

Proposal: Personalized Breast Cancer Prevention by Combining Screening and Diagnostic Decisions

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Abstract. Mammography screening has been shown to be the most effective method for reducing breast cancer mortality. However, it still faces significant inefficiencies, primarily due to high false-positive rates and substantial unnecessary follow-up examinations, such as biopsies. In this research, we aim to address these two inefficiencies by combining screening and post-mammography diagnostic decisions into a unified framework to derive personalized policies for managing patients throughout the breast cancer screening pathway. Although prior research has advanced personalization in breast cancer care, existing studies typically treat screening decisions and post-mammography diagnostic decisions as separate problems. We hypothesize that screening and diagnostic decisions are inherently interconnected, and that addressing them separately could result in suboptimal and less personalized screening pathways for patients. We formulate this problem as a partially observable Markov decision process (POMDP), with two decision variables: (1) determining the optimal timing for mammography (screening decisions), and (2) selecting the appropriate follow-up examination method (diagnostic decisions).

Key words: partially observable Markov decision processes, dynamic programming, decision analysis, medical decision making, breast cancer, mammography screening, personalized screening

1. Introduction

Breast cancer is the first and most prevalent cancer diagnosed among women in the UK, with approximately 50,107 cases reported in 2023 (National Disease Registration Service (NDRS 2025)). Breast cancer is also the second leading cause of cancer death among women in the UK, accounting for approximately 9,347 deaths in 2023 (NDRS 2025). It is estimated that 70,300 new cases of breast cancer will be diagnosed in 2040, meaning that about 1 in 7 women will be diagnosed with breast cancer (NDRS 2025). Early diagnosis of breast cancer is critically important, as it significantly improves survival rates by allowing interventions at stages when the cancer is more localized (Eby et al. 2022, Helvie et al. 2014, Pocobelli and Weiss 2015). This impact is evident in the dramatic

increase in the 5-year survival rate, which rises from 23% at stage 4 to 92% at stage 2 (Ellison and Saint-Jacques 2023).

Mammography screening remains the most effective method for early breast cancer detection and reducing its mortality rate at the population level, which can detect abnormalities in breast tissue 1.5 to 2.3 years before symptoms appear or are noticeable by patients (Løberg et al. 2015, Tabár 2018, Duffy 2020). In the UK, the age-standardized mortality rate dropped from 53.16 per 100,000 women in 1993 to 33.15 in 2019, largely attributed to increased screening and improved treatments (NDRS 2025). This trend, along with the age-standardized incidence rate, is illustrated in Figure 3. Although the breast cancer incidence rate rose in the 1980s-90s due to increased mammography use and hormonal factors, it has since been stabilized. While several randomized control trials (RCTs) have demonstrated the benefit of mammography screening programs in reducing breast cancer mortality by about 20% (Marmot et al. 2013), several meta-analyses and studies show that these programs still face significant inefficiencies, primarily due to two sources: high rate of false-positive and high rate of unnecessary follow-up examinations (Løberg et al. 2015). We aim to build our work focusing on these two sources of inefficiency.

False-positive mammograms, the primary source of inefficiency in screening programs, occur when a suspicious finding is incorrectly interpreted as cancerous, prompting additional diagnostic tests that ultimately confirm no cancer. False positives arise in 2.5–14% of screening mammograms, translating to about 392,000 false positives among 2.8 million mammograms in Canada in 2018 (Løberg et al. 2015, CCS 2023). Several factors contribute to these errors. Dense breast tissue can obscure imaging, making benign and malignant patterns harder to distinguish, an issue more common in younger women (Corsetti et al. 2008). Benign conditions such as cysts, fibroadenomas, or calcifications may also appear abnormal. The expertise and risk behavior of radiologists further influence outcomes, as variability in interpretations can produce false positives in borderline cases (Alberdi et al. 2011). These errors cause substantial patient anxiety (Brewer et al. 2007), lead to unnecessary follow-up tests and overtreatment, and contribute to population-level over-screening.

Unnecessary follow-up examinations are the second major source of inefficiency. After mammography, patients either return to routine screening or undergo additional procedures, such as diagnostic mammograms, biopsies, ultrasounds, or MRIs, often scheduled immediately or within 3, 6, or 12 months. To standardize reporting and management, radiologists use the BI-RADS system (Magny et al. 2023), which classifies findings from 1 to 6 with corresponding recommendations (Table 1). However, its subjectivity, shaped by radiologists' expertise and risk tolerance, can lead

to overestimation of the cancer risk and many false-positive assessments (Alberdi et al. 2011). Its broad guidance is particularly problematic for category 4, which recommends biopsy across a very wide risk range (2–98%). Most BI-RADS 4 findings (70–80%) are later found to be benign after biopsy (Liu et al. 2024), underscoring the prevalence of unnecessary biopsies and the need for more personalized follow-up strategies.

