Simulation of Chronic Diseases Screening: Revisiting Policies Effect

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Abstract In this paper, a simulation tool based on a statistical simulation approach is presented to help US Veterans Affairs (VA) and Congress policymakers to have a better picture of different policies in chronic disease screening. We investigated different policies in two criteria; revisit intervals and panel size (number of clinicians). Our developed tool's simulation results shows more expenses in longer interval policies while these policies have higher rates for access to care within 30 days and have no significant weakness in capacity efficiency. Beside, VA recent plan to make an *on demand* panel size policy may cause some risks in non-symptomatic patients' conditions, but it is he superior policy considering three indices of access, capacity and costs.

1. Introduction

Primary care is one of the most affecting issues in public health, however, we don't know enough about its optimum timing, content and quality of visits, especially for chronic diseases screening [1,2]. In this paper, with the purpose of helping policymakers in department of Veterans Affairs (VA) and US Congress, we try to simulate different screening policies and the effect of such policies on access. Therefore, we made use of discrete time approach to simulate different patients' appointment making procedure by clinicians to investigate their results on access for a revisit within 30 days after a patient call.

Mass screening has always been an important issue for every nationwide health system, because a considerable number of elders in each society have at least one chronic illness [3]. In this regard, having an effective screening policy is necessary for both healthcare authority, policy makers and patients. We verified the presented model by a software tool written in Visual Basic for Application (VBA) to investigate access to care, Health Outcomes (HO) costs and capacity usage efficiency of each policy. According to the implementation results, the Screening Simulator (Sc Si) resembles the effects of different appointment policies on patients' access for a revisit, which can give a very good managerial insight to the healthcare authority and policy makers about the optimum policy on revisits intervals and cost evaluations.

2. Related works

In order to deal with screening problems, some works try to present general frameworks. [4-8]. Some others tried to have some cost-effectiveness evaluations [9-11]. There is also a number of works on healthcare delivery and decision making using Operations Research (OR) and mathematical modeling techniques like machine learning and linear programming [12-23]. Schlessinger and Eddy presented a mathematical model to cover all clinical, procedural and administrative aspects of health care. This model simulates the procedure and has two parts; psychological and care process, the Archimedes model [24]. Following this model, there are some other works, each tried to develop a corner of the basic Archimedes [25-28]. In order to deal with clinical appointment planning, so many works are in the literature and the concentration of these works varies from finding a good trade-off between fairness and revenue to forecasting of future demands [29-40]. There have been some works on considering patients' behavior and preferences and/or their satisfaction effects on appointment [41-43].

There is another question with no certain answer about which policy (prolonging or shortening) for the revisits intervals suits the access? There are so many works trying to answer this question in the literature

[44,2,45,46]. Cause there are some works asserting the prolonging policy [1,47-50], while there exist works applauding the opposite hypothesis [51-56].

Finally, Eddy's research provides a good introduction of the cancer screening problem and provides a Markov Chain-based approach to model the breast cancer screening [57]. This work is the basis of our problem.

3. Screening problem and solution method

3.1. Problem of chronic diseases screening

Health center clinicians are responsible for chronic disease screening. Each chronic disease has its special attributes to be considered for revisits scheduling. Moreover, each patient will have his/her health condition and arriving behavior for planned appointments. For instance, some patients may be able to feel some signs of acuteness, by which they can tell their general Clinical Situation (CS) is possibly getting worse. There is also some factors of screening procedure by changing which, the screening policies can be adjusted. For example, one important factor is the last age in which screening has to stop.

Patients may have one more chronic diseases, or no chronic disease at the time of the initiation. In addition, they have a history of last time they were visited by the physicians. Some patients may be able to detect signs of symptoms and, because of that, they are prone to show up earlier for a revisit. Some others may be compelled by some difficulties. In this regard, the more a patient is aware of his/her condition the more chance he/she has to detect a possible symptomatic condition (we call it *diagnosis ability* of patients). Based on patients' situation for each disease, physicians may detect different level of illness. For instance, physician *A* may set a 120 days interval (4 months) before the next revisit for disease *A*, while physician B sets it for 90 days (3 months) for disease B. Planning for the next revisit is based on shorter (or the shortest) interval, which, in this example, is 90 days later (see Figure 1).

Based on revisiting policy, there may be limits for maximum and minimum intervals between revisits and physicians set next revisits date within the maximum and minimum allowed intervals. There is also a direct relation between physician's prognosis evaluation and the next revisit date. The worse the prognosis results be, the shorter interval will be set for the next revisit (see Figure 2).

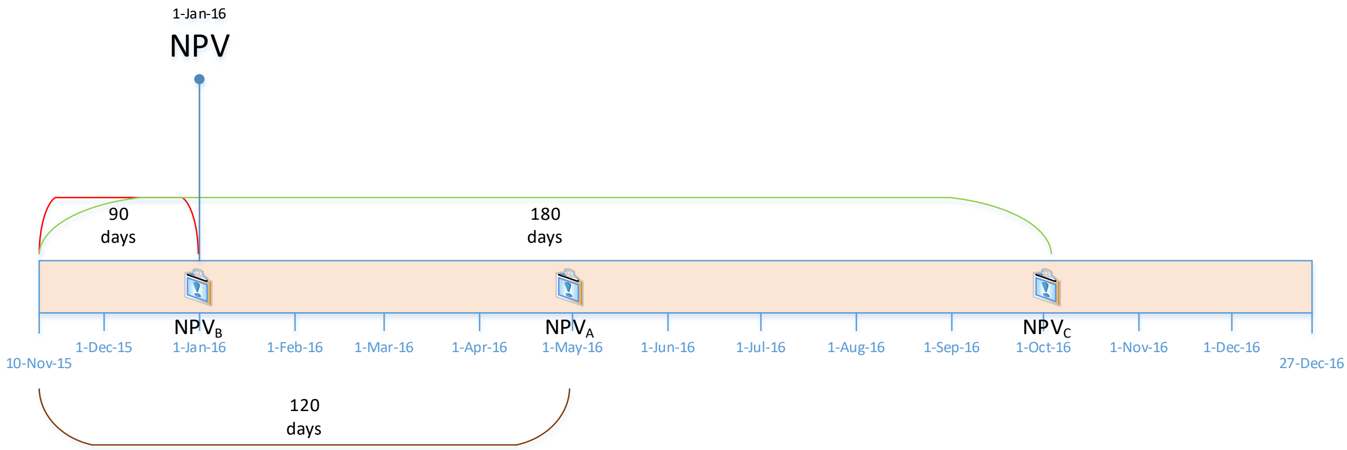

Figure 1. How the next planned revisit is set

Each prognosis of physicians may be combined by a level of preciseness, which may affect their diagnosis results and cause some deviations from patient's real CS. This is due to the experienced level of the practitioner(s). Therefore, the more expert are the physician(s), the less flawed his prognosis results would be. In this regard, there will always be considered some sort of possible mistake in diagnosis processes based on how much experienced is the physician. As Figure 2 shows, the worse a prognosis result become, the less days would be assigned for the next revisit.

