Estimating future health technology diffusion using expert beliefs calibrated to an established diffusion model

Abstract

Objectives: Estimates of future health technology diffusion, or future uptake over time, are a requirement for different analyses performed within health technology assessments. Methods for obtaining such estimates include constant uptake estimates based on expert opinion or analogous technologies, and extrapolation from initial data points using parametric curves – but remain divorced from established diffusion theory and modelling. We propose an approach to obtaining diffusion estimates using experts' beliefs calibrated to an established diffusion model to address this methodological gap.

Methods: We performed an elicitation of experts' beliefs on future diffusion of a new preterm birth screening illustrative case study technology. The elicited quantities were chosen such that they could be calibrated to yield the parameters of the Bass model of new product growth, which was chosen based on a review of the diffusion literature.

Results: With the elicitation of only three quantities per diffusion curve, our approach enabled us to quantify uncertainty about diffusion of the new technology in different scenarios. Pooled results showed that the attainable number of adoptions was predicted to be relatively low compared with what was thought possible. Further research evidence improved the attainable number of adoptions only slightly but resulted in greater speed of diffusion.

Conclusions: The proposed approach of eliciting experts' beliefs about diffusion and informing the Bass model has the potential to fill the methodological gap evident in value of implementation and research, as well as budget impact and some cost-effectiveness analyses.

Highlights

Estimates of future health technology implementation are a requirement for different analyses performed within health technology assessments (HTAs). Methods for obtaining such estimates have included simple uptake estimates held constant over the time horizon based on expert opinion or analogous technologies – but remain divorced from established diffusion theory and modelling.

This paper adds a new approach to obtaining diffusion estimates, using experts' beliefs calibrated to an established diffusion model to address this methodological gap. This approach can help inform value of implementation and research, as well as budget impact and cost-effectiveness analyses, which are increasingly relevant in HTA decision-making.

1. Introduction

Estimates of health technology uptake, or diffusion when considered over time, are of increasing importance in health technology assessment (HTA) decision-making. The definition of uptake, for the purposes of this article, is the number of units of a technology purchased through the health system relating to a specific medical indication. Diffusion is defined as the process of uptake growth over time (1). For instance, numerous studies are performed to assess the value of implementation measures (2-7), for which both the potential diffusion with the implementation measure and the counterfactual (what happens if we opt to not invest in implementation) are needed (7, 8). In budget impact analyses, the requirement for an estimate of the affected population also necessitates an estimate of the likely market share or uptake of a new technology, preferably of dynamic nature (9, 10). In cost-effectiveness analyses, recent research showed that prices of medical devices may decline with increasing uptake and this mechanism was implemented in a cost-effectiveness framework that enabled the assessment of dynamic cost-effectiveness and price-volume agreements (1, 11). Finally, value of research studies have investigated the potential effect of research on diffusion, and highlighted that quantification of the effect of research on diffusion enables better estimation of the value of research (12, 13). These HTA themes thus have in common that diffusion estimates are often required for their appropriate consideration.

Existing studies using uptake estimates within HTA have relied heavily on the use of constant uptake estimates, based on similar technologies or expert opinion (14). Alternatively, parametric curves were used to inform dynamic uptake curves (2, 3). The issue with the first approach is that health technology uptake is unlikely to be best represented by a single uptake estimate held constant across future time periods, as was shown in empirical evidence from many different countries (15). A literature review concluded that uptake generally varies over time and is heterogeneous at therapeutic class level as well as at the technology level (7). The second approach, extrapolating future diffusion from available data points, suffers from two issues: first, fitting parametric curves through a few data points can result in vastly different diffusion patterns, because these curves do not typically account for a likely ceiling value or the speed of diffusion based on diffusion theory insights. More sophisticated methods of extrapolating diffusion from existing data are available in the forecasting literature (16, 17). Second, HTA decision-making requires the diffusion estimate to be available prior to the launch of the technology, creating many situations in which uptake estimates for a technology in question are not available. In summary,

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there is a need for methods that help predict technology uptake prior to technology introduction, and that allow estimation of diffusion, rather than constant uptake rates.

We therefore reviewed the forecasting and diffusion literature in search for methods to estimate diffusion prior to technology introduction. Diffusion theory was established by Rogers in 1962, suggesting that diffusion of goods typically follows an s-shaped curve, time being presented on the x-axis and cumulative per period uptake on the y-axis (18). The s-shape resulted from the assumption that populations are heterogeneous in their propensity to innovate, with innovators having a relatively small threshold to technology adoption and imitators having a relatively higher threshold (16). Rogers assumed that the threshold sizes were distributed normally among the population (18).

It furthermore became evident that there is a limited number of tools available to researchers who wish to predict diffusion prior to technology introduction, called pre-launch forecasting in the diffusion literature (17). The two methods typically used for pre-launch forecasting are "guessing by analogy" and subjective judgements (17). Guessing by analogy involves (a) choosing technologies that can be considered as analogous by using pre-specified criteria and (b) using available time series data for the analogous technologies to predict sales of the new technology (19-21). In health care, such guessing by analogy applications appear to be limited to estimates of constant uptake. Limitations associated with this approach include that little is known on how analogies should be chosen (19), the unavailability of similar products in certain technology types (20), selection bias caused by diffusion data of unsuccessful products rarely being available (20) and elapsed time since the analogous technology was introduced, which may have brought about other exogenous factors influencing diffusion patterns (22).

