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Methodological Article

Estimating Future Health Technology Diffusion Using Expert Beliefs Calibrated to an Established Diffusion Model

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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 on extrapolation from initial data points using parametric curves—but remain divorced from established diffusion theory and modeling. We propose an approach to obtaining diffusion estimates using experts' beliefs calibrated to an established diffusion model to address this methodologic 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 methodologic gap evident in value of implementation and research, as well as budget impact and some cost-effectiveness analyses.

Keywords: budget impact analysis, cost effectiveness, diffusion of innovations, elicitation, value of information.

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 care 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 periods, as was shown in empirical evidence from many different countries [15]. A literature review concluded that uptake generally varies over time

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and is heterogeneous at the 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, 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].

Furthermore, it became evident that there is a limited number of tools available to researchers who wish to predict diffusion prior to technology introduction, called *prelaunch forecasting* in the diffusion literature [17]. The two methods typically used for prelaunch forecasting are "guessing by analogy" and subjective judgements [17]. Guessing by analogy involves (1) choosing technologies that can be considered as analogous by using prespecified criteria and (2) 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 little being 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 with guessing by analogy, subjective judgement methods provide the advantage of enabling experts to consider technology- and time-specific conditions. However, published studies typically have failed to quantify the uncertainty associated with the forecasts and did 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 article, we therefore aim to develop a novel approach to estimating diffusion of health technologies using a formal process of elicitation of experts' beliefs and to 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 article is structured as follows: We first present the diffusion model in the Methods section 1, then propose an approach to estimating this by eliciting observable quantities and calibrating these (section 2). We describe background on the case study technology (section 3) and provide more detail on the elicitation study (section 4). In the Results section, the outcomes of the application in the illustrative example are provided, and we also provide Discussion and Conclusions sections.

Methods

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]. In brief, the Bass model 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 rearranged to yield the number of adoptions in period t:

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

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].

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: (1) the attainable number of adoptions (which we denote as m); (2) the number of adoptions in the first year after technology introduction (denoted as $N1$); and (3) 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