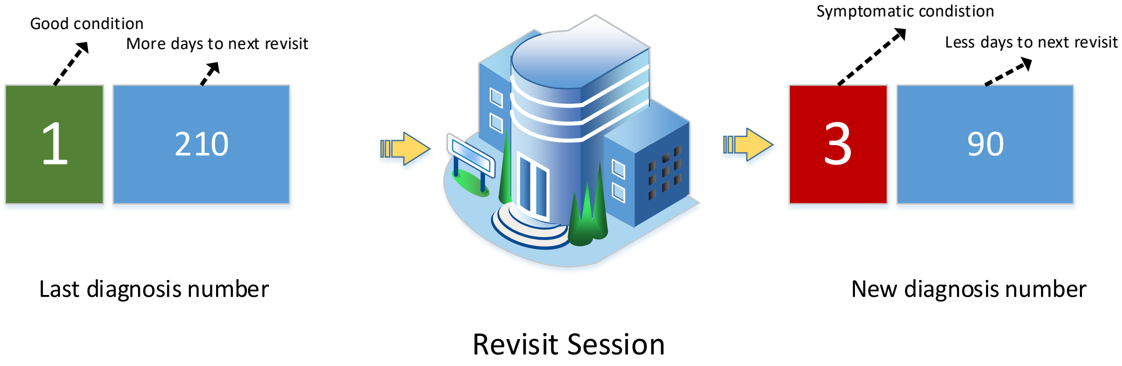

Figure 2. prognosis process of one revisit

Sometimes, we have some other patients, who call for an urgent visit for the first time (walk-in patients). Therefore, practitioners have to assign some slots to these urgent patients and delay the routine (non-symptomatic) patients' appointments. There is also an option for the authority to train the patients about their diseases and empower their diagnosis ability (e.g. Patient Assessment of Chronic Illness Care) which will develop patients' *diagnosis ability*. The main issue of this paper is to simulate the screening through considering all these factors to have a better strategic decision making insight about possible effects of changes in appointments making procedures on access to care, especially in the district of VA.

3.2. Discrete time screening simulation Model

Our presented approach is an event-based time-varying state-varying discrete time simulation. In each step of simulation, we simulate an update of next revisit and the patient's clinical status. We considered 10 important variables which are effective in each update and also are effected by some of the other variables. The relationship between the variables and their combination effect on X[1] is mentioned:

Equation 1

$$X_i = \{f(\mathrm{age}_{i-1}), \underbrace{f(d_{1i-1}),\ldots,f(\mathrm{d}_{ni-1})}_{diagnosis}, \overbrace{f(LV_{i-1)}, f(\mathrm{NPV}_{i-1}), f(\mathrm{NAV}_{i-1})}^{dates}, DA, \mathrm{CS}_{i-1}\}$$

For each patient we have a status array comprising of 10 *variables* and their effects on patients CS after each (revisit). These variables are patient's age, last visit prognosis data, visiting dates, diagnosis ability of the patient and his clinical situation (last revisit health outcomes), Equation 1 shows the *state* array of each patient after each revisit.

The last age, at which the screening, due to clinical considerations, will no longer be conducted is one of the policy making parameters. Each patient, has his/her related status (X), which rids on a variety of variables like his age, last prognosis of physicians, last visit date, his actual visit date, his ability to recognize

[1] Here, *f()* means that each factor's effect on the *state* array. *f()s* are not considered the same here and they just are for showing that there is a function to introduce.

or feel possible symptoms (diagnosis ability), physicians expertise level and the health outcome of the last visit along with the possible relationships held in between these variables. In other words, *X* is a status indicator array for each patient. In each update, the model will run the X_i for the i^{th} event for each patient.

3.2.1. Model sets and variables

Sets:

I= {1,2,…,i} updates (revisit) count

N= {1,2,…,n} chronic disease type

J= {1,2,…,j} chronic disease situation

K= {1,2,…,k} all of the patients considered in the simulation

Variables:

age_i: the age of the patient after revisit i

d_{ni}: We call it *prognosis number* of the revisit i of disease type n , which is a four digits number; the first left number represents physician *prognosis decision* and the three remaining digits represent number of days to the next visit, which the physician suggests.

K^{jn}**:** The random value for the situation j of disease n, which is customized based on the disease considerations and physician's prognosis to make intervals for the next revisit. It provides a three-digit number, which is attached to the right of *prognosis decision* of the physician to shape the *prognosis number* (d_{in})

LV_i: the date at which the last visit before the revisit i has happened

NPV_i: the *next planned visit* date of revisit i

NAV_i: the *next actual visit* date of revisit i

DA: represents the patient's diagnosis ability. It nudges 1 if patient have this ability and nudges 0 otherwise.

CS_i: patient's *clinical situation*

Parameters:

Delay: Number of days patient may come later than the NPV (can have distribution).

S^{max}**:** Number of days patient would come sooner than his *next planned revisit* date (can have distribution).

LAge: The age at which screening will no longer be conducted

DevCost: Cost of each day of deviation between planned revisit date and actual revisit day.

3.2.2. Model attributes

In this section we introduce the simulation variables and their relationships, which is translated into mathematical terms through the equations and figures.

