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The Financial Implications of Using Decision Tree Analysis for Publicly Funded Health Care Screening in Canada

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This article demonstrates that decision trees have several applications in screening for incidences of various cancers in the publicly funded health care system of Canada. This article reviews previous research on the design of various types of decision trees to identify the relevant decision-making parameters that should be incorporated into enhanced usage of decision trees. This article proposes a methodology for screening breast and prostate cancers. While an accounting is made for various financial costs and benefits, comments are made on the limitations of the modeling exercise through identification of problems in assigning probabilities, the use of samples in ascertaining population parameters, ethical concerns, and measuring a cost per life year. This article concludes with prospects for future research including private sector versus public sector financing and the incorporation of opportunity costs into the decision-making process.

Keywords: decision trees, health care financing, prostate cancer, breast cancer

Introduction

Decision analysis can be defined as the "quantitative method from which to systematically analyze choices and consequences of those choices under uncertainty" (Haddix, Teutsch, & Corso, 2003, p. 80). These methods are applied to many disciplines in both the private and public sectors to assist in the decision-making process, especially under constraints of limited financial resources. The need is particularly great in the public sector, which is concerned with cost control and public sector auditing standards based on economic, effectiveness, and efficiency concerns. A decision tree is commonly used in decision analysis as a "graphical representation of alternative sequential decisions and the possible outcomes of those decisions" (Ross, Westerfield, Jaffe, & Roberts, 2011, p. 240).

This study outlines how decision tree analysis can be a very important tool, which can effectively be used to enhance the quality of decision-making in health care policy decisions. It is a systematic management science, stochastic-based method of applying a probabilistic analysis to actual decisions that identify appropriate costs and translate those costs into usable data to assist policy makers in making financial and strategic choices among various alternatives. In the private sector, the application of decision trees is relatively straightforward with the principal goal to maximize the specified objective function, often expressed in terms of net present value. The application of decision analysis in the public sector, however, often involves several other variables and considerations, some of which are not easily quantifiable in monetary terms. These

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decisions nonetheless have a considerable impact on the public funds being expended. These expenditures have accountability and transparency as key decision-making criteria.

First, the decisions made involve the expenditure of public sector funds and must, therefore, provide the greatest benefit to the population. Decisions cannot simply be made from a limited number of alternatives, but must take into account additional considerations, such as opportunity costs. Second, in health care expenditures, the application of decision tree analysis readily identifies the association between a dollar value and a life. Costs are generally calculated based on a "life-year saved" or the cost to extend the life of one individual by one year. The idea of putting a price tag on human life often makes decision makers uncomfortable, thereby limiting the application of decision tree analysis. This paper outlines the potential usages of the decision tree analysis method in the establishment of health care sector policy and applies the technique to two specific health screening initiatives, breast cancer and prostate cancer, in order to demonstrate how accountability and cost control of public funds may be achieved.

Literature Review

Origins of Decision Analysis

Decision analytic models were identified as early as the 18th century through pioneers in the field, such as Bernoulli in 1738 and Bayes in 1763. Bernoulli was interested in the fact that when choosing among alternatives, individuals often do not follow an expected value model. He established an expected utility model to explain this phenomenon. Bayes is perhaps best known for his formulation of the Bayes Theorem, which subsequently laid the foundation for Bayesian statistics. This theorem focuses on incorporating additional new information to revise existing probability estimates (Smith & von Winterfeldt, 2004). It was, however, not until 1963 that decision tree analysis was proposed. Morgan and Sonquist (1963) were the first to devise a methodology, which they called automatic interaction detection (AID), although they cited earlier preliminary works by others in the field. This model was later refined by the same authors in 1971. Kass (1980) further improved the model by integrating a significance threshold through the incorporation of the chi-squared statistic. This model was named chi-squared automatic interaction detection (CHAID) (Smith & von Winterfelt, 2004). Other models have subsequently been proposed, including Morgan and Messenger (1973), Iterative Dichotomiser 3 (ID3) (Quinlan, 1979), C4.5 (Quinlan, 1987), C5 (Quinlan, 1993), QUEST (Loh & Shih, 1997), and OCI (Murthy, Simon, Salzburg, & Beigel, 1994). Statistical Analysis System (SAS) algorithms are also popular and take the methodology a step further by incorporating univariate splits (Smith & Winterfelt, 2004; Neville, 1999). Various components of decision tree analysis used in the health care sector are presented in Figure 1, which employs lung cancer screening to illustrate the process (Marshall, Simpson, Earle, & Chu, 2001).

