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THE CASE FOR INCORPORATING HETEROGENEITY AND MALLEABILITY OF PATIENT SCREENING BEHAVIOR IN SIMULATION MODELS

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ABSTRACT

Simulation models have been used extensively to evaluate and aid in planning of health screening strategies in health care. In typical simulation models, patient screening behavior is often assumed as homogeneous (patient characteristics do not influence the probability of undergoing screening) and rigid (invariant with time, and not malleable by screening interventions), and modeled as such. However, patient screening behavior in reality is heterogeneous and malleable. Disregarding these realities affect the model functionality and modeling outcomes. We propose two general simulation model structures: one representing a typical existing simulation model and another representing a simulation model that incorporates heterogeneity and malleability of patient screening behavior. We then illustrate both model structures by implementing it in the case of Diabetic Retinopathy eye screening. Comparison of the two resulting models indicate that heterogeneity and malleability of patient screening behavior should be addressed in simulation models to improve model functionality and precision of outcome estimates.

1 INTRODUCTION

Simulation models have been used extensively to evaluate and aid in planning of health screening strategies in health care. Patient screening compliance (whether or not a patient adheres to screening guidelines and goes for screening) has a large role on the effectiveness of the screening program outcomes, since patients need to come for screening to realize the benefits of screening. Thus, it is important to address patient screening compliance in a manner that reflects reality in the simulation model, since it is an important determinant of health outcomes and thus cost-benefit of screening strategies.

However, there are limitations in the way current typical simulation models take patient compliance into account. In typical simulation models, patient screening behavior is often assumed as homogeneous (patient characteristics do not influence the probability of undergoing screening) and rigid (invariant with time, and not malleable by screening interventions), and modeled as such.

However, patient screening behavior in reality is heterogeneous (affected by patient characteristics) and malleable by intervention and time. For instance, several studies have shown that females are more likely to go for screening services than males (Thomas et al. 1995) (showing heterogeneity of patient compliance), patients' likelihood of screening compliance is fluid and may change with age (Weinberg et al. 2004) or disease severity (i.e. patient compliance is malleable with time), and policymakers can implement policies that will increase screening rates, such as by removing financial barriers to screening through mandatory health insurance and no out-of-pocket costs for screening services in the Affordable Care Act / ACA (i.e. patient compliance is malleable by intervention).

Disregarding these realities will have an effect on the simulation model functionality and precision of the modeling outcomes. First, without addressing the malleability of screening compliance by interventions, we limit model functionality as we will be unable to evaluate screening policies that intend to improve compliance, such as the ACA. Second, without addressing the heterogeneity and malleability with time of screening compliance, we will end up with imprecise estimates of true screening rates and thus outcome estimates.

Several papers have explored the incorporation of patient behavior into simulation models (Brailsford and Schmidt 2003; Brailsford, Harper, and Sykes 2012; Durham and Casman 2011). These approaches use the mathematical formulation of psychological / behavior models such as the HBM (Health Belief Model) and TPB (Theory of Planned Behavior) to model patient behavior. These formulations have the advantage of enabling the modeler to have more control over behaviors at an individual level. However, to construct a validated patient behavior model that represent patient behavior accurately using these formulations require survey data that measure the constructs of HBM or TPB as well as patient screening compliance for the disease of interest. Such surveys are often not readily available or may have a small sample size, which limits generalizability.

This paper utilizes readily available empirical data in public surveys such as CHIS (California Health Interview Survey), NHIS (National Health Interview Survey), BRFSS (Behavioral Risk Factor Surveillance Systems), or NHANES (National Health And Nutrition Examination Survey) to construct the patient behavior model. Such surveys regularly collect data on a wide array of patient characteristics and patient behavior (such as attendance for breast cancer screening, colonoscopy, Diabetic Retinopathy screening, and adherence with prescribed self-care, such as checking blood glucose levels regularly), allowing for the construction of various patient behavior models. They also have a substantial sample size and are designed to be representative of the state or national population.

This paper demonstrates a simple method of constructing a patient behavior model whereby the probability of patient screening compliance is conditioned on patient characteristics and intervention considered. In this case, we use regression analysis on empirical data to obtain the parameters for the screening compliance probability equation that incorporates patient characteristics and intervention.

The simplicity and familiarity of this method to researchers and practitioners outside the Operational Research and Simulation Modeling domain might have the added benefit of facilitating their adoption of simulation modeling methods that incorporate patient behavior in the spheres of public health and health services research.