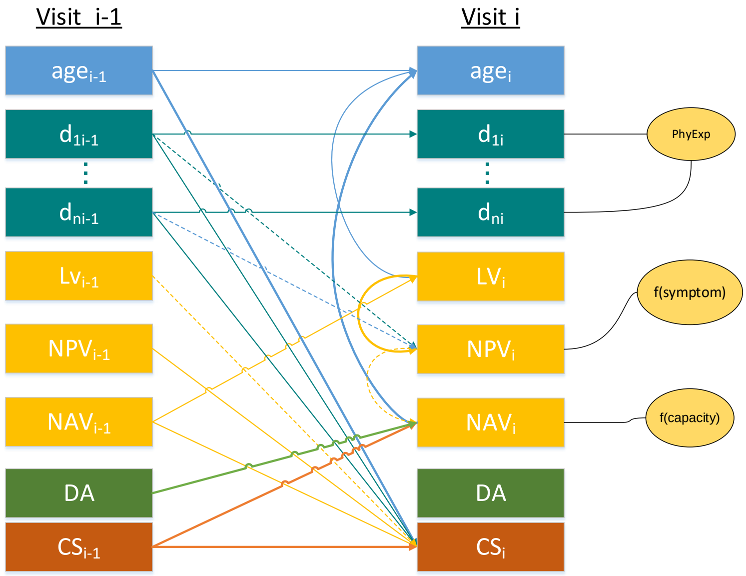

Figure 3. how each update happens for each patient in the model

As Figure 3 shows the whole situation, in each update for each patient, we have these relationships held between the 10 *variables* of the *state array* X_i. The equations of this process and the related figures are given below:

Equation 2

$$age_i = age_{i-1} + (NAV_i - LV_i)$$

As Equation 2 shows, the age variable is driven from the last revisit (LV), next *actual* date (NAV)and the last update of age variable. Therefore, the difference between NAV_i and LV_i will be added to the age_{i-1} in days and the resulting number is the age_i.

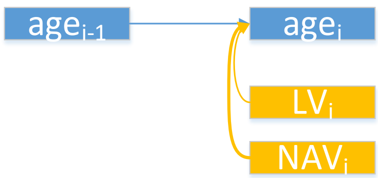

Figure 4. illustration of the age_i equation

Each of the physicians' prognosis are affected by the previews prognosis results, last patient's CS and physician's level of experience function (see appendix). In other words, each prognosis result rides on last prognosis result (d_{ni-1}), last patient situation (CS_{i-1}) and physicians' expertise level (PhE). $CS_{i-1}$is not clear for the physician, so the prognosis results may be different with the CS. To have a good perspective of different health practitioners' level, we introduced *PhE*, which models the accuracy of physicians prognosis based on how experienced they are in their work.

We consider three level for the practitioners (physicians and nurses); they are either *very expert*, *medium expert* or *not so expert*. The more expert they are, the less deviations and flaws is possible in their prognosis results.

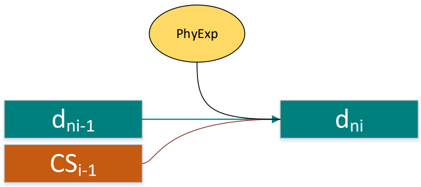

Figure 5. illustration of the d_{ni} equation

d_{ni} is a four-digit number (see Equation 3). The first left digit represents the visit diagnosis result by physicians and nurses, which is 1 if no sign of disease n is recognized, 2 if the disease n recognized but the prognosis suggests low developments of the illness and 3 if there is a prognosis of possible symptom or worse situations (acuteness). The remaining three digits of each d_n represents the interval physician decides until the next revisit. This means if d_n=2180, then it means that the physician noticed disease d_n in patient and based on his/her condition, physician appoints the next visit for 6 months (180 days) later. Let us call this date *next planned visit* (NPV) date.

For the d_{ni} we have:

Equation 3

$$d_{ni} = \begin{cases} 1 \ \ and\ K^{1n} & if\ \ (FirstLeft\,(d_{ni-1})\ /\ 3) \times ((CS_{i-1})\ /\ 4) \times \mathrm{PhE}\ < 0.33 \\ 2\ and\ K^{2n} & if\ \ 0.34 \le (FirstLeft\,(d_{ni-1})\ /\ 3) \times ((CS_{i-1})\ /\ 4) \times \mathrm{PhE}\ < 0.66 \\ 3\ and\ K^{3n} & if\ \ 0.66 \le (FirstLeft\,(d_{ni-1})\ /\ 3) \times ((CS_{i-1})\ /\ 4) \times \mathrm{PhE}\ \le 1 \end{cases}$$

Last visit (LV_i) of the current state of each patient is *actually* the last time he/she comes to the clinic and for that, it is equal to the *actual date* at which the previews visit has happened. There is an important consideration; because the LV_i is to be considered in the process of some other variables like NPV_i and NAV_i, the **Error! Not a valid bookmark self-reference.**, like Equation 2 would be used nearly after all other variables. This point will be so important at the time of writing the simulator's codes in the programming stage.

Equation 4

$$LV_i = NAV_{i-1}$$

Figure 6. illustration of the LVi equation

To plan for the next visit, it is important that when is the earliest day for next visit. Because we want to have best health outcomes, the patient will be asked to come back based on the earliest NPV, which is the minimum of all NPVs of last update. In other words, if we have three chronic diseases and the last update of *prognosis numbers* (d_{ni}) are 1210, 1180 and 3120 respectively, then our NPV dates are 210,180 and 120 days later, therefore, the NPV_i is planned for 120 days after the LV_{i-1}.

Equation 5

$$NPV_i = LV_i + \min\{\mathrm{ThreeRight}(\mathrm{d}_{1i-1}), \ldots, \mathrm{ThreeRight}(\mathrm{d}_{ni-1})\} - \mathrm{f}(\mathrm{Syptom})$$

Sometimes, CS may turn into symptomatic situations. At such events, based on patient's symptom diagnosis ability (DA) he will call for an urgent revisit. This will affect the NPV. We modeled this occasion by introducing f(symptom), which will give number of days to be excluded from NPV (see appendix). To plan for the next visit, it is important that when is the earliest day for next visit. Because we want to have best health outcomes, the patient will be asked to come back based on the earliest NPV, which is the minimum of all NPVs of last update. In other words, if we have three chronic diseases and the last update of *prognosis numbers* (d_{ni}) are 1210, 1180 and 3120 respectively, then our NPV dates are 210,180 and 120 days later, therefore, the NPV_i is planned for 120 days after the LV_{i-1}. Equation 5 shows how it affects the NPV.

