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Where should we target our research effort? A data-based model for determining priorities for smoking cessation research and healthcare delivery in general practice

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Abstract

Background: Researchers and decision makers must constantly make decisions about how they allocate their limited time and health dollars across a number of health interventions and priorities. Given the scarcity of resources, it is critical that decisions are evidence based to give the best chance that the initiatives implemented will, with maximum efficiency, improve health outcomes. While complex mathematical models are available to inform such decision making, the skills required to perform sophisticated analyses are often outside the reach of those who need them. This paper presents a simple Excel-based calculator, readily accessible by policy makers and lay users, that can help inform the decision making process and the choices available to decision makers, while simultaneously highlighting important gaps in the available information.

Aims: To demonstrate the utility of the data-based calculator in a test case, by comparing the relative effectiveness and cost-effectiveness of strategies to increase smoking cessation rates in the general practice setting.

Methods: The data-based calculator comprises a simple spreadsheet in Microsoft Excel. Model parameters (effectiveness, prevalence and cost) were obtained from the literature and used to compare population health and cost outcomes for smoking cessation in general practice under three scenarios: baseline conditions, implementing an intervention to increase detection of smoking (option 1), and implementing an intervention to increase the effectiveness of smoking cessation support offered to smokers (option 2).

Results: Under the model assumptions, option 1 produced more successful outcomes and was a more cost effective option than option 2.

Conclusions: This Excel calculator presents an easily accessible tool to help researchers and others assess the cost effectiveness and reach of two different approaches for intervening on smoking in general practice. The model can be easily modified to allow different comparisons and may be helpful as a guide for making decisions about where to allocate research effort and funding.

JEL Classification:

Keywords

cost-effectiveness — general practice — detection — smoking — smoking cessation

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Introduction

Allocating research and healthcare delivery resources: where should we concentrate our efforts?

The need to make decisions about the allocation of research funding and healthcare delivery resources between competing demands occurs in healthcare systems across the world. Decision makers need to decide how they will allocate their resources across a number of health interventions that, in many cases, have a common outcome but with different effectiveness and cost. For example, the choices might be between spending limited funds on smoking prevention targeting: remote Aboriginal and Torres Strait Islander communities; initiatives delivered through General Practitioner (GP) surgeries; or Quitlines. The challenge of allocating healthcare and research funding to optimise health outcomes is critical. Given

the scarcity of resources, it is crucial to ensure that research activity and health spending decisions are made using the most up-to-date and best available information with the greatest potential to improve health outcomes, and that decision making is not purely technocratic, emotional or arbitrary.

A need for a simplified decision tool

There are various models that can be used for decision making, and complex mathematical models are now the norm. For example, decision analysis has developed into a sophisticated field with a matching array of algorithms and software to examine relative costs and consequences of alternative courses of action. However, the use of decision analysis techniques is often constrained by their complexity. Decision makers cannot always access the skills required perform a sophisticated analysis (Brailsford, 2015; Rautenberg et al., 2016). In addition, gaps in the data needed to undertake a decision analysis are not always known. There is a need for a simple tool, readily accessible by policy makers and lay users, that can help inform the decision making process and the choices available to decision makers, while simultaneously highlighting important gaps in the available information. Against this background, a basic decision tool was developed as a starting point to guide decision making about the investment of limited resources in a number of health-related fields. The model is a simple cost-effectiveness calculator, presented in Excel. The model is a derivation of a decision tree, and uses a logic modelling approach to filter data through the sequence of steps assumed to determine outcomes associated with screening and treatment in public health settings. In this manuscript we demonstrate the utility of the cost-effectiveness calculator in a test case involving a range of strategies to improve smoking cessation rates in general practice.