Additionally, we want to explore whether patient screening behavior is indeed important to consider when evaluating screening strategies using simulation models. Specifically, we want to investigate the benefit of incorporating greater complexity / realism in the patient behavior component of the model as opposed to using traditional healthcare simulation models that incorporate patient compliance in a simplistic way (typically using an overall percentage of compliance). To achieve that, we first propose two general simulation model structures: one representing typical existing simulation model and another representing simulation model that incorporates heterogeneity and malleability of patient screening behavior. We then illustrate both model structures by implementing it in the case of Diabetic Retinopathy eye screening. We then compare the two resulting models in terms of model functionality and precision of outcome estimates to determine if indeed heterogeneity and malleability of patient screening behavior are important to incorporate in simulation models.

2 GENERAL SIMULATION MODEL FRAMEWORK

2.1 High-level Modeling Framework

To make the case that heterogeneity and malleability need to be considered, we first propose two general model frameworks, model 1 and model 2. Shown in figure 1, model 1 is an abstraction of typical simulation model structures in which patient compliance is assumed to be homogeneous and not

malleable, and such in the diagram it is unaffected by other parameters and is a fixed input parameter. Shown in figure 2, model 2 is a representation of a simulation model structure that does incorporate heterogeneity and malleability of patient compliance, thus patient compliance is no longer a fixed input parameter, but a mediating variable affected by patient characteristics and screening strategy (i.e. the intervention at hand). In model 1, probability of patient compliance is unconditional; in model 2, it is conditional on the patient characteristics (i.e. incorporating patient heterogeneity) and screening strategy (i.e. incorporating malleability of screening behavior by the intervention / screening strategy used).

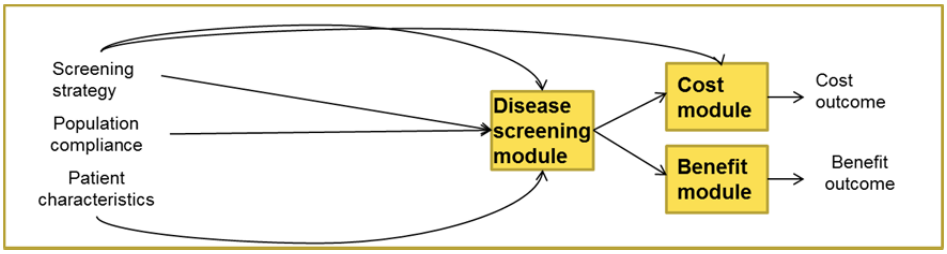

Figure 1: Model 1 – A representation of a typical simulation model structure.

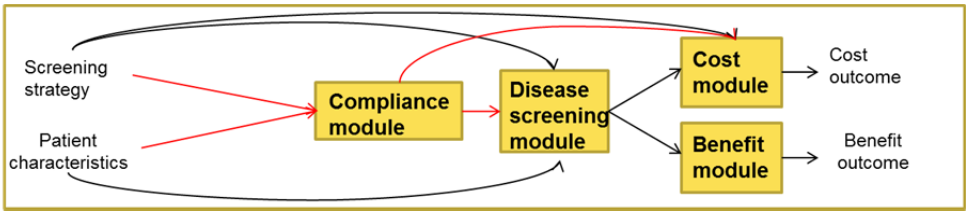

Figure 2: Model 2 – Simulation model structure incorporating heterogeneity and malleability of patient screening behavior.

The figures above give a high-level conceptual view and are not intended to depict all factors and variables responsible for the outcomes associated with screening comprehensively. The model contains other interacting elements not portrayed in the diagram, which would be elaborated on in the following sections.

The table below summarizes the effect of incorporating heterogeneity and malleability of patient compliance on model functionality and precision of outcome estimates.

Table 1. Effect of differences in model specifications on model functionality and precision of outcome estimates.