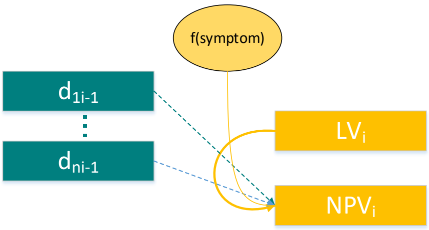

Figure 7. illustration of NPV_i equation

For the NAV_i, based on the patient's clinical situation, CS_{i-1} (which is the health outcome of the previews revisit), if he has the diagnosis ability (DA>0.5), then he has the ability of recognizing possible symptoms and want to come for a visit before the previously planned NPV_{i-1}. However, he may be lazy or have some difficulties for attending at the exact NPV_{i-1}, like distance between home and clinic. We assume that if a patient has diagnosis abilities, then he is more prone to come to the clinic *by* the date of NPV and if he does not have such abilities, then it is more possible for him to arrive at the clinic for a visit *from* the NPV date.

Equation 6

$$NAV_i = NPV_i - (\mathrm{CS}_{i-1} \times \mathrm{DA} \times S^{\max} \times \mathrm{R}) + (\mathrm{Delay} \times (1 - \mathrm{DA})) + \mathrm{f}(\mathrm{capacity})$$

Moreover, the clinic would have a finite patients' reception each day. Therefore, it is possible that at the exact day patient would attend for a revisit, all the possible capacity be assigned to the routine and/or walk-ins patients. It such situations, the revisit date will be postponed day by day until a day with not allocated and free capacity be found. We insert this issue into our simulation model by introducing the f(capacity). The pseudo code for f(capacity) can be found in the appendix.

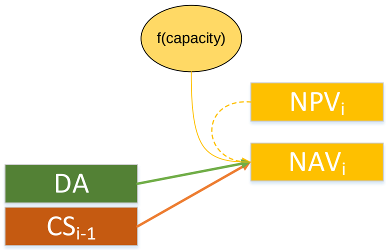

Figure 8. illustration of NAV_i equation

We put S^{max} to make the diagnosis ability more effective. It can be an integer value, which means the patient with diagnosis abilities, at the situation of having one or more chronic diseases ($CS_{i-1}>1$), may come back for the i^{th} visit at S days before his previously scheduled NPV_{i-1}. On the other hand, *Delay* is another arbitrary number, which if be late, the patient would postpone his attendance for the next visit. As we mentioned before, we assume that patient without diagnosis ability ($DA<0.5$) are expected more to have such lateness.

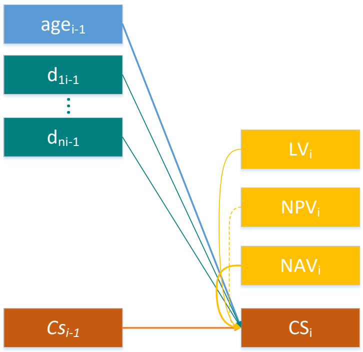

Figure 9. illustration of CS_i equation

The *CS* is the so-called *health outcome*, which is driven from all of the aforementioned variables like *age*, *LV* and so forth. Through Equation 7 a patient's *clinical situation* in i^{th} update (CS_i) of the simulation (his/her i^{th} revisit) can be with no sign of any chronic diseases in the screening model ($CS_i=1$), have some one or more diseases with less developed signs ($CS_i=2$), shows some sort of symptomatic and acute signs in one ore more diseases ($CS_i=3$) or be dead ($CS_i=4$). All of the possible values for CS_i are considered as screening *health outcomes* of the i^{th} revisit.

For the CS_i we have:

Equation 7

$$CS_i = \begin{cases} 1 & if \ \ (\frac{age_i}{LAge}) \times (\frac{\sum ThreeLeft(d_{ji})}{4 \times Intvl}) \times (\frac{|NAV_i - NPV_i| + 1}{NPV_i - LV_i}) \times (\frac{CS_{i-1}}{4}) < 0.3 \\ 2 & if \ \ 0.3 \le (\frac{age_i}{LAge}) \times (\frac{\sum ThreeLeft(d_{ji})}{4 \times Intvl}) \times (\frac{|NAV_i - NPV_i| + 1}{NPV_i - LV_i}) \times (\frac{CS_{i-1}}{4}) < 0.6 \\ 3 & if \ \ 0.6 \le (\frac{age_i}{LAge}) \times (\frac{\sum ThreeLeft(d_{ji})}{4 \times Intvl}) \times (\frac{|NAV_i - NPV_i| + 1}{NPV_i - LV_i}) \times (\frac{CS_{i-1}}{4}) \le 0.85 \\ 4 & if \ 0.85 \le (\frac{age_i}{LAge}) \times (\frac{\sum ThreeLeft(d_{ji})}{4 \times Intvl}) \times (\frac{|NAV_i - NPV_i| + 1}{NPV_i - LV_i}) \times (\frac{CS_{i-1}}{4}) \end{cases}$$

It is necessary to mention that if some diseases are considered as symptomatic by physicians or health practitioners, the related CS_i would not be the same. In other words, after the i^{th} revisit, patient may have symptomatic situation in one or more diseases, but at the same time his/her CS can be equal to 1 or 2 or 3 based on the effect of other factors affecting the CS_i.

3.3. ScSi tool

To verify the screening simulation model, and to illustrate the effects of different screening policies, we developed a tool in VBA environment. In this section we mention the the Screening Simulator (ScSi) main attributes. ScSi is designed based on the model defined in the above section and will give the possible effects of different policies for the procedure of screening scheduling be clinicians. We represent two main indices for the quantitative evaluations on each policy; health outcomes and access to care. To have a quantitative picture of health outcomes, we assigned certain monetary penalty (DevCost) for each day of deviation from the planned visit day. Therefore, the Health Outcome cost would be the summation of all deviations from all *NPV*s along with eventual penalty cost on symptoms and death incidence. The second part of this quantitative evaluation is access evaluation. Access is the possibility of getting a revisit within certain days after calling for it by the patient. Here, assume access will be considered for the appointments within 30 days after the patient call for them. Therefore, for the access evaluations we can have the portion of urgent calls, who have gotten a revisit within 30 days after calling for it. Further information about ScSi can be found in the appendix.