Compared to guessing by analogy, subjective judgement methods provide the advantage of enabling experts to consider technology- and time-specific conditions. However, published studies typically fail to quantify the uncertainty associated with the forecasts and do not use the structure of formal diffusion models (17). Without an assessment of uncertainty, resulting forecasts are of limited use to decision-makers. The use of approaches that do not use a formal forecasting model also introduces bias (17).

We conclude that the requirement for diffusion estimates at the time of HTA stands in stark contrast to the dearth of methods permitting an estimation of diffusion in accordance with diffusion theory available to health economic analysts at present. In this paper, we therefore aim to develop a novel approach to estimating diffusion of health technologies using a formal process of elicitation of experts' beliefs, and calibrating these to an established diffusion model. Given the complexity of the topic, we see particular value in a detailed methods guide for interested researchers. We illustrate our approach in a case study on a preterm birth screening technology. The paper is structured as follows: we first present the diffusion model in the Methods Section 2.1, then propose an approach to estimating this by eliciting observable quantities and calibrating these (Section 2.2). We describe background on the case study technology (Section 2.3) and provide more detail on the elicitation study (Section 2.4). In Section 3, we present results of the application in the illustrative example, and we provide a Discussion and Conclusion in Sections 4 and 5.

2. Methods

2.1 The diffusion model

The most widely cited model for diffusion of innovations is the Bass model of new product growth (16), which represents the sigmoid shape of diffusion first proposed by Rogers (18). For short the Bass model, it was developed in 1969 (23) as an adaptation of a logistic model that reflects the effects of 'innovation' and 'imitation', to be consistent with diffusion literature (18):

$$P(t) = p + q * \frac{N_{t-1}}{m} \tag{1}$$

Where P(t) is the probability of adoption in period t, p the coefficient of innovation or external influence, q the coefficient of imitation or internal influence, m the number of attainable adoptions, and N_{t-1} the number of cumulative adoptions up to the previous period t-1.

This equation is commonly re-arranged to yield the number of adoptions in period t:

$$n_t = p(m - N_{t-1}) + q \frac{N_{t-1}}{m}(m - N_{t-1}) \qquad (2)$$

Where n_t is the number of per period adoptions in period t.

To give an intuition about these parameters, note first that the number of attainable adoptions m does not necessarily coincide with any normative idea of what the maximum number of potential adoptions could be. Second, equation (1) shows that if $q = 0, P(t) = p$ across all periods t, which means that imitation plays no role in the diffusion of the technology and the probability of adoption in a period stays constant. If $p = 0$, however, imitation factor q solely dictates the speed by which the attainable number of adoptions is reached by determining the proportion of the remaining $(m - N_{t-1})$ non-adopters that will adopt in period t. The term $p + q$ controls the scale and the term $\frac{q}{p}$ controls the shape of the diffusion curve, with $\frac{q}{p} > 1$ ensuring the s-shape of the cumulative diffusion curve. Parameters p and q are therefore interdependent. Reported ranges for parameters p and q from a meta-analysis of diffusion curves in a variety of industries were (0.000021; 0.03297) and (0.2013; 1.67260) respectively (24).

2.2 Eliciting beliefs about diffusion

The Bass model parameters are not straightforward to elicit because they are not observable quantities (25, 26) – expressing an opinion about the value of the coefficients of innovation or imitation is cognitively challenging. Another challenge is to keep the elicited summaries to a particular type rather than eliciting a mix of absolute numbers, proportions and odds ratios (27).

Given these challenges, our proposed solution is to elicit uncertainty about the following three quantities: the attainable number of adoptions (which we denote as m), the number of adoptions in the first year after technology introduction (denoted as N1), and the point of inflection, described as the number of years after which the number of adoptions starts to decline (*t'*). The elicited quantity m is equivalent to the Bass model parameter m, whereas quantities N1 and *t'* require further computation to generate the Bass model parameters p and q. Unfortunately, there is no simple algebraic solution that converts observable quantities into Bass model parameters. Kim, Hong (22) found algebraic solutions for the logistic model but not for the Bass model. However, the logistic model cannot reflect asymmetrical diffusion curves. Another study found an algebraic

solution for quantities that we considered less intuitive, such as the sum of Bass model parameters p and q (28). Instead, we used a numerical approximation using minimisation of the sum of squared error terms on the three elicited quantities. This entailed using excel solver to calculate the error terms between the elicited information and the fitted diffusion curve in each solver trial run until the sum of squared error terms was minimised. The computation of parameter values was performed for 1,000 random samples from the probability distributions of the three elicited quantities to yield distributions of parameters p and q.