Effect on	**Model 1**	**Model 2**
Functionality	Cannot evaluate screening strategies that intends to improve patient compliance	Can evaluate screening strategies that intends to improve patient compliance
Precision of estimates: Health outcomes	Imprecise estimates as it ignores correlation of compliance with other parameters	Provides more precise estimates of health outcomes
Precision of estimates: Screening cost	Imprecise estimates as it ignores correlation of compliance with other parameters	Provides more precise estimates of screening cost

3 ILLUSTRATIVE EXAMPLE: DIABETIC RETINOPATHY EYE SCREENING

To illustrate the general conceptual models above and to compare model functionality and outcomes, the two models are implemented for the case of Diabetic Retinopathy (DR) eye screening. DR is chosen because it is an important problem: DR, a chronic complication of diabetes that results in retinal damage, is the leading cause of blindness among working age Americans (Seema and Davis 2009). DR screening can be very effective in identifying patients at high risk for DR for treatment, and treatment for DR is highly effective in halting the progress of the disease and preventing blindness (Javitt et al. 1994). However, compliance with eye screening guidelines – which is outlined by the NEI (National Eye Institute) to include a comprehensive dilated eye exam at least once a year for people with diabetes - is very low, and this is especially so for the underserved community (Paz et al. 2006).

As simulation modeling methods for DR eye screening are well-established in the literature (Dasbach et al. 1991; Brailsford and Schmidt 2003; Harper et al. 2003), the focus of this paper is not on the DR disease progression simulation model itself, but on the patient behavior model and the investigation of the benefit of the added complexity in the patient behavior model versus a simplistic patient behavior model. To give sufficient coverage for those topics while adhering to the length limitation of this paper, only an overview of the DR progression model profile and parameters are given here. The detailed model profile, including listing of the assumptions, detailed model structures, and parameters can be requested from the corresponding author.

3.1 Overview

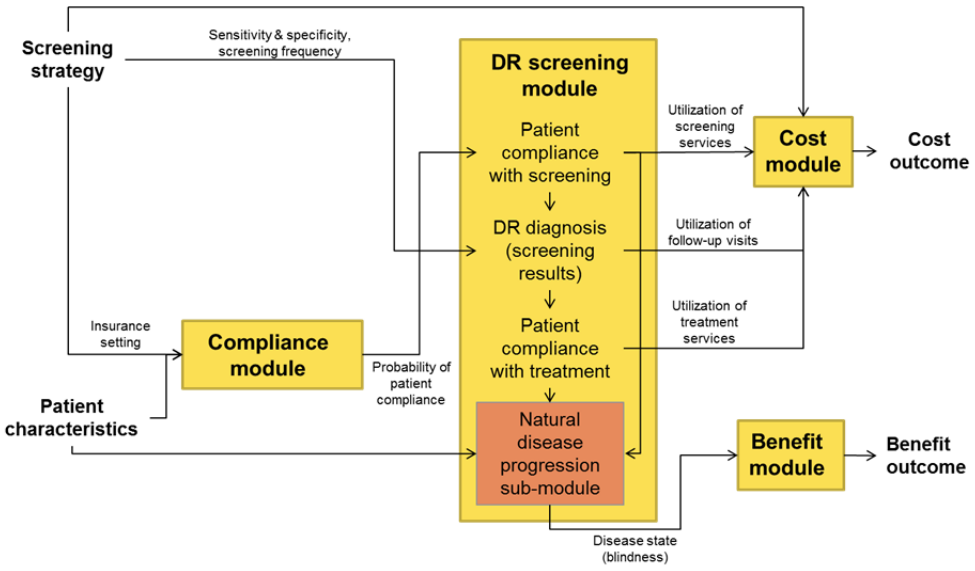

Figure 3. DR screening simulation modeling schema for model 2.

Both models 1 and 2 are built for the case of DR eye screening. This simulation model is a Monte Carlo Markov simulation of individual patient life histories to constitute a relevant cohort population. The simulation model models a population with Type II diabetes consisting of individual patient life histories in which Diabetic Retinopathy may develop and the effect of various screening strategies on compliance, time of diagnosis, blindness, and overall societal cost-benefit. The models are constructed in Matlab 9.1. The detailed modeling schema for model 2 is shown in figure 3. The detailed modeling schema for model 1 is not shown since model 1 is a subset of model 2.

The patient population cohort simulated here represents the Type II diabetes patients in the Los Angeles County Department of Health Services (LACDHS) clinics, 42265 patients in total. The patient population cohort used in this simulation model is representative of California population with Type II diabetes (it is assumed that the Los Angeles diabetic population is similar to the California diabetic population) and is based on the 2009 California Health Interview Survey (CHIS), a representative telephone survey of California population (CHIS Sample Design 2007).

