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INCORPORATING HUMAN BEHAVIOR IN HEALTHCARE SIMULATION MODELS

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ABSTRACT

For many years, simulation has been used to evaluate the outcomes from medical interventions designed to improve patients' health. However in practice these outcomes can be greatly affected by patient behavior. For example, patients may not complete a course of a prescribed medication because they find the side-effects unpleasant. A study designed to evaluate this medication which ignores such behavioral factors may give unreliable results. In this paper we discuss some of the issues involved in incorporating human factors in simulation models, and we describe two models for screening for different diseases which have attempted to include behavioral factors.

1 INTRODUCTION

Operations Research (OR) has been applied in the domain of healthcare for more than 40 years. The UK OR Society and the UK National Health Service (NHS) held a joint Colloquium on hospital appointment systems as far back as 1962 (Jackson, 1964). Since the 1960's OR models have been successfully used to assist clinical decision-making, facility location and planning, resource allocation, evaluation of treatments, and organizational redesign. Simulation is one of the most commonly used OR approaches, and is widely regarded as the technique of choice in healthcare because of its power and flexibility (Davies and Davies, 1994).

In this paper we consider the specific application of simulation modeling for the evaluation of medical treatments, or more generally healthcare interventions, which can include new medical technologies, screening programs, public health measures such as fluoridation of water, and health education initiatives such as smoking cessation programs. Evaluation in this context means not only clinical effectiveness (does the intervention work?), but also cost-effectiveness (does it represent value for money?).

Traditionally, the clinical effectiveness of a new treatment or intervention has always been evaluated through a randomized controlled trial (RCT). In an RCT the test population is divided randomly; some patients receive the new treatment, and others receive either a placebo or the current best available treatment. The RCT is regarded in the field of medicine as the "gold standard", but has considerable disadvantages in terms of cost and time. Of course there will always be a need for clinical trials of new drugs, but simulation modeling can replicate the effects of the intervention in the trial population in a fraction of the time needed for a full-scale RCT, and can then be used to conduct experiments which would be unethical or impracticable to carry out in practice, for example restricting the treatment to selected sub-populations, or treating the entire population of a large city.

Simulation can provide additional cost-effectiveness measures to aid healthcare managers, who have to choose whether to invest in particular treatments or technologies, some of which are extremely expensive. In most health economies, difficult choices have to be made between what treatments should be offered, given limited budgets, and this can lead to a "postcode lottery" where the availability of a drug depends on where you live. The controversy in the UK in spring 2006 as to whether the breast cancer drug Herceptin should be available to all patients, or just a subset, (BBC News, 2006) illustrates this dilemma. Ideally these choices would be made in a fair and objective way, based on all the latest information with regard to present and expected future outcomes. In the UK, modeling (of some kind) is now required by the National Institute of Health and Clinical Excellence (NICE) to support economic evaluations in making recommendations for the use of new technologies (National Institute for Clinical Excellence, 2004) and is thus widely used in the United Kingdom in determining which new drugs and other technologies should be funded.

It is self-evident that individual behavior can influence health outcomes. For example, adherence to treatment, in terms of taking a drug correctly (or even taking it at all) is a major factor and has been found in clinical studies to be surprisingly low, even among people with chronic or life-

threatening conditions. A systematic review by McNabb (1997) discussed the attitudes of patients with diabetes to all aspects of their treatment. McNabb found that adherence to insulin injections and other medication varied considerably between studies, from as low as 20% in one study to 80% in another. Adherence to medical advice about diet was about 65%, to monitoring recommendations (e.g. daily recording of blood sugar levels) was between 57% and 70%, and to exercise was very low (between 19% and 30%). McNabb suggests this may be due in part to imprecise instructions by doctors, or by difficulties in comparing adherence (missing a once daily insulin injection is far more serious than missing one 4-times-a-day tablet, but both are measured equally).

People may choose not to attend screening programs because they perceive the test as painful, expensive, a waste of time or merely inconvenient. Lifestyle choices such as diet, exercise and smoking can affect health. Therefore any model which ignores these behavioral factors could give unreliable results.

