Toward Useful System Dynamics Models of Physician Reimbursement and Population Health

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Abstract. System dynamics models are widely used for applications in health care. Modelling of different reimbursement systems is a comparatively new field of application. This paper tries to identify the core dynamic structures and feedback loops that drive such models. We created a simplified model of physician reimbursement that includes the interaction between patients, their disease state, and the pressures on physician behaviour from reimbursement and their workload.

Several simulated scenarios show that its behaviour is plausible and in line with theories on the influence of different reimbursement systems.

Introduction

In the past, system dynamics (SD) has found many areas of application. Health care is one example. Homer and Hirsch [1] list various health care topics where system dynamics has been applied, from disease epidemiology and drug addiction to patient flows in emergency departments and health care capacity planning.

They also suggest that system dynamics could be helpful in creating more complete models of population health, which might incorporate multiple interacting diseases.

One field of study where no standard modelling approach has been established yet is the analysis of different reimbursement systems for providers of health care.

Models in this area of application should answer the question of which schemes of payment for doctors are optimal and what possible consequences of each scheme could be. They must be able to incorporate, for example, the influence of reimbursement on treatment decisions and health consequences for patients. All diseases that lead to the consumption of health services play a role in this problem (not just one as in typical decision-analytic modelling of isolated health care interventions), which makes it even harder to deal with.

First applications of simulation modelling of physician reimbursement include a system dynamics model of group practices [2] and an agent-based model for the study on per case flat rates in the extramural health care sector, the GAP-DRG model [3]. In this paper, we investigate the core dynamic structures that drive those models. Every epidemic model, for example, uses the positive feedback loop caused by more infectious people infecting even more additional individuals who in turn become infectious, even though implementation can differ depending on the modelling method.

It would be beneficial if such core dynamic structures could be also identified for health care reimbursement systems. We use the structured modelling process of SD in order to create a simplified model of physician reimbursement that includes the interaction between patients, their disease state, and the pressures on physician behaviour from reimbursement and their workload. The focus lies on the dynamic structure. Parameters are set to plausible values, but not parametrized from data.

Note. This article is a revised and shortened version of Chapter 6 of the author's PhD thesis [4].

1 Problem and Textual Model Description

A good modelling study starts with a description of the problem or research question that should be answered. In the case of reimbursement systems in extramural health care, one of the central questions is how different reimbursement systems influence the amount of provided health services, the quality of service, and the costs for the payer as well as how an optimal reimbursement system should be designed. According to Czypionka et al. [5], most of the theory of optimal service reimbursement is based upon the work of Ellis and McGuire [6], who develop an analytical model and derive conclusions from solving for an optimum of the physicians' utility function, which includes their profit (more specifically, the profit of the hospitals where they are employed) and the benefit to the patients.

Such models do not study dynamic behaviour and how physicians react over time to potentially changing pressures in the system. Physicians' treatment decisions can produce feedback by changing the future need of the patients, which in turn influences their decisions (e.g., if their workload changes). Therefore, dynamic simulation models might add additional insight to the already available theory. The central research question is thus which dynamic behaviour physician's choice of service extent shows under different reimbursement systems and how it influences patient health (i.e., which quality is achieved).

It follows that a model must include at minimum the health state of the population, its influence on the physicians and their treatment decisions (which amount of services they provide), and the feedback of the treatment to the health of the population. There are many different factors influencing medical decision making [7], but we focus on two of them, physician income and workload.

1.1 The health of the population

Consider a fixed population of n individuals. People with good health are part of the *healthy population* (HP). They may become symptomatically ill with an *average incidence rate* (IR), which depends on a *fractional incidence rate* (fir) after which they belong to the *sick population seeking treatment* ($SPST$). In this state, individuals are in need of medical treatment and will consult physicians.

Patients who get *successful treatments* (ST) become healthy again. However, there are also *unsuccessful treatments* (UT) that do not fully cure them. Such individuals are then part of the *latently sick population* (LSP). As such, they do not immediately need medical treatment, but after *relapses* (R), which take on average the *time to relapse* (ttr), they become again *sick population seeking treatment*.

This model structure keeps track of diseased individuals. It also allows that they stay ill without immediately seeking treatment. However, the kind of disease or the occurrence of multiple parallel diseases are not considered. Furthermore, the model does not explicitly keep track of chronic diseases that may never heal. These simplifications are due to the focus on dynamics instead of detail, which could be added in later modelling steps but would complicate the models in a first step and thus hinder insight.

What is new in this model structure, compared to the models in [2] and [3], is the possibility of taking quality into account. Higher quality manifests in a higher *fraction of success* (FOS) of treatments. In the GAP-DRG model, medical services have no influence on patients' state of health, and the group practice model does not consider the health of the patients explicitly.

