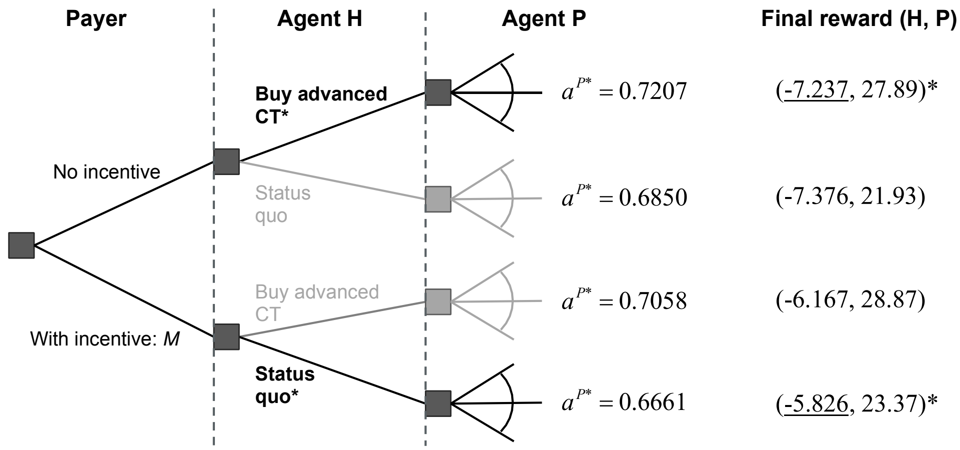


Figure 6. Analysis result of base case

The analysis shows that the payer can achieve a reduction in CT scan rate from 0.7207 to 0.6661, i.e., a 5.46 percent point change, by offering an incentive. The reduction is a combination of two effects: (1) payer incentives discourage hospital from CT scanner purchase which in turn reduces CT scan rate, and (2) payer incentives directly motivate physicians to reduce CT scan rate.

First, we analyze the magnitude of effect (1). If no incentive is offered, agent H's optimal decision is a_1^H (buy advanced CT scanner), which, due to the CT scanner's improved diagnostic capabilities, increases agent P's optimal scan rate a^{P*} from 0.6850, under status quo, to 0.7207 – a 3.57 percent point increase. In the scenario with incentives, agent H's optimal decision is a_2^H (status quo), and the not buying a CT scanner decision leads to a CT scan reduction of 3.97 percent points (0.7058-0.6661).

Analyzing effect (2), we find that given the purchase of a new CT scanner, the incentive reduces a^{P*} from 0.7207 to 0.7058, a 1.49 percent point reduction. Given no equipment purchase, the effect of the incentive on a^{P*} is even more pronounced: a 1.89 percent point reduction (0.6850-

0.6661). Comparing both effects, we see that investment effect (1) is stronger than the incentive effect (2) in this numerical example.

Figure 7 graphically illustrates the effect of incentive and investment on CT scan rate and physicians' reward. Comparing physicians' rewards under all four possible investment and incentive scenarios, we see that the investment effect (1) is also stronger than the incentive effect (2) with respect to physician rewards.

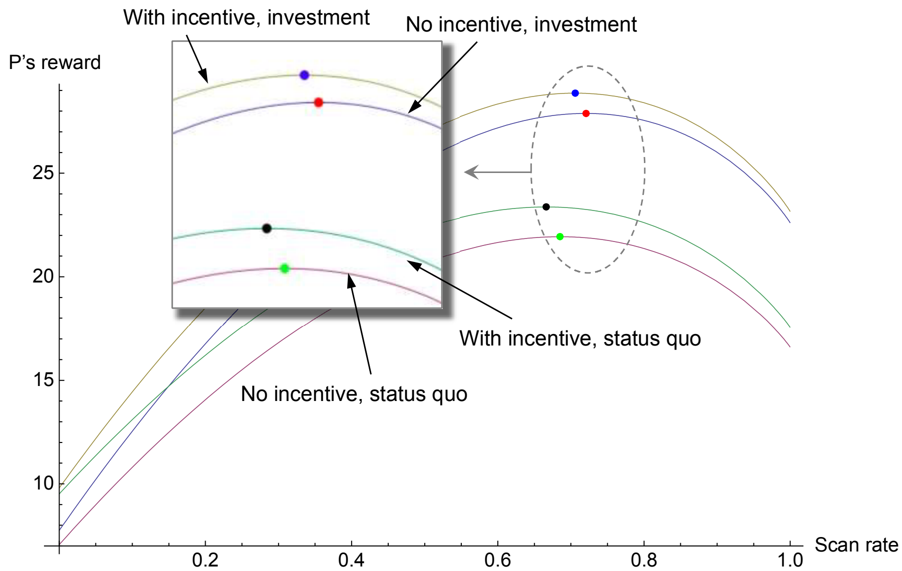


Figure 7. Agent P's optimal scan rate and final reward

Of course, these results depend on the parameters chosen in the numerical example. Therefore, we analyzed the effect of two key parameters: the investment cost k_1 (CT scan purchase price) and the diagnosis rate improvement Δ. We conducted a sensitivity analysis for these parameters. Figure 8 shows the parameters' effect on the hospital's investment decision.