A problem associated with estimation of parameters in the classic Bass model is that it can result in an unrealistic 'oscillating' curve at specific combinations of parameters p and q because of its time-continuous presentation of discrete data. This arose as a consequence of simplifying the process for the experts by eliciting parameter values independently and ignoring the correlation between uncertain parameters. To overcome this feature, we used the Satoh adaptation of the Bass model (29), which applies a discrete analogue of a quadratic first order equation to the Bass model to make it discrete in time rather than continuous in time, such that:

$$N_t = m \left(\frac{1 - \left(\frac{1 - (q + p)}{1 + (q + p)}\right)^{\frac{t}{2}}}{1 + \frac{q}{p}\left(\frac{1 - (q + p)}{1 + (q + p)}\right)^{\frac{t}{2}}} \right) \quad (3)$$

where N_t is the cumulative number of adoptions in period t.

2.3 Background on the case study technology

The illustrative case study technology is a new device that can help determine whether a pregnant woman is likely to have a preterm birth. This device is still in development and accuracy data are confidential. Compared to the existing standard option, an early study showed that the new technology would be more sensitive and more specific. However, sensitivity was still considered relatively low. The new technology would be easy to use, address capacity issues with the existing technology, its purchase would not be exceedingly costly, but it would be associated with some consumable cost. Treatment options if tested positive include progesterone and cervical cerclage. There were 231 obstetric units in England, which would be expected to purchase one or more devices each (in order to ensure simultaneous use and back-up).

2.4 Elicitation of expert*s'* beliefs about the diffusion curve of the new preterm birth screening technology

Elicitation of experts' beliefs is a widely-used method to obtain quantitative experts' judgements reflecting parameter uncertainty (25). It describes "the process of capturing expert knowledge about one or more *uncertain quantities in the form of a probability distribution"* (30). Structured approaches to elicit experts' beliefs have been found to reduce bias (26) and tools and software packages are readily available, for example, the Sheffield Elicitation Framework (SHELF) (30). Structured elicitation of experts' beliefs requires thorough preparation and consideration of many aspects that require a methodological choice by the analyst (31, 32). We briefly summarise the main decisions in the following, according to reporting guidelines for use of expert judgement (32). More detail can be found in the elicitation protocol in the appendix and the R package on the SHELF website (30).

We recruited three obstetricians from different locations and types of hospitals in England. In order to qualify for the study, they had to fulfil criteria of having a tangible level of expertise, an understanding of the general problem area, and no conflict of interest. Tangible expertise required that experts had knowledge about the therapeutic area (preterm birth), treatment and diagnostic options in the area, and were familiar with the commissioning process of new health technologies. Obstetricians practicing in English hospitals were considered generally eligible for the reasons that: 1) diffusion for the preterm birth screening technology was limited to patients in England for this illustrative example; 2) in England, the technology would be made available to hospitals with obstetric units that assess women at high risk of preterm birth; and 3) the key customers are obstetricians, typically involved throughout the procurement decision-making process. The experts' deeper tangible expertise was established within a preceding qualitative study.

Possible biases and heuristics were discussed and experts encouraged to avoid these. Training of experts should involve following the process of elicitation through for a quantity that is unknown to the experts but knowable in principle (25). For this, the number of preterm births in England was elicited from each expert, using a scalar quantity in keeping with the quantities elicited in the main study. We used the tertile method, a variable interval method in which experts are asked about the median of an uncertain quantity, X, say, such that $p(X < median) = 0.5$, and then the first and third tertiles such that $p(X < t_1) = {}^1\!/_3$ and $p(X < t_3) = {}^2\!/_3$,

respectively. Separate face-to-face sessions were held with each expert and gamma distributions fitted to their elicited values. The distributions were then combined across experts using linear mathematical pooling, with equal weights for the experts. One pilot was performed, and no changes were made to the protocol subsequently.

Within the provision of background information, experts were provided a document with general background on preterm birth statistics, the accuracy data of the new and the current technologies and other information mentioned in Section 2.3, a brief background on diffusion theory, and a presentation of findings from the preceding qualitative study, which suggested that further research would be desirable to establish the predictive accuracy of this technology. We therefore performed the elicitation exercise twice: once for a scenario based on the current evidence of predictive accuracy, and once more for a hypothetical scenario in which new evidence on the device's accuracy was available. We provide a view to the mechanism by which any change in diffusion could be attained with the availability of further research evidence by reporting experts' rationales for their estimates of the "with research" diffusion curve. These qualitative statements were obtained as part of one of the steps in SHELF, fitting the distribution and feedback.

3. Results

In summary, the pooled elicitation results (Tables 1 and 2, Figure 1) suggest that the maximum attainable number of adoptions for the preterm birth screening device in England will be at 140 devices without further research and at 146 with further research evidence. These are relatively small numbers given that there are 231 obstetric units in England and that most units would be expected to purchase more than one device. A very small number of adoptions would occur in the first year, at a mean of six adoptions, or thirteen adoptions with the availability of more research evidence. The rationale given by the experts was that in the first year, potential purchasers would mainly be hospitals that were involved in the development of the technology or those that had research grants for it (Table 3 and Figure 2). The number of years at which the maximum number of per-period adoptions is reached was estimated to be at a mean of six years, or five years with more research, with the rationale being that a greater evidence base would enter the consciousness of clinicians sooner.

