Optimal Information Collection Policies in a Markov Decision Process Framework

Supplemental Materials

Cipriano LE, Goldhaber-Fiebert JD, Liu S, Weber TA

Appendix A. Supplemental Methods

Appendix A.1. Application of linear INMB to HCV screening example

A schematic of the decision problem is presented in Figure 2.

Let λ be the willingness-to-pay threshold, q_1 the test sensitivity, q_2 the test specificity, $C_S > 0$ the cost of the screening test, $B_S \leqslant 0$ the quality-of-life loss from the screening test, $C_{FP} \geqslant 0$ the cost of correcting a false-positive test result, $B_{FP} \leqslant 0$ the quality-of-life loss from a false-positive test result. Furthermore, the lifetime discounted costs and benefits of the true-positive, false-negative, and true-negative screening outcomes are denoted by C_1, C_2, C_3, and B_1, B_2, B_3, respectively.

The net monetary benefit (NB) of the decision not to screen cohort t is

$$\mathrm{NB}_{\mathrm{NoScreening}} = \lambda\left(\tilde{p}_t B_2 + (1-\tilde{p}_t)B_3\right) - \left(\tilde{p}_t C_2 + (1-\tilde{p}_t)C_3\right). \tag{A.1}$$

The net monetary benefit of the decision to screen cohort t is

$$\begin{aligned}\mathrm{NB}_{\mathrm{Screening}} =& \lambda\left(\tilde{p}_t q_1 B_1 + \tilde{p}_t(1-q_1)B_2 + (1-\tilde{p}_t)(1-q_2)(B_3+B_{FP}) + (1-\tilde{p}_t)q_2 B_3 + B_S\right) \\ &- \left(\tilde{p}_t q_1 C_1 + \tilde{p}_t(1-q_1)C_2 + (1-\tilde{p}_t)(1-q_2)(C_3+C_{FP}) + (1-\tilde{p}_t)q_2 C_3 + C_S\right).\end{aligned} \tag{A.2}$$

The incremental net monetary benefit (INMB) of screening compared to the alternative of not screening is computed as the difference between Eq. (A.2) and Eq. (A.1):

$$\begin{aligned}
\text{INMB}_{\text{Screening}} =& \text{NB}_{\text{Screening}} - \text{NB}_{\text{NoScreening}} \\
=& \lambda\left(\tilde{p}_t q_1 B_1 + \tilde{p}_t(1-q_1)B_2 + (1-\tilde{p}_t)(1-q_2)(B_3+B_{FP}) + (1-\tilde{p}_t)q_2 B_3 + B_S\right) \\
& - \left(\tilde{p}_t q_1 C_1 + \tilde{p}_t(1-q_1)C_2 + (1-\tilde{p}_t)(1-q_2)(C_3+C_{FP}) + (1-\tilde{p}_t)q_2 C_3 + C_S\right) \\
& - \left(\lambda\left(\tilde{p}_t B_2 + (1-\tilde{p}_t)B_3\right) - \left(\tilde{p}_t C_2 + (1-\tilde{p}_t)C_3\right)\right) \\
=& \tilde{p}_t\left(q_1\left[\lambda(B_1-B_2) - (C_1-C_2)\right] - (1-q_2)\left[\lambda B_{FP} - C_{FP}\right]\right) \\
& + \lambda B_S - C_S + (1-q_2)(\lambda B_{FP} - C_{FP})
\end{aligned}$$

With the terms collected, it is clear that INMB of screening compared to no screening at time t can be written $\text{INMB}_t = \tilde{\theta}_t \tilde{p}_t - \gamma$ where,

$$\tilde{\theta}_t = q_1\left[\lambda(B_1-B_2) - (C_1-C_2)\right] - (1-q_2)\left[\lambda B_{FP} - C_{FP}\right] > 0$$

and

$$\gamma = C_S - \lambda B_S - (1-q_2)(\lambda B_{FP} - C_{FP}) > 0.$$

Appendix A.2. Linear decomposition of $\tilde{\theta}_t$ into a function of $\tilde{F}_t$

We decompose $\tilde{\theta}_t$, the marginal benefit from early diagnosis and treatment, into a linear function of $\tilde{F}_t$, the fibrosis-stage distribution at screen-detected diagnosis.

The lifetime discounted costs and quality-adjusted life-years for an HCV-positive individual (C_1, C_2, B_1, and B_2) are each linear functions of $\tilde{F}_t$. As an example, we can write

$$C_1 = C_{1,F0}\tilde{F}_{0,t} + C_{1,F1}\tilde{F}_{1,t} + C_{1,F2}\tilde{F}_{2,t} + C_{1,F3}\tilde{F}_{3,t} + C_{1,F4}\tilde{F}_{4,t},$$

where $C_{1,F0}$, $C_{1,F1}$, $C_{1,F2}$, $C_{1,F3}$, and $C_{1,F4}$ are the lifetime discounted costs for an HCV-positive individual diagnosed through screening at age 50 at fibrosis stage F0, F1, F2, F3, and F4, respectively.

