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Multilevel Simulations of Health Delivery Systems: A Prospective Tool for Policy, Strategy, Planning, and Management

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Computer simulations are effective tools for addressing enterprise transformation in terms of alternative organizational policies, operating procedures, and allocations of resources. We present a multilevel approach to computationally model health delivery enterprises. This approach is illustrated by its application to an employer-based prevention and wellness program. The decision of interest in this application concerns the design of prevention and wellness programs that are self-sustaining and provide a positive return on investment for the overall enterprise. The nature of this decision is shown to have enormous implications for how delivery services are organized.

Key words: health delivery; diabetes; coronary heart disease; transformation; multilevel model; organizational simulation
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1. Introduction

Breakthroughs in medical science and innovations in clinical practices offer enormous opportunities for impressive improvements in the health and well-being of society. Returns on investments in these endeavors have the potential to be substantial. However, we will not realize the greatest returns with our current system of health delivery (Reid et al. 2005, Rouse and Cortese 2010). Many see a need to engineer or design a system that can provide high-quality, affordable health for everyone. Engineering health delivery will require that the current nondesigned enterprise be substantially transformed (Rouse 2006).

This paper argues for the use of computational methods in pursuit of this engineering endeavor to support enterprise transformation. Multilevel simulations can provide the means to explore a wide range of possibilities, thereby enabling the early discarding of bad ideas and refinement of good ones. This will enable "driving the future" before "writing the check." One would never develop and deploy an airplane without first simulating its behavior and performance. However, this happens all too often in healthcare in terms of policies, strategies, plans, and management practices that are rolled out with little, if any, consideration of higher-order and unintended consequences (Reid et al. 2005, Rouse and Cortese 2010).

Computational modeling of organizations has a rich history in terms of both research and practice (Prietula et al. 1998, Rouse and Boff 2005). This approach has achieved credibility in organization science (Burton 2003, Burton and Obel 2011). It is also commonly used by the military (Rouse and Boff 2005). Simulation of physics-based systems has long been in common use, but the simulation of behavioral and social phenomena has only matured in the past decade or so. It is of particular value for exploring alternative organizational concepts that do not yet exist and, hence, cannot be explored empirically. The transformation of health delivery is, therefore, a prime candidate for exploration via organizational simulation—for example, using online games to explore new ways of managing health delivery (Basole et al. 2012).

This paper outlines another type of organizational simulation, i.e., multilevel modeling, and illustrates the application of this new approach to an employer-based prevention and wellness program. The decision of interest in this application concerns the possibility of changing from a capitated system of payment to an outcomes-based payment system. For prevention and wellness, the outcomes of interest are risk reductions—in this application, for diabetes mellitus (DM) and coronary heart disease (CHD). Risk reductions were assessed using clinical measures as inputs to disease incidence models developed using well-recognized national data sets. More generally, the application illustrated in this paper is concerned with the design of prevention and wellness programs that are self-sustaining and provide a positive return on investment for the overall enterprise. The contributions of this paper are (1) a new approach to organizational simulation and (2) the application of this approach to prevention and wellness.

1.1. Driving Forces

Why is the transformation of health delivery so important now? There are several drivers. Insurance reform will be followed by healthcare reform. The emphasis will shift from covering more people to changing delivery practices. The range of changes included in future healthcare reform is highly uncertain. Providers and payers need to be able to consider very different hypothetical scenarios. Employers' economic burden for providing healthcare, due to cost shifting from Medicare and Medicaid patients, is unsustainable (Rouse 2009, 2010a). This hidden tax leads to competitive disadvantages in the global marketplace (Meyer and Johnson 1983). Employees' unhealthy lifestyles are increasing the incidence and cost of chronic diseases, leaving employers to absorb both increased healthcare costs and the costs of lost productivity (Burton et al. 1998).

Healthcare providers will have to adapt to new revenue models. For example, they may be paid for outcomes rather than procedures. Improved quality and lower costs will be central. Providers will have to differentiate good (profitable) and bad (not profitable) revenue, which means that they will need to understand and manage their costs at the level of each step of each process.

Responsibility for outcomes will lead to a more networked organization to enable accessing the most cost-effective capabilities needed to ensure outcomes (Shortell and Casalino 2008). The most expensive asset, the physician, will increasingly be focused on the most complex activities, leaving other lower-paid professionals to perform functions requiring less training. Contracting, partnering, and managing such a network model will, therefore, be increasingly central—and more risky in the sense that outcomes will be at risk. Without acceptable outcomes, there may be little, if any, revenue.

The transformation of health delivery will involve many decisions at all levels of the system. These decisions should be evidence based in the sense that data and analytics should be central to decision making. The tendency to base decisions on anecdotal experiences with the old system will wane, and more rigorous approaches will be adopted.

1.2. Types of Decisions

What types of decisions will be central to transforming the delivery system? The overarching issue concerns how best to organize in response to the driving forces summarized above (Reid et al. 2005, Rouse and Cortese 2010). It is clear from the best performers in health delivery, as well as many other domains, that a superior way to approach this issue is to focus on the processes whereby health is delivered to people. These processes include prevention and wellness, outpatient chronic disease management, and inpatient care delivery.

Thinking in terms of processes is different than thinking in terms of departments and functions or specialties. A process orientation focuses on how value is provided to those receiving health services. Value is concerned with health outcomes, service prices, and service levels. A process orientation causes providers to see themselves in terms of value streams or networks that create desired outcomes for customers with acceptable prices and service levels.

Given this orientation, central decisions are associated with mapping and optimizing careflow processes. This includes deciding on the sequencing and timing of process steps, as well as the allocation and scheduling of capacity to them. Because not all people have the same needs, decisions must be made about stratifying patient flows by tailoring them to risk levels, as well as creating the means of reducing risks (e.g., wellness).

There are also decisions surrounding the scaling of the delivery system. An example of such a decision would be ramping up new offerings from what worked for a pilot cohort to a much larger patient population. Related decisions concern the extent to which customized plans can be delivered by standardized processes. In other words, how can customization be delivered at scale?

Changing revenue models presents substantial challenges. Adapting to payment for outcomes rather than fee-for-service models means that providers have to scrutinize processes to determine where value is most (and least) added. When payers no longer reimburse costs, then providers have to understand costs much more deeply than they commonly do now. Many procedures will have to be streamlined, others will need to be delivered in a nontraditional setting or by alternative personnel, and many are likely to be eliminated or shifted to the patients via various forms of e-visits.

The impacts of reduced Medicare/Medicaid reimbursements will also require decisions about who to serve and how to serve them. Some providers already limit the number of Medicare/Medicaid patients they serve. They may also decide to use very streamlined processes, effectively providing low-end services for those who cannot afford high-end services. The many hospital providers who have closed their emergency rooms or physicians who have changed to a concierge practice model are clear indicators of this strategy.

Another class of decisions concerns optimizing employer-based programs. Such programs are increasingly focused on prevention and wellness, targeting employees with high risks of DM or CHD, for example. Many employers are building in-house clinics to provide convenient low-cost care to employees, typically with the management and staffing outsourced.