The trade-off between the benefits and risks of mammography screening is a nuanced issue. While more frequent screening improves early detection and reduces mortality, it also raises the likelihood of false positives and unnecessary follow-up procedures. Public guidelines typically specify the recommended starting and ending ages and the screening frequency (annual, biennial, or triennial). As shown in Table 2, these guidelines differ notably across programs, especially in the recommended starting age. Since the launch of public screening programs in the 1980s, several organizations have revised their recommendations. For example, the U.S. Preventive Services Task Force (USPSTF) lowered the starting age from 50 to 40 in 2023 (USPSTF 2024). However, disagreement persists among public healthcare organizations regarding when to begin and end screening and how often to screen. For instance, unlike many U.S. programs, the UK’s National Health Service breast screening programme (BSP) and the Canadian Task Force on Preventive Health Care do not recommend initiating screening at age 40 (National Health Service 2025, CTFPHC 2024).

Supporters of earlier screening argue that breast cancer is more aggressive in younger women (Jayasinghe et al. 2005). Tumor doubling times illustrate this pattern, with a median of 80 days for women under 50, compared with 157 days for ages 50–70 and 188 days for women over 70 (Peer et al. 1993, Michaelson et al. 1999). Critics, however, emphasize the higher false-positive rates in younger women due to denser breast tissue and the need for more cautious guidelines (Kerlikowske et al. 2000). Faster tumor progression in younger women may also increase the likelihood of interval cancers, reducing screening effectiveness. This debate has received substantial media coverage (NYTimes 2024, CBC 2024), including ethical discussions that highlight the tension between saving lives and exposing many to unnecessary stress, anxiety, and medical procedures (Prevention 2016).

An emerging approach to this controversy is the personalization of screening and diagnostic policies, as numerous studies emphasize tailoring guidelines based on factors beyond age, such as demographics, family history, breast density, prior mammograms, and genetics (Gail and Rimer 1998, Ayer et al. 2012). Since breast cancer risk varies within the same age group, personalized policies can improve life-saving outcomes for high-risk women while reducing unnecessary

screening and diagnostic procedures for low-risk women. Although prior research has advanced personalization in breast cancer screening, most studies treat personalized screening schedules and post-mammography diagnostic decisions as separate problems. In practice, however, these decisions are sequentially dependent: more frequent screenings can increase false positives and downstream diagnostics, while diagnostic outcomes influence subsequent screening choices and timing. We hypothesize that these decisions are inherently interconnected and that analyzing them in isolation may lead to suboptimal and less personalized screening pathways.

In this research, we aim to combine screening decisions and post-mammography diagnostic decisions into a unified framework for designing personalized policies to manage patients throughout the breast cancer screening pathway. We formulate this problem as a partially observable Markov decision process (POMDP), with two decision variables: (1) determining the optimal timing for mammography (screening decisions), and (2) selecting the appropriate follow-up examination method (diagnostic decisions). Building on this framework, we address the following core research questions:

- **RQ1:** How do screening frequency and post-mammography diagnostic choices interact dynamically within breast cancer screening pathway?
- **RQ2:** To what extent does combining screening and post-mammography diagnostic decisions improve clinical outcomes and resource efficiency for different risk subgroups?
- **RQ3:** What is the impact of integrating genetic testing into the breast cancer screening pathway on the reduction of unnecessary biopsies and overall healthcare costs?

In the next section, we review the related literature, highlighting existing gaps and our contributions to this body of research. The complete problem definition and POMDP formulation are provided in the extended version of this proposal (Milani 2025).

2. Literature Review

Cancer screening and diagnostic decisions have been widely studied in the operations research literature for over four decades (see Alagoz et al. (2011) and Ivy (2009)). Within the breast cancer setting, studies are broadly categorized into population- and personal-level modeling approaches. Population-level studies optimize screening policies for large cohorts based on average risk factors such as age (see Koleva-Kolarova et al. (2015) and Henderson et al. (2024)). Personal-level studies, by contrast, tailor decisions to individual characteristics beyond age, such as breast density, gene mutations, and prior test results, offering a more individualized approach. Two distinct research

streams explore personalization in the breast cancer setting. One stream focuses on optimizing personalized screening schedules for healthy women, without addressing diagnostic decision-making processes. The other stream concentrates on developing optimal policies for personalized post-mammography diagnostic decisions within regular public screening intervals, overlooking the potential for more personalized screening schedules.