Using symmetric notation for the expanded forms of C_2, B_1, and B_2, we can write $\tilde{\theta}_t$ as a linear function of $\tilde{F}_t$:

$$\begin{aligned}
\tilde{\theta}_t =& q_1\left[\lambda(B_1 - B_2) - (C_1 - C_2)\right] - (1 - q_2)\left[\lambda B_{FP} - C_{FP}\right] \\
=& q_1[(\lambda(B_{1,F0} - B_{2,F0}) - (C_{1,F0} - C_{2,F0}))\,\tilde{F}_{0,t} + (\lambda(B_{1,F1} - B_{2,F1}) - (C_{1,F1} - C_{2,F1}))\,\tilde{F}_{1,t} \\
&+ (\lambda(B_{1,F2} - B_{2,F2}) - (C_{1,F2} - C_{2,F2}))\,\tilde{F}_{2,t} + (\lambda(B_{1,F3} - B_{2,F3}) - (C_{1,F3} - C_{2,F3}))\,\tilde{F}_{3,t} \\
&+ (\lambda(B_{1,F4} - B_{2,F4}) - (C_{1,F4} - C_{2,F4}))\,\tilde{F}_{4,t}] - (1 - q_2)\left[\lambda B_{FP} - C_{FP}\right].
\end{aligned}$$

Since $\tilde{\theta}_t$ is a linear function of $\tilde{F}_t$, INMB_t is also a linear function of $\tilde{F}_t$.

Appendix A.3. Recursive Partitioning to Create 'Representative' Posterior Fibrosis-Stage Distributions

We used recursive partitioning regression to identify classes of similar posterior distributions [50]. Recursive partitioning is a technique that builds a classification rule with the objective of identifying homogeneous strata through a process in which the population is divided into smaller and smaller samples ("nodes"). Our initial 'population' consisted of $200,000$ simulated realizations of $\tilde{w}_t(m_t = 200, y_t = y_0)$. For each realization, we computed the corresponding posterior distribution, $\hat{y}_t$, and the marginal benefit from early diagnosis and treatment, $\tilde{\theta}_t(\hat{y}_t)$, which we used as our measure of similarity in the recursive partitioning regression. To identify which variable provides the best split, we used the ANOVA method which uses the splitting criteria $SS_T - (SS_L + SS_R)$, where SS_T is the total sum of squares for the current node and SS_R and SS_L are the total sums of squares for the right and left sons, respectively. This criterion is equivalent to choosing the split to maximize the between-groups sum-of-squared differences in a simple analysis of variance [63]. A split is only considered if at least 20 realizations will be in each son node and the increase in R^2 is greater than 0.01. The procedure ends when neither of these conditions can be satisfied. Applying the recursive partition to the $200,000$ simulated studies resulted in 24 posterior distribution classifications (Figure A.1).

The probability mass functions of the 'representative' posterior distributions were determined using the average proportion of each fibrosis-stage among members of each classification (Figure A.2A). The probability of each representative posterior was determined using the frequency of its classification (Figure A.2B). The expected value of collecting information about $\tilde{F}_t$ was then the value of the optimal action given each possible representative posterior, weighted by the probability of that posterior.