4. Screening Simulation in practice

To have a better insight of different policy making scenarios for screening, in this section we will investigate the implications of different policies. Revisits intervals and the panel size (number of clinicians) are among the most important factors in screening policymaking. Considering that both prolonging and shortening the revisit intervals are suggested in previews works, one policy making question would be asked about intervals. VA authority recently made an intention on do away with the appointments and have all the patient shows on demand, which means smaller panel size for health centers. We will have a look what would be this policy's implications comparing to the policy of surpassing panel size.

Concerning policies which pertaining to revisit intervals, it seems prolonging policy will free more capacity for walk-ins and symptomatic situations and eventually raise the access to care. However, too long intervals can affect the non-symptomatic patients due to lowering the chance of acuteness and symptoms detections and make their calls for revisits more frequently. This can lessen the access to care and raise the health outcomes costs. To do away with the appointing for chronic disease screening, there would be smaller panel size needed in clinics. It seems that despite being hectic of sorts in the beginning, the revisits may find a pattern which suits the demands. However, when capacity shortage happens, this policy can affect the non-symptomatic patients' appointments, which can raise the symptom incidence.

To get an optimal policy with specific revisiting intervals and panel size decision, which will give the best access and health outcome at the same time, we will investigate four scenarios on revisit intervals and panel size policy. The four scenarios are 6^+ months and 6^- months for intervals policies, and on demand and surpassing the demand for the panel size policies. The initial parameters for ScSi tool are given in Table 1.

Table 1. parameter setting for ScSi tool

Parameter name	Amount is set
Number of updates	10 revisits
Cost per deviation	8 $
Cost per symptom incidence	150 $
Cost per death incidence	2000 $
Last age for screening	85 years old
Access to care	Within 30 days
Minimum number of each day's walk-ins	0
Maximum number of each day's walk-ins	3
Practitioners expertise level	Medium (at most 30% flawing)
Patient training programs	No
Number of patients	101

We used the information of 101 patients, of whom 50% has *diagnosis ability* (*DA>0.5)* and 33 with at least one chronic disease (none of them have symptoms). The age average was 51.2 years old. As Table 1 shows, in this setting no patient training program is used. We must mention that all of the costs (per deviation, symptom incidence and death incidence) are estimated according to Loring et al work on chronic diseases costs [58]. With this setting for basic parameters, in the next subsections we investigate the implications of different screening policy.

4.1. Policies based on revisits intervals

4.1.1. 6^+ months revisit policy

In this policy, clinicians set revisit intervals for more than 6 months later. As there has to be upper and lower allowed revisit intervals to set, the 6^+ months policy means the average of minimum and maximum interval allowed has to be more than 6 months. The panel size for this policy consists of 3 physicians and 3 nurses. According to Equation 10 (see the appendix), we have 6 time slots for each day.

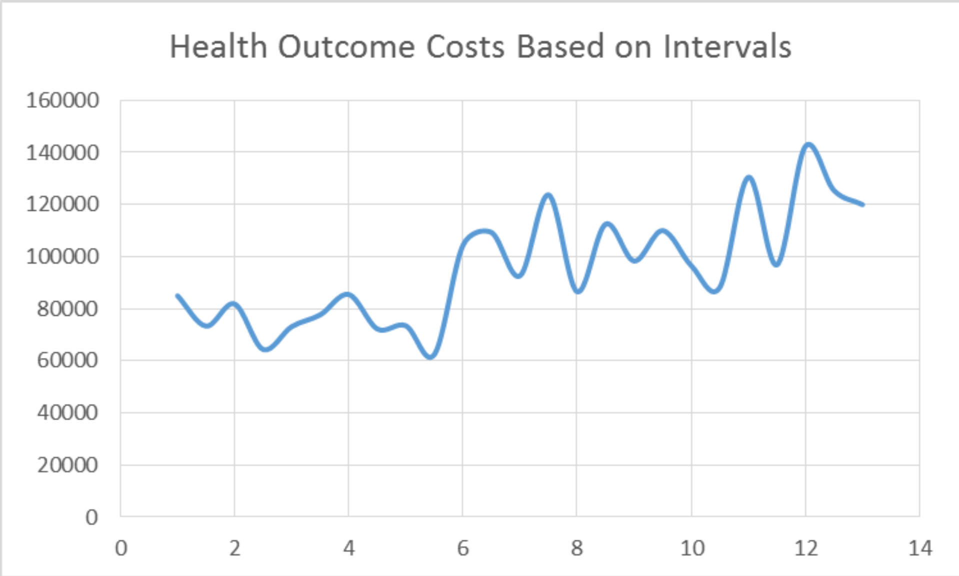

Figure 10. Health outcome costs estimations results based on different revisit interval policies (Results are given by ScSi).

According to Figure 10, there is no significant difference in HO costs along the 6^- policies. But it will raise continuously through 6^+ policies. This can be due to higher symptoms and/or death incidence.

4.1.2. 6^- months revisit policy

Based on this policy, clinicians set revisit intervals for less than 6 months later. Same as the previews policy, the 6^- months policy means the average of minimum and maximum interval allowed has to be less than 6 months. The panel size for this policy is same as what it was for the *6^+ month policy*, therefore, we have 6 time slots for each day.

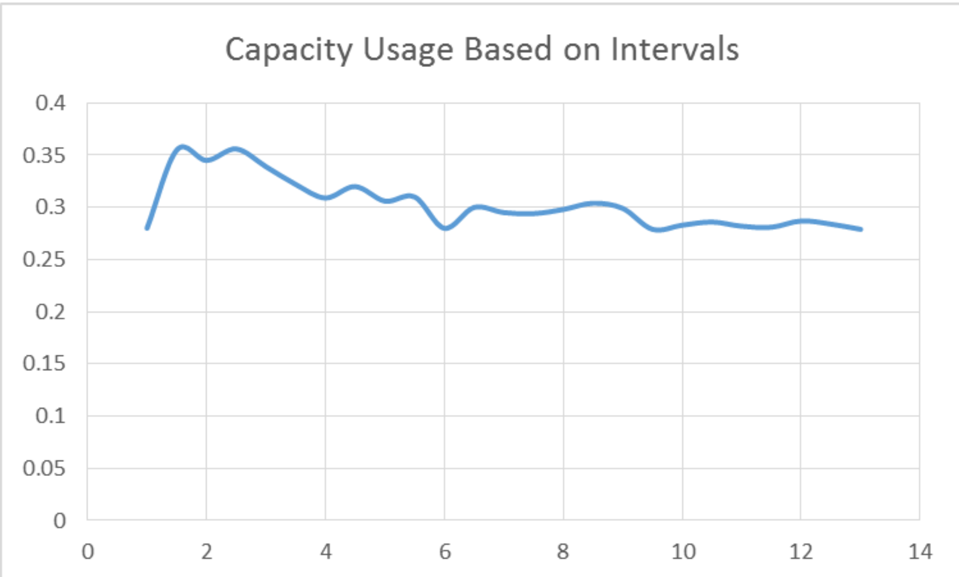

Figure 11. Capacity uasage rates based on different revisit interval policies (These results are from ScSi output).