2.1. Personalized Screening Decisions

The seminal work by Ayer et al. (2012) was the first to incorporate both dynamic factors (e.g., previous screening results and family history) and static factors (e.g., age and race). Their POMDP model generates personalized screening schedules that adapt over time and are not necessarily fixed to a regular pattern. For instance, a healthy woman who has undergone annual screening for five years with all negative results may be recommended to extend her next screening interval to over two years. These intervals continue to adjust based on changes in her health status. Building on this work, Ayer et al. (2015) addressed the same problem but incorporated non-perfect patient adherence behavior. They showed that when screening strategies are optimized based on average adherence, the effect on patients with low adherence is relatively small, but patients with high adherence may be adversely affected. In both studies, mammography outcomes are simplified to positive or negative, ignoring BI-RADS assessments, and positive mammograms automatically lead to biopsy without any follow-up diagnostic decision-making process.

2.2. Personalized Post-Mammography Diagnostic Decisions

To address the high rate of benign biopsies, Chhatwal et al. (2010) were the first to tailor diagnostic decisions using both mammographic and demographic features. Their MDP model considers biopsy as the only follow-up within an annual screening regime. They assume that all women undergo annual screening, and after each mammogram the decision is either immediate biopsy or waiting until the next screening. The resulting age- and risk-based policies are therefore restricted to a binary action set, omitting other diagnostic options such as short-term follow-up, ultrasound, or MRI. Alagoz et al. (2013) extended this model by adding short-term diagnostic mammography as a third action and derived age- and risk-based threshold policies.

Tunç et al. (2022) further advanced this stream by proposing a large-scale MDP that defines patient states as risk distributions over cancer stages. To handle the resulting complexity, they used dimension-reduction techniques and a divide-and-search algorithm to compute feasible upper bounds on decision thresholds, showing that incorporating cancer stages can substantially reduce

overdiagnosis. All of these studies assume unlimited resources. The only work considering cost-effectiveness is Ayvaci et al. (2012), which incorporates budget constraints and derives dynamic, threshold-based policies based on age, cancer risk, and budget levels, again choosing among three post-mammography options.

Ayvaci et al. (2018) is the only study accounting for patients' strategic behavior, which models heterogeneous patient preferences through distinct utility functions. They show that incorporating patient preferences may reduce population-level survival duration but can make care delivery more effective and potentially more efficient. While all these models can be adapted to non-annual screening, they still assume fixed, non-personalized intervals.

2.3. Existing Gap

Screening and diagnostic decisions are inherently interconnected, and analyzing them separately may yield suboptimal policies for two main reasons. First, these decisions are sequentially dependent. Screening choices affect diagnostic outcomes since more frequent screenings increase false positives and unnecessary follow-ups, as noted by (Ayer et al. 2012). Diagnostic decisions, in turn, shape future screening since the results of diagnostic tests (especially false positives) inform subsequent screenings, and procedures like biopsies may require temporary adjustments to the screening schedule due to healing needs. Second, separating screening and diagnostic models overlooks critical feedback loops in sequential decision-making. These loops help manage evolving uncertainty by incorporating the patient's health trajectory and prior screening outcomes into future decisions. Ignoring them can lead to diagnostic actions that fail to reflect changes in the patient's risk profile or history, further contributing to less effective decision-making.

2.4. Our Contributions

From the application standpoint: (1) Rather than analyzing screening and diagnostic decisions separately, we propose a holistic framework that captures their interdependent effects. (2) Our model includes an additional diagnostic option, gene testing, which also requires follow-up actions. Gene testing has received limited attention in the operations research literature, largely due to historically high costs. However, recent advances and increasing adoption in national programs have made it a key component of modern prevention strategies (Thapa et al. 2025). Motivated by this shift, we incorporate gene testing to evaluate its operational impact and cost-effectiveness in reducing unnecessary follow-ups and healthcare costs.

On the theoretical side, we propose a POMDP model that differs from conventional formulations in healthcare operations management. In our setting, the time to observe outcomes varies across

decisions: short-term follow-up yields results after six months, whereas biopsy and gene-testing results are available almost immediately. Consequently, the model operates with decision-dependent time periods, with transition epochs following each action. This feature can be valuable in other healthcare contexts where outcome timing differs, for example, in diabetes management, where medication adjustments may take weeks to show effects while rapid-acting insulin works almost immediately. Finally, we analyze the model's structural properties to derive simple, threshold-based policies that are easy to understand and implement.