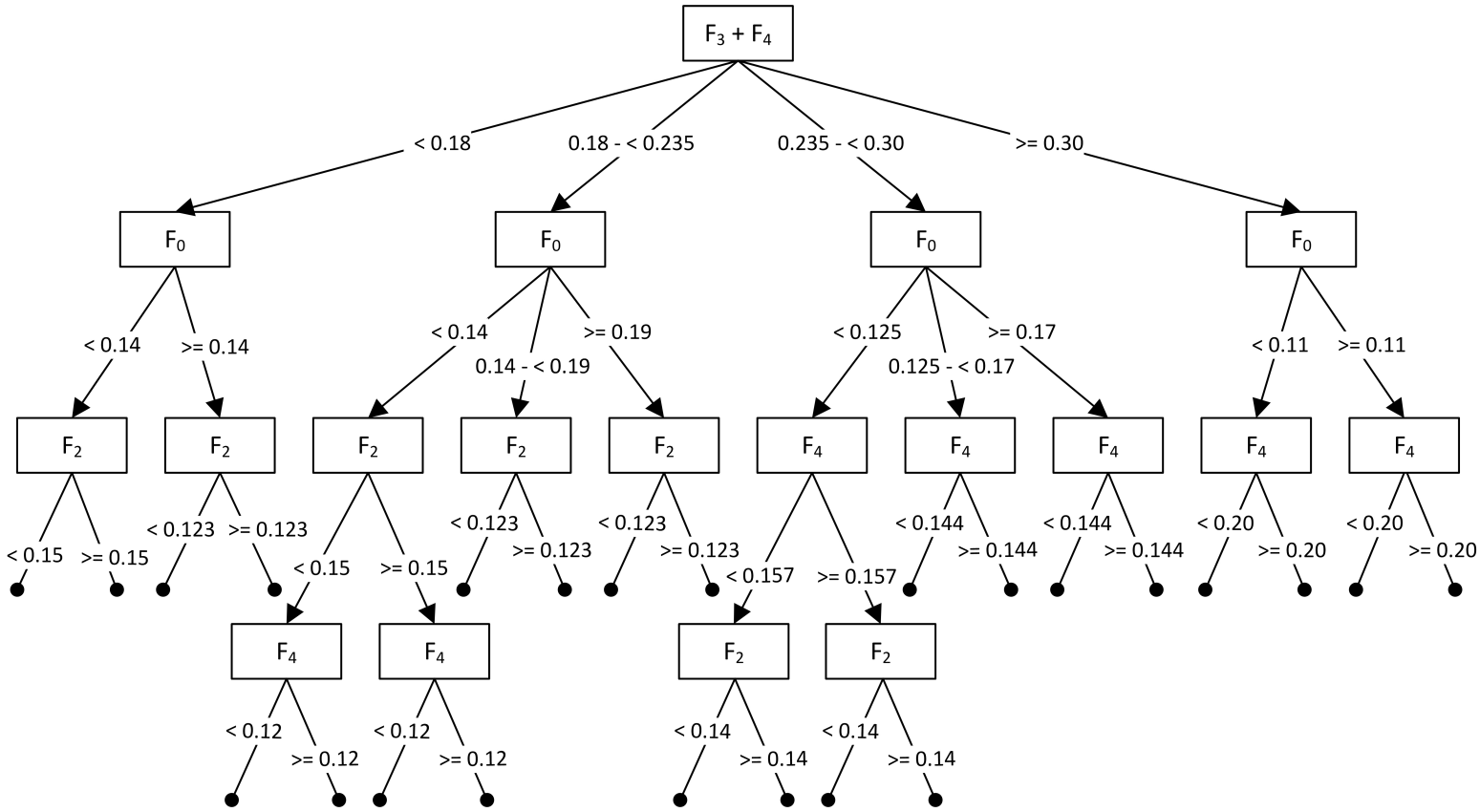


Figure A.1: Simplified schematic of recursive partitioning tree used to classify possible posterior distributions from a study of the fibrosis-stage distribution. Fibrosis stages are denoted by F_0, F_1, F_2, F_3, F_4. The probability mass functions over fibrosis stages are classified by the probability of individuals being in fibrosis stages 3 or 4 ($F_3 + F_4$), then on the probability of individuals being in F_0, then further on the probability of being in F_2 and/or F_4.

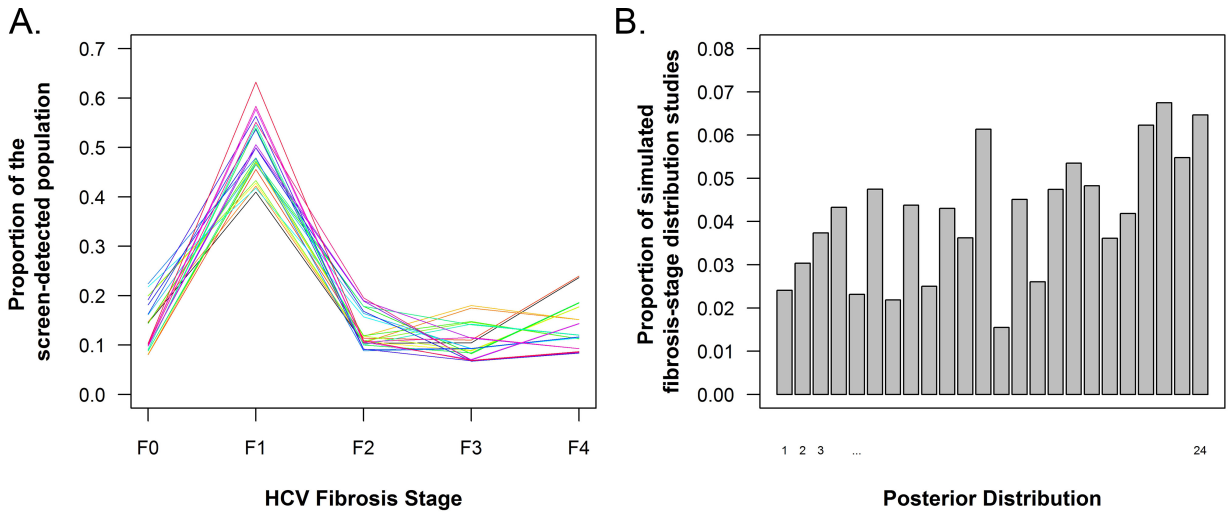
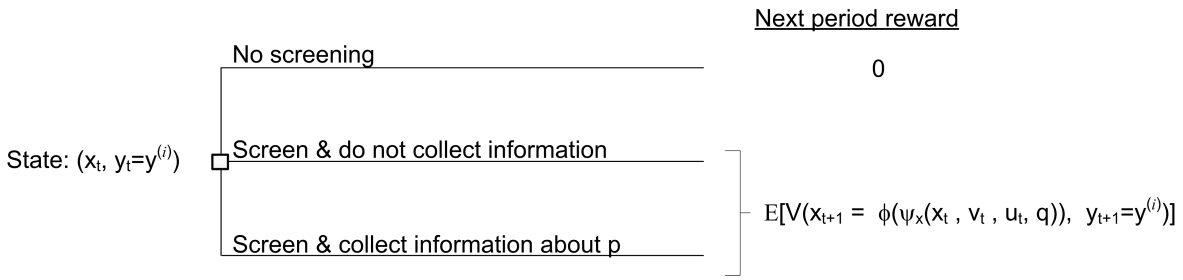


Figure A.2: (A) Probability mass function for each of the 24 'representative' posterior distributions determined through recursive partitioning regression. (B) Proportion of the $200,000$ simulated studies of fibrosis-stage distribution ($m_t = 200$) in each posterior distribution classification determined through recursive partitioning regression.