This decision tree is a model for a cost effectiveness analysis (CEA) used to demonstrate the potential benefit of offering lung cancer screening to high-risk individuals. Following the tree from left to right, the first split in the tree is shown with a square box, which represents a decision node when the physician will decide whether or not to offer the screening. Should the physician choose to screen, the next split in the tree should be shown with a circle, which represents a chance node wherein there is a probability that the screening test will come back either positive or negative. There can be numerous chance nodes in a decision tree. The exact number depends on the scenario being evaluated. Many of the branches end with a triangle, which represents a terminal node or the end of possible outcomes for that branch. At each chance node, there are two or more

possible outcomes. In this example, each chance node is followed by only two possible outcomes. The probability for each outcome is assigned. These probabilities must sum to 1.0 and follow the usual statistical criteria of being mutually exclusive and exhaustive. These values should be derived from the highest quality evidence available to reflect objective or quantitative probability estimates. When no published data exist for such probabilities, expert opinion could then be sought to reflect subjective or qualitative probabilities. The probabilities assigned to each chance node may be different depending on the personal characteristics of a patient. For instance, using the lung cancer example, the probability of having a positive screening test would change depending on the age of the patient undergoing the screening. Likewise, the smoking status of a patient would also impact the screening outcome. These issues are addressed using a sensitivity analysis, which is discussed in a further section.

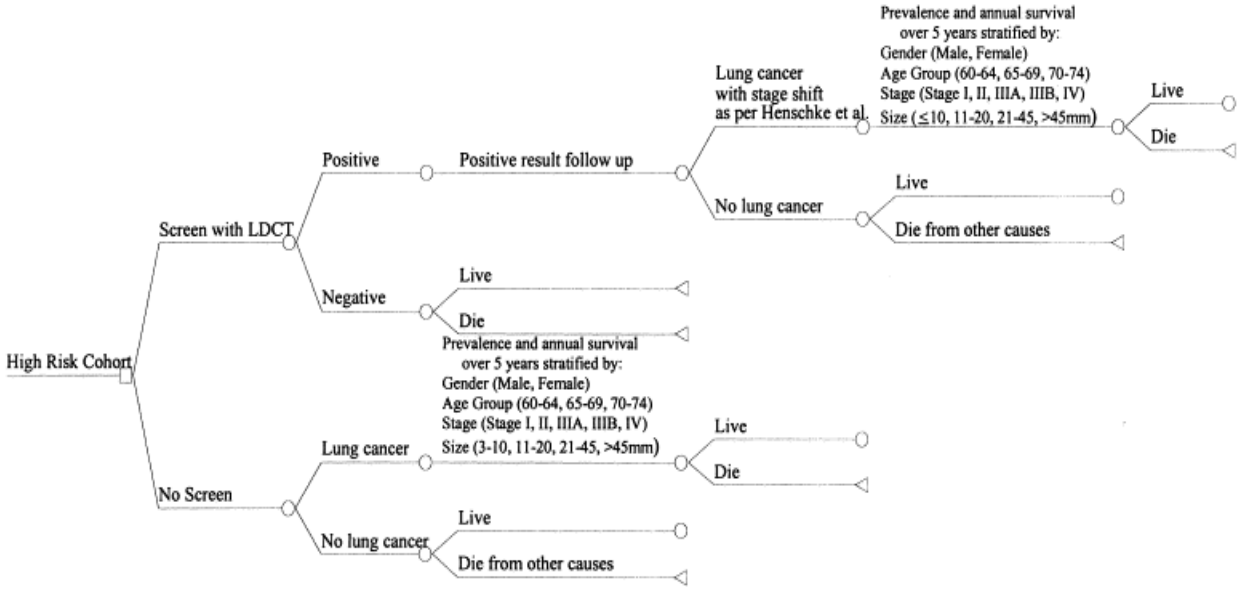

Figure 1. Decision tree for lung cancer screening imitative.

Each branch in this decision tree represents a different path that a patient might take with respect to lung cancer screening. Consequently, each branch would have a different overall financial requirement on the health care system, which in Canada is financed through the public sector. The total cost of each branch would be determined by including all financial impacts incurred from those series of events. The value for each branch is the mean cost associated with that particular line of treatment. In addition to the total cost for each branch, there is also an assigned life-measure. This is usually assigned in terms of life years and is the number of years that an individual who follows that pathway is expected to live. At the terminal nodes, when the patient dies, the life years assigned to that branch would be zero.