To provide an overview of the individual experts' beliefs, Table 3 and Figure 2 present the results for each expert. Expert 1, who predicted the flattest diffusion curve, thought that the device's accuracy was not

convincing. Expert 2 had similar reservations but considered that more evidence, even showing the same result, would help with the evaluation process. Expert 3 thought that the maximum number of adoptions was constrained by the adversity to innovation in the England National Health Service (NHS) but they thought that the device would diffuse quickly within these constraints and that further evidence would speed up the diffusion process slightly.

Computing the distributions of p and q from the elicited distributions resulted in mean values of 0.031 and 0.472, respectively, for the current scenario and 0.058 and 0.543, respectively, for the further research scenario (Table 1). The exact p and q values lack an intuitive interpretation but can be interpreted in the context of the general statements outlined in Section 2.1 of this paper. Uncertainty about the shape of the "without evidence" diffusion curve is presented in Figure 3, in which the mean diffusion curve is plotted along with the curves obtained when the 95% credible interval values of parameters p, q and m are used.

4. Discussion

In this paper, we have presented a novel approach to predicting diffusion of new health technologies using elicitation of experts' beliefs about uncertain values to inform an adaptation of the Bass model of diffusion. We applied our approach to estimating diffusion of a new preterm birth screening technology for two counterfactual scenarios of with and without the availability of further research evidence. Pooled results showed that the attainable number of adoptions was predicted to be below what was thought to be possible for a new device in this therapeutic area. This was mainly attributed to relatively unconvincing accuracy evidence for the device and the general adversity to change that was thought to be present in the England NHS. The availability of further research evidence could improve the maximum attainable number of adoptions only slightly but resulted in greater speed of diffusion.

The method presented in this paper is of particular relevance considering the lack of methods in the literature that addresses the requirements for dynamic estimates of technology implementation in the context of different types of analyses commonly performed within HTAs. More practically, the elicited diffusion curves for the new case study technology can inform further studies on the value of implementation of the collection of further research evidence, which can potentially speed up diffusion (12). Budget impact analysis could be performed

with these estimates. In value of research studies, the impact of collecting further research evidence can be assessed in terms of both the increase in implementation and the decrease of uncertainty. Finally, cost-effectiveness of this technology could be modelled including price-volume agreements and the uncertainty about diffusion could be appropriately reflected in the probabilistic sensitivity analysis. Our paper offers an approach to obtaining the technology-specific and probabilistic diffusion estimates required for these analyses prior to technology introduction, a currently unexplored topic (17). The approach presented here improves upon the commonly used methods of using data from analogous technologies and deterministic expert or analyst judgements by providing estimates that reflect uncertainty about diffusion based on a widely validated diffusion model.

The strength of this approach lies in the ability to estimate diffusion for the technology lifetime from only three elicited quantities. Our approach also enables the use of available expert knowledge, rather than being dependent on diffusion data for other technologies. Data on analogous health technologies are sparse, amongst others because of patent protection leading to long lags until competitors can enter the market. The Bass model of diffusion was chosen because of a strong evidence base in support of its ability to predict diffusion well in different industries. No other models had the same evidence base. Another strength is the elicitation of uncertainty information, with the possible 'diffusion space' including a range of possibilities for different paths of diffusion that could become reality given that certain events occur (such as a new competitor entering the market).

It may be perceived as a limitation that relatively little information is provided on our illustrative case study. We felt that a focus on the new approach was more appropriate. We wish to highlight that the choice of experts, the avoidance of heuristics and bias in elicitation, and the appropriate briefing on the technology and possible influencing factors and future developments deserve more attention and refer the reader to the wider elicitation literature (25-27, 31-33). The number of experts used should furthermore be carefully assessed. We used 3 experts and thought this was possibly sufficient to characterise the uncertainty about future diffusion. However, Grigore et al. since then suggested between 6 and 12 experts (31), and hence, the use of only 3 experts may be a limitation. A technical limitation is that we univariately elicited beliefs about quantities that are likely to be interdependent. This, and the use of the Satoh adaptation of the Bass model, may have led to the introduction of bias that we were unable to quantify.

Alternative methodological choices in the elicitation of expert opinion include fixed interval methods such as the roulette method, which divide the sample space into fixed intervals and ask for the probabilities of these (27, 34). Variable interval methods (such as the tertile method used here), in contrast, offer more flexibility for the expert but may sacrifice simplicity and there is no conclusive evidence on which method performs best (35). Another method is the so-called hybrid, in which experts are asked to provide information about the lowest and highest possible value as well as the most likely value of a quantity of interest (36).