1.3. Complexity of Decision Making

Why is making such decisions seen as rife with complexity? One source of complexity is the interactions among different levels of the system, elaborated in the next section. Government incentives and inhibitions (e.g., regulations) affect enterprise strategies for providers, payers, and employers, as well as suppliers such as medical device and pharmaceutical companies. These enterprise strategies influence the management of the universe of organizations involved across the system. Organizational management, in turn, affects process operations and health delivery. The goal is evidence-based decision making at all of these levels (Reid et al. 2005, Rouse and Cortese 2010).

Other sources of complexity for executives and managers at all levels include the many alternative policies on a wide range of issues, the reality of outcomes often being uncertain and/or delayed (e.g., the returns on prevention), and the difficulty of understanding higher-order and exploring unintended consequences. The fact that there are typically so many independent business entities that interact in multiple, and often conflicting, ways is an enormous source of complexity (Rouse 2000, 2008). This results in many types of poorly understood and poorly managed interactions among the aforementioned system levels.

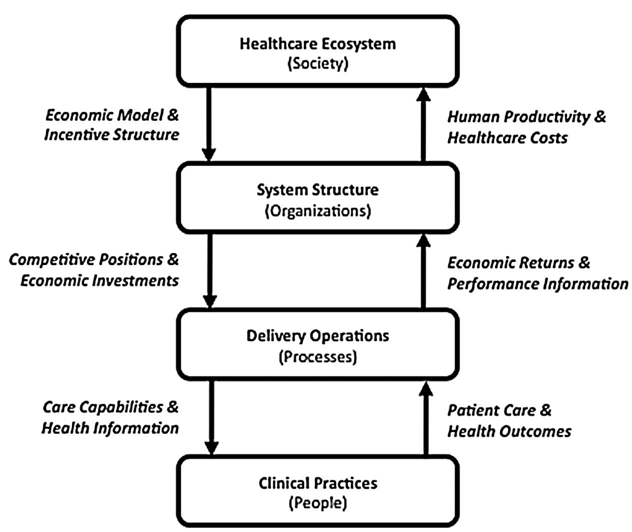
Multilevel simulations can help to cope with this complexity by enabling timely exploration of likely outcomes of decisions before deploying them. Ideally, people can interact, via large-screen displays with various dashboard controls and visualizations, with these simulations to explore a wide range of variations of organization and process designs. In this way, they can determine the sensitivity of health outcomes and financial performance to variations of key parameters. This is what we mean by *driving the future before writing the check*.

2. Enterprise of Health Delivery

Consider the architecture of the enterprise of health delivery shown in Figure 1 (Rouse 2009, Rouse and Cortese 2010, Grossmann et al. 2011). The efficiencies that can be gained at the lowest level (clinical practices) are limited by capabilities and information provided by the next level (delivery operations). For example, as discussed previously, functionally organized practices are much less efficient than those where delivery is organized around care processes (Reid et al. 2005, Rouse and Cortese 2010).

Similarly, the efficiencies that can be gained in operations are limited by the nature of the level above (system structure). Functional operations are driven by organizations structured around specialties (e.g., anesthesiology and radiology). When the different specialties are actually different businesses with independent economic objectives, then process-oriented thinking becomes quite difficult. At an extreme, if a business (e.g., organization or functional unit) within the enterprise owns only an expensive magnetic resonance imaging system, then the

Figure 1. The Enterprise of Health Delivery



Note. Adapted from Rouse and Cortese (2010).

objective is to employ it as often as possible to satisfy the individual business needs even if that increases overall costs of care. This is a good example of "suboptimization" within a system.

And, of course, efficiencies in system structure are limited by the healthcare ecosystem in which organizations operate. The ecosystem sets the "rules of the game." If, for example, the rules attach no value to healthy, productive people, then the focus will be on providing acceptable service over the short term at minimum cost. Because the definition of "acceptable" is often difficult to agree upon, the greatest weight is usually placed on minimizing use of the most expensive and profitable procedures and cost control. Differing experiences of other countries also provide ample evidence of the range of impacts of the ecosystem.

The fee-for-service model central to healthcare in the United States ensures that provider income is linked to activities rather than outcomes. The focus on disease and restoration of health rather than wellness and productivity ensures that healthcare expenditures will be viewed as costs rather than investments (Rouse et al. 2010, Rouse 2010b). Recasting of "the problem" in terms of outcomes characterized by wellness and productivity may enable identification and pursuit of efficiencies that could not be imagined within our current frame of reference.

3. Application: Employer-Based Prevention and Wellness

This section focuses on applying the multilevel model to projecting the economic benefits of employer-based prevention and wellness. There are two overarching issues. First, is the cost of prevention and wellness worth it in terms of downstream savings of healthcare costs and productivity losses? The general answer is often "yes" (Berry et al. 2010), but employers are interested in a specific answer for their population of employees and covered lives, not a general answer for all people. Obviously, depending on the nature of their businesses, these populations can be substantially different.

It is useful to note that economic valuation of investments in people—in terms of training, education, safety, health, and work productivity—often indicates a strong return on investment (ROI), with one central caveat (Rouse 2010b). If the investing entity is the same entity that realizes the returns, the economic case is often compelling. On the other hand, if the two entities differ (e.g., companies invest and the employee's next employer or the federal government sees lower costs), then the investor tends to see this outlay as a cost and tries to minimize it (Rouse 2010b).

The second issue concerns employees' compliance with prevention and wellness programs. Men in particular often avoid routine medical examinations. Hence, health risks are unknown until onset of diseases. Thus, it can be difficult to ensure the returns of proven prevention and wellness programs. There are a variety of findings from behavioral economics that can help in this regard (Volpp et al. 2011). However, this is beyond the scope of this paper, in that we focus on the economic returns for those employees who do choose to participate.

3.1. Emory/Georgia Tech Predictive Health Institute

The Predictive Health Institute (PHI) is a joint initiative of Emory University and the Georgia Institute of Technology. Within PHI, the Center for Health Discovery and Well Being™ (CHDWB) is a demonstration project focusing on health in its broadest context, exploring novel biomarkers that predict health or its loss, and affecting lifestyles in ways that favorably effect health risks. A goal of the center is to define, predict, and maintain health throughout the human life span. The studies done in the center complement other ongoing longitudinal studies on aging (Brigham 2010, Rask et al. 2011).

The center is intended to be a health-focused facility that serves essentially healthy people and does not deliver traditional medical care. The initial cohort is a random sample of fully employed, productive, Emory University personnel who are 60% female, 58% white (non-Hispanic), 24% African American, 3% Hispanic, 15% Asian, and less than 1% other. Inclusion criteria were male or female employees aged 18 and older and absence of hospitalization in the previous year except for accidents. Participants understand that the center is not a medical care facility and that this program complements, but does not substitute for, appropriate medical care (Brigham 2010).