The most efficient policies in capacity usage are among *6^- moths interval policies* (see Figure 11). Considering that for all policies based on revisits interval a 6 slots/day panel size is used, between 1.5 to 3 intervals highest possible capacity usage can be reached. There is no significant change in capacity efficiency for policies after 4 months interval.

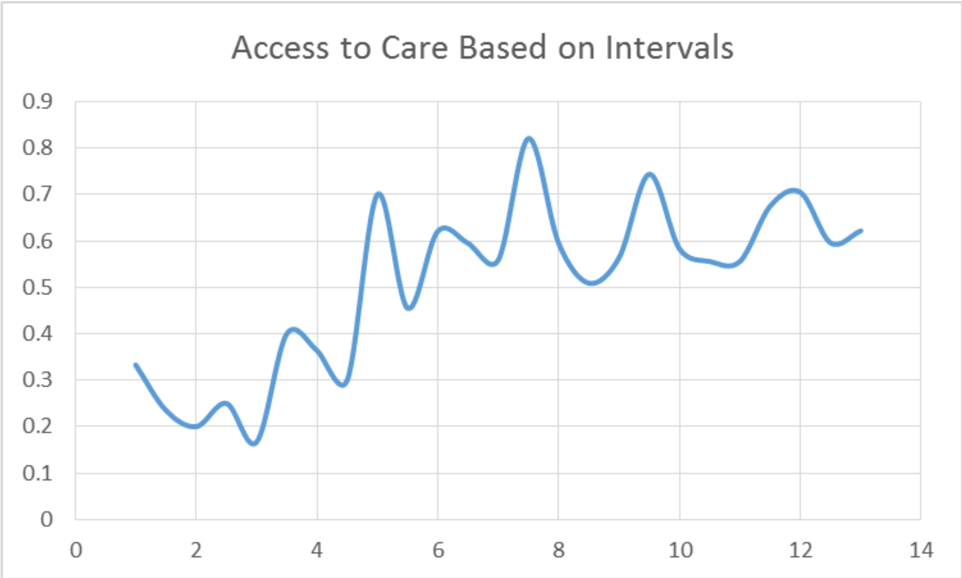

Figure 12. Access to care probability based on different revisit interval policies (based on ScSi output).

Another important factor is the *access to care.* There can be seen a trend in access to care which starts from 6^- intervals and nudge the 8 moths interval. Then it remain around 0.5 to 0.7 canal gently but never experiences lowest *access to care* rates, which are located in 6^- months policies.

4.2. Policies based on panel size

To do away with the appointment means that the panel size to be just as number of patients usually come for a revisit. For instance, if we have usually 4 patients (non-symptomatic) coming for a revisit, then based on available slots calculation method (see Equation 10 in the appendix) at most 2 physicians and 2 nurse are needed in the panel size. Obviously, the tool will postpone non-symptomatic patient for the walk-in (urgent) patients. Here we make a constant revisit interval with an average of 8 moths (min=6 months and max=10 months) and make changes in the panel sizes. All other parameters are kept same as Table 1.

4.2.1. On demand panel policy

To make an on demand panel policy, is to revisit the patients just on demand. We translate this in our model as the least possible panel size comprising of 1 physician and 1 nurse. This panel size will give a 2 slots/day capacity to the clinic.

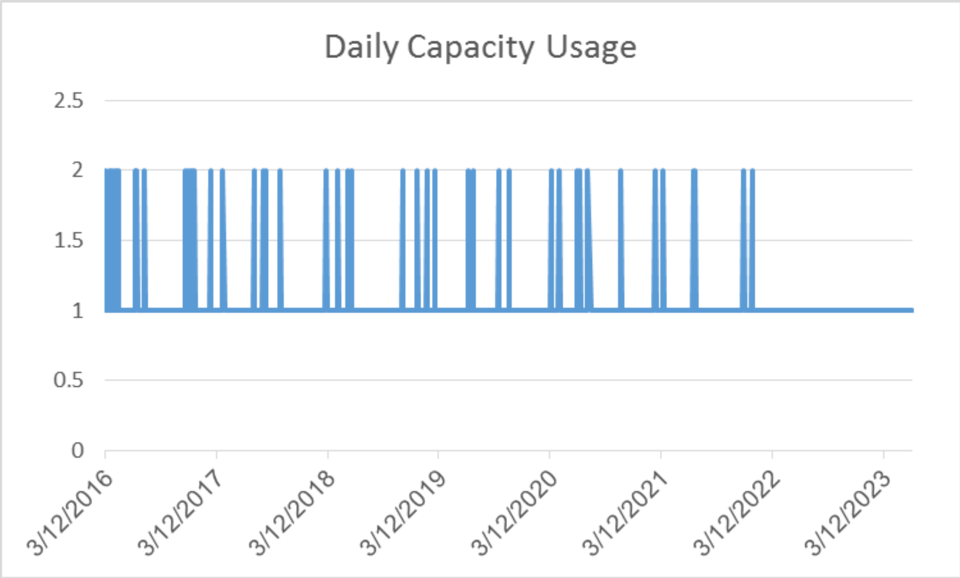

Figure 13. Daily capacity usage with a panel of 1 physician and 1 nurse (2 slots/day)

Figure 13 illustrates the ScSi output on daily capacity usage for the *on demand* policy. As Figure 13 shows, there is a long-lasting hectic behavior in daily capacity usage, and the last revisit day is 10/15/2023.

4.2.2. Medium panel policy

A medium panel size, here, is a panel size of 3 physicians and 3 nurses, which will give a 6 slots/day capacity. We put these policy in practice and Figure 14 shows the results.