3. Problem Definition

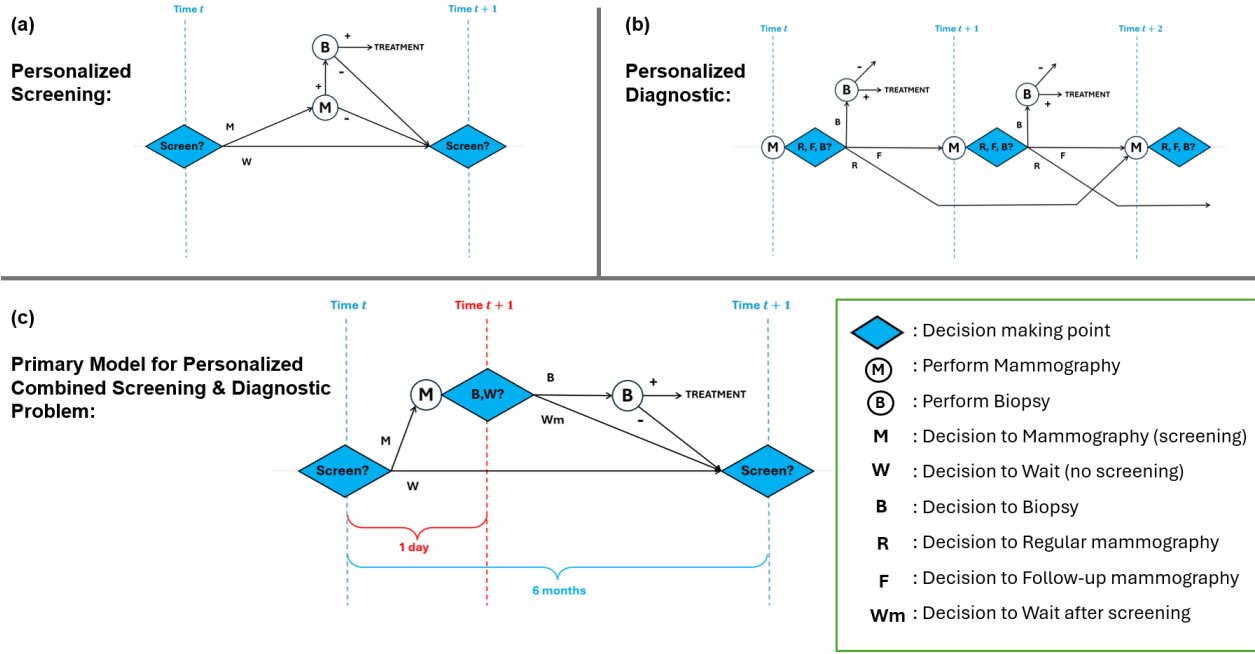
3.1. Breast Cancer Screening Problem

As discussed in §1, public mammography screening programs typically recommend only the start and end ages for screening and the frequency of screenings. Women meeting the eligibility criteria, asymptomatic women within the prescribed age range and not having had a mammogram within the screening interval, receive invitation letters, and can undergo mammography without requiring a doctor's visit or referral. For high-risk women, consulting a physician is often recommended to determine the appropriate timing and method of screening.

In the context of personalized screening policies, a sequential decision-making process is employed (Ayer et al. 2012, 2015). Figure 1a shows a simplified process diagram for these models. In this process, at each decision point, the decision-maker must decide whether to refer an asymptomatic woman for a screening mammogram or wait until the next decision point, six months later. As seen in Figure 1a, these models assume binary outcomes for mammograms, with positive mammogram results leading to immediate biopsies. If the biopsy is positive, the patient exits the decision process and begins treatment; otherwise, the decision process continues. For the sake of simplicity, we omit death and self-diagnosis transitions from the diagrams of Figure 1. This process accounts for dynamic factors such as the most recent test results and family history, so the resulting schedules can be more flexible and adjusted in response to mammogram outcomes rather than public guidelines' fixed periodic intervals; for example, consecutive negative results may lead to longer future intervals between screenings.

3.2. Post-Mammography Diagnostic Problem

The BI-RADS system is a widely used framework for managing follow-up diagnostic examinations and assisting radiologists in their diagnostic decision-making. However, as discussed in §1, this system is often too generalized, requiring radiologists to rely on their own experience in many cases, which may introduce bias.