Intervening for smoking in general practice

Although smoking rates in Australia have declined significantly over recent decades, the prevalence of smoking amongst adults was estimated to be 14.7% in 2014/15 (ABS, 2015). General Practitioners (GPs) are uniquely placed to provide preventive healthcare including the provision of smoking cessation advice, and see approximately 81% of the Australian population each year (ABS, 2013). Current clinical practice guidelines recommend that GPs assess smoking status and interest in quitting for every patient over the age of 10 years (RACGP RBT, 2009). However, many general practitioners fail to detect their patients as smokers (Bryant et al., 2015), and therefore cannot take the next step and provide support and/or advice. For example, Australian data suggest that between 32% and 66% of self-reported current smokers are correctly identified as such by their GPs, with international data suggesting similar rates of ascertainment of smoking status (Bryant et al., 2015; Dickinson et al., 1989; Heywood et al., 1994; Humair et al., 1998; and Murray et al., 2008). Smoking cessation treatment is also associated with poor success rates. Guidelines recommend that GP's provide brief advice and support using the 5A's method to individuals who smoke (RACGP RBT, 2009), however the effectiveness of brief advice been shown to be approximately 5% (Reid, 1996). Therefore, strategies to improve both the ascertainment of smoking status ("detection of smoking") by GPs, and the effectiveness of treatments offered to current smokers in the general practice setting are needed.

Aims

In this study we demonstrate the utility of the cost-effectiveness calculator for comparing the relative effectiveness and cost-effectiveness of increasing GP detection of smoking in general practice (via screening of patients on a touchscreen computer prior to their appointment and feedback of smoking status to GPs), versus increasing the effectiveness of smoking cessation support and advice (GPs provide referral and follow-up to those detected as at risk) in the general practice setting.

Methods

Development of the model

The core objective of this model was to provide a decision-making tool or model that would enable a *User*, without a strong economic or statistical background and with access only to the data that is reasonably available in their area of interest, to rationally compare alternative health interventions that may comprise different methods and/or target different sub-populations. The development of the model was broadly based upon a decision analytic framework and drew on aspects of both decision trees and cost-effectiveness analysis. Despite the model's according simplicity, it is underpinned by a number of theoretical and modelling principles that seek to firstly ensure the effectiveness of the model, and secondly to educate potential users in the basic principles for such analysis. These principles, containing those summarised by Sun (2008) and Philips et al. (2006), include:

- There is a clear statement of the decision problem;
- The perspective of the model is that of the healthcare system;
- The alternative interventions under consideration must have a common health outcome e.g. cost per successful treatment. This common outcome precludes the obligation to incorporate utility values;
- The proposed interventions should be adequately defined and justified;
- The model has descriptive and internal validity implying that its assumptions, structure and results are reliable, rational and intuitive, and the direction of the inputs and outputs follow as expected (Weinstein et al., (2003);
- The model is transparent and reproducible;

- The model is not intended to capture the impact of patients moving through various health states as disease progresses. Given the model's limited time horizon, the choice of *outcome measure* must comprise an intermediary endpoint (based on sourced evidence) that is consistent with the desired outcomes of the interventions. Adequate comprehension of discount rates, present values and similar concepts are removed as hurdles for *Users* under this approach;

- The model prompts for source references that inform the probabilities assigned in the model. The quality of the data (RCT, observational, expert) should be considered through this process.

Description of the model

The model comprises a simple spreadsheet in Microsoft Excel including six steps. The *User* is prompted to first enter data in three key areas:

1. **Population:** define and quantify the population of interest;

2. **Target group:** define and quantify the target of the intervention;

3. **Detection:** enter the proportion of the target group attending the setting of interest;

   Once the target population is adequately described and quantified, the *User* enters data related to:

4. **Awareness of risk (after intervention if applicable):** the proportion of the target group attending the setting of interest (in this case, general practice) who are detected for the condition of interest. If an intervention is used to improve detection, details including a text description of the intervention and cost per participant are entered here;

5. **Intervention reach and adherence:** a description of who is eligible for the intervention, intervention details including what is provided for those who are detected as having the condition of interest, and the unit cost of the intervention. For the described intervention, the *User* is asked to estimate:

   i. Reach: The proportion of individuals who would be willing to participate in the intervention;

   ii. Adherence: The proportion of individuals who would comply with the offered intervention;

6. **Effect on outcome:** a description of the outcome measure of intervention success and the expected proportion of individuals complying with the intervention that will achieve a successful outcome following the intervention (note that only dichotomous outcomes are considered in this model);

For each of the steps 4-6 above, when the *User* enters the relevant proportions, the model calculates the number of persons at each level in the model, and uses this output in the subsequent step. For example, when the *User* enters (Step 4.) the proportion of the target group attending the setting of interest who are detected for the condition of interest, the model calculates the corresponding number of persons in this group, i.e. the total number of individuals detected as being at risk. The model then uses this as the starting figure at Step 5. Thus model filters down from the total population to the number of eligible patients at each level.