The final cost and life-measure associated with each possible choice, in this example to screen or not to screen, is determined by folding back the tree. This is achieved by multiplying the total cost at each terminal node by the probabilities at the preceding chance node. The two values are then summed to yield the total cost for a chance node. This process continues until there is an expected cost associated with each decision. The same process is duplicated using the life years for each branch to provide the expected life years at each respective choice in the tree. The cost per life year saved is then calculated by dividing the calculated expected cost by the expected number of life years. The probabilities and expected costs used as inputs in the decision

tree analysis represent the average patient based on the best available evidence, which is categorized as the base-case analysis.

Incorporating Utility

In some scenarios, the final expected value of an alternative is insufficient to make a decision, as not all decisions are based on a dollar value alone; instead, they incorporate personal values and circumstances. To account for this additional dimension, a utility measure is used. This is a measure of the amount of satisfaction derived from a particular state. For instance, using the lung cancer example above, patients who were screened positive for lung cancer and, as a result of an early treatment, are able to extend their expected lives by one year, the quality of life that they experience may be less than a person who was screened negative for lung cancer. Though these individuals are alive, their satisfaction with that state, and hence their utility, may not be the same (Drummond, Sculpher, Torrance, O'Brien, & Stoddart, 2005).

Utility can be measured in a number of ways. The simplest approach would be to use a ranking scale wherein individuals are provided with a list of possible outcomes or states and asked to rank them on a continuum. These rankings are then converted to a value between zero and one through logistic regression. Standard gamble and time trade-off methods can also be used to apply utilities to a set of outcomes or states (Drummond et al., 2005).

One method for measuring utility that is gaining popularity in the field of health economics is conjoint analysis. Traditionally used in consumer research or environmental valuations, conjoint analysis is based on the theory that goods or services are valued by the characteristics used to describe them rather than the product or service by themselves (Ryan, 2004). Therefore, the value on a good or service depends on an individual's perceived value of those particular characteristics (Louviere, Hensher, & Swait, 2000). Conjoint analysis uses surveys to assess how the combined effects of attributes lead to choice. Such surveys would include a variety of scenarios with respondents being asked to make a choice among them. Surveys can be conducted in a variety of ways, either by rating, ranking, or by making discrete choices. Preferences for various scenarios are subsequently converted to a utility value through regression analysis (Hancock, 2010). Utility measures are then incorporated into the decision analysis by multiplying the utility factor by the number of life years to obtain the quality-adjusted life year.

Scope of Decision Tree Analysis

The main function of a decision tree analysis is to provide a framework for decisions when uncertainty exists. They fulfill five functions (Drummond et al., 2005):

(1) Provide structure. This is achieved by reflecting all the possible options and decisions, along with their respective outcomes, for a particular health event;

(2) Incorporate evidence. Most clinical studies do not incorporate all relevant alternatives or financial information; rather, they often only compare two options from a pure efficacy perspective. The decision tree provides the framework in which various sources of evidence can be used as inputs for the defined parameters;

(3) Evaluate alternatives. Once the evidence is populated in the decision tree, the analysis will translate that evidence into estimates of costs and effects. The results enable decision makers to select the most optimal choice;

(4) Account for uncertainty and variability. Decision tree models allow the decision maker to make assessments based on the existing types of uncertainty (e.g., model structure or input parameters);

(5) Identify areas for future research. Finally, the decision tree can help researchers to identify priority areas for future research.

In the health care sector, decision tree analysis can be very effective for informing different types of decisions. For example, they can help to target a particular intervention, such as a vaccination program. Further, a decision tree aids in the identification of sub-groups from the population that would receive the greatest benefit from various expenditures. As well, a decision tree could evaluate different strategies for a particular issue, such as surgery versus medication management or the frequency of administering a screening program. Decision trees are also very useful for prioritizing programs for investment (Haddix et al., 2003).

In the private sector, the outcome to be evaluated using a decision tree analysis is to identify the most profitable option among two or more alternatives. The present value of each alternative is calculated to determine which investment would provide the greatest enhancement of value. This is in contrast to the outcomes desired in the public sector, such as health care, which are often intended to maximize the benefits to society through various programs and services.