The areas *status quo* and *buy CT scanner* are separated by phase transition lines, which indicate at which values of k_1 and Δ a switch of the optimal decision occurs. The line to the lower left indicates the phase transition given no incentive, while the upper right line demarcates the phase transition with incentives. The area where $k_1 > 0$ is infeasible, since this would imply a gain, not an expense resulting from the purchase. Not surprisingly, a high diagnosis rate improvement and a low investment cost favor the purchase of a CT scanner.

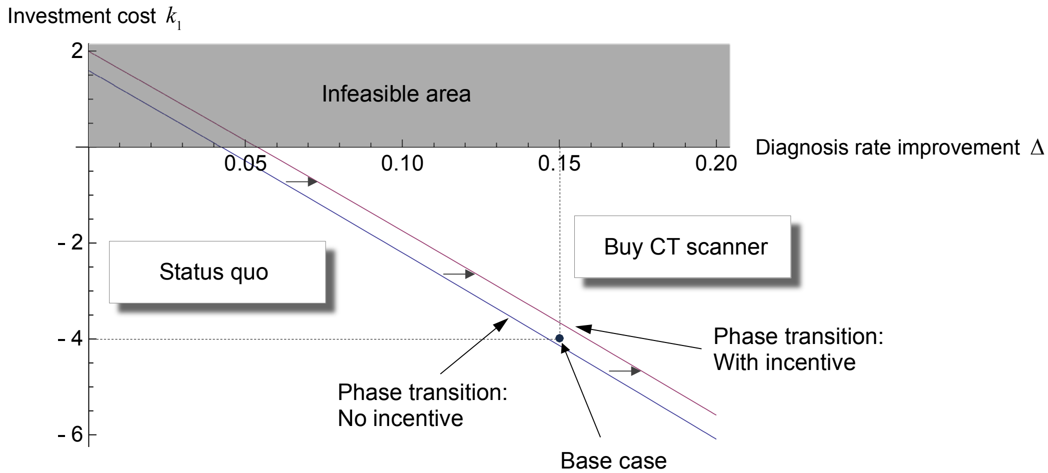


Figure 8. Sensitivity analysis of agent H's optimal decision

With incentives, the transition line shifts to the right, which means that for the same investment cost, an investment has to generate higher improvement in CT scan accuracy to motivate a purchase. Similarly, for the same level of CT scan accuracy improvement, an investment has to be less expensive to trigger a purchase by agent H. In conclusion, the incentive reduces agent H's investment propensity.

The functional form of the phase transition lines can be determined analytically, but equations are too large to display effectively. We derive a linear approximation based on the numerical example of the phase transition lines, which are shown in Table 2.

Table 2. Phase transition lines of agent H's investment decision (linear approximations)

	No incentive	**With incentive**
Investment: $E(r_{final}^{H} \mid a_1^{H}, a^{P*}) > E(r_{final}^{H} \mid a_2^{H}, a^{P*})$	$0 \geq k_1 > 1.6 - 38.4\Delta$	$0 \geq k_1 > 2.0 - 37.9\Delta$
Status quo: $E(r_{final}^{H} \mid a_1^{H}, a^{P*}) < E(r_{final}^{H} \mid a_2^{H}, a^{P*})$	$k_1 < 1.6 - 38.4\Delta \leq 0$	$k_1 < 2.0 - 37.9\Delta \leq 0$

5.2 Optimal Incentive Distribution Mechanism: Effect of Cost Benchmark *M* and Sharing Percentage *m*

So far, we have assumed that the cost benchmark *M* and the sharing percentage *m* are fixed. However, the payer can vary the cost benchmark, and agent H can set the sharing percentage when forming an ACO with agent P. The optimal decisions for these two parameter is explored in this section.

We determine the optimal decisions by varying cost benchmark *M* and analyzing the resulting agent response. Table 3 summarizes the results. It shows how the optimal decisions of agents H and P, the incentive from the payer, and the final rewards are affected by different values of benchmark *M*. The shaded areas indicate the optimal decisions and outcomes, i.e., how the agents would optimally play this game. A change in agents' optimal decision is marked with boxes.