Outcomes generated by the model

Estimates for the effectiveness of the interventions and the respective costs entered above are consequently utilised to derive a series of model outcomes. Where possible, data used for the parameters should be sourced from the evidence-based literature (but indeed these could be hypothesised for comparison purposes). Baseline data (i.e. the scenario of no intervention, or treatment as usual) are required to be entered in order to allow various options to be compared to baseline, in terms of: the incremental cost compared to baseline; incremental number of successes compared to baseline; and the incremental cost effectiveness ratio (ICER). The ICER is the ratio of the change in cost to the change in effectiveness of each option compared to baseline. The ICER provides an estimate of the additional cost per successful outcome associated with each option when compared to baseline.

Implementation of the model

To illustrate the utility of the model, a hypothetical example is presented for a funding allocation between two different proposed smoking interventions in the General Practice setting. An overview of the model and example data are presented in Figure 1. The model seeks to inform the decision despite the proposed interventions possessing varying effect sizes and different implementation costs. Baseline data was entered into the model assuming no interventions are implemented, and assuming that GPs will offer brief advice and support using the 5A's method to individuals who they identify as smokers, as recommended under current guidelines. Option 1 consists of an intervention to increase the proportion of current smokers who are detected as being at risk by their GP, involving screening of patients in the waiting room on a touchscreen computer, and the provision of feedback to the GP about the patient's smoking status prior to the consultation. This option does not include any intervention to improve the treatment or follow-up of those detected as smokers, and assumes that identified smokers will be offered the same 5A's brief advice and support as under baseline conditions. Option 2 consists of an intervention to provide more intensive treatment for smokers, by offering referral and follow-up to those detected as at-risk. This intervention does not include any strategy to increase detection of those who are at-risk. This option also assumes that GPs will offer the more intensive intervention involving referral and follow-up to all detected smokers, in

place of the baseline 5A's brief advice and support. The common *parameters* used in the model were the target population, effect size and cost.

Results

Hypothetical data for each of the steps 1-6 in the model are presented in Table 1. Data was drawn from the literature where possible, and references for data sources are indicated using footnotes in Table 1 and shown in Table 2.

Using the model to explore the hypothetical example above, option 1, which consisted of an intervention to increase the detection of smokers by GPs, was both more effective and more expensive than baseline. Option 1 (increase detection) resulted in an estimated additional 8,963 smokers successfully abstinent at 6 months post intervention (compared to baseline), at an estimated cost of $320 per successful outcome (compared to $220 per successful outcome under baseline conditions). Under Option 1, every additional successful outcome costs an additional $100 above baseline.

In comparison, option 2, consisting of an intervention to deliver more intensive cessation support via GP referral for counselling and follow-up represents a less effective and more expensive option than baseline. Option 2 (increase intervention effectiveness) results in 24,550 *fewer* smokers successfully abstinent at 6 months post intervention (compared to baseline) and costs $1,444 per success, compared to $220 per successful outcome under baseline conditions.

Compared to baseline, the ICER indicates the ratio of the change in cost to the change in effectiveness for each option, and was $980 for option 1 compared to -$1506 for option 2. The negative ICER for option 2 indicates that this option is less effective than baseline. A comparison of ICERs indicates that option 1 is more cost effective than option 2. A summary of the implementation of the model using the example data is shown in Figure 1.

Discussion

Funds for research and service delivery in healthcare systems are already scare and the situation is worsening; healthcare budgets are being increasingly stretched elsewhere by demands generated from ageing populations and the rising prevalence of chronic disease (Bauer et al., 2014; Denton and Spencer, 2010). This means a more explicit, direct and rational approach is needed determine where funding for research and healthcare delivery is spent. Decisions about how to allocate healthcare funding, resources and research effort are being made every day by government and non-government organisations. Often, these decisions are made based on individual's perceptions of effectiveness independently of considering available data. Although cost-effectiveness software is commercially available, associated costs and a lack of reliable input data can be barriers to their use. The simple, Excel-based cost-effectiveness calculator presented here is freely available, and is aimed at providing researchers and policy makers a useful starting point in thinking through the key parameters which influence health outcomes and costs. From this starting point, more complex modelling may be based.