Time Effects for Decision Analysis

In most circumstances, health care decisions have effects that are realized not only today but have ramifications for the future as well. Consequently, the problem of non-synchronicity arises between the time when program costs are incurred and the time when the benefits of that program are realized subsequently. For this reason, the time value of money needs to be considered carefully. The financial technique used to reconcile the differential timing of benefits and costs is through the discounting of those future benefits and costs, not all of which can be easily expressed in monetary terms (Haddix et al., 2003). There has been a considerable debate concerning the use of discounting and the time value of money stemming from the fact that both cost and utility need to be measured. Discounting costs without discounting utility result in the cost of the health outcome decreasing over time (see Table 1) (Haddix et al., 2003).

The discount rate used to discount cash flows is a reflection of the perspective taken. In the private sector, generally, the discount rate is the cost of capital. In the public sector, however, different perspectives are utilized to determine the appropriate discount rate. From a societal perspective, the discount rate would be a reflection of what society is willing to currently sacrifice for future perceived benefits. This perspective differs from that of an individual as people’s preferences for benefits that society receives as a whole generally differ from the benefits that they would pay for and receive as individuals. This situation holds because people may have altruistic feelings towards a society and they associate their children as being parts of a future society that may benefit from current investments. For these reasons, the discount rate associated with a societal perspective is often lower than an individual’s discount rate. Alternatively, the payer’s perspective (the government or a health care organization) could be taken. In this scenario, the discount would be higher, as there is always a preference for averting costs at the present rather than in the future (Haddix et al., 2003).

In addition to discounting, the time horizon for an economic evaluation needs to be considered, which refers to the length of time over which the costs and outcomes resulting from the health intervention are included. Some health interventions, such as a flu vaccine, might have a short time horizon, as all the potential benefits would be realized within short time frames, often less than a year. Other interventions, such as a screening program, may have a very long-term horizon, as an early detection could result in benefits for the remainder of the person’s life (Haddix et al., 2003).

Table 1

Recommendations for Discounting Costs and Benefits

Recommendations for discounting costs and benefits
1. "Future costs and health outcomes should be discounted to present value". 2. "Future costs and health outcomes should be discounted at the same rate". 3. "A 3% real discount rate should be used. A 5% discount rate may also be used for purposes of comparability with older studies or studies from other settings. No adjustments for inflation in the future should be made because this is a real (not a nominal) discount rate. Perform sensitivity analysis on the discount rate over a reasonable range, for example, from 0% to 10%".

Note. Source: Haddix et al. (2003, p. 95).

Managing Uncertainty

The medical evidence that is used to populate a decision tree has several elements that possess varying degrees of uncertainty. Sample populations that are used in clinical trials are meant to mimic the behavior of the general population; however, even with a large sample, its behavior can only estimate the behavior of the general population. To account for this uncertainty, confidence intervals are placed around each point estimate (Donnan, 2009). The results of decision trees represent the amount of resources that an average hypothetical patient would use. Since the evidence used in the base-case analysis has an inherent uncertainty and given that there is considerable variability among patients in the general population, further analysis should be conducted to account for these factors. In decision tree analysis, uncertainty and variability are dealt with using a sensitivity analysis (Donnan, 2009). Such analysis can help answer the following questions (Haddix et al., 2003, pp. 114-115):

(1) If the numerical estimate of a probability or an outcome is changed, how does the expected utility or expected value change?

(2) Do the conclusions change when the probability or an outcome is assigned values that lie within a reasonable range?

(3) How much would an estimate have to change to produce a different result?

(4) What value would a variable have to be for two strategies to be of an equal expected value?

(5) What happens to the results of the model if the best case scenario or the worst case scenario estimates are used?

Sensitivity analysis is conducted by varying model parameters, such as costs and probabilities, to assess the impact on the outcomes. For example, the probability of a positive screening test might be estimated to be 0.09 based on a recent study; however, other slightly older studies may report probabilities ranging from 0.02 to 0.21. Probabilities from within that range can be substituted into the model to assess the impact of the overall result of the analysis. When only one value is changed at a time, this is called a one-way sensitivity analysis. Two-way sensitivity analyses, when two values are substituted, are also commonly conducted.

Probabilistic sensitivity analysis is a method of substituting multiple values at the same time. Monte Carlo simulation is a form of probabilistic sensitivity analysis that is commonly conducted by using a computer, many of which have software packages capable of performing the simulations. In the analysis, many simulations (between 10,000 and 1,000,000) are generated using various combinations of values in a pre-set range. This analysis generates confidence intervals around the point estimate calculated from the base-case analysis (Haddix et al., 2003).