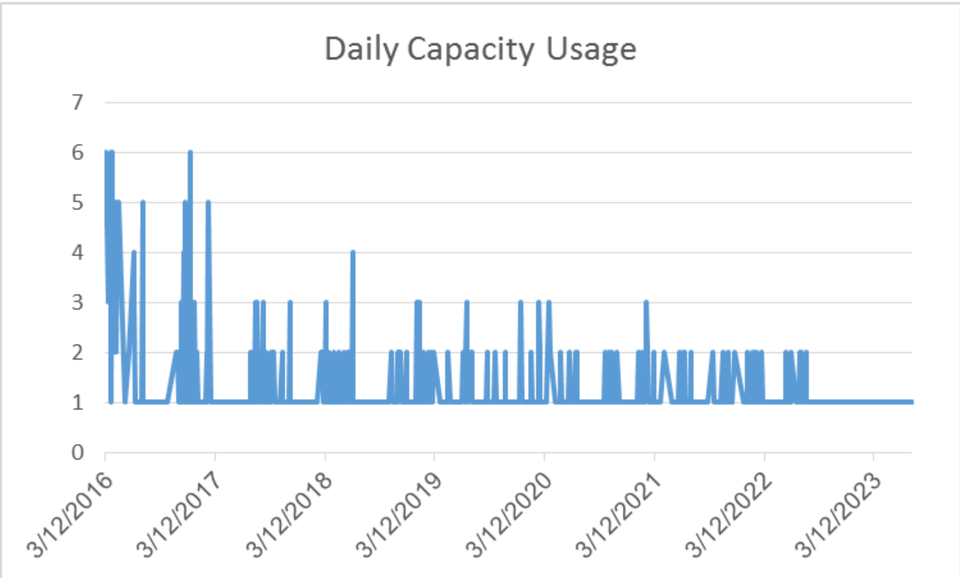

Figure 14. Daily Capacity usage based on an panel size of 3 physicians and 3 nurses (6 slots/day)

In Figure 14 we can see that the hectic behavior of capacity usage is less than *on demand policy*. but we can see that despite the beginning date of simulation, most of the times capacity usage is less than 50%. The last revisit day of medium panel policy is planned on 7/15/2023.

4.2.3. Surpassing panel policy

In this policy, we consider a bigger panel size than the expected average of routine (non-symptomatic) patients count. Therefore, the *surpassing panel policy* here is translated in 10 physicians along with 10 nurses, which means a panel size of 20 slots/day.

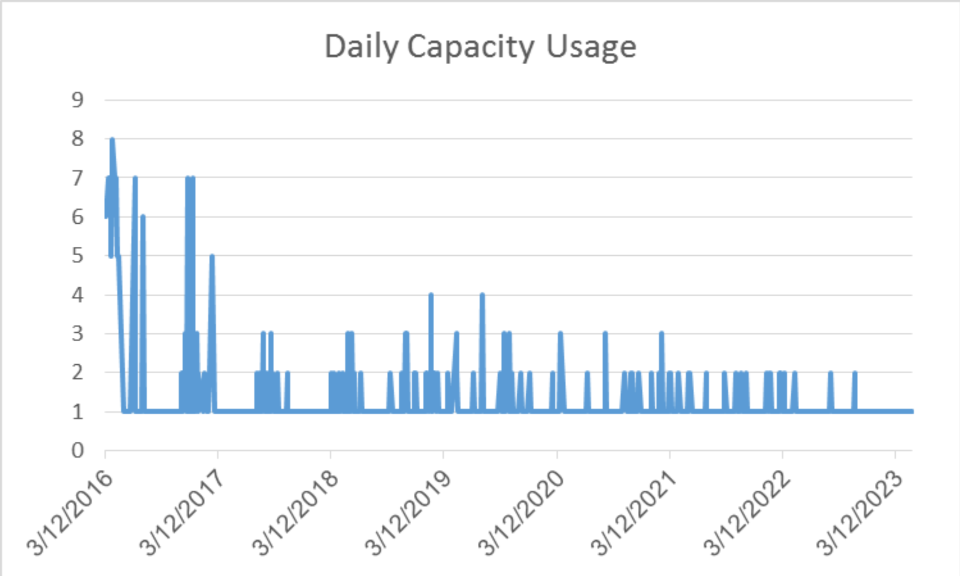

Figure 15. Daily Capacity usage based on an panel size of 10 physicians and 10 nurses (20 slots/day)

As is detectable in Figure 15, the hectic behavior is reduced but the unused available slots are much more that *on demand* and *medium panel policies.* Moreover, the last revisit date is on 5/6/2023.

Table 2. Comparing the three policies on panel size

panel policy	access to care	daily capacity usage	HO[2] costs
on demand	57.80%	1	$ 108,542
meduim	52.70%	29.60%	$ 125,506
surpassing	40.50%	7.20%	$ 108,516

In Table 2 a comparison is shown based on three factors of access to care, capacity usage and HO costs. As it is shown finely, the highest capacity usage and access to care along with the lowest HO costs are reachable through the *on demand policy*. It seems the *surpassing panel policy* is the least efficient panel policy.

5. Discussion

Derived results from our developed tool, ScSi, gives some insights about how different policies in revisiting intervals and panel sizes will affect important factors in chronic diseases screening. According to these results, we can suggest that *6⁻ months policies* force less costs. This can be due to better HOs (lower symptoms and death incidence), which means *6⁺ months policies* cannot be preferred to the *6⁻ months policies*, considering patients situations importance. Moreover, lower revisit intervals give higher *capacity usage* (in medium panel sizes). However, talking about *access to care* rate, the *6⁺ months policies* have

[2] Health Costs

shown better performance. Particularly, the highest access to care can be gained at 7.5 months revisit intervals, while 3 months intervals are prone to result in lowest access.

To discuss about the panel size, it seems that the *on demand* policy will have the latest revisits dates comparing to *medium* and *surpassing* panel size policies. This can be translated as the result of very little panel size (2 slots/day), which led to a postponement in non-symptomatic. This postponement can rise the risk of missing the opportunity of on-time symptom detection for these patients. However, it will get a pattern after a while, which – by postponing some non-symptomatic patients' revisits dates – will adopt itself to the demand. Moreover, this policy is the superior policy considering the three important factors of *access*, *capacity* and *costs* (see Table 2).