Appendix A.4. Two-Stage Markov Decision Process

We identified the optimal mapping from beliefs about $\tilde{p}_t$ and $\tilde{\theta}_t$ to actions using value iteration in two stages (Figure A.3). First, we identified the optimal mapping from beliefs about $\tilde{p}_t$ to actions for each possible posterior distribution from a study of $\tilde{\theta}_t$. In this stage, only the three classes of actions were considered: *'do not screen and do not collect information'*, *'screen and do not collect information'*, *'screen and collect information about* $\tilde{p}_t$*'*. The results of the first stage were used to determine the expected value of the actions *'screen and collect information about* $\tilde{\theta}_t$*'* and *'screen and collect information about* $\tilde{p}_t$ *and* $\tilde{\theta}_t$*'* in stage two. In the second stage, we identified the optimal mapping from beliefs about $\tilde{p}_t$ to actions given $\tilde{\theta}_0$ and we considered all five possible classes of actions: $u_t = (0, 0, 0)$, *'no intervention (and do not collect sample information)'*; $u_t = (1, 0, 0)$, *'do intervention and do not collect sample information'*; $u_t = (1, n_t, 0)$, *'do intervention and sample* n_t *individuals to learn about* $\tilde{p}_t$*'*; $u_t = (1, 0, m_t)$, *'do intervention and sample* m_t *individuals to learn about* $\tilde{\theta}_t$*'*; $u_t = (1, n_t, m_t)$, *'do intervention, sample* n_t *individuals to learn about* $\tilde{p}_t$*, and sample* m_t *individuals to learn about* $\tilde{\theta}_t$*'*.

Stage 1: For each possible posterior belief $y^{(i)}$, i = 1, 2, 3,… , identify the optimal mapping from beliefs (x_t, y_t=$y^{(i)}$) to actions and $V(x_t, y_t=y^{(i)})$ given the optimal actions.



Stage 2: For prior belief, (x_t, y_t=y_0), and corresponding probability distribution over posterior beliefs, $y^{(i)}$, i = 1, 2, 3,… , identify the optimal mapping from beliefs (x_t, y_t=y_0) to actions.

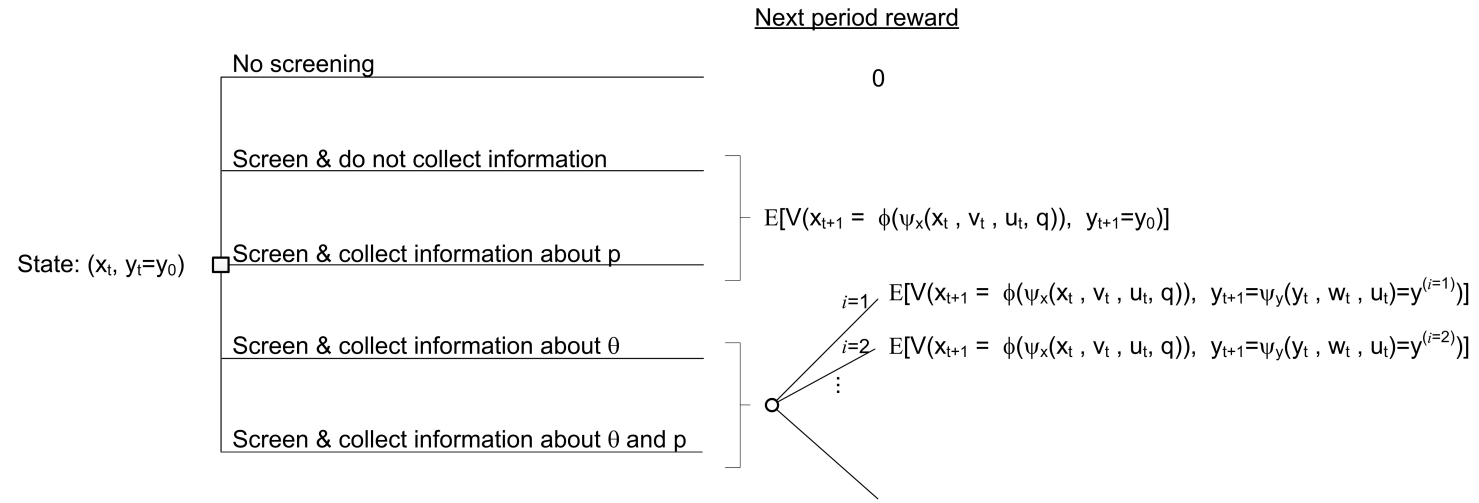


Figure A.3: Schematic of the two-stage approach to numerical implementation of the dynamic program.

Appendix B. Supplemental Results

Appendix B.1. Optimal time to stop intervention without information collection

We summarize these findings from [26] extending the notation to consider an uncertain $\tilde{\theta}$, so we can refer to the equations in the next section.

If information is prohibitively costly or practically infeasible to collect, Eq. (3) simplifies to

$$V_{\text{NoInfo}}(x, y) = \max_{d \in \{0,1\}} \{d(\mu_\theta(y)\mu_p(x) - \gamma) + \delta V_{\text{NoInfo}}(\phi(x), y)\},$$

for all (x, y), as there is no Bayesian updating and ψ_x and ψ_y reduce to identity maps. For all states (x, y) for which the optimal strategy is to stop (i.e., not to do the intervention), stopping remains optimal in the future because of the decreasing trend of $\tilde{p}_t$. Indeed, since for $z \in (0, 1)$, $\mu_p(\phi(x)) = z\mu_p(x) < \mu_p(x)$, we have that for all states where $V_{\text{NoInfo}}(x, y) = 0$, it is also the case that $V_{\text{NoInfo}}(\phi(x), y) = 0$. Hence, for $\mu_p(x_t) \leq \frac{\gamma}{\mu_\theta(y_t)}$ it is optimal to stop the intervention.