The length of the simulation period is 30 years. The entire simulation is run 30 times as a Monte Carlo simulation to achieve an acceptable Square Error of Mean (SEM)/mean ratio.

The DR screening module structure and parameter values are based on a seminal paper on using simulation to evaluate DR screening strategy by Dasbach et al. (1991). This DR screening module uses a Markovian DR natural disease progression model that is modified by screening and treatment. Utilization of various health care services is tracked in the simulation to calculate costs, and patients' disease states are also tracked to calculate benefits of the screening strategies.

Evaluation of net benefit is done using the societal perspective. Cost-benefit analysis is used to determine the societal net benefit of each screening strategy scenario considered. Costs include screening and treatment costs, and consider both fixed and variable costs. The benefits include savings from averted direct and indirect medical and non-medical costs as well as savings from averted productivity losses. Direct medical costs include both eye-related medical costs, such as eyeglasses and ophthalmologist visits. Indirect medical costs include non-eye-related costs, which are medical costs due to secondary outcomes of blindness, including depression and injury. Direct nonmedical costs include nursing home care and long term care include visits from nurses and counselors and home rehabilitation and therapy as well as other types of home care. Cost parameters are taken from the Bureau of Labor Statistics and a Veteran Administrations study (Lairson et al. 1992). Benefit parameters are taken from Rein et al. (2006) and Javitt, Zhou, and Wilke (2007). All cost and benefit figures are converted to 2012 dollars using the CPI index. All future costs and benefits are discounted by 5%.

Both models will be used to evaluate screening strategies consisting of three components (modality, screening frequency, and insurance); for each screening strategy component, we will have two alternatives to choose from. Thus, we will have a total of 2^3=8 possible screening strategy scenarios to consider. The screening strategy components and alternatives are given in table 2.

Table 2. Screening strategy components and alternatives considered.

	Alternatives	
Screening strategy components	1	2
Screening modality	Status quo (Opthalmoscope)	Non-mydriatic camera
Screening frequency	Status quo (Annual)	Biennial (every 2 years)
Insurance	Status quo	Mandatory health insurance

3.2 Incorporating Heterogeneity and Malleability of Patient Compliance

To incorporate heterogeneity and malleability of patient compliance, the probability of patient compliance is conditioned on patient characteristics and the screening strategy (intervention) used. To populate the coefficients in this compliance module, we need to know the effect of patient characteristics and patient-level screening strategy on compliance. To do so, we perform logistic regression analysis on data from California Health Interview Survey (CHIS) 2009 with the following variables:

Dependent variable: Compliance

Independent variables:

- Demographics (age, race, sex, living within 200% poverty level, married, education level, employment status)

- Comorbidity (presence of one or more additional diseases co-occurring with diabetes) and disease severity (high blood pressure, heart disease, on insulin)
- Access (having insurance in the past 12 months)
- Quality of Care (doctor checking blood glucose / HbA1C level, doctor checking feet, doctor helping to coordinate services)
- Self-care (smoking, frequency of physical exercise, frequency of eating fast food, frequency of eating fruit & vegetables, frequency of checking HbA1C level)
- Self-efficacy (confidence to control and manage diabetes)

The results of the regression analysis are used to populate the coefficients of the baseline compliance equation reflecting the relationship between compliance and patient characteristics and the coefficients for the patient-level compliance module equation reflecting the relationship between compliance and patient-level screening strategy component (i.e. status quo insurance vs mandatory health insurance).

First, to incorporate the heterogeneity of patient screening behavior, the baseline patient compliance is calculated based on patient characteristics using the following logistic regression equation:

$$logit\ (p_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_m x_{mi},$$

Where:

$$p_i = baseline\ probability\ of\ compliance\ of\ patient\ i$$
$$\beta_m = coefficient\ for\ variable\ x_m$$
$$x_{mi} = independent\ variable\ m\ (e.g. age, whether\ on\ insulin, having\ insurance, etc) of\ patient\ i$$

Then, to incorporate the malleability of patient compliance by the intervention (in this case insurance), we modify the baseline patient compliance equation above to obtain the following patient-level equation:

$$logit\ (p_i^*) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_m {x_{mi}}^*$$

Where:

$$x_{mi}^* = \begin{cases} 1, & if\ screening\ strategy\ component\ m\ targets\ patient\ compliance \\ x_{mi}, & if\ screening\ strategy\ component\ m\ does\ not\ target\ patient\ compliance \end{cases}$$
$$p_i^* = modified\ probability\ of\ compliance\ of\ patient\ i\ after\ patient - level\ screening\ strategy\ component\ are\ applied$$

This equation for example sets every patient's insurance variable to one if mandatory health insurance is selected in the screening strategy scenario. Note that this does not affect every patient's probability of screening compliance equally, as this will only affect the probability of screening compliance of patients who did not have health insurance in the first place.