The results can be interpreted as follows: when benchmark *M* is sufficiently large, agent H's optimal strategy is to keep the entire incentive to itself ($m^* = 0$). When *M* is sufficiently small, agent H will give the entire incentive to agent P ($m^* = 1$) as it maximizes agent H's reward. The reason is that for large *M*, which is a less demanding cost benchmark that results in higher incentives from the payer, agent H benefits more from keeping the incentive than from the cost savings that results from the change in agent P's decision if the incentive is passed on. In contrast, for small *M*, and consequentially low incentives from the payer, agent H benefits more from the cost savings resulting from agent P's reduction of CT scan rates. Hence, agent H passes on the entire incentive to induce the most significant change in agent P's decision.

Table 3. Impact of benchmark M on rewards and decisions

	M	35	34	33	32	31	30	29	28
Investment	m^*	0	0	0	0	1	1	1	1
	a^{P*}	0.7207	0.7207	0.7207	0.7207	0.6904	0.6904	0.6904	0.6904
	$E\left(r_{final}^{H} \mid a_1^H, m^*, a^{P*}\right)$	-5.299	-5.799	-6.299	-6.799	-7.101	-7.101	-7.101	-7.101
	$E\left(r_{final}^{P} \mid a_1^H, m^*, a^{P*}\right)$	27.89	27.89	27.89	27.89	27.87	27.37	26.87	26.37
	$g^H\left(a_1^H, m^*, a^{P*}\right)$	1.938	1.438	0.9378	0.4378	0.02868	-0.4713	-0.9713	-1.471
Status quo	m^*	0	0	0	0	0	0	1	1
	a^{P*}	0.6850	0.6850	0.6850	0.6850	0.6850	0.6850	0.6467	0.6467
	$E\left(r_{final}^{H} \mid a_2^H, m^*, a^{P*}\right)$	-4.530	-5.030	-5.530	-6.030	-6.530	-7.030	-7.204	-7.204
	$E\left(r_{final}^{P} \mid a_2^H, m^*, a^{P*}\right)$	21.93	21.93	21.93	21.93	21.93	21.93	21.84	21.84
	$g^H\left(a_2^H, m^*, a^{P*}\right)$	2.845	2.345	1.845	1.345	0.8451	0.3451	-0.04002	-0.5400
	a_h^{H*}	a_2^H	a_2^H	a_2^H	a_2^H	a_2^H	a_2^H	a_1^H	a_1^H

Benchmark M also affects agent H's optimal investment decision a_h^{H*}. For large values of M (here, $M \geq 30$), agent H's optimal decision is status quo. For small M values, i.e., a more challenging cost benchmark, agent H's optimal response is to invest in a new CT scanner. The reason for the change in a_h^{H*} is mainly due to the switch of the optimal sharing percentage m^* from 0 and 1 that coincided with the change in agent H's decision. For $m^* = 1$, agent H passes on all incentives to agent P, thus does not benefit from cost savings, and consequentially prefers to buy a new CT scanner resulting in higher cost (i.e., more profit for agent H) and improved hospital reputation. For $m^* = 0$, agent H keeps all incentives and thus prefers status quo as it reduces hospital costs and increases incentive payments from the payer.

The switch of agent H's investment decision a_h^{H*} and the switch of sharing percentage m^* do not necessarily occur together. For example, changes in k_1 alone can lead to a change in a_h^{H*}, without affecting *m*. In other words, agent H's optimal investment decision cannot be determined by a single variable or phenomenon, but needs to be evaluated based on all relevant data.

Another observation is that for a given value of m^*, i.e., $m^* = 0$ or $m^* = 1$, agent P's optimal scan rate a^{P*} is not affected by *M*. In fact, the analytical solution of a^{P*} does not contain variable *M*, which confirms the observation of the numerical analysis shown in Table 3. This means a change in *M* does not necessarily affect agent P's decision. A change in agent P's decision can only be achieved if the change in *M* results in a change in agent H's decisions, i.e., investment decision or incentive distribution decision.

For $m^* = 0$, agent P's decision is not altered and is identical to the scenario without incentive, implying that the cost and CT scan reduction goal of the incentive is not achieved. Only for $m^* = 1$, when agent H gives the entire incentive to agent P, is the CT scan rate reduced. For the payer, this means that it needs to set a low benchmark *M* to achieve the CT scan and cost reduction goal of its shared incentive program. However, a low benchmark *M* makes the purchase of a CT scanner more likely, which in turn increases the CT scan rate. In our numerical example, the payer's most preferred outcome (first best) of no new CT scanner purchase and CT scan rate reduction through physician incentives ($m^*=1$) could not be achieved. For different parameters, e.g., $r^P\left(s_{1,\cdot}^P\right)=6$ instead of 5, this first best outcome is possible.