2 PSYCHOLOGICAL MODELS OF HEALTH BEHAVIOR

Three of the best known psychological models for health behavior are Rosenstock and Becker's Health Belief model (1996, 1974), Ajzen's Theory of Planned Behavior (1988, 1991) and Wallston's Multidimensional Health Locus of Control model (1992). The Health Belief Model is the oldest, most widely used and best known of all the models (Conner and Norman, 1995). This model is shown in Figure 1. Its variables are not technical psychological terms and can be understood by a lay person. Its disadvantages for modeling include the fact that there is no precise connection among some of the variables, so there is no obvious formal model structure. It also lacks some variables which have been found in practice to be important, e.g. intentions to perform an action and social pressures. However, the four basic constructs (perceived susceptibility, severity, benefits and barriers) are easily understood and interpreted.

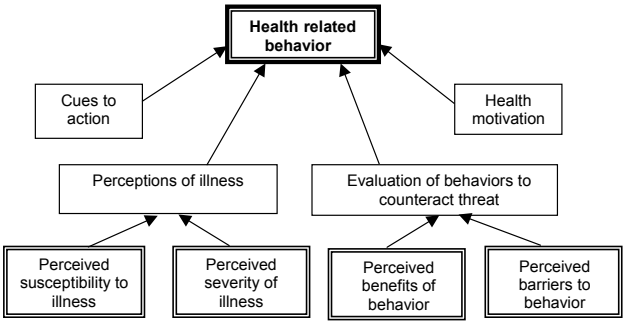

Figure 1: The health belief model

The Health Locus of Control (HLC) model (Wallston, 1992) is based on Rotter's well-established Locus of Control model (Rotter, 1954) in which two different psychological frameworks determine behavior. Internal locus of control (LC) is where an individual believes that events are a consequence of his or her own actions. External LC is where a person believes that events are determined by factors beyond the individual's control. Wallston developed this model in a health context and called it the multidimensional HLC. This measures the likelihood of a given health behavior along three axes, the first representing internal LC. External LC is divided into two aspects: Powerful Others and Chance (fate). The Internal LC axis is seen as the most important in healthy people. Powerful Others is mainly seen as an explanation for sick role behavior, such as compliance with medical advice. Chance, or fatalism, is interpreted as a feeling of lack of control. In practice, this model is a weak predictor of health behavior (Conner and Norman, 1995) and does not incorporate any concept of the value placed by an individual on their health.

The Theory of Planned Behavior (Ajzen, 1988, 1991) is an extension of the Theory of Reasoned Action (Fishbein and Ajzen, 1985). Fishbein and Ajzen argue that the equations represent the effects of learning; they do not suggest that people actually perform these calculations consciously! The model is shown in Figure 2. Intentions are determined by

- Attitudes (overall evaluations of the behavior by the individual).
- Subjective norms (do significant others think you should engage in the behavior).
- Perceived behavioral control (do I have the ability to perform this behavior?).

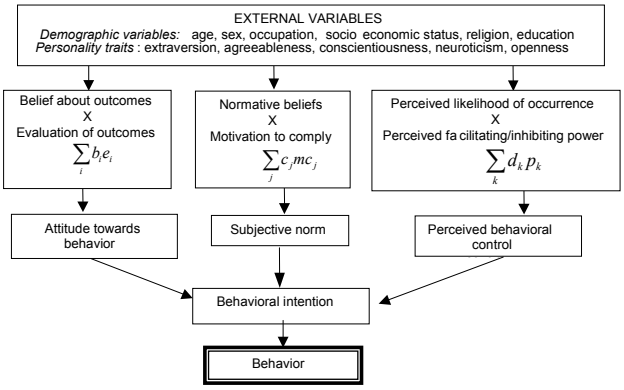

Figure 2: The theory of planned behavior

This model appears to have the greatest potential to be modeled mathematically. According to this model, motivation to behave in a given way is determined by the extent to which people believe the behavior will lead to outcomes which they value, that other people whose opinions they

value want them to do it, and they believe they have the necessary resources and opportunities to do it.

The model has been widely tested and successfully applied (Conner and Norman, 1995). It incorporates many important cognitive variables: intentions, outcome expectancies and perceived behavioral control. It also incorporates social pressures and makes clear causal links between variables and behavior. It is this model which is used in the second illustrative example in this paper, screening for breast cancer.