The application of the multilevel model focused on the roughly 700 people in this cohort and their risks of DM and CHD. We calculated each person's risk of each disease using Wilson's DM and CHD risk models based on the Framingham data set (Wilson et al. 1998, Wilson et al. 2007), using CHDWB's initial individual assessments of blood pressure, fasting glucose level, etc. Subsequent assessment data were used to estimate annual risk changes as a function of initial risks of each disease.

Decreased risks imply increased average times until disease onset. This results in cost savings in terms of more years without the costs of treating the disease and lost productivity due to absenteeism and presenteeism.

Annual costs of healthcare and productivity losses for DM and CHD were based on national sources (e.g., American Diabetes Association 2008, Lloyd-Jones et al. 2010), as well as, where possible, analysis of Emory claims data.

3.2. Model Levels

The model contains the four levels shown in Figure 1: the *ecosystem* level, the *organization* level, the *process* level, and the *people* level. Each level introduces a corresponding conceptual set of issues and decisions for both the payer and the provider. In this case, the Human Resources (HR) department at Emory University is the payer responsible for healthcare costs for university employees, whereas the PHI is the provider focused on prevention and maintenance of employee health.

The *ecosystem* level allows decision makers to test different combinations of policies from the perspective of HR. For instance, this level determines the allocation of payment to PHI based on a hybrid capitated or pay-for-outcome formula. It also involves choices of parameters such as projected healthcare inflation rate, general economy inflation rate, and discount rate that affect the economic valuation of the prevention and wellness program. One of the greatest concerns of HR is achieving a satisfactory ROI on any investments in prevention and wellness.

The concerns at the *organization* level include the economic sustainability of PHI—its revenue must be equal to or greater than its costs. To achieve sustainability, PHI must appropriately design its operational processes and rules. Two issues are central. What risk levels should be used to stratify the participant population? What assessment and coaching processes should be employed for each strata of the population? Other *organization*-level considerations include the growth rate of the participant population, the age ranges targeted for growth, and the program duration before participants are moved to "maintenance."

The *process* level represents the daily operations of PHI. Participants visit PHI every 6 to 12 months. Seven health partners employed by PHI perform assessments, work with participants to set health goals, and perform follow-up calls or emails to monitor participants and encourage them to follow their plan. All these activities are captured in the *process* level. The costs of these activities are aggregated and reflected in the *organization* level as the costs of running PHI.

The *people* level is the replication of the actual population of PHI participants. During the last two years, roughly 700 participants have joined this prevention and wellness program. Each of them has various assessment measurements recorded such as blood pressure, fasting glucose level, etc.—because PHI is, in part, a research project; approximately 2,000 variables are measured at each assessment encounter. Each participant is instantiated in the model as an agent. Based on the assessment measurements, the risk of developing DM or CHD is computed for each agent. Then, total healthcare costs are estimated for the participant's remaining life based on his or her risk level for each disease. The reduced amount of aggregated total healthcare cost achieved by PHI is an *ecosystem*-level benefit to the HR organization.

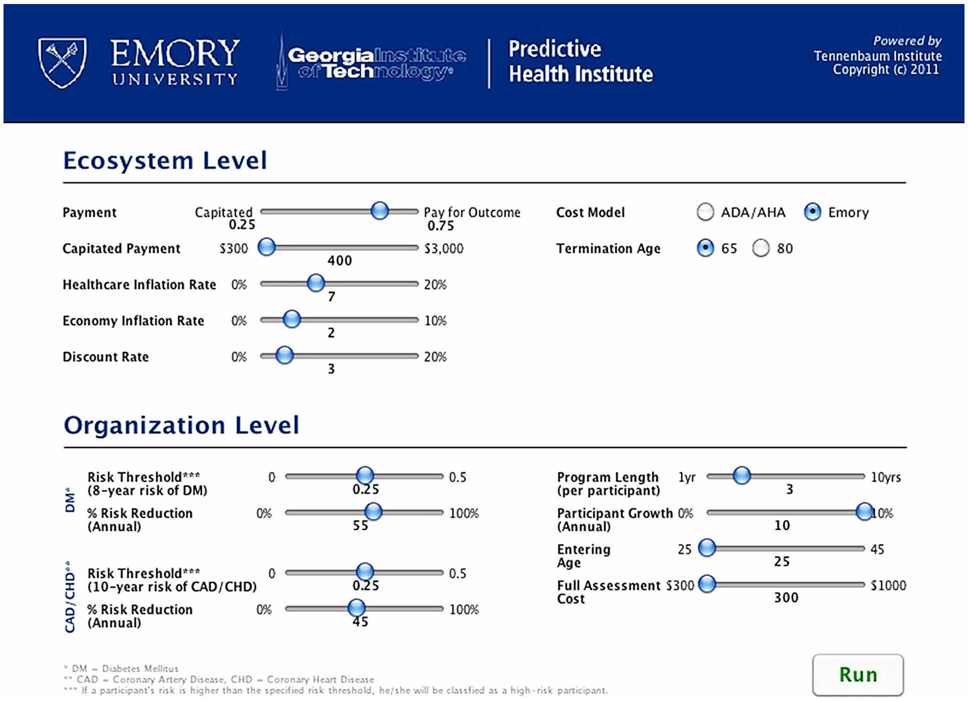
We implemented the four-level model in AnyLogic, version 6.7. Runs of the multilevel simulation are set up using the dashboard in Figure 2. Beyond the decision variables discussed above, decision makers can decide what data source to employ to parameterize the models—either data from the American Diabetes Association (ADA) and the American Heart Association (AHA) or data specific to Emory employees. Decision makers can choose to only count savings until age 65 or to also project postretirement savings.

The bottom half of the dashboard provides for inputs from *organization*-level decision makers—namely, PHI employees. Beyond the variables mentioned above, these decision makers must choose how to stratify the participant population into low- and high-risk groups for each disease. Once PHI employees choose a level on the risk threshold slider, a set point appears on the percent risk reduction slider that represents what PHI is actually achieving based on analysis of their ongoing assessment data. Decision makers can choose to operate at the set point by moving the slider to this point, or they can explore the consequences of larger or smaller risk reductions.

Figure 3 shows the *people* level of the model, which is represented as an agent-based simulation. Each agent represents an Emory employee with an assessment record and computed risks levels for DM and CHD. The color coding shows the status of each employee (e.g., experiencing first visit, interacting with his or her health partner, carrying on with everyday life). This level also shows the current distribution of risk levels in the population. Note that attrition was represented by actual participants no longer appearing in the clinical data set; the percentage attrition was very small.

Figure 4 depicts the *process* level of the model. Table 1 provides definitions of the terms in Figure 4. These processes represent how participants flow through the care system for assessments, plan development, and goal setting at PHI; the execution and facilitation of plans away from PHI; and the maintenance mode once the goals

Figure 2. Multilevel Simulation Dashboard



are achieved. The discrete-event model at this level simulates how participants consume the capacities of PHI, both in terms of time and money.