Alternative distributions could be used for the quantities of interest. In particular, where the number for 100% of adoptions is known (i.e. where there is an upper bound to uptake), it may be easier for experts to think about proportions of adoptions. More research is required to establish whether this would be the case and whether the elicited quantities could then easily be back-calculated to estimate the diffusion model parameters.

There is no consensus on whether behavioural or mathematical aggregation of expert opinions should be used. Whilst behavioural aggregation through discussion and adjustment of beliefs in a group setting offers the advantage that a consensus can be found, this method also tends to produce over-confident judgements (27). Mathematical aggregation, however, neglects the different opinions of the experts. Due to time constraints, we were unable to perform a feedback round, in a technique that is known as the Delphi method and has previously been applied to forecasting (37).

It should be highlighted that researchers performing such an exercise may wish to be careful in the study design to avoid any anchoring bias between scenarios. In our 'with research' scenario, the newly generated hypothetical evidence was conditional on the currently existing evidence and we therefore did not perceive any anchoring as problematic. But when independent scenarios are elicited, a timely separation of the elicitation exercises is advisable to avoid anchoring.

Alternative diffusion models may be used. The applicability of diffusion theory to health technologies may be compromised by health technologies being subject to different rules and adoption mechanisms compared to technologies in other industries. Other prediction models should arguably be tested in comparison with the Bass model, to assess their performance in predicting diffusion in the health technology sector.

Scope for further research includes applying our approach to more technologies. Its performance in accurately forecasting diffusion in comparison with other forecasting methods should be assessed once sufficient empirical data becomes available. Methodological research is furthermore required in elicitation techniques, in particular multivariate elicitation of interdependent quantities.

5. Conclusion

The proposed approach of eliciting experts' beliefs about diffusion and informing the Bass model has the potential to fill the methodological gap evident in predicting diffusion for use in value of implementation and research, as well as budget impact and cost-effectiveness analyses. This approach may be useful to analysts wishing to consider technology-specific diffusion and to formally represent the associated uncertainty.

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Tables

Table 1. Pooled elicited quantities and Bass model parameters

Without further research					With further research				
Variable	Mean	SD	Median	CI	Variable	Mean	SD	Median	CI
m	140	69	128.84	(39-304)	m	146	66.1	136.16	(46-301)
n1	4.99	2.04	4.71	(1.8-9.7)	n1	10.5	4.12	9.96	(4.0-20)
t'	6.26	1.34	6.16	(3.9-9.1)	t'	5.21	1.52	5.06	(2.7-8.6)
Without further research					**With further research**				
Bass model parameter	Mean	SD	Median	CI	Bass model parameter	Mean	SD	Median	CI
p	0.031	0.02	0.026	(0.005-0.083)	p	0.058	0.038	0.049	(0.013-0.157)
q	0.472	0.176	0.482	(0.2-0.806)	q	0.543	0.136	0.524	(0.313-0.826)
Key: m - number of attainable adoptions, n1 - number of adoptions in period 1, t' - time at which number of adoptions starts to decline, SD - standard deviation, CI - credible intervals									

Table 2. Cumulative adoptions as per pooled elicited diffusion curves

	Nt	
Year	Without research	With research
1	6	13
2	15	33
3	29	59
4	47	87
5	67	110
6	87	126
7	104	135
8	117	140
9	126	143
10	131	145
11	135	145
12	137	146
13	138	146
14	139	146
15	139	146
16	140	146
17	140	146
18	140	146
19	140	146
20	140	146
Key: Nt - cumulative number of purchases in period t		

Table 3. Experts' individual elicited quantities

Expert	1		2		3	
Elicited quantity	Mean	95% CI	Mean	95% CI	Mean	95% CI
m - without research	54.2	(10-150)	158.8	(30-230)	204.4	(30-410)
m - with research	68.7	(20-150)	174.2	(60-250)	204.4	(30-410)
n1 - without research	2.3	(0-5)	5.7	(2-15)	7.1	(2-10)
n1 - with research	2.3	(0-5)	5.7	(2-15)	23.7	(10-40)
t' - without research	5.1	(3-8)	9.9	(7-13)	3.5	(2-6)
t' - with research	5.1	(3-8)	8.2	(5-11)	2.6	(1-5)
Key: m - number of attainable adoptions, n1 - number of adoptions in period 1, t' - time at which number of adoptions starts to decline, CI - credible interval						