Figure 1 Simplified Primary Models for Separate and Combined Screening and Diagnostic Problems

In personalized diagnostic decision models, a sequential decision-making process occurs after each regular screening mammogram (Chhatwal et al. 2010, Ayvaci et al. 2012, Alagoz et al. 2013, Tunç et al. 2022). Existing models for personalized post-mammography decisions typically consider three alternative decisions/actions after assessing a screening mammogram: (1) continue regular screening (12 months later); (2) recommend short-term follow-up diagnostic mammography (6 months later); or (3) perform an immediate biopsy. Figure 1b presents a simplified process diagram for these models, in which patients exit the decision-making process after a biopsy, regardless of the result, and no death transitions are considered.

As per discussions with our clinical collaborator, a Medical Oncologist at the University of Calgary, the real-world practices are more complex than these models reflect. For example, follow-up diagnostic mammograms may be recommended within a 1- to 6-month window, rather than a fixed six-month period. Additionally, other diagnostic methods, such as breast-dedicated ultrasound and MRI, are frequently used to confirm abnormalities. Even after negative biopsy results, physicians may recommend further follow-up diagnostic tests to verify the negative findings. Moreover, in practice, post-diagnostic examinations often involve a concordance check, where new findings are compared with previous ones to ensure consistency. Discussions with the Cancer Centre at the University of Calgary also highlighted the expanding role of genetic testing in guiding screening

pathways. Currently used for high-risk women, genetic testing is expected to become more affordable and accessible to broader sub-populations in the near future. Our model incorporates genetic testing as an option within the screening pathway, and we aim to conduct a cost-effectiveness analysis to assess its potential for reducing unnecessary biopsies and overall healthcare costs.

3.3. Primary Model for Combining Screening and Diagnostic Problems

When considering both screening and diagnostic problems together, a key challenge arises in defining decision epochs, necessitating a different modeling approach from the existing literature. Figure 1c presents a simplified version of our proposed combined screening and diagnostic problem, where, in addition to the screening decision, only two types of diagnostic actions are available: (1) regular screening and; (2) biopsy. At the start of each six-month epoch, the decision-maker must choose between performing a mammogram or waiting until the next six-month period. If the model decides to screen, after assessing the mammogram results and the patient's individual characteristics, it must then decide whether to wait until the next six-month epoch or proceed with a biopsy. If the biopsy result is positive, the patient exits the decision process and begins treatment; otherwise, the decision process continues. The key structural difference between the disjointed and combined models is as follows: As shown in Figure 1a and Figure 1b, existing disjointed models typically assume six-month decision epochs with only one decision point in each epoch. However, as illustrated in Figure 1c, in the combined problem, two decision points occur within each six-month interval. Combining screening and diagnostic decisions introduces an additional type of decision period, lasting approximately one day, to account for the time required to process mammogram or other test results. Thus, if a screening mammogram is performed, a new decision point emerges the following day. This complexity necessitates defining two types of decision epochs with different lengths, leading to a fundamentally different modeling approach. In essence, nested decisions are required, where certain actions trigger a subsequent decision-making process with distinct decision options.

4. Model Formulation

We formulate the combined screening and diagnostic problem as a discrete-time, finite-horizon partially observable Markov decision process (POMDP) model, where a single decision-maker determines the timing of screenings and the method of diagnosis for a woman before breast cancer is confirmed. The decision-maker's objective is to maximize the patient's total expected weighted reward, assuming an unconstrained budget. The weights assigned to the rewards are exogenously

Time t

b_t → Screening Decision

Screening Decision branches into: M (Mammography) and W (Wait).

M → Post Mammo Decision

Post Mammo Decision branches into: F (Follow-up), G (Gene Testing), B (Biopsy), and W (Wait).

G → Post Gene Test Decision

Post Gene Test Decision branches into: F (Follow-up), B (Biopsy), and W (Wait).

B → Start Treatment (X)

Time $t+1$

Belief vectors: b_{t+1} (from F, G, B, W of Time t), b_{t+1} (from W of Time t).

Decisions: PMD_{t+1} (from b_{t+1}), PMD_{t+1} (from b_{t+1}).

Time $t+2$

Belief vectors: b_{t+2} (from PMD_{t+1}), b_{t+2} (from b_{t+1}), b_{t+2} (from b_{t+1}).