Figure 5 shows the *ecosystem* and *organization* levels of the model. The provider organization, PHI, decides how to stratify participant flows and seeks to have revenues equal or exceed costs. The payer organization, HR, sets the rules of the game as depicted on the dashboard in Figure 2. HR's ROI from PHI's services is shown in net present values using the discount rate shown in Figure 2. The returns achievable with various combinations of the parameters in Figure 2 are presented in §3.4.

Figure 3. People Level of the Model

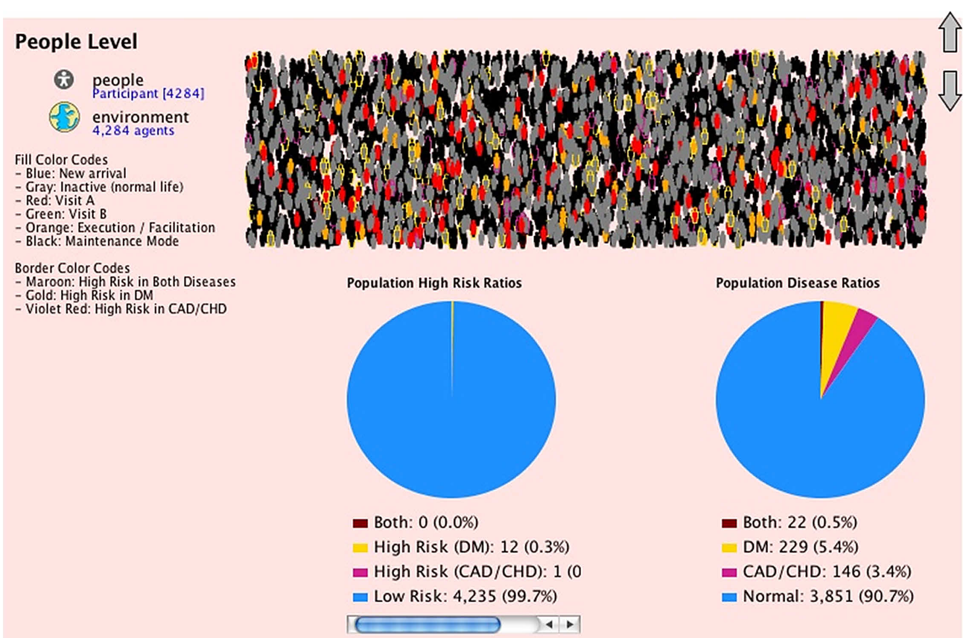
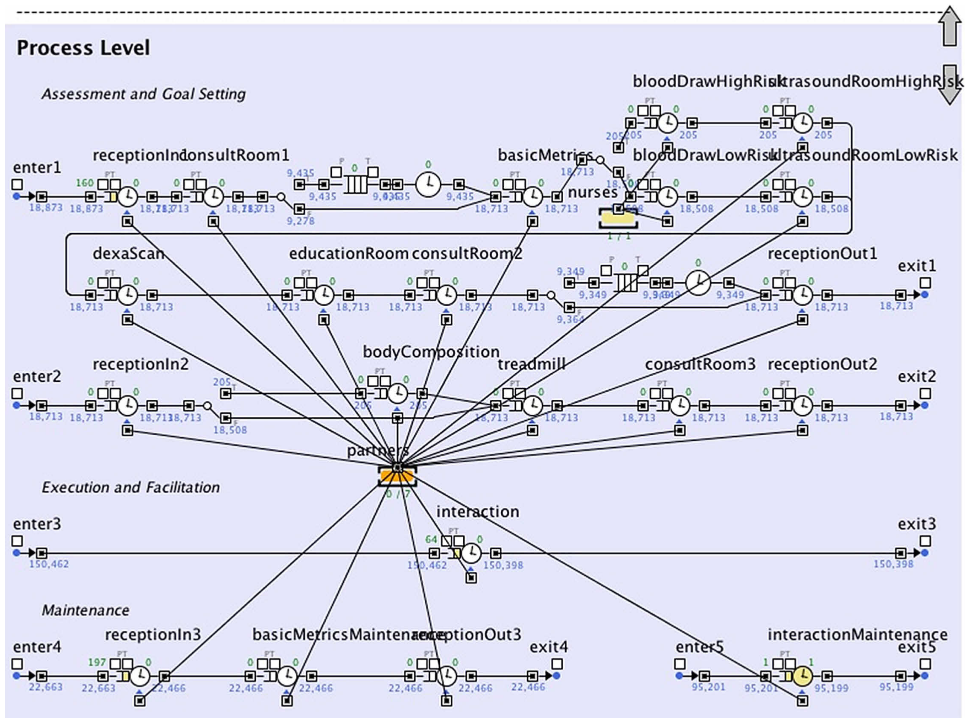


Figure 4. Process Level of the Model



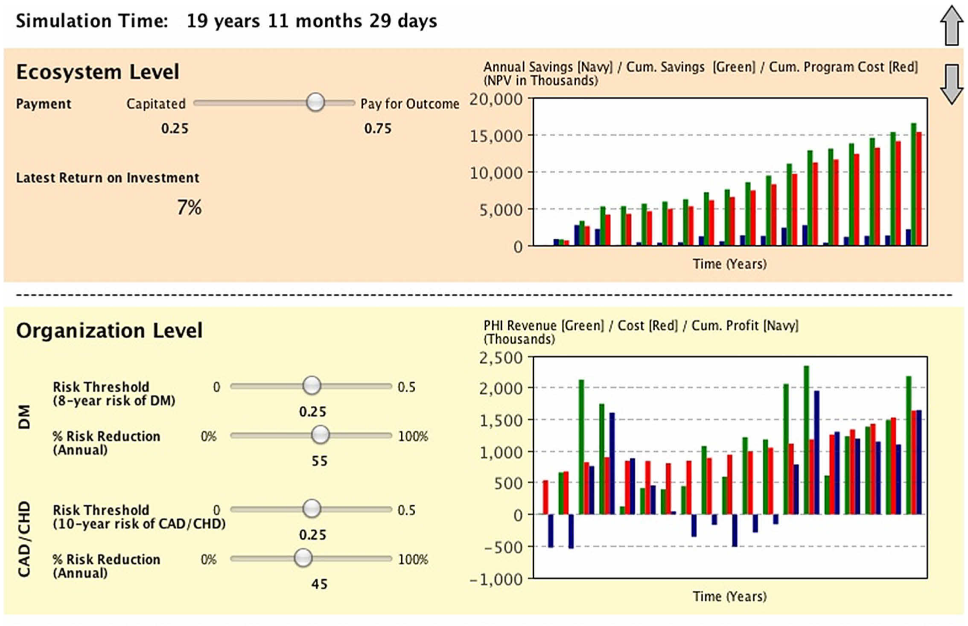
3.3. Parameter Estimation

3.3.1. Projected Disease Risks. The annual risk reductions achievable are important inputs, shown in both Figures 2 and 5. For DM, as noted earlier, we used Wilson's model to project eight-year risk. The Wilson model utilizes fasting glucose level, body mass index, high-density lipoprotein (HDL)-C level, parental history of DM,