1.2 Cases and services per doctor

Persons in the *sick population seeking treatment* generate a certain amount of *cases* (C) for physicians per day at a *case rate per person* ($crpp$). For every case, an individual changes his or her state to either healthy or latently sick.

1.3 Workload and reimbursement

It is assumed that the more services per day a physician has to perform the higher his *workload* (W), which is measured relative to a *standard service volume* (ssv), is. However, doctors do not instantaneously adapt their *perceived workload* (PW), upon which their reactions are based, but only after a certain *time to perceive workload* ($ttpw$).

In general, reimbursement is some mixture of per case flat rates and fee-for-service payment. The *reimbursement per doctor* (RPD) thus consists of the *case reimbursement* (CR), which is calculated from the *cases per doctor* and the *per case flat rate* ($pcfr$), and the *service reimbursement* (SR), which equals the *services per doctor* times the *average service tariff* (ast).

Again, doctors adapt their *perceived reimbursement* (PR) after a certain *time to perceive reimbursement* ($ttpr$). The *normalized reimbursement* (NR) is then the reimbursement relative to some *standard reimbursement* (sr).

1.4 Service extent and its influence on the success of treatment

The service extent measures how many services doctors provide relative to the true service need per doctor. Thus, values under 1 correspond to under-provision and value above 1 to over-provision of services.

Both the perceived reimbursement and workload of a doctor influence his or her service extent. If both assume their standard values they exercise the *standard effect of reimbursement on service extent* ($serse$) and the *standard effect of workload on service extent* ($sewse$). In this case, the *effect of reimbursement on service extent* ($ERSE$) and the *effect of workload on service extent* ($EWSE$) both assume the value 1. If reimbursement increases, its effect on *service extent* decreases, because doctors do not have to work as much to reach their target income. Furthermore, if workload increases, its effect on *service extent* also decreases, because doctors try to spend less time on each patient to reduce their workload.

The model assumes that there is both a *positve effect of service extent* ($PESE$) and a *harmful effect of service extent* ($HESE$). If the service extent equals 1 the *fraction of success* equals the *optimal fraction of success* ($ofos$). A lower service extent decreases the *positive effect of service extent*, because doctors do not provide all necessary services. Conversely, a higher service extent leads to a *harmful effect of service extent*. In both cases, the resulting *fraction of success* will be suboptimal.

2 Feedback in the Model

The described structure includes several feedback loops. Figure 1 shows a simplified causal loop diagram of the model.

The most obvious feedback loops B1 (Target Income) and B2 (Desired Workload) are balancing loops through service extent and reimbursement or workload:

Balancing loop B1 (target income)

The more services per case doctors provide, the higher the reimbursement. When they perceive an increase in reimbursement they in turn reduce their service extent.

Balancing loop B2 (desired workload):

In the same manner as with reimbursement, doctors who perceive an increased workload decrease their service extent.

There is also a reinforcing loop R1 (Prevention), which involves the health of the population and the positive effect of service extent on the fraction of success. On the other hand, B3 (Bad Treatment) is another balancing loop and involves the harmful effects of overtreatment.

Reinforcing loop R1 (prevention)

If service extent increases and more individuals become healthy through the positive effects of service extent, physicians' workload and reimbursement decrease, because future cases are prevented. Thus, they have more time and motivation to increase their service extent. Note that this feedback loop is only active if the service extent is below the optimal level.

Balancing loop B3 (bad treatment)

This feedback loop, on the contrary, becomes active if the service extent is above the optimal level. The harmful effects of services increase and thus more people become latently sick. In the long term, this leads to more relapses and more cases. Workload and reimbursement increase, which provokes a decrease in service extent.

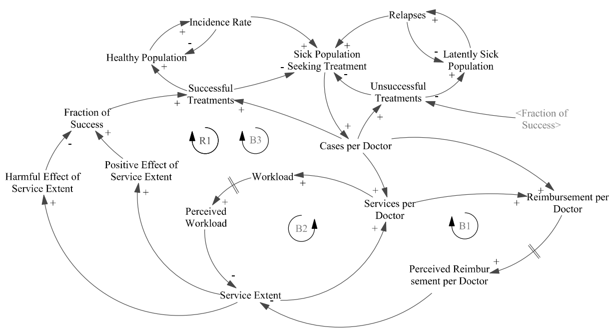

Figure 1: Simplified causal diagram of the physician reimbursement model.

3 Stock and Flow Structure

After the creation of a causal diagram, it is necessary to determine which variables are stocks or flows. The model mainly includes the stocks of healthy individuals, sick individuals seeking treatment, and latently sick individuals. It follows that flows are the variables that influence these stocks.

Physicians perceive their workload and reimbursement only with a delay (they average the input over time). If these delays are, for example, first order exponential delays, then their implementation also involves a stock. Thus, the model includes three explicit and two implicit stocks. For a detailed description of model equations and parameters, see [4]. Plausible values based on educated guesses were chosen for the parameters.