Limitations of Decision Analysis

Despite the usefulness of decision tree analysis, there are several limitations to consider. First, there are

rarely cost and probability values for all input parameters that perfectly reflect the decision to be made. In such circumstances, estimates and assumptions are made. Though these estimates and assumptions are based on expert opinion and experience, they are not necessarily perfect substitutes for actual data, which is often seen as a weakness of decision tree analysis. However, the reality in most circumstances is that a decision needs to be made regardless of the limited available evidence. Expert experience, in conjunction with some quantitative evidence, is often better than non-evidence based decisions.

Decision analyses are largely based on models across populations or samples, and, as such, cannot reflect all the complexities of individual patients. Co-morbidities and patient preferences, for instance, are not incorporated into the model. For these reasons, decision tree analysis is not reliable for predicting individual patient outcomes and costs. Rather, the models are more useful across population-based decisions to aid in the allocation of scarce resources to particular services and programs. The presence of any source of bias in a study will decrease its validity. For instance, if the decision-making body is also conducting the analysis, reviewer bias could be present. Despite taking careful measures to reduce bias, it is not always possible to eliminate it entirely. Reviewers may be influenced by personal or family experiences related to the decision to be made or they may be interested in cutting costs, and as a result, they may not consider all of the potential benefits to the population. In either case, the reviewer's perspective may not be completely objective.

Sometimes, decision tree analysis can be considered ethically problematic. Though decision tree analysis attempts to include all relevant alternatives for a particular decision, in reality, there exists a fixed amount of fiscal resources to offer programs and services for an entire government department. Deciding to spend more on a particular screening initiative means that less money is expended on other programs. Decision tree analysis cannot evaluate the opportunity costs involved in a particular decision.

Lastly, the interpretation of cost per life year has also been a cause for debate. What is an acceptable cost? Are there cut-off limits at which point certain alternatives under review will not be considered? These questions are very subjective and are often influenced by the political landscape, competing programs, and personal preferences. An unwritten rule of thumb in the Canadian health care system suggests alternatives that cost less than $100,000 per life year saved are considered to be cost-effective; however, there is no established best practice for interpreting these values.

Application of Decision Tree Analysis

Breast Cancer Screening

Globally, breast cancer is the most common form of cancer and the most frequent cause of cancer-related death among women. In 2008, it was estimated that 1.38 million new cases of breast cancer were diagnosed globally and an estimated 458,000 women died from the disease (Ferlay, Shin, Bray, Forman, Mathers, & Parkin, 2010). Canada has one of the highest breast cancer incidence rates in the world (Ferlay et al., 2010). Among Canadian women, it is the most frequently diagnosed cancer and is the second leading cause of cancer mortality. Approximately 23,600 cases and 5,100 cancer-related deaths were experienced in 2011. Fortunately, the incidence rate is declining, largely due to the uptake of mammography screening and the improved quality of screening and treatment therapies (Canadian Cancer Society, 2011).

The latest guidelines from the Canadian Medical Association recommend mammography as the screening tool of choice for women with an average risk of breast cancer. The association recommends against routinely using magnetic resonance imaging (MRI), clinical breast examination, or breast self-examination for this

purpose. Screening with mammography was recommended for women aged 50 and older at a frequency of every two to three years and not recommended for women less than 50 years of age (The Canadian Task Force on Preventative Health Care, 2011).

These guidelines were refuted by the Canadian Breast Cancer Foundation in a press release dated November 21, 2011, stating that there is evidence to support breast cancer screening in women between 40 and 49 years of age. Sandra Palmaro, the chief executive officer (CEO) of the Canadian Breast Cancer Foundation, stated that "scientific evidence demonstrates that earlier detection and diagnosis can save lives among women 40-49 by at least 25%". She further stated that screening helps locate smaller tumors that have not yet spread making them easier to treat, thereby resulting in less morbidity to the patient (Canadian Breast Cancer Foundation, 2012).

The mixed messaging that exists with respect to the age to commence screening for average risk women is evident in the inconsistent screening criteria set forth by each Canadian province and territory (see Appendix A). For example, in April 2012, the Government of Newfoundland and Labrador announced that women between the ages of 40 and 49 will now be eligible for breast cancer screening with mammography, provided they have a referral from their family physicians. The next section applies a decision tree analytic model to this complex debate between providing breast cancer screening to women of average risk starting at age 40 and age 50.