Table 1. Definitions of Process Steps

Process	Step	Activity
Assessment and goal setting ("A" visit)	Reception	Check-in and meet partner
	Consult room	Informed consent, preliminary questionnaire
	Changing room	Change clothes (optional)
	Basic metrics	Height, weight, blood pressure measurements
	Lab	Blood draw (depending on risk level)
	Ultrasound room	Ultrasound scanning (depending on risk level)
	Dexa scan	Body composition
	Education room	Surveys
	Consult room	Mini-cognitive exam
	Changing room	Change clothes (optional)
	Reception	Check-out
Assessment and goal setting ("B" visit)	Reception	Check-in
	Body composition	Skinfold calipers, waist-to-hip measurements (optional only for high-risk participants)
	Treadmill	Maximal oxygen consumption
	Consult room	Review results, create health plan
	Reception	Check-out
Execution and facilitation	Interaction	Phone call or email follow-ups
Maintenance (visit)	Reception	Check-in
	Basic metrics	Height, weight, blood pressure measurements
	Reception	Check-out
Maintenance (follow-up)	Interaction	Phone call or email follow-ups

Figure 5. Ecosystem and Organization Levels of the Model



triglyceride level, and blood pressure to estimate the probability a person will develop DM in the next eight years (Wilson et al. 2007). Figure 6 shows the relationship between the magnitudes of risk reduction over the PHI enrollment period versus initial risk levels when each person joined PHI. Most participants had a minimum level of risk, so they did not have a potential for risk reduction. The large red circle near the origin represents these low-risk people. A relatively small number of people achieved substantial risk reductions. For example, the dot in the bottom right corner represents a participant who came in with the highest possible risk and eliminated most of this risk during PHI enrollment. There is, of course, another group of participants who had various risk levels and achieved little reduction—represented by the dots parallel to the x axis.

Regarding CHD, we employed another model developed by Wilson and his colleagues, which uses age, low-density lipoprotein-C level, cholesterol level, HDL-C level, blood pressure, DM incidence, and smoking behavior as inputs to compute predictions of the probability of CHD in the next 10 years (Wilson et al. 1998). Note that as participants' age, the risk of CHD increases even when other input variables do not change. Figure 7 shows the relationship between the magnitudes of CHD risk reduction over the PHI enrollment period versus initial

Figure 6. Reductions of Risks of Diabetes Mellitus

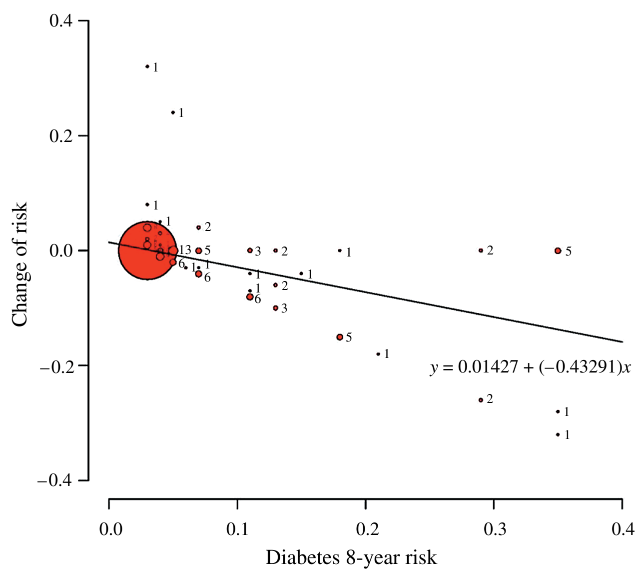
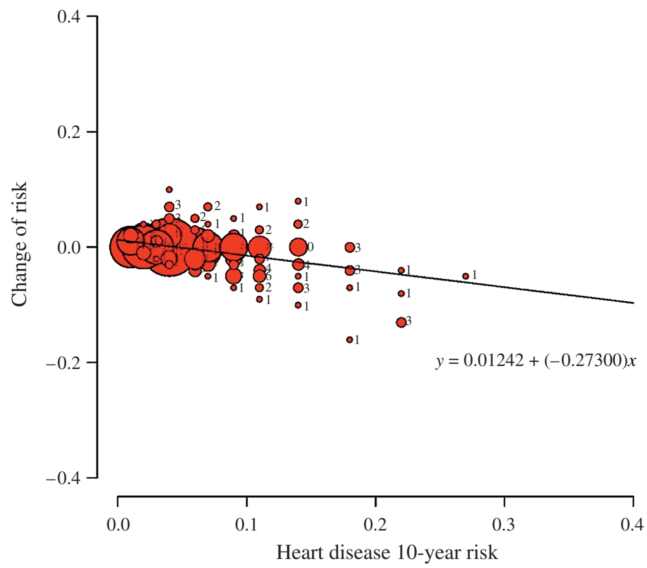


Figure 7. Reductions of Risks of Coronary Heart Disease



risk levels when each person joined PHI. These trend lines were fit to the whole data set, even though most participants had no changes of risk levels over time; thus, apparent outliers had little impact on the fits.

The risk probabilities, $P8$ for DM and $P10$ for CHD, denote the probability of DM incidence in the next 8 years and the probability of CHD incidence in the next 10 years—the outputs of Wilson's models. These multiyear probabilities were decomposed into single-year probabilities, $P1$. The average time until disease onset was then calculated as $Time = 1/P1$, which assumes that disease onset is a Markov process. (Note that this is a fairly common assumption when modeling health processes.) As risks were reduced over time for any particular participant, $P1$ decreases, and hence the time until disease onset increases. These increases in time represent downstream savings due to healthcare costs avoided by delaying the onset of DM and CHD. Note that this time often increases to beyond the likely date of death.

3.3.2. Projecting Costs of Risk Reduction. The costs of achieving these risk reductions are those associated with operating the *process* level of the model. Each step consumes an amount of time, determined from a random draw from a triangular distribution with average, minimum, and maximum estimated for each process step. (Data were unavailable to estimate actual probability distributions.) This time costs an amount based on an hourly rate for personnel, equipment, and facilities, including maintenance costs. Investments in equipment and facilities are amortized over the number of simulated years. These costs are escalated in future years by the economic inflation rate set in the dashboard shown in Figure 2.

3.3.3. Projected Downstream Costs Avoided. Projected healthcare costs incurred by simulated individuals diagnosed with DM or CHD were determined in two ways. The first approach was based on national cost studies published by the ADA and the AHA. The second approach used Emory claims data to estimate costs specific to the population from which PHI participants were drawn. Table 2 contains cost estimates produced by both methods. It also contains costs resulting from loss of productivity, calculated as follows.