Restricting attention to the interesting case where $\mu(x_0) \geq \frac{\gamma}{\mu_\theta(y_0)}$ and using the fact that $\mu_p(x_t) = z^t \mu_p(x_0)$, we can identify the optimal time to stop the intervention, $T(\tilde{p}(x_0), \tilde{\theta}(y_0))$, which is the first period in which the intervention has a nonpositive expected INMB. Specifically, we seek the minimum value of t such that $E[g(\tilde{p}_t, \tilde{\theta}_t, u_t)] = 0$:

$$\begin{aligned}
E\left[g(\tilde{p}_t, \tilde{\theta}_t, u_t = (d_t = 1, n_t = 0, m_t = 0))\right] &= 0 \\
\mu_\theta(y_0)\mu_p(x_t) - \gamma &= 0 \\
\mu_\theta(y_0) z^t \mu_p(x_0) - \gamma &= 0 \\
z^t &= \frac{\gamma}{\mu_\theta(y_0)\mu_p(x_0)} \\
t &= \frac{1}{\ln(z)} \ln\left(\frac{\gamma}{\mu_\theta(y_0)\mu_p(x_0)}\right).
\end{aligned}$$

Since decisions can only be made at discrete time intervals, we identify the optimal time to stop the intervention, $T(\tilde{p}(x_0), \tilde{\theta}(y_0))$, as the first integer period in which the intervention has a nonpositive INMB

$$T(\tilde{p}(x_0), \tilde{\theta}(y_0)) = \left\lceil \frac{1}{\ln(z)} \ln\left(\frac{\gamma}{\mu_\theta(y_0)\mu_p(x_0)}\right) \right\rceil. \tag{B.1}$$

Finally, given any initial state (x_0, y_0), the value of implementing the optimal stopping policy for $t \in \{0, ..., T(\tilde{p}(x_0), \tilde{\theta}(y_0)) - 1\}$ is given by

$$\begin{aligned} V_{\text{NoInfo}}(x_0, y_0) &= \sum_{t=0}^{T(\tilde{p}(x_0),\tilde{\theta}(y_0))-1} \delta^t \left(\mu_\theta(y_0) z^t \mu_p(x_0) - \gamma\right) \\ &= \mu_\theta(y_0)\mu_p(x_0)\left(\frac{1-(\delta z)^{T(\tilde{p}(x_0),\tilde{\theta}(y_0))}}{1-\delta z}\right) - \gamma\left(\frac{1-\delta^{T(\tilde{p}(x_0),\tilde{\theta}(y_0))}}{1-\delta}\right). \end{aligned} \tag{B.2}$$

Appendix B.2. Proof of Main Result

Proposition. *For the case where information about the time-varying parameter, $\tilde{p}_t$, is prohibitively costly or practically infeasible to collect, it may be optimal to delay information collection about the time-invariant parameter, $\tilde{\theta}_t$.*

Proof. Consider $\tilde{\theta}_t \in \{\theta_L, \theta_H\}$, where $\theta_L < \theta_H$ and the probability that $\tilde{\theta}_t = \theta_H$ is $y_0 \in (0, 1)$. Perfect information about $\tilde{\theta}_t$ is available at any time at a positive cost κ_y. Given the prior belief (x_0, y_0), the optimal time to stop the intervention without information collection is denoted $T(\tilde{p}(x_0), \tilde{\theta}(y_0))$ and determined using Eq. (B.1). With perfect information, the optimal time to stop the intervention is $T(\tilde{p}(x_0), \theta_L)$ or $T(\tilde{p}(x_0), \theta_H)$, where $T(\tilde{p}(x_0), \theta_L) \leqslant T(\tilde{p}(x_0), \tilde{\theta}(y_0)) \leqslant T(\tilde{p}(x_0), \theta_H)$.

For $t_1 \in [0, T(\tilde{p}(x_0), \theta_L) - 1]$, we calculate the value of acquiring additional information at time t_1 by subtracting the expected value without information from the expected value with information collected at t_1. Canceling out common terms we obtain

$$\text{VOI}_1(t_1) = y_0 \left(\sum_{t=T(\tilde{p}(x_0),\tilde{\theta}(y_0))}^{T(\tilde{p}(x_0),\theta_H)-1} \delta^t(\theta_H \mu_p(x_t) - \gamma) \right) - (1 - y_0) \left(\sum_{t=T(\tilde{p}(x_0),\theta_L)}^{T(\tilde{p}(x_0),\tilde{\theta}(y_0))-1} \delta^t(\theta_L \mu_p(x_t) - \gamma) \right).$$

The first term represents the gain in value associated with continuing the intervention until $T(\tilde{p}(x_0), \theta_H) - 1$ rather than stopping at time $T(\tilde{p}(x_0), \tilde{\theta}(y_0))$ after learning that $\tilde{\theta}_t = \theta_H$. The second term represents the consequences avoided by learning that $\tilde{\theta}_t = \theta_L$ and, therefore, stopping the intervention at time $T(\tilde{p}(x_0), \theta_L)$ rather than stopping later at time $T(\tilde{p}(x_0), \tilde{\theta}(y_0))$. Note that the sum in the second term is negative since $\theta_L \mu_p(x_t) - \gamma < 0$ for $t \geqslant T(\tilde{p}(x_0), \theta_L)$.

If $\text{VOI}_1(t_1) - \delta^{t_1}\kappa_y > 0$ for any $t_1 \in [0, T(\tilde{p}(x_0), \theta_L) - 1]$, then the optimal action is to delay information collection (at least) until $T(\tilde{p}(x_0), \theta_L) - 1$ because $\text{VOI}_1(t_1)$ does not depend on t_1 while $\delta^{t_1}\kappa_y$ is decreasing in t_1.