Figures

Figure 1. Diffusion with and without further evidence collection
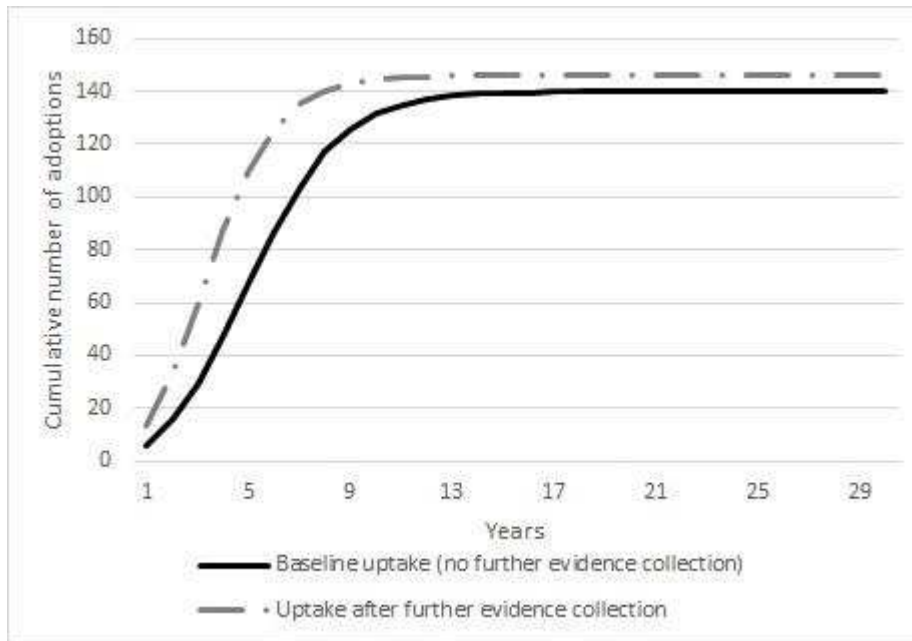

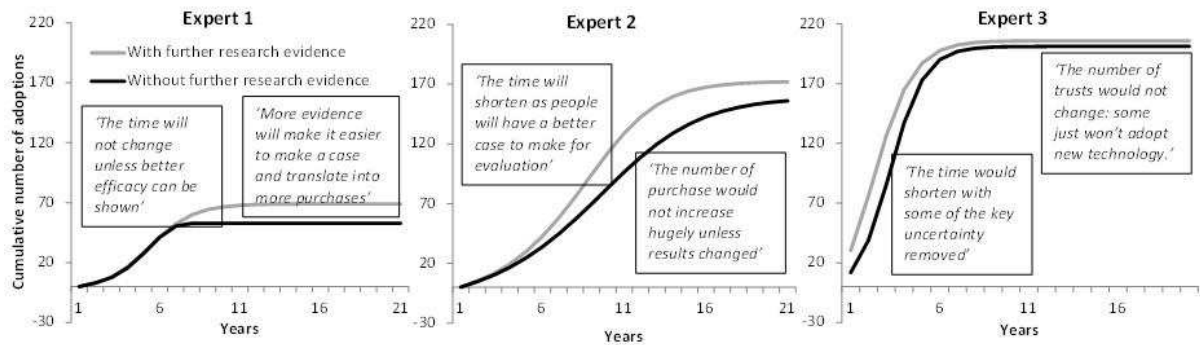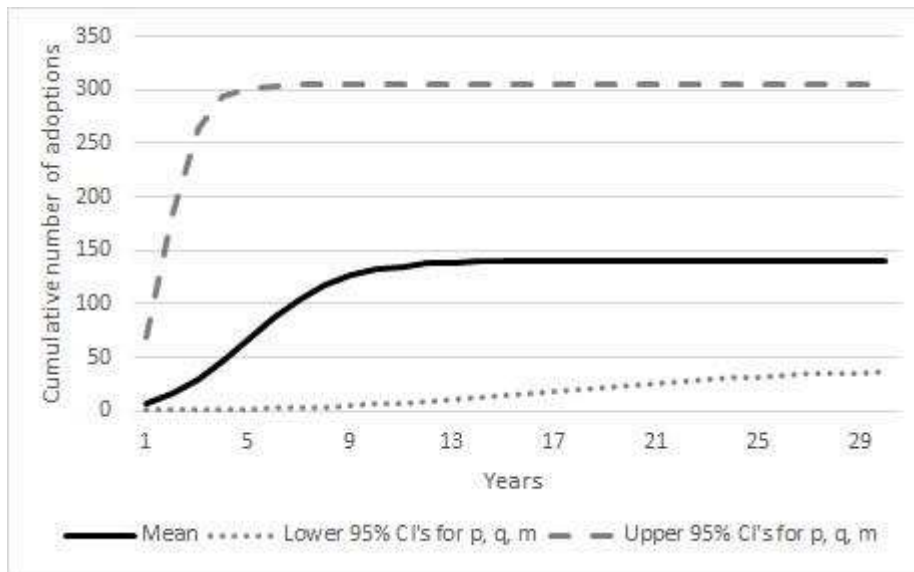**Figure 2. Diffusion curves and justifications elicited from different experts**

Figure 3. Uncertainty about "without further evidence" diffusion curve

Appendix

Quantifying factors that will influence usage of a new technology for pre-term birth screening in the UK