3 SCREENING FOR DISEASE

Screening refers to the testing of people who are at risk of developing a given condition, with the aim of early identification and diagnosis of that condition. The people screened may be perfectly healthy, for example women who are routinely screened for cervical or breast cancer. Alternatively, they may already have a precursor condition, for example patients with diabetes who are screened for diabetic retinopathy, a complication which can lead to blindness if untreated. For screening to be worthwhile, there must be benefits in early detection, either to the individual themselves in terms of improved prognosis and treatment, or to society in general, for example preventing the spread of infectious diseases. In terms of cost-effectiveness, a screening program must be designed to target the at-risk population as accurately as possible. Program planners must trade off the cost of screening too large a population, and thus performing many "unnecessary" tests, against the cost of not screening enough people and thereby missing cases. The costs of the screening program must be weighed against the costs of the disease if undetected. The test itself must trade off cost and pain/inconvenience to the patient against the accuracy of the test. Unfortunately, in general the cheaper and quicker the test, the less accurate it will be in terms of sensitivity (the probability that the test will correctly identify a true positive) and specificity (the probability that the test will correctly identify a true negative). The most accurate tests, such as biopsies, tend to be invasive and need to be carried out in a hospital setting.

Simulation models have been used for many years to evaluate the cost-effectiveness of screening programs. A simulation model has huge advantages over an RCT, in that typically such programs need to be evaluated over the lifetime of the at-risk population and so a trial of 40 or 50 years might be required. A range of decisions concerning the target population, the screening frequency, the setting (e.g. primary care or hospital), and the test itself can be tested and cost-effectiveness measures derived. These measures can include cost per life year saved, cost per quality-adjusted life year saved (in the case of people with other conditions, or where lack of treatment leads to disability rather than death), cost per case detected, number of screens required to detect one case, and so on. The results need to be discounted, in that the costs of a screening program are incurred from the outset, whereas the benefits may not accrue until many years in the future.

4 SCREENING FOR DIABETIC RETINOPATHY

Retinopathy is one of the most serious complications of diabetes. It can lead to blindness if untreated, but can, if detected sufficiently early, be successfully treated by laser. The patient is often unaware of the early signs of disease, so screening and timely treatment can be very effective in the prevention of blindness. Many different screening programs exist, with no clinical consensus about the ideal setting (e.g., hospital clinic, high-street optometrist, primary care), the ideal screener (e.g., specialist ophthalmologist, diabetic consultant, general practitioner) or the ideal interval between screens. A discrete-event simulation (DES) model was developed for the UK NHS (Davies et al, 2000, 2002, 2004) in order to investigate these different modalities and make recommendations to the NHS about good practice.

One of the interesting findings of this work was the key role played by patient compliance with screening, namely the probability that a person will attend for screening when invited on a given occasion. This result led Davies et al to recommend that screening methods which achieve a high compliance level are desirable. However their simulation modeled compliance only as a fixed probability of attendance, and did not model the behavior of individuals explicitly.

An attempt to include human behavior in this model was made by Brailsford and Schmidt (2003), using Schmidt's PECS architecture (Schmidt, 2000). PECS is founded on the view that Physical, Emotional, Cognitive and Social aspects need to be taken into account in any model of human behavior. Although PECS is a theoretical architecture, it was first implemented in an agent-based simulation framework and has been used to identify emergent patterns of behavior (Schmidt, 2000). In the retinopathy model, the PECS framework was combined with the Health Belief Model.

A number of factors known to affect attendance were identified from the literature. For example, in screening for breast cancer it is known that the number of previous attendances is a key factor in predicting future attendance (Weinberg et al, 1995). These factors also included health motivation (defined as good, medium or poor), perceived physical state (the patient's known stage of retinopathy), emotion (anxiety), perceived susceptibility to disease, knowledge about the disease, belief about disease prevalence, and social status, defined as the educational level.

These elements were linked together to form the HBM constructs, shown in Figure 3 below, in which the PECS elements are shown in shaded boxes which influence the

various constructs within the HBM. For example, a well-educated person is more likely to make a rational judgment, based on medical evidence, about the value of attending for screening. The connections between the elements in Figure 3 are specific to diabetic retinopathy. A different disease application would require different interpretations of the relationships between the PECS components and the HBM constructs.