Proposed Decision Tree Model for Breast Cancer Screening

Presented in Figure 2 is a decision tree representing the course of events that might occur when a women of average risk for breast cancer is offered screening using mammography starting at age 40 compared to age 50. Though other forms of screening, such as breast self-examination, clinical breast exam, and MRI are also available, they are not recommended for a routine examination in this population and are, therefore, not represented in this model.

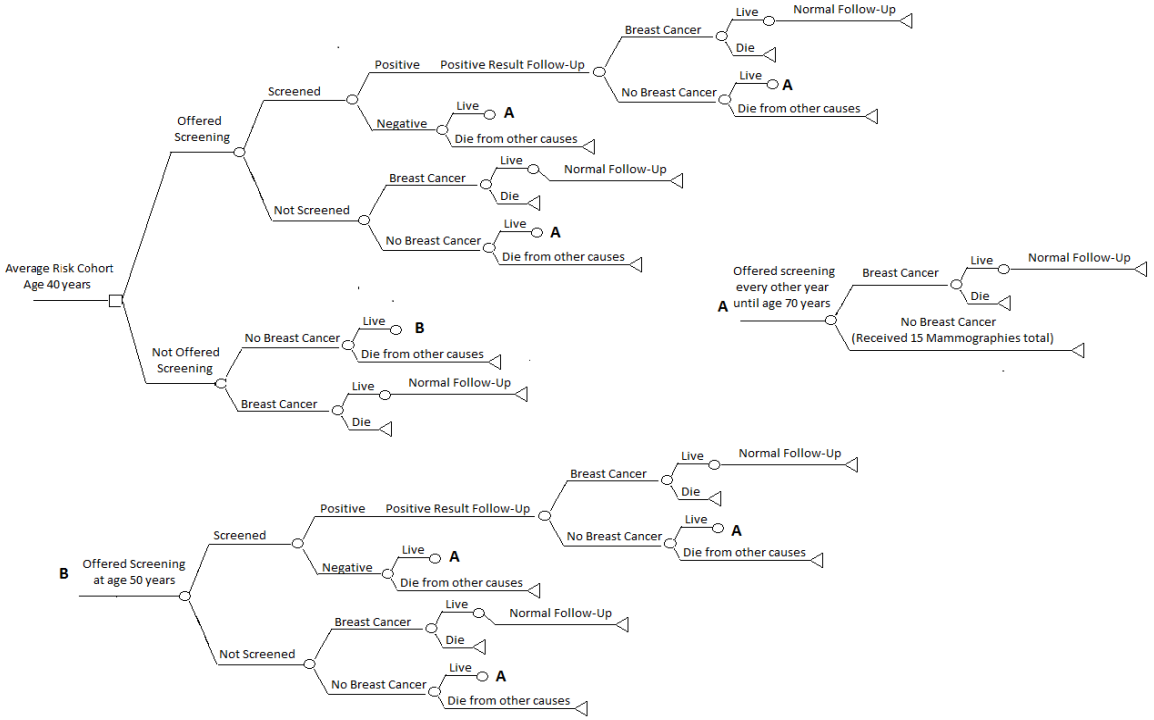

Figure 2. Decision analytic model for breast cancer screening.

The above decision tree model is built on a 30-year time horizon based on the standard of practice for breast cancer screening in Canada. Women become eligible for screening at 40 or 50 depending on the province and become ineligible after 69 years of age (see Appendix A). The cohort selected for this model consists of women aged 40 with an average risk for developing a breast cancer. For simplicity, the assumption has been made that mammography will be offered every two years, based on the latest Canadian guidelines that recommend screening every two to three years (The Canadian Task Force on Preventative Health Care, 2011).

Starting on the left hand side of the tree, the decision node represents when women would either be offered breast cancer screening using mammography or not offered screening until age 50. Despite being offered screening services, the women may still choose not to avail of these services. This is represented by the first chance node on the upper branch of the tree. Those not screened will either develop a breast cancer or will not. Those with a breast cancer can live or die from their disease and those without a breast cancer can live or die from other causes. Those who choose to be screened can either have a positive or negative test. Those with a positive test will require follow-up testing. False positives or patients who do not have a breast cancer can live or die from other causes, while those with a true positive will require disease management and may live or die from their disease. Patients who have a negative test and live for two more years will continue to receive mammography screening every two years. Some assumptions have been made to simplify this model. First, it is assumed that if an individual makes the initial choice to have a mammography, then she will continue to opt for screening regularly throughout her eligible years. Second, once patients move on to routine screening (starting at the second mammography), should she develop a breast cancer, an average age for diagnosis of 61 years would be applied.