For $t_2 \in [T(\tilde{p}(x_0), \theta_L) - 1, T(\tilde{p}(x_0), \theta_H) - 1]$, we calculate the value of acquiring additional information at time t_2 by subtracting the expected value without information from the expected value with information collected at t_2. Canceling out common terms we obtain

$$\text{VOI}_2(t_2) = y_0 \left(\sum_{t=T(\tilde{p}(x_0), \tilde{\theta}(y_0))}^{T(\tilde{p}(x_0), \theta_H)-1} \delta^t (\theta_H \mu_p(x_t) - \gamma) \right) - (1 - y_0) \left(\sum_{t=t_2+1}^{T(\tilde{p}(x_0), \tilde{\theta}(y_0))-1} \delta^t (\theta_L \mu_p(x_t) - \gamma) \right).$$

The first term represents the gain in value associated with continuing the intervention until $T(\tilde{p}(x_0), \theta_H) - 1$ after learning that $\tilde{\theta}_t = \theta_H$. The second term represents the consequences avoided by immediately stopping the intervention after learning that $\tilde{\theta}_t = \theta_L$.

If $\text{VOI}_2(t_2) - \delta^{t_2}\kappa_y > 0$ for any $t_2 \in [T(\tilde{p}(x_0), \theta_L) - 1, T(\tilde{p}(x_0), \theta_H) - 1]$, then there exists a unique optimal time, $t^*_{\text{Info}}(x_0, y_0)$, to acquire perfect information about $\tilde{\theta}$ at cost κ_y because $VOI_2(t_2)$ and $\delta^{t_2}\kappa_y$ are both decreasing in t_2. We find the optimal time by solving for the period where we prefer collecting information immediately to waiting an additional period. Specifically, we find t_2 such that

$$VOI_2(t_2) - \delta^{t_2}\kappa_y > VOI_2(t_2 + 1) - \delta^{t_2+1}\kappa_y.$$

Through algebraic rearrangement, we obtain

$$t^*_{\text{Info}}(x_0, y_0) = \left\lceil \frac{1}{\ln(z)} \ln \left(\frac{\gamma}{\theta_L \mu(x_0)} - \frac{(1 - \delta)\kappa_y}{\delta(1 - y_0)\theta_L \mu(x_0)} \right) \right\rceil. \tag{B.3}$$

Comparing Eq. (B.3) to $T(\tilde{p}(x_0), \theta_L)$ reveals it may be optimal to delay information collection because $t^*_{\text{Info}}(x_0, y_0) \geqslant T(\tilde{p}(x_0), \theta_L)$. The intuition is that because of the time value of money, it is beneficial to delay information about even a static parameter until a time when the information is likely to become decision-relevant. □

Appendix B.3. Properties of the value function which guarantee a unique solution

When information is available about $\tilde{p}_t$ and $\tilde{\theta}_t$ in any period, the state space is compact in terms of $\mu_p(x_t)$, $\sigma_p^2(x_t)$, and $\mu_\theta(y_t)$. Therefore, a unique optimal set of actions exists if the optimal value function is monotonic (i.e., nondecreasing) in each of $\mu_p(x_t)$, $\sigma_p^2(x_t)$, and $\mu_\theta(y_t)$ for each possible action. This is true in this case because the current-period reward is nondecreasing and the transitions are stochastically nondecreasing in each of $\mu_p(x_t)$, $\sigma_p^2(x_t)$, and $\mu_\theta(y_t)$ for each action [64]. The unique solution can then be identified for specific cases using numerical methods.

References

[1] Wolk R, Shamsuzzaman AS, Somers VK. Obesity, sleep apnea, and hypertension. Hypertension. 2003;42(6):1067–1074.

[2] Lipscombe LL, Hux JE. Trends in diabetes prevalence, incidence, and mortality in Ontario, Canada 1995–2005: a population-based study. The Lancet. 2007;369(9563):750–756.

[3] Cowie CC, Rust KF, Ford ES, Eberhardt MS, Byrd-Holt DD, Li C, et al. Full accounting of diabetes and pre-diabetes in the US population in 1988–1994 and 2005–2006. Diabetes Care. 2009;32(2):287–294.

[4] Cheng L, Eng C, Nieman LZ, Kapadia AS, Du XL. Trends in colorectal cancer incidence by anatomic site and disease stage in the United States from 1976 to 2005. American Journal of Clinical Oncology. 2011;34(6):573–580.

[5] Nelson DE, Giovino GA, Shopland DR, Mowery PD, Mills SL, Eriksen MP. Trends in cigarette smoking among US adolescents, 1974 through 1991. American Journal of Public Health. 1995;85(1):34–40.

[6] Jia H, Lubetkin EI. Recent trends and geographic patterns of the burden of disease attributable to smoking. Value in Health. 2010;13(8):958–964.

[7] Cipriano LE, Romanus D, Earle CC, Neville BA, Halpern EF, Gazelle GS, et al. Lung cancer treatment costs, including patient responsibility, by disease stage and treatment modality, 1992 to 2003. Value in Health. 2011;14(1):41–52.

[8] Hoyle M. Future drug prices and cost-effectiveness analyses. Pharmacoeconomics. 2008;26(7):589–602.

[9] Chesson HW, Flagg EW, Koutsky L, Hsu K, Unger ER, Shlay JC, et al. Modeling the impact of quadrivalent HPV vaccination on the incidence of Pap test abnormalities in the United States. Vaccine. 2013;31(29):3019–3024.

[10] Kulasingam SL, Myers ER. Potential health and economic impact of adding a human papillomavirus vaccine to screening programs. Journal of the American Medical Association. 2003;290(6):781–789.

[11] Thorn J, Coast J, Andronis L. Interpretation of the expected value of perfect information and research recommendations: a systematic review and empirical investigation. Medical Decision Making. 2016;36(3):285–295.