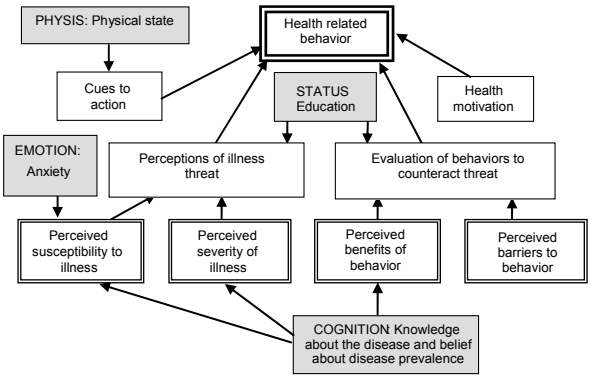

Figure 3: the HBM combined with PECS for diabetic retinopathy screening

In the DES model a population of diabetic patients is tracked over time. Each patient is an individual entity in the model, with his or her own characteristics, such as their history of disease and record of attendance for screening. The HBM/PECS approach was implemented by assigning numerical attributes, representing the various psychological characteristics, to the patient entities. The stage of retinopathy was already known for every person in the simulation, and the number of previous screening attendances was recorded for each patient. Anxiety, perceived susceptibility, knowledge of disease, belief about disease prevalence, health motivation and educational level were given values between 0 and 1. The four PECS components were then calculated from these attributes, and finally the probability of attendance was calculated as a binary decision variable.

The model used artificial data and the above equations were defined in a plausible but fairly arbitrary way. Therefore the results from this model are artifacts of the functional forms of these equations, and are not in any sense reliable, although they are plausible. However, in theory, by varying the psychological attributes it would be possible to investigate the effects of education programs aimed to increase people's knowledge of the disease, or reduce their anxiety, for example. The conclusions from this work were that the HBM is probably not the best vehicle for modeling, and that an approach which allowed the incorporation of reliable quantitative data for the psychological parameters would be much better, but that including such factors in a DES model was definitely possible in future.

5 SCREENING FOR BREAST CANCER

Breast cancer is the most common cancer in England, with about 36,500 new cases diagnosed in 2003 (UK Office for National Statistics, 2006). The death rate in 2003 was 29 deaths per 100,000 women, making it the most common cause of cancer death in women in the UK. Early diagnosis is associated with improved survival (UK Office for National Statistics, 2006). Screening tests include self-examination, physical examination by a health professional, and mammography (X-ray).

In the US, breast cancer is second only to lung cancer as a cause of cancer death in women (American Cancer Society, 2006). In 2006, about 40,970 women and 460 men are estimated to die from breast cancer in the United States (American Cancer Society, 2006), but in recent years death rates have been declining, possibly due to early detection and improved treatment. It is estimated that in 2006 about 212,920 new cases of breast cancer will be diagnosed among US women. Women living in North America have the highest rate of breast cancer in the world (American Cancer Society, 2006).

The UK breast screening program was introduced in 1988. Initially, mammography was offered every three years to all women aged between 50 and 64, and to women aged 65 and over on request. From 2001, this began to be extended to women in England aged 65 to 70, and to women over 70 on request. In 2003-04, three quarters of women aged 50-64 invited for screening in England underwent screening for breast cancer, and over 1.4 million women are screened each year (UK National Statistics Office, 2006).

Simulation models to evaluate breast cancer screening programs were developed as far back as the 1970's in the UK (Knox, 1973) and the 1980's in the Netherlands (the MISCAN model, Habbema et al, 1985). More recent models include Janson and Zoeteleif 's Monte Carlo simulation model (1997). Indeed breast cancer screening can be regarded as one of the classic areas for the application of simulation modeling in healthcare.

5.1 The simulation model

As part of her doctoral thesis, Sykes has developed a DES model representing the natural history of breast cancer in a cohort of women. Each woman entity was tracked through her life history. Various models for tumor growth have been proposed in the literature, and Sykes tested both a generalized logistic model (Spratt et al, 1993a, 1993b)

$$V(t) = 1.1(10)^6 \left[1023 e^{\frac{-1}{4} bt} + 1 \right]^{-4} \qquad (1)$$

and an exponential model (Friberg and Mattson, 1997)

$$V(t) = 10^{-6} e^{\frac{t \ln(2)}{\alpha}} \tag{2}$$

where *V(t)* represents the tumor volume at time *t*, *b* is the intrinsic growth rate (modeled by a lognormal distribution with mean ln(-5.84) and standard deviation ln(1.04)), and α represents the tumor doubling time, modeled by a lognormal distribution with mean ln(5.12) and standard deviation ln(0.77).

The age of onset of cancer was calculated from the UK South West Cancer Intelligence Service (South West Public Health Observatory, 2006), back-calculating from the size of tumor at registration using the above growth models. Finally, mortality rates from breast cancer and from other causes were derived from UK national statistics (UK National Statistics, 2006).

The probability of detection depends on the size of the tumor, and on the test itself. The model uses data from Michaelson et al (2003) and Tabar et al (2002). Michaelson's data was fitted to a Weibull (1.2, 1.03) distribution to give the probability of detection by mammography.