Findings of the model

The results of modelling the hypothetical example above indicate that option 1, which involved increasing the detection of smoking by GPs, was a more cost effective option than implementing a more intensive GP intervention for those who are detected as smokers, at an approximate cost of $5 per person screened. This is an important illustration of the utility of the model, given that health care providers or policy makers might assume that offering a more intensive intervention would produce a better outcome. Yet consideration also needs to be given to reach and adherence. For example, if patient adherence with the intervention offered in option 2 (i.e. the number of patients who attend the referral session offered) could be increased from 30% to 60%, option 2 would produce more incremental successful outcomes than baseline or option 1 (although at a higher cost per successful outcome than option 1; data not shown). Similarly, if the effectiveness of the more intensive intervention offered in option 2 could be increased to 26%, option 2 would produce more incremental successful outcomes than option 1 and baseline (again at a higher cost per successful outcome than either option 1 or baseline). If both adherence with option 2 could be increased to 60%, and the cost reduced to $25 per intervention, then option 2 would produce more incremental successful outcomes at a lower cost per successful outcome than option 1, and would become the more cost effective option. Such parameters can be easily manipulated using this simple Excel calculator, to allow the outcomes to be explored under a range of assumptions. In the example modelled, little data were available about the costs and outcomes of screening to improve detection of smoking, while data about expected reach and adherence of a more intensive smoking cessation intervention were heterogeneous and variable. The model allows the *User* to easily alter the input and rerun the model to explore the impact of variation in these assumptions on the outcomes. In this way the *User* can undertake an informal sensitivity analysis by manipulating key inputs into the model and observing the impact of this on model outcomes. Outcomes including the incremental cost compared to baseline, incremental number of successes and the ICER can all be used to inform policy decisions.

Limitations of the approach

A number of limitations of this model should be considered. Firstly, while the simplicity of the model emphasises transparency and engagement, this necessitates limitations. The developed modelling framework is more simplistic than other types of decision making models, meaning the data provides only an approximation. The complexity of disease pathways is reduced to a single critical parameter being, for this example, the intervention effect size. This highlights the importance of the quality of evidence upon which these probabilities are estimated. Accordingly, the capacity of a *User* to exercise dis-

Step	Definition	Proportion	Unit Cost of intervention	No. of persons
(1) Population	*Australian population aged 18yrs+*	n/a		15,055,403
(2) Target group	*Current smokers*[a]	14.7%		2,213,144
(3) Opportunity for detection	*Proportion of target group attending GP at least once per annum*[b]	81%		1,792,647
(4) GP awareness of risk	*Proportion detected by GPs as at risk*	n/a		15,055,403
	Baseline: (no intervention)[c]	66%	$0	1,183,147
	Option 1: (intervention: **iPad screening in waiting room**)[d]	76%	$5	1,362,412
	Option 2: (no change to baseline)[c]	66%	$0	1,183,147
(5) i. Reach	*Proportion detected by GPs, willing to participate in treatment intervention*			
	Baseline: (GP brief advice)[e]	100%	$11	1,183,147
	Option 1: (no change to baseline)[e]	100%	$11	1,362,412
	Option 2: (GP intervention: referral and follow-up)[f]	65%	$65	769,046
(5) ii. Adherence	*Proportion detected, willing and complying with treatment intervention*			
	Baseline: (GP brief advice)[e]	100%		1,183,147
	Option 1: (no change to baseline)[e]	100%		1,362,412
	Option 2: (GP intervention: referral and follow-up)[f]	30%		230,714
(6) Effect on outcome	*Proportion achieving point prevalence abstinence at 6 months*			
	Baseline: (GP brief advice)[e]	5%		59,157
	Option 1: (no change to baseline)[e]	5%		68,121
	Option 2: (GP intervention: referral and follow-up)[f]	15%		34,607