Script

1. Introduction

- Introduce yourself
- Explain that the aim is to quantify beliefs about future purchases of Technology A for PTB screening in the UK
- Explain that this study will inform an economic model
- Explain that this is part of a PhD study that looks into how adoptions affect the evaluation of a technology
- Explain that I wish to develop a standard approach by which experts are being asked about adoption of innovative technologies
- Explain that this study is a so-called elicitation of expert beliefs by which experts quantify their opinions about some unknown quantities of interest
- Explain that having a feeling of uncertainty with their opinion is fine and can be addressed using this method
- Reassure re: confidentiality and anonymity.
    - Highlight that no individual will be identified.
- Remind about length of meeting – approximately 1 hour 30 mins
- Check if participant has any questions at all at this stage
- Ask participants to sign consent form to provide written consent for participation
- Thank the participants for agreeing to participate

2. Training

- Explain that we will now conduct training using one example quantity that is not used for this study
- Explain that we will elicit beliefs about the number of pregnant women delivering their baby pre-maturely in England, called X in the following
- Refer to number of hospital births under bullet point 1. in background document as a help and tabular overview of how percentages translate to numbers
- Provide calculator and sheet of paper
- **[R: Change dir → Desktop; then source("shelf2.R")]**

- Ask experts to provide a range such that it is extremely unlikely but not entirely impossible that X falls outside that interval (lower bound L to upper bound U) **[tertile.single(Lo=X1, Up=X2)]**
- Ask experts to state the median M, a number at which it will be as likely for X to be larger than the median as smaller than the median. This is a value such that the proposition that 'X lies below the median' is equally likely to 'X lies above the median'.
- Ask experts to state upper and lower tertiles (T1 and T2) by considering the range from L to U and dividing it into three equally likely intervals.
  - Point out that of course M will have to lie between T1 and T2.
  - Point out that this is like giving an interval at which they are 33% confident that X will fall into it
  - Ask experts to regard each of the three ranges (L to T1, T1 to T2 and T2 to U) as equally likely.
  - Ask experts to regard also as equally likely the ranges T1 to M and M to T2.
  - Point out that values of X close to M are likely more probable than values of X close to L and U, that is the intervals T1 to M and M to T2 will be narrower than the intervals L to T1 or T2 to U.
- When tertiles are decided on, show histogram and ask whether they think that the 3 boxes are indeed equally likely **[press show histogram]**
- Then show the fitted distribution (gamma) as density function **[press first gamma, then density]** and tell them their estimated mean
- Reveal real results of number of pre-mature births in England (2011-2012): 42,000 which is equal to 6.3%.

3. Structuring
- Remind of background that was sent in advance of the meeting
- Ask whether they want to go briefly through the explanation of Technology A in background doc (point 2)
- Explain study results
- Present LRs and sensitivity, specificity
- Explain about uptake using the background document (point 4)
- Explain 3 different uptake curves
- Explain that this means elicitation of m, n1 and t'
- Explain that later, we will look at m, n1 and t' under the assumption that further trials have been conducted
- Highlight that in total we will elicit 6 quantities (if time permits)
- **Fill in expertise and declaration of interests in form 1**

4. Elicitation

- Explain that the first quantity to be elicited is the number of Technology A devices sold across all obstetric units in England (m1).
- Remind them that they can use the information in point 1-4 from the background sheet.

- **For m1: the number of Technology A devices potentially sold across all obstetric units in England**
- Ask experts to provide a range such that it is extremely unlikely but not entirely impossible that m1 falls outside that interval (lower bound L to upper bound U).
  [tertile.single(Lo=L,Up=U)]
- Double-check by asking whether they really think that there is 0% chance that m1 will fall outside this range.
- Ask experts to state the median M, a number at which it will be as likely for m1 to be larger than the median as smaller than the median. This is a value such that the proposition that 'm1 lies below the median' is equally likely to 'm1 lies above the median'. **[write down on Elicitation part 2]**
- Ask experts to state lower and upper tertiles (T1 and T2) by considering the range from L to U and dividing it into three equally likely intervals.
    - Point out that of course M will have to lie between T1 and T2.
    - Point out that this is like giving an interval at which they are 33% confident that m1 will fall into it
    - Ask experts to regard also as equally likely the ranges T1 to M and M to T2.
    - Point out that values of m1 close to M are more probable than values of m1 close to L and U, that is the intervals T1 to M and M to T2 will be narrower than the intervals L to T1 or T2 to U.
- **Record median and tertiles in Elicitation part 2.**
- When tertiles are decided on, show histogram and ask whether they think that the 3 boxes are indeed equally likely **[press show histogram]**
- Then show the fitted distribution (gamma) as density function **[press first gamma, then density]** and tell them their estimated mean
- Ask whether experts are happy with their own distribution or whether they would like their judgements changed (tell them mean and 90% percentiles)
    - **Record any changes in Elicitation part 2 - Fitting**
- Ask experts to individually explain their rationales for their distributions.
- **Record chosen distribution in Elicitation part 2**, including median, tertiles and distribution.

- **Then elicit (according to the same protocol):**
- **n1-1: the number of purchases of Technology A in hospitals in first year**

- **t'1: the number of years at which the purchases per period peak**

- **m2: the number of potential purchases of Technology A given new evidence**

- **n1-2: the number of purchases of Technology A in first year given new evidence**

- **t'2: the number of years at which the purchases per period peak given new evidence**

5. Conclusion
- Highlight that this work will enable the preliminary economic evaluation of Technology A in PTB screening, including setting research priorities.