5.2 The behavioral data

Rutter (2002) carried out a study of the Theory of Planned Behavior using 2058 randomly sampled women from three UK health authorities. The questionnaire comprises demographic and socio-economic information, as well as recognized measures for the qualitative constructs in the TPB.

The questionnaire was sent out to the random sample of women before they were invited for their screening session. Answers to the majority of questions were requested on an ordinal rating scale, and the final calculated measures of attitude to mammography, subjective norms relating to mammography screening and perceived behavioral control, in relation to screening attendance, are all scalar variables calculated from the rating scale responses. The dataset also includes the attendance/non-attendance information for each woman at the subsequent screening session, as well as the next screening session three years later, collected from the relevant mammographic screening clinics.

Under the TPB the three variables, attitude, perceived behavioral control (PBC), and subjective norms, join together in a linear regression equation to predict intention to attend. Intention to attend and PBC then go on to predict the behavior itself with their own regression weights. If this is the case, then it should also be possible to model attendance directly as a function of the three predictor variables, and effectively skip the intermediate variable of intention, as shown in equation (3) below. Since attendance is a binary response variable, (either the woman attended or she did not), the probability of attendance, π, can be regarded as the result of a Bernoulli trial with probability π of success. The probability π can then be modeled as a linear function of the three inputs attitude, subjective norms, and PBC, denoted X_1, X_2, and X_3 respectively. In order to ensure π lies between 0 and 1, a logistic transformation is performed such that

$$\ln\left(\frac{\pi(\underline{\beta}, \underline{X})}{1-\pi(\underline{\beta}, \underline{X})}\right) = \beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3 \tag{3}$$

The values of the β_i were then estimated by maximum likelihood methods. In his study, Rutter found the TPB to be a strong predictor of attendance, but the three variables (attitude, perceived behavioral control, and subjective norms) were highly correlated. Instead of creating a multivariate distribution capturing this correlation, and then using this to sample values for the simulation, specific values of the β_i were assigned to the simulation entities at random, according to empirical values observed in the data for individual women in Rutter's study, and the equation

$$\pi = \frac{\exp(\beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3)}{1 + \exp(\beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3)} \tag{4}$$

was used to calculate the probability of attendance. At any given screening visit, a uniform random number is sampled and if this is less than or equal to π, then the woman will attend.

5.3 Using the Model

Outputs from the model include the number of screens performed, the number of cancers detected, the number of cancer deaths, the number of non-cancer deaths and statistics relating to the size of tumors at detection. The model can be used for comparison against a baseline of no screening, or, more realistically, a baseline corresponding to current policy. The model collects data on the "life-trajectory" of every woman, enabling further analysis to be performed to calculate the total number of life-years saved by a particular screening program. The model was validated against UK screening and detection data. Clearly, it can be used in a traditional mode, setting π equal to a constant, and simply varying the screening interval or the age bands within which mammography is offered, to enable the user to compare the clinical effectiveness and the cost-effectiveness of screening programs in a conventional way.

However it is also possible to use the model to investigate the effects of behavioral interventions. Such interventions could include education campaigns designed to

increase women's belief in their own perceived behavioral control, or to raise awareness and thereby change women's attitudes, for example. The model is currently being used to carry out experiments with a range of arbitrary modifications to the β_I ,parameters, representing the effects of changes in attitude or perceived behavioral control as a result of interventions. The next stage of the work will be to consider how such changes could realistically be achieved in practice, and to use the model with psychologists and health policy planners in order to estimate the impact of interventions designed to modify behavior in terms of attitude, perceived behavioral control, and subjective norms. This will potentially aid decision-making and help to answer questions such as "can we achieve the same benefits through a media advertisement campaign as we could through some expensive new technology?"

6 CONCLUSIONS

In the past decade, human behavior has been increasingly recognized as being of importance in the design and evaluation of manufacturing systems (Youndt et al, 1996). In the UK, Baines et al (2005) have developed a framework for incorporating human performance in simulation models of manufacturing systems. In this model, worker performance is viewed as the result of an interaction between three groups of factors: factors concerned with the individual worker, factors related to the physical working environment, and factors related to the organisational working environment.

In this paper we have shown that it is indeed possible to incorporate recognized, measurable psychological variables in a discrete-event simulation model of a healthcare intervention, and to use these factors to determine realistically whether or not a person chooses to comply with this intervention. The possibility of explicitly modeling the effects of interventions designed to change behavior is even more exciting.

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