Table 3 suggests that m^* is always either 0 or 1. However, $0<m^*<1$ can occur. As shown in Figure 9, an interval of M where m^* lies between 0 and 1 exists, but is with [29.85, 29.95] very small.

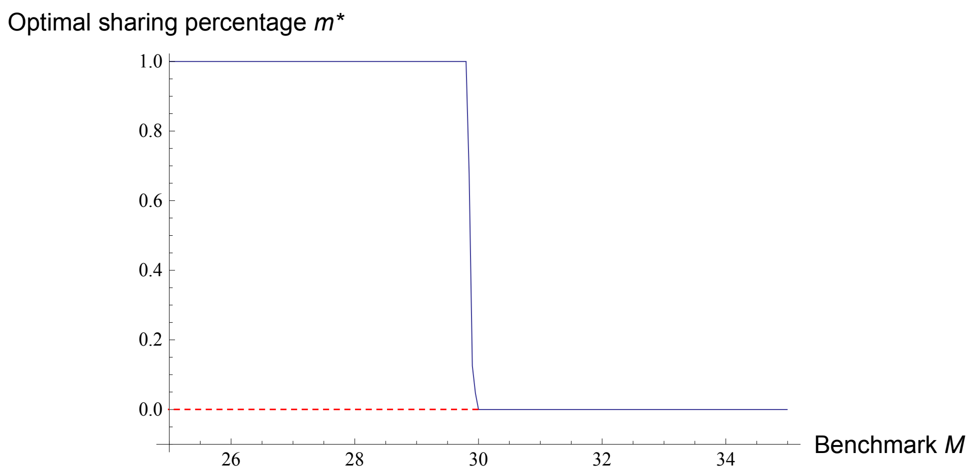


Figure 9. The effect of benchmark *M* on optimal sharing percentage m^*

To find out whether the interval is generally small, or if this is an artifact of the parameters of the numerical example, we conducted a sensitivity analysis. We varied key model parameters, one at a time, by +10% of their original value to explore the effect the interval of *M* where $0<m^*<1$. Table 4 summarizes the results of the analysis.

Table 4. Parameter sensitivity analysis

	Initial value	New value	M at transition $m^*=1 \to m^*<1$	M at transition $m^*>0 \to m^*=0$	Interval length of M for $0<m^*<1$
Base case	-	-	29.85	29.95	0.10
$\Pr^H\left(s_1^H \mid a_1^H\right)$	0.9	0.99	29.3	30.0	0.7
$\Pr^H\left(s_1^H \mid a_2^H\right)$	0.1	0.11	29.91	30.00	0.09
k_1	-4	-4.4	29.82	29.99	0.17
$r^H\left(s_1^H\right)$	-10	-11	29.4	30.1	0.7
$\Pr^P\left(s_{1,\cdot}^P \mid a_1^P\right)$	0.8	0.88	30.3	30.8	0.5
$\Pr^P\left(s_{1,\cdot}^P \mid a_2^P\right)$	0.2	0.22	29.9	30.0	0.1
$\Pr^P\left(s_{\cdot,1}^P \mid a_1^P\right)$	0.8	0.88	30.14	30.15	0.01
$\Pr^P\left(s_{\cdot,1}^P \mid a_2^P\right)$	0.5	0.55	29.1	29.9	0.8
$r^P\left(s_{1,\cdot}^P\right)$	5	5.5	31.3	31.9	0.6
$f\left(x \mid min, max, mode\right)$	(-60,20,100)	(-58,22,102)	30.87	30.88	0.01
Δ	0.15	0.165	31.02	31.03	0.01

Parameter changes affect the value of M at the transition points of m^* with varying magnitudes. The maximum length of an interval is 0.8, with most of the interval lengths less than 0.17. The analysis indicates that the interval length of M for which $0<m^*<1$ is generally small. From a practical perspective, we can say that agent H's optimal decision of incentive sharing is either $m^*=0$ or $m^*=1$, and values in between are rare.

6. Conclusion

This paper considered a multi-level health care system consisting of physicians, hospital, and payer. An analytical approach was proposed that can evaluate the multi-level effects of incentives on the use and investment of medical technologies. MSSP ACOs were chosen as the problem setting, and CT as an exemplary medical technology. Using MSDT, we modeled the decisions of agents and their responses to incentives, taking into account the effects that decisions and outcomes of agents at various levels have on one another.