4 MODEL COMPARISON

After building models 1 and 2 for the case of DR screening, we compare the resulting models to determine the effect of incorporating heterogeneity and malleability of patient screening behavior on model functionality and outcome estimates.

4.1 Effect of Incorporating Malleability of Patient Screening Behavior on Functionality

Incorporating the malleability of patient screening behavior allows for the evaluation of a greater range of scenarios. Models 1 and 2 can evaluate different mechanisms of influence of an intervention. The structure of model 1 does not allow for evaluation of multi-level screening strategy components addressing behavioral modification involving screening compliance. Thus, model 2 can be used to evaluate screening strategies that include components that cannot be evaluated by model 1, i.e. health insurance in this case.

In all the tables below, numbers "1" and "2" in the scenario refer to alternatives "1" and "2" of each screening strategy component respectively. Thus, scenario no 1 in table 3 refers to the status quo scenario (modality 1 and screening frequency 1 both refer to status quo), scenario 2 refers to using non-mydriatic camera as the modality (i.e. modality 2) with annual screening frequency (i.e. screening frequency 1 or status quo), and so on.

Table 3. Model 1 results: averted blindness, costs of screening & treatment, and net benefit.

Scenario no	Scenario		Averted blindness (years)			Costs of screening & treatment	Societal net benefit
	Modality	Screening frequency	Total	<65 year old	≥65 year old		
1	1	1	3714	2549	1164	$14,275,600	$77,078,377
2	2	1	4341	2989	1353	$22,374,990	$84,513,634
3	1	2	2784	1945	839	$8,895,480	$60,061,836
4	2	2	3443	2399	1044	$13,577,702	$71,613,024

Table 3 and 4 shows the results for model 1 and 2 respectively. As shown in table 4, the results show similar trends as the results of model 1 for the first 4 scenarios, with scenario 3 resulting in the highest averted blindness and costs of screening and treatment, while scenario 3 results in the lowest averted blindness and also lowest costs of screening and treatment. While the trends are similar, the actual numbers differ between the results from model 1 and 2 for scenarios 1-4. These differences in precision of the outcome estimates are later discussed in section 4.3.

Scenarios 5-8 evaluate scenarios 1-4 with one additional component of health insurance; scenarios 1-4 consider status quo insurance, while scenarios 5-8 consider mandatory health insurance as a patient-level intervention to increase screening compliance. As mandatory health insurance will increase screening rates across the board, scenarios 5-8 each have higher averted blindness and also higher costs of screening and treatment than each of their counterparts in scenarios 1-4 where there is no health insurance intervention. Thus, out of the 8 scenario alternatives, the alternative with the highest averted blindness as well as the highest of cost of screening and treatment is scenario 6 (annual nonmydriatic camera screening with mandatory health insurance), the counterpart of scenario 2 with an additional intervention in the form of mandatory health insurance.

Table 4. Model 2 results: averted blindness, costs of screening and treatment, and net benefit.

Scenario no	Scenario			Averted blindness (years)			Costs of screening & treatment	Societal net benefit
	Modality	Scr_freq	Insurance	Total	<65 year old	≥ 65 year old		
1	1	1	1	3301	2172	1129	$13,423,416	$66,679,765
2	2	1	1	3912	2583	1329	$21,020,459	$73,960,934
3	1	2	1	2393	1579	814	$8,289,272	$49,860,791
4	2	2	1	2991	1966	1025	$12,678,415	$59,859,596
5	1	1	2	3440	2280	1160	$13,869,158	$69,780,689
6	2	1	2	4057	2698	1359	$21,741,748	$76,966,750
7	1	2	2	2520	1679	840	$8,583,082	$52,808,107
8	2	2	2	3132	2079	1053	$13,120,004	$63,077,999

4.2 Effect of incorporating malleability of patient screening behavior with time on precision of outcome estimates

Model 2 uses a compliance model that is dynamic (malleable with time), in that a patient's probability of compliance increases (i.e. does not remain static) as they age, reflecting a patient's tendency to adhere to screening guidelines more as they age (this has been shown in different screening cases beyond DR screening, both in cross-sectional (Weinberg et al. 2004) and longitudinal studies (Thomas et al. 1995). The dynamicity of the compliance model also has an effect on the compliance and thus outcomes.