[12] Uthman RT, Sutton AJ, Jackson LJ, Uthman OA. Does directly administered antiretroviral therapy represent good value for money in sub-Saharan Africa? A cost-utility and value of information analysis. PloS one. 2018;13(1):e0191465.

[13] Bennette CS, Veenstra DL, Basu A, Baker LH, Ramsey SD, Carlson JJ. Development and evaluation of an approach to using value of information analyses for real-time prioritization decisions within SWOG, a large cancer clinical trials cooperative group. Medical Decision Making. 2016;36(5):641–651.

[14] Hall PS, Smith A, Hulme C, Vargas-Palacios A, Makris A, Hughes-Davies L, et al. Value of information analysis of multiparameter tests for chemotherapy in early breast cancer: the OPTIMA Prelim Trial. Value in Health. 2017;20(10):1311–1318.

[15] Gc VS, Suhrcke M, Hardeman W, Sutton S, Wilson EC. Cost-effectiveness and value of information analysis of brief interventions to promote physical activity in primary care. Value in Health. 2018;21(1):18–26.

[16] Eckermann S, Karnon J, Willan AR. The value of value of information. PharmacoEconomics. 2010;28(9):699–709.

[17] Carlson JJ, Thariani R, Roth J, Gralow J, Henry NL, Esmail L, et al. Value-of-information analysis within a stakeholder-driven research prioritization process in a US setting: an application in cancer genomics. Medical Decision Making. 2013;33(4):463–471.

[18] Siebert U, Rochau U, Claxton K. When is enough evidence enough? Using systematic decision analysis and value-of-information analysis to determine the need for further evidence. Zeitschrift fur Evidenz, Fortbildung und Qualitat im Gesundheitswesen. 2013;107(910):575 – 584.

[19] Tuffaha HW, Gordon LG, Scuffham PA. Value of information analysis in healthcare: a review of principles and applications. Journal of Medical Economics. 2014;17(6):377–383.

[20] Wallner K, Shapiro AJ, Senior PA, McCabe C. Cost effectiveness and value of information analyses of islet cell transplantation in the management of unstabletype 1 diabetes mellitus. BMC Endocrine Disorders. 2016;16(1):17.

[21] Ades A, Lu G, Claxton K. Expected value of sample information calculations in medical decision modeling. Medical Decision Making. 2004;24(2):207–227.

[22] Claxton K, Ginnelly L, Sculpher M, Philips Z, Palmer S. A pilot study on the use of decision theory and value of information analysis as part of the NHS Health Technology Assessment programme. York Publishing; 2004.

[23] Philips Z, Claxton K, Palmer S. The half-life of truth: what are appropriate time horizons for research decisions? Medical Decision Making. 2008;28(3):287–299.

[24] Hoyle M, Anderson R. Whose costs and benefits? Why economic evaluations should simulate both prevalent and all future incident patient cohorts. Medical Decision Making. 2010;30(4):426–437.

[25] Grimm SE, Dixon S, Stevens JW. When future change matters: modeling future price and diffusion in health technology assessments of medical devices. Value in Health. 2016;19(6):720–726.

[26] Cipriano LE, Weber TA. Population-level intervention and information collection in dynamic healthcare policy. Health care management science. In Press, September 8, 2018 Available at: `https://doi.org/101007/s10729-017-9415-5`.

[27] Liu S, Cipriano LE, Holodniy M, Goldhaber-Fiebert JD. Cost-effectiveness analysis of risk-factor guided and birth-cohort screening for chronic hepatitis C infection in the United States. PLoS One. 2013;8(3):e58975.

[28] Liu S, Barnett PG, Holodniy M, Lo J, Joyce VR, Gidwani R, et al. Cost-effectiveness of treatments for genotype 1 hepatitis C virus infection in non-VA and VA populations. MDM Policy & Practice. 2016;1(1):2381468316671946.

[29] Chak E, Talal AH, Sherman KE, Schiff ER, Saab S. Hepatitis C virus infection in USA: an estimate of true prevalence. Liver International. 2011;31(8):1090–1101.

[30] Armstrong GL, Wasley A, Simard EP, McQuillan GM, Kuhnert WL, Alter MJ. The prevalence of hepatitis C virus infection in the United States, 1999 through 2002. Annals of Internal Medicine. 2006;144(10):705–714.

[31] Denniston MM, Klevens RM, McQuillan GM, Jiles RB. Awareness of infection, knowledge of hepatitis C, and medical follow-up among individuals testing positive for hepatitis C: National Health and Nutrition Examination Survey 2001-2008. Hepatology. 2012;55(6):1652–1661.

[32] Rein DB, Smith BD, Wittenborn JS, Lesesne SB, Wagner LD, Roblin DW, et al. The cost-effectiveness of birth-cohort screening for hepatitis C antibody in US primary care settings. Annals of Internal Medicine. 2012;156(4):263–270.

[33] Coffin PO, Scott JD, Golden MR, Sullivan SD. Cost-effectiveness and population outcomes of general population screening for hepatitis C. Clinical Infectious Diseases. 2012;54(9):1259–1271.

[34] McGarry LJ, Pawar VS, Panchmatia HR, Rubin JL, Davis GL, Younossi ZM, et al. Economic model of a birth cohort screening program for hepatitis C virus. Hepatology. 2012;55(5):1344–1355.

[35] Eckman MH, Talal AH, Gordon SC, Schiff E, Sherman KE. Cost-effectiveness of screening for chronic hepatitis C infection in the United States. Clinical Infectious Diseases. 2013;56(10):1382–1393.