MODEL OUTCOMES

Cost/exposure	*Cost per participant exposed to intervention*	
	Baseline:	$11
	Option 1:	$16
	Option 2:	$65
Cost/outcome	*Cost per successful outcome*	
	Baseline:	$220
	Option 1:	$320
	Option 2:	$1444
Incremental cost	*Incremental cost compared to baseline*	
	Option 1:	$8,783,970
	Option 2:	$36,973,342
Incremental number successfully treated	*Incremental number of successes compared to baseline*	
	Option 1:	$8,963
	Option 2:	$-24,550
ICER	*Incremental cost effectiveness ratio*	
	Option 1:	$980
	Option 2:	$-1,506

Table 1. Model parameters and output under usual care, option 1 and option 2. Active intervention components at relevant steps are bolded.

Footnote and description	Reference and notes
(a) Current smokers	- ABS (2015).
(b) Size of target group attending GP	- ABS (2013): Data is for the proportion of the Australian population aged 15 years and over who attend a GP at least once annually.
(c) GP detection of risk: baseline	- GP detection of current smokers was assumed to be 66% based on detection rates reported by Heywood et al. (1994) and Bryant et al. (2015).
(d) GP detection of risk: intervention	- No data on waiting room intervention to increase detection of smokers was identified; An increase in detection of 10% (from 66% to 76%) was hypothesised for an iPad waiting room screening intervention, at an estimated cost of $5 per person screened.
(e) GP brief advice	- Patient reach and adherence was assumed to be 100% (i.e. all patients were assumed to be willing to participate and comply with the GP offering brief advice within the standard consultation). - Costs for brief advice were calculated as $11 per patient (assuming 3 mins @ $37.05/10 minute standard consult (AAPM, 2015). - Brief advice was assumed to achieve a point prevalence rate of 5% at 6 months post intervention based on rates reported by Butler et al. (1999), 5%; Reus et al. (2008), 13%; Reid et al. (1996), up to 5%; and Anczak et al. (2003), 5%.
(f) GP referral and follow-up	- A reach of 65% was assumed for GP referral and follow-up, based on results reported by Lichtenstein et al. (1992) (where 53% of GP patients agreed to attend a group smoking cessation program) and Fiore et al. (2004) (where 69% of participants agreed to enrolled in smoking cessation counselling sessions). - Adherence with the intervention was estimated at 30%, based on 11% attendance reported by Lichtenstein et al. (1992), and 41% attendance at all sessions reported by Fiore et al. (2004). - The cost of providing counselling and GP referral and follow-up was estimated at $65 per smoker. - The intervention was assumed to achieve a 15% abstinence rate at 6 months post-intervention, based on quit rates for more intensive physician counselling or interventions reported by Butler et al. (1999), 15%; Anczak et al. (2003), 20%; and Reus et al. (2008), 22%.

Table 2. References and explanation for data used in the model (footnotes refer to those used in Table 1).

cretion in their choice of evidence for probability assumptions may be limiting. The veracity of 'evidence' in public health can be contentious even amongst experts (Kemm, 2006). For the determination of large differences in potential interventions, this constraint should not undermine the value of the model to decision making. Less definitive results remain valuable through the indication that stronger evidence or more sophisticated analysis may be required. This simple type of modelling could be utilised as a first step in considering the effectiveness of approaches, with more sophisticated models utilised when required. Secondly, some of the data needed for the model may not available or has to be inferred or assumed. For example, in this hypothetical example, data about the effectiveness of touchscreen waiting room screening for detection of smokers, and associated costs, were not available in the literature and had to be estimated in order to run the model; while data about reach and adherence were similarly estimated using the available data as a guide. Another limitation is that major policy decisions *should* be based on sophisticated modelling to examine, for example, the sensitivity of results to changes in parameters, the reality is that accessing this information is both costly and time consuming. An important barrier to the use of high level evidence is its access and availability (Van de Goor et al., 2017).

Conclusions

To optimise the allocation of healthcare resources and funding in a specified area, it is necessary to identify the intervention approaches most likely to be effective and reach a large proportion of the population. Our model presents an easily accessible and useful starting point for considering the cost-effectiveness and reach of two different intervention approaches for intervening on smoking in general practice. Under the assumptions made above, the results of this modelling suggest that increasing detection will result in the greatest benefit in terms of smoking cessation health outcomes, at the lowest cost. This simple model has significant scope to help guide policy makers and researchers in identifying where to allocate research effort and funding. The model is available from the authors on request.