The cost of DM in the United States was obtained from a 2008 report by the ADA (American Diabetes Association 2008). The report estimated \$116 billion in medical expenditures and \$31.3 billion in reduced productivity (excluding mortality) during 2007. Given the estimate of 17.5 million people with diagnosed DM in 2007, per-capita costs were \$6,649 in medical expenditures and \$1,790 in reduced productivity. The report also estimated per-capita medical expenditures of \$3,808 for ages 0–44, \$5,094 for ages 45–64, and \$9,713 for ages 65 and older. In the simulation, age-appropriate values are used for individuals with DM when "ADA/AHA" is selected under "Cost Model."

The cost of CHD in the United States was drawn from a 2010 statistical update and a 2011 forecast by the AHA (Lloyd-Jones et al. 2010, Heidenreich et al. 2011). The statistical update estimated \$96.0 billion in direct medical costs and \$11.3 billion in lost productivity due to morbidity during 2010. Using the projected 2010 CHD prevalence of 8.0% from the forecast, and the 2010 United States population of 308.7 million, these costs were spread among 24.7 million people (U.S. Census Bureau 2011). This yielded per-capita values of \$3,887 in medical costs and \$457 in lost productivity. These values are used in the simulation for all individuals with

Table 2. Annual Per-Capita Costs (U.S. Dollars) of Diabetes Mellitus and Coronary Heart Disease

	Diabetes mellitus		Coronary heart disease	
	Medical cost	Productivity cost	Medical cost	Productivity cost
National estimates				
All ages	6,649	1,790	3,887	457
Ages 0–44	3,808	1,790	3,887	457
Ages 45–64	5,094	1,790	3,887	457
Ages 65+	9,713	0	3,887	0
Emory estimate				
All ages	3,762	1,790	6,523	457
Ages 0–44	3,043	1,790	4,350	457
Ages 45–64	3,492	1,790	5,905	457
Ages 65+	4,193	0	6,705	0

CHD when "ADA/AHA" is selected under "Cost Model," because costs by age range were not available in the statistical update.

In addition to the national cost estimates for DM and CHD described above, estimates specific to the Emory population were prepared from a database of all claims paid under Emory's Aetna-administered health plan from October 2007 through December 2010. This process began by identifying individuals treated under appropriate diagnosis codes from the International Classification of Diseases, 9th Revision (ICD-9). DM patients were defined as those who received at least two procedures under an ICD-9 code starting with 250 (250.*), excluding codes ending in 1 or 3 (250.*1 or 250.*3) to avoid inclusion of treatments for DM Type I. CHD patients were defined as those who received at least one procedure under an ICD-9 code starting with 410, 411, 412, 413, or 414 (410.*, 411.*, 412.*, 413.*, or 414.*).

After patient sets were identified for each disease, total medical costs were determined by summing coinsurance amount, copay amount, deductible amount, net payment amount, and third-party amount for all procedures and prescriptions administered to each patient in the set. Costs were annualized by determining the total cost per year of eligibility for each patient. To determine the portion of total costs attributable to each disease and its complications, baseline groups were constructed from the set of individuals who received treatment for neither DM nor CHD, with the median age of each patient set equal to the median age of its baseline. The increase in annualized costs above the baseline was then used as the marginal cost of each disease. Given the small patient population in some comparisons, median costs were used for the Emory population cost estimates. This reduced the impact of a few patients with extraordinarily high costs and provided safe but conservative estimates.

Based on the methods described above, the per-capita DM costs for the Emory population were $3,762 for all ages, $3,043 for ages 0–44, $3,492 for ages 45–64, and $4,193 for ages 65 and older. Claims-based CHD costs were $6,523 for all ages, $4,350 for ages 0–44, $5,905 for ages 45–64, and $6,705 for ages 65 and older. The claims-based cost figures given here are used in the simulation when "Emory" is selected under "Cost Model." Further, all of the above costs are escalated in future years by the healthcare inflation rate set in the dashboard shown in Figure 2.

3.3.4. Projecting Returns on Investment. The logic of the economic valuation is as follows. PHI incurs costs of operating its processes to reduce the risks of DM and CHD for its population of participants. The resulting risk reductions delay the onset of these diseases for participants, often beyond their projected life span. This results in cost avoidance, both for treatment of these diseases and lost work productivity. This savings yields future cash flow to HR that enables them to provide revenue to PHI. However, because these savings will occur in the future and the investment must be made now, one needs to consider factors such as expected inflation. The result for PHI and HR consists of two times series each, one for costs and one for revenues. The difference between revenues and costs represents profit or loss. The net present value of this time series is then calculated using the discount rate shown on Figure 2. The ROI shown in Figure 6 is calculated from the latest (most recent year) ratio of savings to costs.

3.4. Representative Results

The dashboard allows a wide range of users (e.g., decision makers, policy analysts, organizational designers) to change model parameters and view the simulation outcomes in real time. However, model parameters have many complex interdependencies that may lead to nonintuitive outcomes for PHI and Emory HR. Given the number of parameters, it would be quite time consuming for a user to manually vary parameter configurations to evaluate all possible outcomes. To provide a comprehensive view of the interaction dynamics of parameters and resulting economic outcomes, we conducted an experimental simulation using a parameter variation approach. The experimental design is outlined in Table 3. The total number of unique configurations is 189,000; each configuration was replicated 100 times. For each configuration we captured three economic performance measures: the average profit to PHI, the ROI to Emory HR, and the aggregate economic gain to Emory, which is the sum of PHI profits and HR returns.

We focus our results discussion on "economically attractive" configurations under which PHI is a sustainable organization and Emory HR also has a positive ROI. Several significant results are found. Each is best appreciated through a series of three "solution space" graphs shown in Figures 8–10. All assume a risk stratification approach not actually used by PHI. Under the traditional approach, all participants receive the same full assessment and coaching program to fulfill PHI research aims. Our risk stratification argues for differentiation of participants, in which only participants with a 25% risk of DM and/or CHD receive the full assessment and coaching program. We elaborate on the implications of this stratification later.

Figures 8(a)–8(c) illustrate the economic outcomes for PHI, Emory HR, and Emory as a whole, respectively, as a function of participants' age at entrance into the program ("entering age") and the age through which savings are accumulated ("terminal age"). Each of these figures assumes current and realistic levels of economic inflation (3%), health inflation (7%), discount rate (2%), capitated payment amount ($500), and a 50:50 split between capitation and payment for outcomes (i.e., $Payment = 0.5$). Clearly, early intervention to reduce risk provides the greatest returns because a longer time frame provides more time to accrue the cost savings. Moreover, the interests of all the parties—PHI, Emory PHI, and the entire Emory organization—are well aligned because the economic outcomes track closely for all three.