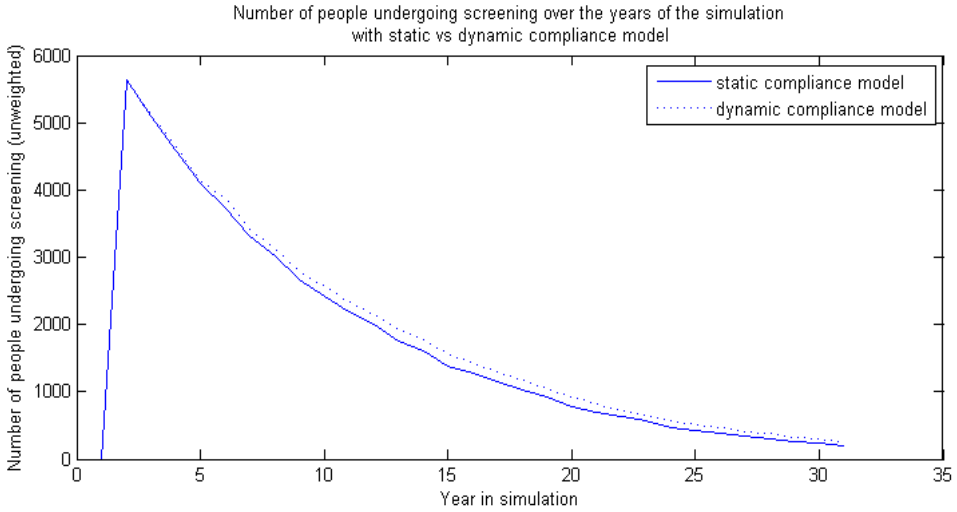

Figure 4. Number of patients undergoing screening over the years of the simulation with static vs. dynamic compliance model for one repetition of the simulation.

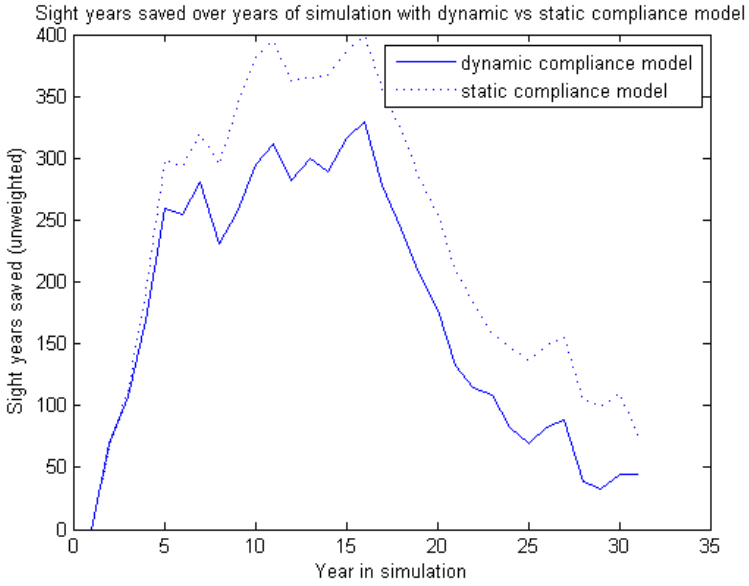

Figure 5. Sight years saved over the years of the simulation with static vs dynamic compliance model for one repetition of the simulation.

Figure 4 shows the effect this has on the number of patients undergoing screening over the years in the simulation for one repetition of the simulation. Both cases start with the same number of people undergoing screening which declines with passing simulation years as patients die in the simulation. However, in the static compliance model, patients retain the compliance probability that they start with in the simulation throughout the simulation. As the older patients who start out with a higher probability of screening compliance die in the simulation, the simulation is left with a pool of patients that are less likely to undergo screening than the one it starts with. In contrast, with the dynamic compliance model, as the older patients die in the simulation, the remaining patients left in the simulation has an increased probability of compliance as they age. Consequently, the case using the static compliance model declines at a lower rate.