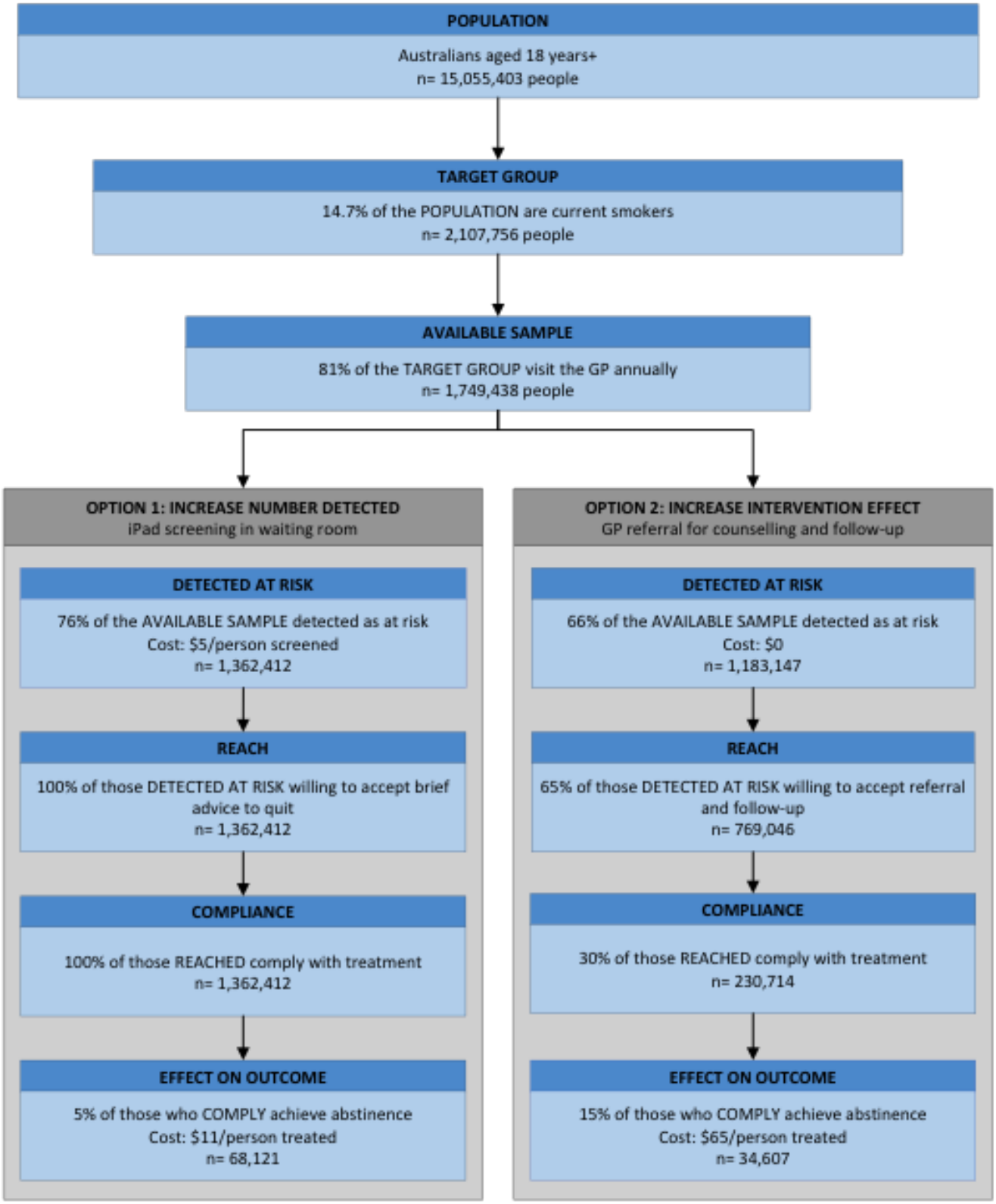

Figure 1. Overview of model and example data for two proposed smoking cessation interventions in the General Practice setting. Note that both options presented here are being compared to baseline (data not shown).

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