Initial values for the stocks in the model are also necessary. For a theoretical analysis, a useful assumption is that the system should be in equilibrium, where the in- and outflows to each stock cancel each other out. This leads to an equation system, which was solved in order to derive the equilibrium values for stocks and delays (see Table 1).

Variable/Parameter	Equilibrium Value	Unit
Healthy Population	85 628.44	Person
Sick Population S. Treatm.	10 015.02	Person
Latently Sick Population	4 356.53	Person
Standard Reimbursement	560.84	Euro/(Doctor*Day)
Standard Service Volume	60.09	Service/(Doctor*Day)

Table 1: Equilibrium values for the physician reimbursement model.

4 Simulation Scenarios

4.1 Base run

In the base run, the model is in equilibrium and thus all variables stay at their equilibrium values. Normalized reimbursement as well as perceived workload are constantly 1.

4.2 Per case flat rates

Per case flat rates do not reimburse single services, but only cases. The average service tariff, ast, is therefore zero in this scenario. On the other hand, the per case flat rate, $pcfr$, must be higher to compensate for the missing service reimbursement. We set it to 56 euros, because this equals the assumed per case flat rate in the base run (20 euros) plus the assumed average service tariff (6 euros) multiplied by the service extent in equilibrium (1.2) and the service need per case (5).

The second effect is that now the service extent does not have a direct influence on reimbursement. Therefore, it does not make sense for a physician to increase it in order to receive more payment (or decrease it if he or she has more than enough). This cuts the causal loop B1 (Target Income), such that the effect of reimbursement on service extent is always 1, which lowers the service extent in comparison to the base run (where standard service extent is 1.2).

Figure 2 and Figure 3 show the results for the sick population and physician reimbursement, workload, and service extent. Only the perceived workload influences the service extent, so it is below the optimal value instead of too high as in the base run. Thus, the doctors provide fewer services to the patients, and their perceived workload decreases. In turn, they increase the service extent slightly. Additionally, the new level of the service extent is more beneficial to the patients than it is in the base run, which causes the number of latently sick patients to drop.

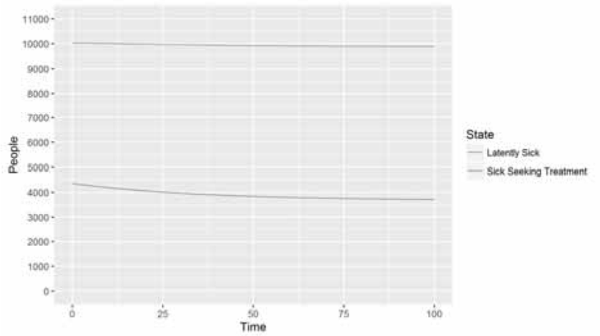

Figure 2: The number of persons who are sick seeking treatment or latently sick in the scenario with per case flat rates as the reimbursement system.

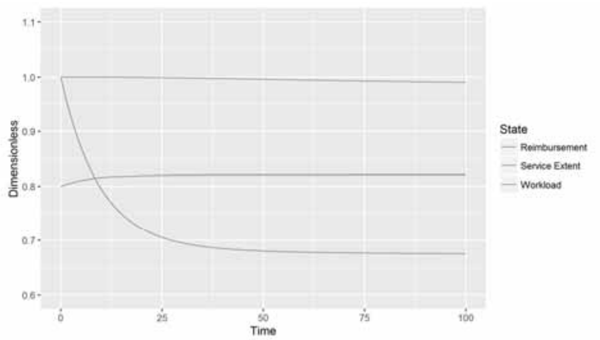

Figure 3: Normalized Reimbursement, perceived workload, and service extent in the scenario with per case flat rates as the reimbursement system.

4.3 Increase of incidence rate

An important test of system behaviour is the reaction to a certain change of an input or a parameter. In this scenario, we assume that the fractional incidence rate doubles from 0.01 to 0.02 after 10 days, which leads to far more individuals getting sick (e.g., during a pandemic).

Figure 4 and Figure 5 show the results. As expected, the number of sick individuals seeking treatment increases sharply after the change in the fractional incidence rate. It saturates at a bit more than 17 thousand. The latently sick population increases nearly linearly.

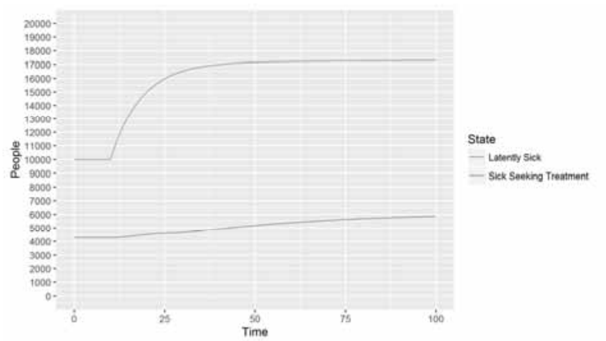

Figure 4: The number of persons who are sick seeking treatment or latently sick in the scenario where the fractional incidence rate changes from 0.01 to 0.02 after 10 days.