This difference in the compliance rate of screening using the two models consequently impact the outcomes. As fewer patients comply with screening in the case of the static model, the averted years of blindness is lower too (as shown in figure 5), affecting the costs and benefits. Thus, the dynamicity (malleability with time) of the compliance model is another important consideration in the model specification.

4.3 Effect of Incorporating Heterogeneity of Patient Screening Behavior on Precision of Outcome estimates

Figures 6 and 7 illustrates aspects of differences in the compliance model specification between model 1 and model 2 which lead to differences in outcome estimates between the two models. Probability of screening compliance is correlated with some factors that influence outcomes, such as age and insulin use.

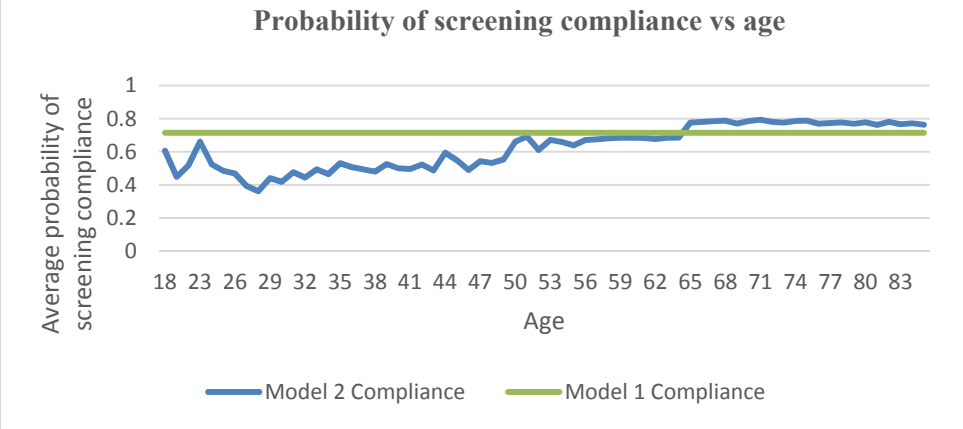

Figure 6. Graphs of probability of screening compliance vs age for models 1 and 2.

Figure 6 plots the average probability of screening compliance of the population at each age group at the beginning of the simulation. For model 2, there is a positive correlation between age and probability of screening compliance (older patients more likely to comply with screening). For model 1, everyone in the simulation has the same probability of screening compliance regardless of age (i.e. the probability of screening compliance is not age dependent. This non-age-dependent probability of screening compliance in model 1 is specified to be the overall mean of probability of screening compliance in model 2.

Figure 7 shows the average probability of screening compliance of the population for those on insulin and those not on insulin at the beginning of the simulation. For model 2, we can see that there is a negative correlation between insulin use and probability of screening compliance, while again, for model 1, everyone in the simulation has the same probability of screening compliance regardless of insulin use.

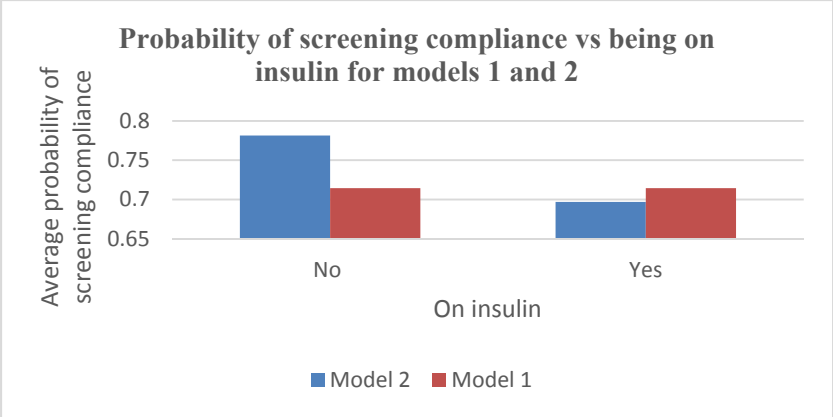

Figure 7. Graphs of probability of screening compliance vs insulin use for models 1 and 2.

Table 5 shows the percentage differences in model outcomes between models 1 and 2. In all scenarios, model 1 overestimates the averted blindness by 10-14%. This overestimation is magnified when using a screening strategy scenario that uses less sensitive modality or lower screening frequency.