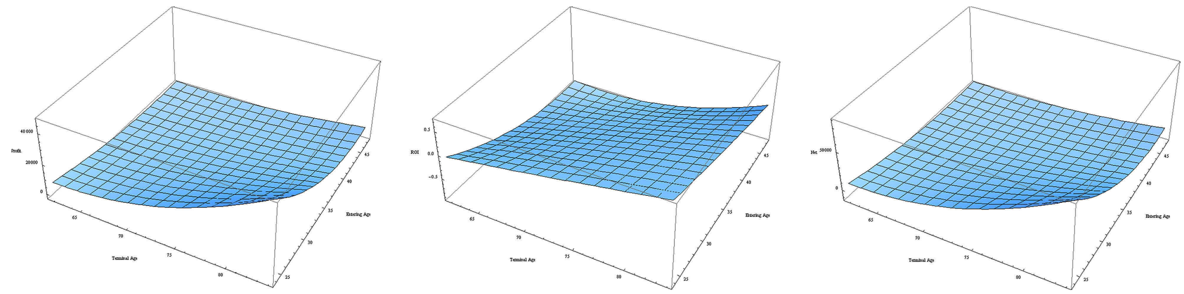
However, it is reasonable to expect that health inflation rates will change over time. Figures 9(a)–9(c) examine this by comparing the economic outcomes for the three parties, under the same conditions as above, as a function of healthcare inflation and the number of years from entering to the terminal age. Similar to the first analysis, economic interests are well aligned, but because Emory HR is spending today's dollars to gain future savings, their ROI is more sensitive to the health inflation rate than to the period over which savings can be gained. In fact, PHI profit is accelerating for higher levels of healthcare inflation rates and difference in entering and terminal age, whereas the ROI for Emory shows a tendency to saturate. These results indicate the relative importance, sensitivity, and influence of healthcare inflation rates to both PHI and Emory HR.

As healthcare delivery moves to alternative payment models, it is important to further understand the influence of pay-for-outcome and capitation levels on economic outcomes for each of the three participants. Figures 10(a)–10(c) illustrate this under the same conditions as above. This analysis strikingly resembles the conflicts of interest in our current "fee for service"-based payment system. Because PHI delivers the same service to all volunteers, a pure capitated payment is essentially a fee for service. Under this (see Figure 10(a)), PHI can be very profitable if the capitated payment is sufficiently large. PHI, on the other hand, does only modestly well by comparison under a payment-for-outcomes system, in large part because its population is not prescreened for people at risk. Emory HR's results are virtually opposite, although it can still do relatively well under the right

Table 3. Experimental Design

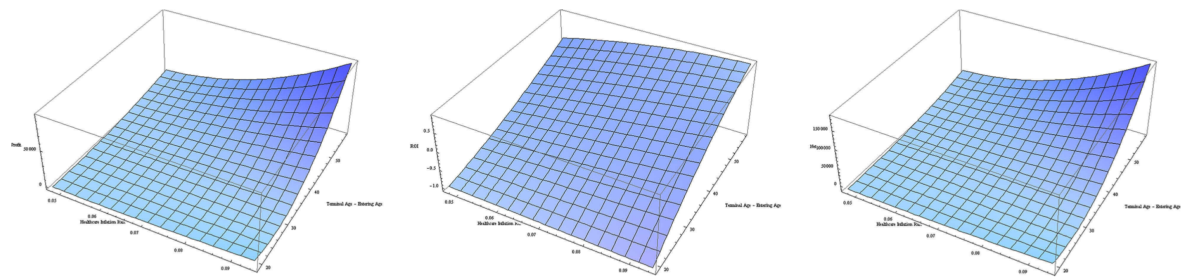
Level	Parameter	Type	Parameter configuration
Ecosystem	Cost model	Fixed	Emory
	Termination age (years)	Fixed	65
	Payment ($)	Vary	$pmt = (0, 0.25, 0.5, \ldots, 1.0)$
	Capitated payment ($)	Vary	$cap = (300, 700, 1{,}100, \ldots, 2{,}700)$
	Healthcare inflation (%)	Vary	$h = (3, 7, 11)$
	Economy inflation (%)	Vary	$e = (2, 4, 6, 8)$
	Discount rate (%)	Vary	$i = (3, 7, 11)$
Organization	DM (% risk reduction)	Fixed	$DM = (0.25, 0.55)$
	CHD (% risk reduction)	Fixed	$CHD = (0.25, 0.45)$
	Program length (years)	Vary	$l = (1, 2, \ldots, 5)$
	Participant growth (%)	Vary	$g = (5, 10)$
	Entering age (years)	Vary	$age = (25, 30, 35)$
	Full assessment cost ($)	Vary	$costa = (200, 400, \ldots, 1{,}000)$

Figure 8. Economic Outcomes: Participant's Entering vs. Terminal Age



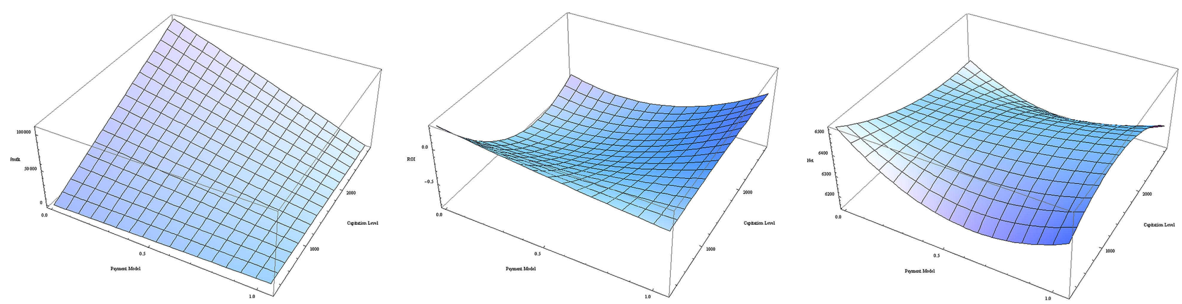
(a) PHI profit (b) HR ROI (c) Aggregate Emory economic gain

Figure 9. Economic Outcomes: Years of Potential Savings vs. Health Inflation Rate



(a) PHI profit (b) HR ROI (c) Aggregate Emory economic gain

Figure 10. Economic Outcomes: Capitation vs. Payment for Risk Reduction



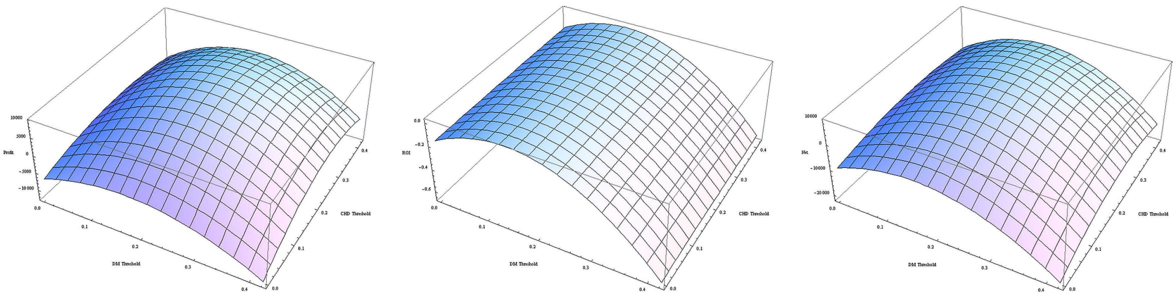
(a) PHI profit (b) HR ROI (c) Aggregate Emory economic gain

blend of capitation and pay for outcome (see Figure 10(b)). Figure 10(c) presents the aggregate results to Emory as a whole and, in some sense, is a surrogate for "society" and its overall gain under various healthcare payment systems. Here, the results are far less intuitive, and in fact, a typical negotiation that finds middle ground, e.g., by splitting the difference, would not achieve anything close to the maximum potential overall societal gain.