Thank the participants for their time and contribution

Quantifying uptake determinants of Technology A for use in pre-term birth screening in the UK

Elicitation briefing notes

The purpose of the elicitation meeting is to obtain probability distributions to represent your uncertainty about various quantities of interest. These are listed in section three of the attached pro forma.

The elicitation will be conducted following the Sheffield Elicitation Framework (SHELF), based on elicitation practice recommended in O'Hagan et al (2006). You will be given training in the process of elicitation at the start of the meeting, which will include a practice exercise to familiarise you with the procedure.

It is important to note that you will not be asked to provide single estimates of any of these quantities. The elicitation process will instead involve considerations such as what a plausible range of values would be for each unknown quantity, and whether, in your opinion, some values are more likely than others. You may have considerable uncertainty about some of these quantities (though less than that of a lay person). This will not be of concern during the elicitation itself, as the outputs from the elicitation will reflect large uncertainty when it is present.

Due to the subjective nature of elicited probability distributions, it is important to make the elicitation process as transparent as possible. A written record will be kept of the meeting, which will include details of experts present at the meeting, a summary of each expert's relevant expertise, and any declarations of interest. It would be helpful if you could complete sections 2 and 4 in the pro forma. A brief summary will be sufficient for section 4, covering expertise relevant to the parameters listed in section 3.

Please note that declarations of interest are recorded for the purposes of transparency only, and will not be used as grounds for exclusion from the elicitation. It is common for experts to be stakeholders in the wider process.

Suggested relevant evidence is listed in section 5. If you wish to add to this list you may do so. Where appropriate, publications/data listed in this section will be made available at the elicitation meeting.

Reference:

O'Hagan, A., Buck, C. E., Daneshkhah, A., Eiser, J. E., Garthwaite, P. H., Jenkinson, D. J., Oakley, J. E. and Rakow, T. (2006). Uncertain Judgements: Eliciting Expert Probabilities. Chichester: Wiley.

Quantifying uptake determinants of Technology A for use in pre-term birth screening in the UK

Pre-elicitation meeting pro forma

1) Background	The purpose of this exercise is to obtain estimates of future purchases for Technolgy A for use in pre-term birth screening. These estimates will then be used in an economic evaluation of this device that will show future cost-effectiveness and help in setting research priorities.
2) Declarations of interests	[To be completed by the expert. Please identify any personal interest that you might have in the outcome of this elicitation exercise, or in the wider context specified above: these can include being an investigator in the trial of Technology A, being involved in the development of Technology A, having any stake or interest in the economic outcomes of Technology A or future research prospects]
3) Parameter definitions	1. The number of potential purchases of Technology A in the NHS England (your expertise of adoption processes in the NHS in your field of work is needed). 2. The number of years at which the purchase rate peaks (your expertise of how long it takes to reach the majority of adopters in the NHS in your field of work is needed). 3. The number of purchases at the peak. 4. The same 3 parameters as above assuming that there is more research available (your expertise of impact of research on adoptions in your field of work is needed).
4) Participant's expertise	[To be completed by the expert. Please briefly identify your expertise in relation to the parameters listed above.]

5) Key relevant evidence	[The expert should add details of any key documents and studies that are relevant to the above parameters, if any.]

To be filled in by the facilitator.

Elicitation title	Quantifying factors that will influence usage of a new technology for pre-term birth screening in the UK
Session	1
Date	
Part 1 start time	

Attendance and roles	
Purpose of elicitation	To obtain estimates of future adoptions for Technology A in pre-term birth with the purpose of performing an economic evaluation
This record	Participants are aware that this elicitation will be conducted using the Sheffield Elicitation Framework, and that this document, including attachments, will form a record of the session.
Orientation and training	Conducted on one quantity: the number of pre-term births in one year in the NHS England
Participants' expertise	
Declarations of interests	
Strengths and weaknesses	
Evidence	
Structuring	1. maximum number of purchases attainable given current evidence
2. number of years at which number of purchases peak given current evidence
3. number of purchases at peak given current evidence
4. maximum number of purchases attainable given availability of further evidence
5. number of years at which number of purchases peak given availability of further research evidence
6. number of purchases at peak given availability of further evidence
Definitions	See structuring

	1. m1	29
	2. n1-1	
	3. t'1	
	4. m2	
	5. n1-2	
	6. t'2	

Part 1 end time	
Attachments	

ELICITATION RECORD – Part 2 – Distribution

Tertile Method

Example for one quanitity - to be filled in by the facilitator.

Elicitation title	Quantifying factors that will influence usage of a new technology for pre-term birth screening in the UK
Session	1
Date	
Quantity	1. maximum number of purchases attainable given current evidence
Start time	

Definition	m1
Evidence	As in background sheet
Plausible range	
Median	
Upper and lower tertiles	
Fitting	
Group elicitation	-
Fitting and feedback	
Chosen distribution	
Discussion	

End time	
Attachments	