Women who are not offered screening at age 40 can either develop a breast cancer or not. Those who do not develop a breast cancer before the age of 50 will then be offered routine screening at age 50 and then follow an identical pathway to women who start screening at age 40. This decision model accounts for the potential of false positives; however, it does not account for the occurrence of false negatives. The assumption is made that the impact of false negatives on the overall model results would not be great enough to change any decisions based on the model. Though not commonly discussed, breast cancer is a disease that can affect both women and men. Male breast cancer accounts for less than 1% of all breast cancer diagnoses (Canadian Cancer Society, 2012) and goes completely unscreened. Though this decision model was designed to evaluate screening guidelines in women, the top branch of this tree could be applied to male breast cancer screening to assess the cost effectiveness of offering screening to this population.

Prostate Cancer Screening

Prostate cancer is the third most commonly diagnosed cancer in men in Canada, with a lifetime risk of diagnosis of 13.6% (Izawa, Klotz, Siemens, Kassouf, So, Jordan, Chetner, & Iansavichene, 2011). Diagnosis prior to the age of 50 is rare, and the lifetime risk of death resulting from a prostate cancer is 2.8%. Seventy percent of prostate cancer deaths occur after the age of 75 (Howlader, Noone, Krapcho, Neyman, Aminou, & Waldron, 2011). Current screening regimens for a prostate cancer include prostate specific antigen (PSA) test, digital rectal exam (DRE), and/or ultrasound. The US Preventative Services Task Force released a recommendation statement that suggests not offering PSA screening to men regardless of their ages (Moyer, 2012). It argues that PSA testing leads to detection of an asymptomatic prostate cancer which, for the majority of men, will never progress or it will progress so slowly that the affected men will remain asymptomatic for the

remainder of their lifetime. The two situations are referred to as “over diagnosis” or “pseudo-disease”, respectively. Since the primary outcome of most screening initiatives is to reduce disease-related mortality and increase the patient’s lifespan, it was deemed that PSA screening tests were of the minimal benefit.

Another important factor that the US Preventative Services Task Force took into consideration was the negative impacts experienced by the men who receive false positive results upon screening. It is estimated that about 80% of positive PSA tests are in fact false positives. These false positive tests result in: negative psychological effects, additional testing including biopsies and associated side effects, and treatment-related side effects on the men who would have never developed a symptomatic disease.

Proposed Decision Tree Model for Prostate Cancer Screening

Presented in Figure 3 is a decision tree depicting the possible course of events that would occur for a man at age 50 or older with an average risk of prostate cancer and an additional life expectancy of at least 10 years. The first branch represents the current standard of care which includes a DRE and a PSA test. The second branch represents the proposed screening program by the US Preventative Services Task Force, which includes a DRE only. The final branch represents the situation where no screening program is offered. This final alternative is included, as it has been shown that screening for a prostate cancer does not actually increase life expectancy.