Legend:

- \parallel : Updating Belief Vector
- \square : Decision Making
- \odot (M) : Mammography
- \odot (W) : Wait
- \odot (F) : Follow-up
- \odot (G) : Gene Testing
- \odot (B) : Biopsy
- \otimes : Start Treatment

4.1. Decision Process Description

At the beginning of each *screening epoch*, we update our belief about the patient’s cancer risk, represented as a probability distribution over the patient’s true health state. Next, we decide whether to screen the patient or not (**M**, **W?**). If we choose not to screen (**W**), the patient progresses to the epoch ($t + 2$), meaning no action is taken for 12 months. If we decide to screen (**M**), we must then determine the post-mammography action (**F**, **G**, **B**, **W?**). If follow-up screening (**F**) is chosen, the patient moves to the next epoch ($t + 1$) for a repeat mammogram. If a biopsy (**B**) is performed and the result is positive, the patient enters treatment, and the process stops; if negative, the patient moves to the epoch ($t + 2$). Choosing the wait option (**W**) also sends the patient to epoch ($t + 2$). If gene testing (**G**) is chosen, we must decide on a post-gene testing action (**F**, **B**, **W?**). The consequences of **F**, **B**, and **W** at this stage are similar to the previous decision point. There are only two absorbing states that terminate the process: death and a positive biopsy result. Figure 2 represents the detailed process diagram of our POMDP model.

4.2. POMDP Formulation

In this section, first, we will explain our novel approach in defining the nested decisions or actions of our POMDP model, then we will explain the notation and components of our POMDP model followed by the optimality equations.

Our approach in defining the nested decisions: To integrate screening and diagnostic decisions, we define three nested layers of decision-making processes within each six-month epoch, as shown in Figure 2. In each epoch, we may engage in one layer of decision-making (if we choose not to screen), two layers (a screening decision followed by a post-mammography decision, if we decide to screen but not proceed with gene testing), or three layers (a screening decision, a post-mammography decision, and a post-gene testing decision, if we decide to screen and then proceed with gene testing).

Time steps: We first define fixed six-month decision epochs, referred to as *screening epochs*. However, the time step index k is also incremented whenever a mammogram, gene test, or biopsy is performed. In other words, time step increments whenever screening or diagnostic decision-making processes occur.

- $k \in \mathcal{K} = \{0, 1, 2, \dots, N\}$ where $N < \infty$.

States: We define the states as the patient's breast cancer risk, rounded to the nearest integer between 0 and 100. In addition to this, we include death (D) and post-biopsy (PB) as the two absorbing states. Let \mathcal{S} represents the state space, and s_k the patient's state at time step k , then:

- $s_k \in \mathcal{S} = \{0, 1, 2, \dots, 100, D, PB\}$

Actions: We define a feasible action set for each decision-making layer. Let \mathcal{A} be the main action set, and a^{SC} , a^{PM} , and a^{PG} represent the feasible action sets for the three decision-making layers: screening, post-mammography, and post-gene testing, respectively. Then, we define:

- $a^{SC} = \{W^{SC}, M^{SC}\}$
- $a^{PM} = \{W^{PM}, F^{PM}, G^{PM}, B^{PM}\}$
- $a^{PG} = \{W^{PG}, F^{PG}, B^{PG}\}$
- $\mathcal{A} = a^{SC} \cup a^{PM} \cup a^{PG}$

Observations: We define observations as the outcomes of screening and diagnostic tests. Each testing method has its own possible observation set. For mammography and gene testing, we assume that a cancer risk, a number between 0 and 100, can be assigned to the patient based on the test results, while biopsy results are classified as either positive or negative. Let \mathcal{O} represent the overall observation set, and o^M , o^G , and o^B represent the observation sets for mammography, gene testing, and biopsy, respectively. Therefore, we define:

- $o^M = o^G = \{0, 1, 2, \dots, 100\}$
- $o^B = \{B+, B-\}$
- $O = o^M \cup o^G \cup o^B$

Core Transition Probabilities: Let \mathcal{P} be the core transition function. This function determines the true state of the system in the next epoch, i.e. $\mathcal{P} = P_k^{(a,o)}(s'|s)$, that is the probability of going to state s' at time $k + 1$ when the current state is s , action a is taken, and observation o is seen in time k . In our setting, o matters since we have some deterministic test results (for biopsy) and subsequent transitions.

Observation Probabilities: Let $Q = P_k^a(o|s)$ be the observation probabilities function, i.e. the probability of observing outcome o of test a at time k when the true state is s . This function basically determines our predictions of test results that are based on the tests' specificity and sensitivity. We consider indices k for the accuracy of test to define them as age-dependent. For instance,

- $P_k^M(o^M = 0|s = 0) = spec_k(M)$
- $P_k^M(o^M = cancerous|s = 0) = 1 - spec_k(M)$

where $spec_k(M)$ is specificity of mammogram for the patient in time k .