6. Conclusion

We make use of new simulation approach to model patients' revisits booking and their appointment behavior. Through implementation of the presented tool, ten effective variables were adjusted to make different clinicians' screening policies. Three output indicators of health outcomes, access to care and capacity usage were evaluated through different policies to illustrate the effectiveness of each policy. policies were designed on two basis; length of revisit intervals and panel size (number of available clinicians). To evaluate these policies, a tool is developed in VBA. As tool's outputs show, despite this fact that longer intervals may cost more because of higher symptom and death rates, these policies can give higher access to care and are not significantly inefficient in use of available capacity. As VA has the intention of having an on demand policy, we investigated different panel size policies. Despite the fact that this policy can affect non-symptomatic patients revisits dates, it is the superior policy according to the three access, capacity and costs indicators.

Appendix

PhyExp function

This function quantitates the effect of clinicians expertise level. Therefore, physicians can be *very expert* (maximum prognosis flaw of 10%), *medium expert* (maximum prognosis flaw of 30%) and *not expert* (maximum prognosis flaw of 50%).

For the PhE we have:

Equation 8

$$PhyExp = \begin{cases} 1 + randbetween(-0.1,0.1) & if\ practitioners\ are\ \boldsymbol{very\ expert} \\ 1 + randbetween(-0.3,0.3) & if\ the\ practitioners\ are\ \boldsymbol{medium\ expert} \\ 1 + randbetween(-0.5,0.5) & if\ the\ practitioners\ are\ \boldsymbol{not\ so\ expert} \end{cases}$$

F(symptom) function

At the event of symptomatic situation, based on the *diagnosis ability* (DA) of the patient, he/she would come earlier than his/her NPV.

Equation 9

$$f(symptom) = DA \times RandBetween(20,30)$$

F(Capacity) function pseudo code

This function will get the initial NAV, and checks if there is free capacity at NAV to set the appointment. If the capacity – considering number of walk-ins, or other non-symptomatic patient – was occupied, then f(Capacity) will find the earliest day with free capacity.

Start
    Input: *initial NAV*
    f(capacity)=0
    Do
        If *Capacity at NAV is available* **then**
            allocate capacity
            exit do
        else
            go for NAV+1
            f(capacity)=f(capacity)+1
        end if
    Loop
Finish

How ScSi works

To verify the chronic disease simulation model, we made use of VBA programming facilities and its spreadsheet modeling advantage made our work so much easier. We designed an easy-to-use User Interface (UI) for the initial factors adjustment (see Figure 10). In the initial window Sc Si, new policies are adjusted by changes in controls. Moreover, there are included some futures like the ability to train the patients by, for example using the so-called Chronic Disease Model (CDM), which can develop patients' diagnosis abilities (DA) through their screening period. More interestingly, based on number of available practitioners (here physicians and nurses), number of visiting sessions (time slots) are calculated [here, we need some refs to cite about how we have decided about everyday time slots].

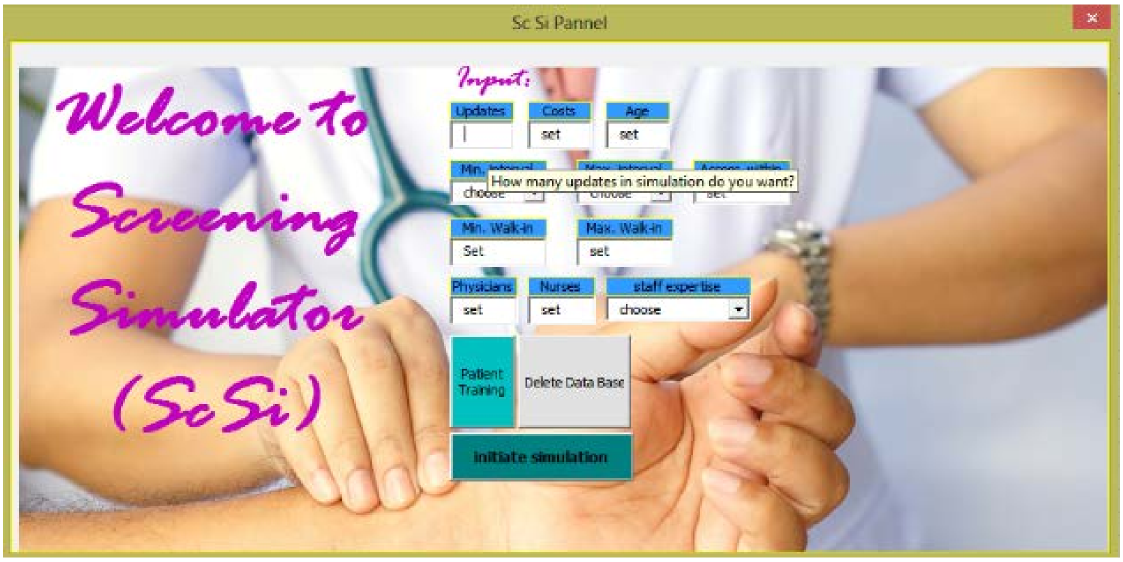

Figure 16. The UI of the Sc Si tool

This can be translated as each day's capacity. The capacity of each day for the non-symptomatic patients, rids on number of walk-ins on that day. We assume that all of the walk-in patients of each day will be seen by the physicians (even in the overtimes if needed) and the non-symptomatic patients' revisits will be postponed, if any slot shortage happens. Number of available slots (AS) in each day of the screening will be calculated based on number of physicians (Phy), nurses (Nur) and walk-in patients (Wi) through Equation 10. *Wi* is an uncertain number an can have a distribution (we have not found any work assessing the walk-ins distribution).

Equation 10

$$AS = \min(2 \times Phy, 3 \times Nur) - Wi$$

The practitioners' expertise level can be included in the simulation, which is effective on their prognosis preciseness. As the results, access to care, death and symptomatic incidences along with other indicators like health outcomes quantitative penalties (costs) are depicted. Here, Sc Si will get just *DevCost* and will calculate the cost per symptom incidence (*DevCost×10)* and death incidence costs *(DevCost×100).* After each run of the simulation, Sc Si saves its data into a spreadsheet database to provide a diagram of access to care probability based on month intervals policies.

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