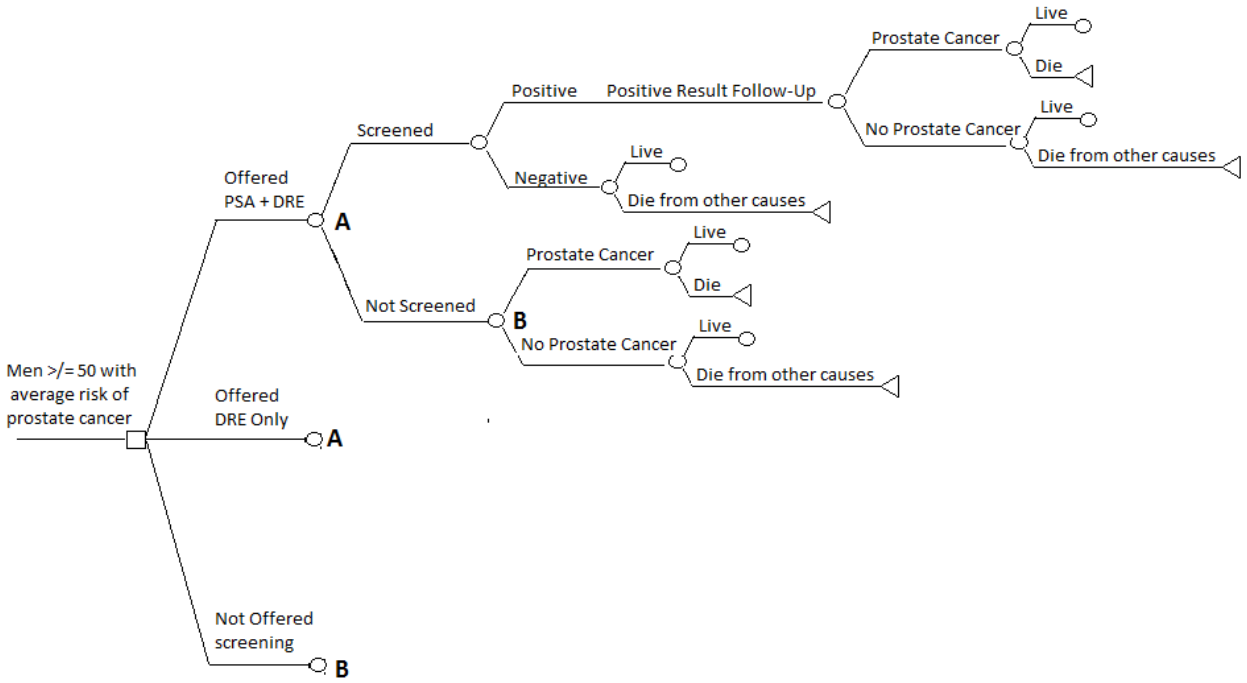

Figure 3. Decision analytic model for prostate cancer screening.

This decision tree is built on a lifelong time horizon and a cohort of men at age 50 and older with an average risk of developing a prostate cancer and a projected life span of at least 10 more years. This model makes the assumption that screening will be offered on an annual basis based on the latest Canadian guidelines for prostate cancer screening. Like breast cancer screening, the occurrence of false negative screening tests was not considered for this model. Starting on the left hand side of the decision tree, the decision node represents

the three previously described scenarios that physicians will offer their male patients. In the first branch, the men are offered a combination of PSA and DRE. Like breast cancer screening, not all men offered prostate cancer screening opt to follow through with the tests. Those who are not screened will either develop a prostate cancer or not and then live or die from other causes. Those who live past one year will continue to be offered routine screening annually. Those who are screened will either have a positive or negative finding. Positive findings will be followed up with further testing to confirm or refute a positive diagnosis. Those with negative screening results will either live and be followed up with regular routine screening or will die from other causes.

Men who are offered only DRE will follow the same decision tree pattern as those who are offered a combination of PSA and DRE (pathway A); however, their associated probabilities will be different due to the fact that the sensitivity and specificity of the DRE alone are different from the combination of the two tests. Men who are not offered any prostate screening will follow the same decision tree pattern as those men who opt not to avail of screening services (pathway B).

Discussion and Prospects for the Future

The decision tree models presented in this paper highlight the complexities that are involved in making policy decisions regarding health screening initiatives. The overall cost of screening initiatives is heavily dependent on the choices that individuals make regarding their own health and the values they place on their state of health. Decision models are important tools for simplifying multiple sources of information into one easy-to-interpret measure.

A major limitation for decision tree analysis in health care is that it is only able to evaluate the alternatives that stem from a single decision or choice. In Canada, however, where there is a publicly funded health care system, fixed fiscal resources and opportunity costs are a reality. If the results of the breast cancer screening decision analysis showed favorable outcomes for people starting screening at 40 years of age, despite an increased overall cost, implementing a policy change results in that incremental cost being forfeited from another health program. To date, there has been no validated methodology for incorporating opportunity costs into cost effectiveness analyses. Future research in this area is warranted and would benefit both the fields of decision analytic modeling and health financing and economics.

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Appendix A: Provincial Breast Screening Policies

Province or territory	Age eligibility for mammography	Referral required between 40 and 49
Newfoundland and Labrador	40-69	Yes
Nova Scotia	40+	Yes
New Brunswick	50-69	Not available
Prince Edward Island	40+	No
Quebec	50-69	Not available
Ontario	50-69	Not available
Manitoba	50-69	Not available
Saskatchewan	50-75	Not available
Alberta	40-69	Yes
British Columbia	40-79	Yes
Northwest Territories	40+	No
Yukon	40+	No
Nunavut	Not available	Not available

Note. Source: Canadian Breast Cancer Foundation (2012).