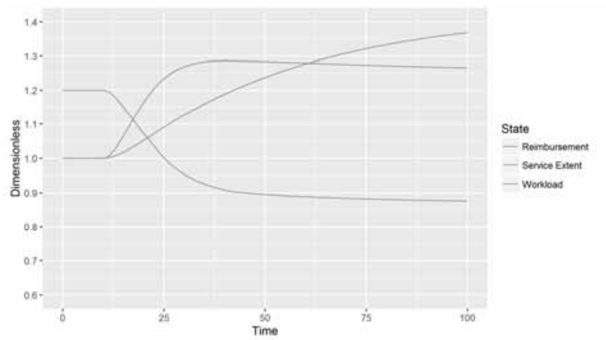

Figure 5: Normalized Reimbursement, perceived workload, and service extent in the scenario where the fractional incidence rate changes from 0.01 to 0.02 after 10 days.

As a result, the perceived workload and reimbursement of the doctors also increase sharply. This causes them to lower the service extent. At about time 50, the perceived workload starts to decrease again.

4.4 Increase of incidence with per case flat rates

Reimbursement with per case flat rates can potentially change the reaction of the system to a higher incidence rate in the population. Thus, this section studies a scenario with both a higher incidence rate and per case flat rates for reimbursement.

Figure **6** and Figure **7** show the corresponding results. The perceived workload of the doctors drops initially because of the lower service extent, which is provoked by the different reimbursement system. However, the perceived workload (and the reimbursement) increases sharply after the change in incidence.

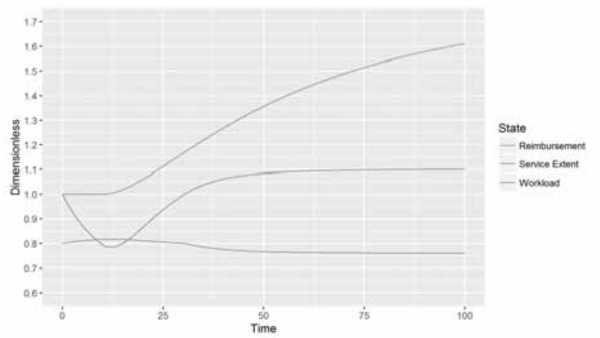

Figure 6: The number of persons who are sick seeking treatment or latently sick in the scenario with an increase in the fractional incidence rate and a per case flat rate reimbursement system.

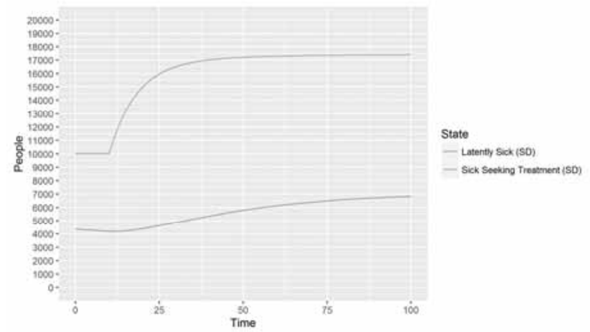

Figure 7: Normalized Reimbursement, perceived workload, and service extent in the scenario with an increase in the fractional incidence rate and a per case flat rate reimbursement system.

This causes service extent to decrease even more. Thus, the treatment is worse than it was in the last section. As a consequence, there are about a thousand more latently sick individuals at the end of simulation than without the per case flat rate reimbursement system. This shows that under the assumptions of the models, the system reacts better under the mixed system of per case flat rates and single service reimbursement.

5 Conclusions

The physician reimbursement model depicts the most important properties of both the GAP-DRG and the group practice model. It incorporates epidemiology (people who develop diseases) as well as physician behaviour based on their workload and their reimbursement, which depends on the applied reimbursement system. However, the model was built to be as simplified and abstract as possible in order to favour dynamic complexity over detail complexity. This facilitates the utilization of the SD modelling process, although it is possible to transform the result into an equivalent agent-based model (see [4]).

The simulation results are plausible and in line with theories on physician behaviour. However, the identification and quantification of the causal effects that are part of a feedback structure from observational data will be a further important area for future research. Robins and Hernán [7] present causal inference methods that allow for the analysis of the causal effect of a time-varying exposure on an outcome, where the exposure is allowed to depend on the former values of measured covariates and vice versa, that is, exposure and confounders form feedback loops. Such methods might therefore also prove valuable for the parametrization of system dynamics simulation models such as the one presented in this paper.

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