Both of the reasons above result in differences between estimates of societal net benefit from model 1 and model 2 ranging from 12–17%.

Table 5. Percentage difference in outcomes of model 1 vs model 2.

Scenario no	Scenario		Averted blindness (% difference)	Costs of screening & treatment (% difference)	Societal net benefit (% difference)
	Modality	Scr_freq			
1	1	1	-11.10	-5.97	-13.49
2	2	1	-9.88	-6.05	-12.49
3	1	2	-14.04	-6.81	-16.98
4	2	2	-13.13	-6.62	-16.41

There are two major reasons related to the difference in the compliance model structure that leads to the overestimation. First, since in model 1 the probability of screening compliance is the same regardless of patient's age, as we can see in figure 6, model 1 ends up overestimating the probabilities of screening compliance of the younger patients and underestimating those of the older patients. As a result, younger patients are more likely to undergo screening and thus have their blindness averted in model 1 than in model 2, while older patients are more likely to undergo screening and have their blindness averted in model 2 than model 1. However, since younger patients would live longer and have more years of averted blindness than the older patients, the number of sight years saved in model 1 ends up higher than it should be due to the inaccurate specification of compliance model.

The second major reason leading to the overestimation is the correlation of screening compliance with diabetes severity (with insulin use as an indicator). Patients on insulin are less likely to go for screening than those not on insulin (perhaps due to lower functional status), but they are also at a higher risk of developing DR and blindness. As seen in figure 7, in model 1, as all patients have the same probability of screening compliance regardless of disease severity, the model ends up inflating the screening compliance probability of patients on insulin and deflating the screening compliance probability of patients not on insulin. Again, this has the result of overestimating the resulting averted blindness since

patients on insulin who are more likely to have DR are more likely to get screened and thus have their DR treated in model 1 than in model 2. This is also the reason the costs of screening are overestimated in model 1 by about 6-7%: in model 1, patients on insulin are more likely to go for screening, but such patients are also more likely to have DR and thus to require treatment, thus incurring higher costs of treatment overall than in model 2.

5 DISCUSSION

This paper has demonstrated the need for better reflection of patient screening behavior / compliance structure and highlights the importance of considering the heterogeneity and malleability of patient screening behavior in simulation models. From the modeler's and the health services researcher's perspective, this new modeling paradigm will allow the evaluation of a wider range of preventive strategies scenarios, especially those involving behavioral interventions. This would allow the policymaker to consider the inclusion of screening strategy components that have different mechanisms to increase compliance to increase screening uptake and maximize the net benefit from screening. In addition, it will also increase precision of modeling estimates even for interventions that could be previously evaluated with existing model structures.

The model comparison has indicated that an incomplete model specification that oversimplifies the compliance structure result in significantly imprecise model estimates in some cases. The degree of imprecision is dependent on the underlying characteristics of compliance structures. Thus, in the interest of model parsimony and simplicity, in cases where there is no underlying relationship between patient screening compliance with other factors that influence outcomes of interest, the modeler might consider a vastly simplified compliance model (such as the one used in model 1, which uses the population compliance as the prevailing compliance probability for every individual). The modeler would need to determine to what extent compliance heterogeneity in the model is warranted to balance model parsimony with precision of the estimates. For instance, in the DR screening example above, we can consider using a simplified compliance model with only components that have the most significant impact on the averted blind years (age and insulin) with minimal loss of precision in model estimates.

Future work is underway to incorporate heterogeneity and malleability of provider behavior into the model, and to propose general methods to parameterize the compliance model beyond the simple method shown here to expand the use of the model for other scenarios pertaining to changing behavior that entail new interventions / combinations of interventions not yet available in publicly available surveys.

6 CONCLUSION

As patient screening behavior is a determinant of health outcomes and thus cost-benefit of screening services, there is a need to consider more realistic behavior models in simulation models. This research has proposed a general simulation model framework that explicitly models the heterogeneity and malleability of patient screening behavior using a simple method that utilizes readily available public survey data and demonstrated the general framework for the case of DR screening. This research also showed that incorporating the heterogeneity and malleability of screening behavior can have significant impact on model functionality and outcomes. For policy analysis, this simulation model framework can evaluate screening strategies that include components to improve screening compliance, allowing for evaluation of a greater range of screening strategies to optimize net benefit, and provide more precise outcome estimates.

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