Reward Functions: We define our total reward function based on six items and their associated costs: (1) the number of mammogram false-positives (f), representing the anxiety cost; (2) the number of mammogram false-negatives (d), representing the cost of a one-period delay in cancer detection; (3) the number of benign biopsy outcomes (u), representing the cost of unnecessary painful follow-up examinations; (4) the number of performed mammograms (m), representing the immediate cost (disutility) of each mammogram; (5) the number of performed biopsies (b), representing the immediate cost (disutility) of each biopsy; and (6) the number of performed gene tests (g), representing the immediate cost (disutility) of each gene test. Let $r_k(s, a, o)$ be the immediate reward in time k when the patient's true state is s , we choose action a , and observation o is seen, and let the $r_k(s, a)$ be the total reward for being in state s and choosing action a , then we will have:

$$\bullet \quad r_k(s, a, o) = \begin{cases} f & \text{when true state is 0 but the test result is not 0 (false-positive).} \\ d & \text{when true state cancerous but we do nothing (delay in detection).} \\ u & \text{when that true state is 0 but we perform biopsy (benign result).} \\ m & \text{every time we perform mammography (disutility of mammography).} \\ b & \text{every time we perform biopsy (disutility of biopsy).} \\ g & \text{every time we perform gene testing (disutility of gene testing).} \end{cases}$$

$$\bullet \quad r_k(s, a) = \sum_{o \in O} P_k^a(o|s) r(s, a, o)$$

The following are some examples of reward function values in specific scenarios:

- $r_k(0, M, o^M = \{\text{cancerous}\}) = f + m$: occurs when the true state is cancer-free, we decide to screen, and the mammogram result shows high cancer risk (false-positive mammogram).
- $r_k(0, B, B-) = u + b$: occurs when the true state is cancer-free, we perform a biopsy, and the result is benign.
- $r_k(s \in \{\text{cancerous}\}, W^{SC}, \cdot) = d$: occurs when the true state is cancerous, but after screening we decide to wait until next epoch, regardless of the mammography result.
- $r_k(s \in \{\text{cancerous}\}, M, o^M = 0) = d + m$: occurs when the true state is cancerous, we decide to screen, and the mammogram result shows nothing (false-negative mammogram).
- $r_k(s \in \{\text{cancerous}\}, B, B-) = d + b$: occurs when the true state is cancerous, we perform biopsy, and the biopsy result is benign (false-negative biopsy).

Belief vector: Let b_k be our belief in time k about the true state of the patient, which is basically a probability distribution over all possible states of the patient.

Updated belief vector: Let b'_k be our expectation about the next true state of the system when in time k we chose action a and saw observation o , which is calculated using the Bayes rule based on the current belief vector and observation in time k as follows.

$$\bullet \quad b'_k = \frac{\sum_S b(s) P_k^a(o|s) P_k^{a,o}(s'|s)}{\sum_S b(s) P_k^a(o|s)}$$

4.3. Optimality Equations

We now present the optimality equations for the simplified primary case discussed in §3.3, where instead of three layers, we have only two layers of decision-making; screening (W, M?), and diagnostic (Wm, B?). Let $V_t^*(b)$ and $V_t^a(b)$ be the maximum total expected reward in time k , when our current belief vector is b , and when we choose action a , respectively.

$$V_k^*(b) = \max\{V_k^W(b), V_k^M(b)\}, \text{ where}$$

$$\begin{aligned}
V_k^W(b) &= \sum_{s \in S} b(s) [r_k(s, W, o) + \sum_{s' \in S} P_k^{(W, o)}(s'|s) V_{k+1}^*(b')], \text{ and} \\
V_k^M(b) &= \sum_{s \in S} b(s) \sum_{o \in O_M} P_k^M(o|s) r_k(s, M, o) + \max\{V_{k+1}^B(b), V_{k+1}^{Wm}(b)\}, \text{ where} \\
V_{k+1}^B(b) &= \sum_{s \in S} b(s) \sum_{o \in O_B} P_{k+1}^B(o|s) [r_{k+1}(s, B, o) + \sum_{s' \in S} P_{k+1}^{(B, o)}(s'|s) V_{k+2}^*(b')], \text{ and} \\
V_{k+1}^{Wm}(b) &= \sum_{s \in S} b(s) [r_{k+1}(s, Wm, o) + \sum_{s' \in S} P_{k+1}^{(Wm, o)}(s'|s) V_{k+2}^*(b')]
\end{aligned}$$