We graphically captured the interactions among agents across system levels through an agent interdependence diagram and a detailed graphical representation. Based upon these graphical modeling tools, we mathematically formulated the hospital's decision process of CT investment and the physicians' decision process of CT usage. We considered the multi-attribute objective functions of hospitals and physicians. Hospitals consider profits and hospital reputation, while physicians consider their income and the health of their patients.

Physicians make the CT usage decision by comparing each patient's estimated CT necessity to the mental threshold. The aggregate behavior of physicians is expressed as the CT scan rate for the patient population. Lastly, we accounted for the bidirectional influence of hospital and physician on each other's decisions and outcomes.

We analyzed the model as a non-repeated, sequential game. First, the payer decides how to reimburse and incentivize ACOs via MSSP by setting a cost benchmark. The ACO hospital then decides how the incentive is distributed between itself and the physicians. It also decides whether to make the CT scanner investment. At last, physicians decide the CT scan rate. We solved the game using the subgame perfect Nash equilibrium concept and backward induction. A numerical example was used, and optimal and equilibrium solutions were derived.

The analysis showed that incentives can reduce CT usage. However, a high benchmark, and with it a high incentive, can turn out to be ineffective in reducing the CT scan rate. The reason is that hospital will keep all incentives and not pass them on to physicians. In contrast, if the benchmark is too low, the cost target is unattainable and would result in penalty payment instead of rewards for ACOs, which could discourage ACOs from participating in the MSSP. At the right benchmark level, the hospital will pass on all incentives to the physicians, which in turn lowers the CT scan rate.

The CT scan rate is also affected by the hospital's investment decision. A new and more advanced CT scanner will lead to more CT scans. Furthermore, a low benchmark will result in a

CT scanner purchase, whereas a high benchmark will discourage an investment by the hospital.

The best outcome (first best) for the payer would be if the hospital passed on all incentives to physicians and would not buy a CT scanner. The second best outcome is achieved when the hospital passes on all incentives to physicians and makes an investment, or when the hospital keeps all the incentives and does not invest. The least desirable result is when the hospital keeps all incentives to itself and invest. Which of these outcomes occurs depends on the system parameters, such as investment cost and effectiveness of CT scanner.

The general insights this paper provides is that using incentives in health care to motivate desirable behavior is more complicated than a two-agent principal-agent model would suggest. The health policy implications are that CMS and other payers would benefit from a detailed, multi-stakeholder and quantitative analysis before introducing payment innovations. For MSSP in particular, we found that the cost benchmark needs to be carefully chosen by CMS for the incentives to be effective. Moreover, ACOs need to purposefully design their internal incentive distribution mechanisms. Lastly, the positive effect of incentives on one stakeholder's decision (e.g., CT scan reduction by physicians) can be negated by the decision response of another stakeholder (e.g., hospitals buys new CT scanner, which increases CT scan rates). This point in particular showcases the need for a multi-level analysis using MSDT or similar methods.

As with all mathematical models of complex socio-technical systems, limitations need to be considered. We assumed that physicians' clinical decisions are driven by financial incentives and the desire to improve patient health. However, factors such as fear of malpractice litigation, physicians' experience with and attitude toward technology, and patient preferences may also play a role. Similarly, hospitals may not only consider profits and hospital reputation when making investment decisions, but a variety of organizational objectives, including physician relationship, patient satisfaction, market share, and limited budgets. Furthermore, the model assumed a single payer with a single payment structure (here MSSP). In reality, hospitals and physicians receive reimbursements from different payers with varying payment schemes, such as prospective payment, retrospective payment, and mixed payment. Taking the entire patient and payer mix into account would likely to change the results. Lastly, we did not explicitly account for temporal dynamics, since we modeled the agent interactions as a single-shot game.

Despite these limitations, the paper provided important insights on the multi-level decision modeling in health care and can serve as basis for further analysis in which the aforementioned limitations are addressed. In future research, the model could be extended to consider the entire payment and incentive mix ACO members receive. In addition, behavioral aspects of decision makers' response to incentives should be included. To account for temporal dynamics, the model could be extended by using Markov decision processes as done for simpler models in Wernz and Deshmukh (2012) and Wernz (2013). Lastly, additional key stakeholders and their decisions, in particular patients and radiologists should be included. A sufficiently comprehensive model that uses real-world data would enable policy makers, payers, ACOs and its members to identify and respond to payment innovations that have the desired effects on all levels of the health care system.

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