[36] Smith BD, Morgan RL, Beckett GA, Falck-Ytter Y, Holtzman D, Ward JW. Hepatitis C virus testing of persons born during 1945–1965: recommendations from the Centers for Disease Control and Prevention. Annals of Internal Medicine. 2012;157(11):817–822.

[37] Moyer VA. Screening for hepatitis C virus infection in adults: US Preventive Services Task Force recommendation statement. Annals of Internal Medicine. 2013;159(5):349–357.

[38] Raiffa H, Schlaifer R. Applied Statistical Decision Theory. Harvard University Press; 1961.

[39] Bellman R. Dynamic Programming. Princeton University Press; 1957.

[40] U S Census Bureau. QT–P1: Age Groups and Sex: 2010; 2010. Available from: `http://www.census.gov/2010census/`.

[41] Gretch DR. Diagnostic tests for hepatitis C. Hepatology. 1997;26(S3):43S–47S.

[42] Hyland C, Kearns S, Young I, Battistutta D, Morgan C. Predictive markers for hepatitis C antibody ELISA specificity in Australian blood donors. Transfusion Medicine. 1992;2(3):207–213.

[43] Gold MR, Siegel JE, Russell LB, Weinstein MC. Cost-effectiveness in health and medicine. Oxford University Press, USA; 1996.

[44] US Bureau of Labor Statistics. Consumer Price Index. Division of Consumer Prices and Price Indexes;. Available from: `http://www.bls.gov/cpi/`.

[45] Weinstein MC, Skinner JA. Comparative effectiveness and health care spending – implications for reform. New England Journal of Medicine. 2010;362(5):460–465.

[46] Innes H, Goldberg D, Dusheiko G, Hayes P, Mills PR, Dillon JF, et al. Patient-important benefits of clearing the hepatitis C virus through treatment: A simulation model. Journal of Hepatology. 2014;60(6):1118–1126.

[47] Liu S, Cipriano LE, Holodniy M, Owens DK, Goldhaber-Fiebert JD. New protease inhibitors for the treatment of chronic hepatitis C: a cost-effectiveness analysis. Annals of Internal Medicine. 2012;156(4):279–290.

[48] Mallette C, Flynn MA, Promrat K. Outcome of screening for hepatitis C virus infection based on risk factors. The American Journal of Gastroenterology. 2008;103(1):131–137.

[49] Center for Medicare and Medicaid Services. Medicare fee schedule. U.S. Department of Health and Human Services; 2010. Available from: `http://www.cms.gov/home/medicare.asp`.

[50] Therneau T, Atkinson B, Ripley B. rpart: Recursive partitioning; 2013. R package version 4.1-1. Available from: `http://CRAN.R-project.org/package=rpart`.

[51] Claxton KP, Sculpher MJ. Using value of information analysis to prioritise health research: Some lessons from recent UK experience. PharmacoEconomics. 2006;24(11):1055–1068.

[52] R Development Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria; 2012. Available from: `http://www.R-project.org/`.

[53] Allison RD, Conry-Cantilena C, Koziol D, Schechterly C, Ness P, Gibble J, et al. A 25-year study of the clinical and histologic outcomes of hepatitis C virus infection and its modes of transmission in a cohort of initially asymptomatic blood donors. Journal of Infectious Diseases. 2012;206(5):654–661.

[54] Schaefer AJ, Bailey MD, Shechter SM, Roberts MS. In: Brandeau ML, Sainfort F, Pierskalla WP, editors. "Chapter 23: Modeling medical treatment using Markov decision processes" in Operations Research and Health Care: A handbook of methods and applications. vol. 70 of International Series in Operations Research and Management Science. Springer US; 2005. p. 593–612.

[55] Alagoz O, Hsu H, Schaefer AJ, Roberts MS. Markov decision processes: a tool for sequential decision making under uncertainty. Medical Decision Making. 2010;30(4):474–483.

[56] Kornish LJ, Keeney RL. Repeated commit-or-defer decisions with a deadline: the influenza vaccine composition. Operations Research. 2008;56(3):527–541.

[57] Özaltın OY, Prokopyev OA, Schaefer AJ, Roberts MS. Optimizing the societal benefits of the annual influenza vaccine: a stochastic programming approach. Operations Research. 2011;59(5):1131–1143.

[58] Alter MJ. Prevention of spread of hepatitis C. Hepatology. 2002;36(5B):s93–s98.

[59] Hall PS, Edlin R, Kharroubi S, Gregory W, McCabe C. Expected net present value of sample information from burden to investment. Medical Decision Making. 2012;32(3):E11–E21.

[60] Andronis L, Barton PM. Adjusting estimates of the expected value of information for implementation: theoretical framework and practical application. Medical Decision Making. 2016;36(3):296–307.

[61] Grimm SE, Dixon S, Stevens JW. Assessing the expected value of research studies in reducing uncertainty and improving implementation dynamics. Medical Decision Making. 2017;37(5):523–533.

[62] Mehrotra A, Zaslavsky AM, Ayanian JZ. Preventive health examinations and preventive gynecological examinations in the United States. Archives of Internal Medicine. 2007;167(17):1876.

[63] Therneau T, Atkinson B. An introduction to recursive partitioning using the rpart routines; 2013. R package version 4.1-1. Available from: `http://cran.r-project.org/web/packages/rpart/vignettes/longintro.pdf`.

[64] Smith JE, McCardle KF. Structural properties of stochastic dynamic programs. Operations Research. 2002;50(5):796–809.