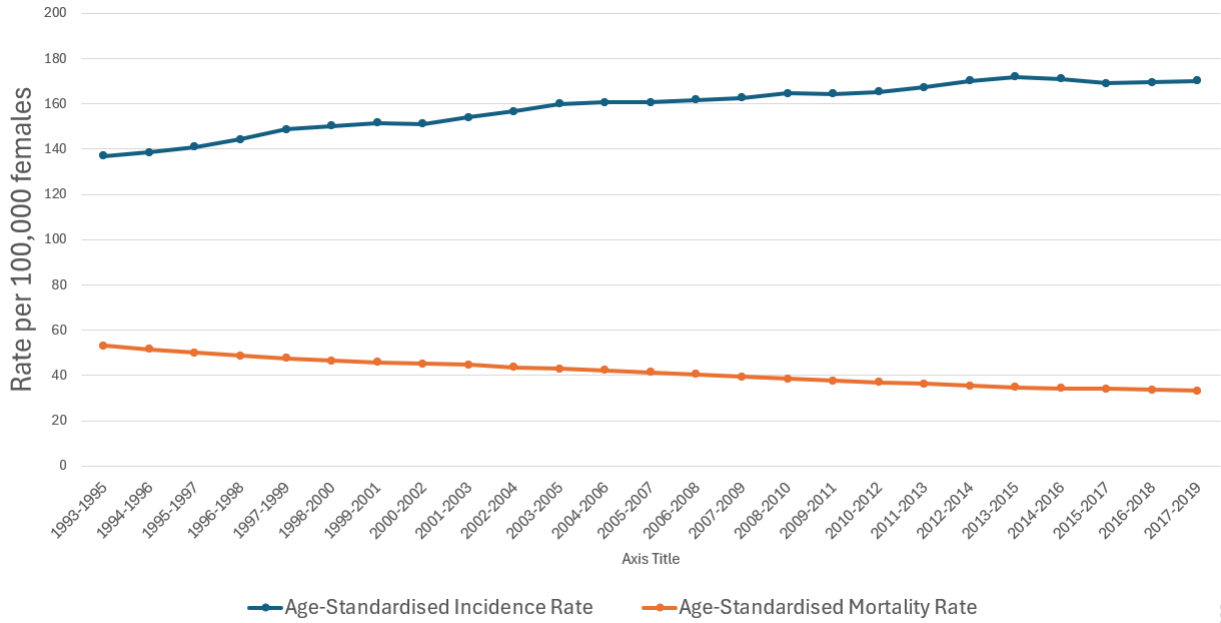
5. Results and Discussion

6. Conclusion

Notes

Appendix A: Illustration of Breast Cancer Incidence and Mortality Rates in the UK

Figure 3 Age-standardized incidence and mortality rate for breast cancer (female), United Kingdom, 1993 to 2019.



Note. Data from National Disease Registration Service (NDRS 2025).

Appendix B: BI-RADS Table

Assessment	Likelihood of Cancer (%)	Diagnostic Recommendation
Category 0: Incomplete	N/A	Recall
Category 1: Negative	Essentially 0	Routine screening
Category 2: Benign	Essentially 0	Routine screening
Category 3: Probably Benign	≥ 0 but ≤ 2	Short-interval (6-month) follow-up
Category 4: Suspicious	> 2 but < 95	Biopsy
Category 5: Highly Suggestive of Malignancy	≥ 95	Biopsy
Category 6: Known Biopsy-Proven Malignancy	N/A	Surgical extraction

Table 1 BI-RADS Categories, Likelihood of Cancer, and Diagnostic Recommendations

Appendix C: Breast Cancer Screening Guidelines

Program	Age Group	Guideline
Alberta Breast Cancer Screening Program (ABCSP) October 2023	40-44	Referral needed
	45-74	Every 2 years
	75+	Referral needed
Canadian Task Force on Preventive Health Care (CTFPHC) May 2024	40-49	Not recommended
	50-74	Every 2 or 3 years
	75+	Referral needed
United Kingdom National Health Service Breast Screening Programme (BSP) 2025	40-49	Not recommended
	50-70	Every 3 years
	71+	Can continue every 3 years if they are healthy
American Cancer Society December 2023	40-44	Have option for every year
	45-54	Every year
	55+	Every 2 years as long as healthy
United States Preventive Services Task Force (USPSTF) April 2024	40-74	Every 2 years
	75+	Insufficient evidence to assess benefits to harms
American College of Physicians (ACP) 2019	40-49	Referral needed
	50-74	Every 2 years
	75+	Discontinue

Table 2 Breast Cancer Screening Guidelines

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