In other words, when we compromise between the returns to HR and PHI, the aggregate returns to Emory are minimized. The best economic results are achieved when *either* PHI's profit is maximized *or* Emory HR's ROI is maximized. There are a variety of reasons why one might choose either extreme. However, there is another possibility. HR could maximize its ROI while providing PHI with a very lean budget. At the end of each year, HR could then provide PHI with a bonus for the actual savings experienced that year. This could be determined by comparing the projected costs for the people in the program to their actual costs of healthcare, absenteeism, and presenteeism. In this way, HR would be sharing actual savings rather than projected savings. The annual bonuses would free PHI of the fear of not being sustainable although, as described below, PHI would need to substantially reorganize its delivery system.

It is also reasonable to expect that future healthcare delivery will need to take into account the risk characteristics of the population. Figures 11(a)–11(c) illustrate the economic trade-offs for varying the level of risk thresholds for DM and CHD. It is interesting to observe that even a small increase in risk stratification beyond no risk stratification at all leads to a beneficial outcome for PHI and Emory as a whole. This benefit continues

Figure 11. Economic Outcomes: Disease Risk Thresholds for Diabetes Mellitus vs. Coronary Heart Disease



(a) PHI profit (b) HR ROI (c) Aggregate Emory economic gain

to increase for both diseases until a certain risk threshold level and then drops off drastically. This happens for two primary reasons: first, as one stratifies by risks, the system does not incur the cost of treating everyone the same way. Second, as one increases the risk thresholds, however, he or she has fewer eligible individuals to treat until, at some point, there are no high-risk individuals left. This result clearly suggests that more beneficial economic outcomes can be gained by establishing appropriately risk stratification levels.

To illustrate the subtlety of this, consider the relationships between DM and CHD. The stratification process must take into consideration that disease-specific risks are not necessarily independent variables. People who have DM have substantially increased risks of CHD (see Wilson's models). Hence, if one were to decrease resources devoted to DM risk reduction to focus resources on CHD risk reduction, the size of the population with CHD would increase because of the decrease in attention to those with high risks of DM. Hence, we get the surfaces shown in Figures 11(a)–11(c).

3.5. Implications of Results

The financial objectives of HR and PHI—which are in conflict—should not be independently optimized; if either loses significantly, the system becomes dysfunctional. HR needs to adopt payment mechanisms under which PHI can redesign its delivery processes to achieve sustainability while also providing HR with an acceptable return on its investment in prevention and wellness.

For PHI to stay in business, it will have to change its business model, stratifying the population by risk levels and tailoring processes to each stratum. This could include an initial low-cost, streamlined assessment and subsequently PHI "lite" for low-risk participants. PHI also needs to develop a low-cost "maintenance" process to sustain reduced risks once they have been achieved.

The relationship of Emory HR and PHI provides an archetypical illustration of the changing healthcare ecosystem. Payment for outcomes is clearly emerging, and the implications for how best to organize for delivery are enormous. These transformed organizations need to be designed or engineered, not just very expensively emerge from trial and error.

This exercise clearly shows the value of multilevel simulation as a tool to explore what-if scenarios in complex health delivery models. Current work is extending this to other scenarios such as the patient-centered medical home, employer-based clinics, and outcome-based payment systems for providers. The component models change, but the overall approach remains the same.

One size does not fit all in prevention and wellness and other aspects of health delivery. This is not surprising. Our approach enables exploring "what if," comparing it to "what is," and tailoring the delivery system to the nature of the population served as well as the priorities of the participating organizations. All of this is done in an interactive, inspectable environment open to participation of all stakeholders.

4. Conclusions

This paper has presented a multilevel approach to organizational simulation of health delivery enterprises. This approach was illustrated using an employer-based prevention and wellness program. We hasten to note that the particular findings of this illustration are specific to Emory University as an employer. Thus, we are not suggesting that the organizational design insights found can be generalized to other employers. At the very least, the models would have to be tailored to the demographics of other employers' personnel. It is also very likely that different employers would entertain different delivery processes.

It is also important to recognize that the findings—i.e., patients should be stratified and each stratum should be addressed differently—are not at all new. What is new is the multilevel computational approach to exploring alternative ways to achieve these ends. Using this approach, we were able to rapidly explore many alternatives, gaining insights into why many intuitively appealing ideas were, in fact, flawed with unacceptable higher-order and unexpected consequences. Similarly, we found a handful of apparently good ideas. These ideas were computationally refined and then readied for empirical evaluation.

For fundamental organizational change to be successful, several competencies are central (Rouse 2006, 2011). Leadership needs to articulate a clear vision of the "to-be" organization and how the "as-is" organization will morph into that future. Organizational simulation provides a powerful means to portray the vision, experience it, and redesign it to better achieve the collective stakeholders' goals and objectives. As shown in this paper, the results can sometimes surprise participants. Seemingly good ideas can have negative higher-order consequences and unintended consequences. For example, the obvious idea of splitting the difference, for the example presented here, turned out to be a very bad idea. Fortunately, this was discovered in the computational organization, not by painfully deploying this bad idea in the real organization only to discover its flaws.

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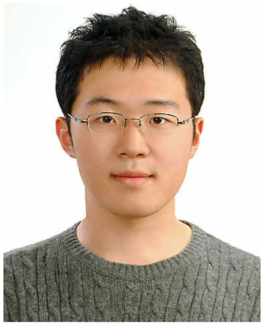

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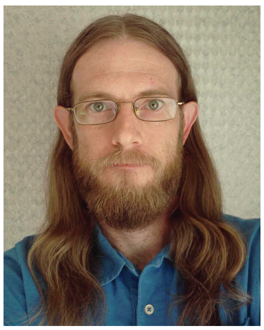

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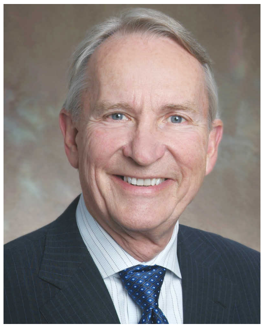
building programs in the use of clinical information and other medical technologies to improve the delivery of healthcare.



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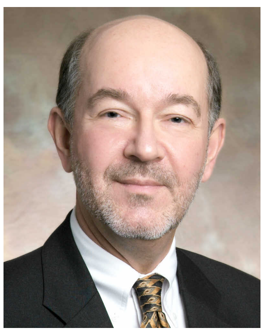

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