

Evidence and belief in regulatory decisions – incorporating expected
utility into decision modelling

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Abstract

Recent changes in the assessment and management of risks has had the effect that greater importance has been placed on relationships between individuals and within groups to inform decision making. In this paper, we provide the theoretical underpinning for an expected utility approach to decision-making. The approach, which is presented using established evidence support logic (TESLA™), integrating the expected utilities in the forming of group decisions. The rationale and basis are described and illustrated through a hypothetical decision context of options for the disposal of animal carcasses that accumulate during disease outbreaks. The approach forms the basis for exploring the richness of risk-based decisions, and representing individual beliefs about the sufficiency of evidence they may advance in support of hypotheses.

Keywords: decision support, uncertainty, risk, group decision making, evidence support logic, expected utility, TESLA™

1. Introduction

Regulatory decision-making is undergoing a revolution in the UK. Proposals for modernising regulation within Government in the 1990s (Cabinet Office, 1999) are being delivered through programmes that focus on ‘better’ and ‘risk-based’ regulation (Pollard et al., 2002; Hutter, 2005). The premise is that a step change can be delivered, with the regulation of risks to occupational and public safety, to the safety of the food chain and to the environment becoming smarter, more focused on high risks, and decisions being more open to external scrutiny and challenge (Davies et al., 2010). In addition, we observe a renewed emphasis on the use of scientific

evidence in government decision-making. These initiatives test our understanding of the technical, political and psychological features of decision-making on risk, particularly in the regulatory and policy development contexts.

Previously, UK Government departments and their agencies have published risk frameworks that set out the technocratic processes of risk management and options appraisal (see Strategy Unit 2002). These spell out how sufficient, dependent and necessary a number of sources of evidence are for providing a solid basis for decision making. However, such decisions involve the consideration of factors well beyond the nature of adverse consequences, their probabilities, and the uncertainties in these conventional dimensions. Risk managers need to consider the costs of risk management, associated social issues, performance of technology (where it plays a part), and governance arrangements critical to ensuring that risks are actively managed by organisations (Pollard *et al.*, 2002). These attributes are reflected in the risk management ‘frameworks’ promoted by governments, regulators, business sectors and individual organisations. Yet in practice decisions are made by individuals within organisational contexts. For risk-based regulation, these are complex decisions requiring:

- (i) clear problem definition (scoping) that identifies the risk under study within the context of the legal statute;
- (ii) the gathering of evidence by multiple parties (professional advisors, researchers, the general public, operators, front line regulatory staff, regulatory policy staff);
- (iii) the structuring of arguments in support of a case, including the assembly of individual lines of evidence with their discrete strengths, and the overall weight of evidence;

72 (iv) the ‘brokering’ of evidence and risk assessments between parties, including
73 between consultants and their clients, internally within organisations, between the
74 regulated and the regulator, and between regulators and policy officials with
75 individuals valuing the benefit and cost in addition to the reputation, trustworthiness
76 and persuasiveness of the provider (Chiu *et al.*, 2009); and
77 (v) peer review of risk assessments and the supporting evidence in conjunction with
78 defensible, robust decisions to be made on risk management, together with the
79 defence of these decisions in the courts, if necessary (Defra, 2011).

80 In practice, the conventional manner of establishing a risk-management
81 framework is likely to take too long to gather sufficient information to inform
82 decisions for the growing number of new imminent risks. As such, expert-elicitation
83 panels have become a common route to produce an evidence-based framework. This
84 approach can achieve results with relative speed and has become invaluable for
85 practitioners of modern risk-based regulation. Expert-elicitation and the interpretation
86 of information are subject to value judgements (regarding the sufficiency of
87 supporting evidence), which are rarely transparent to the end user. As such, there
88 remains a view that these frameworks fail to fully capture the nuances and
89 complexities of decision-making (Oxera, 2000; Petts *et al.*, 2003). For example, the
90 influence that individual preferences (or expected utilities) will have on judgments
91 made regarding the sufficiency, dependency and necessity of supporting evidence.
92 This influence is difficult to identify and indeed to measure, however the impact of
93 such influences are unclear and a model can help to determine how important these
94 influences are in decision making. Previously, Chiu and colleagues (2009) have
95 presented a formal quantitative model for recommendations within a
96 customer/supplier relationship, demonstrating the impact of trust and reputation;

however, this model does not specifically consider the belief and uncertainty that an individual may have in recommendations.

TESLATM (Quintessa, UK), a commercial platform for evidence support logic, is a decision-support tool that addresses issues of transparency within expert elicitation panel decisions, thereby providing unique insights that are not normally included in conventional decision-support tools. TESLATM can be used to describe and simulate complex systems. Environmental decision contexts, complex by their very nature, have been previously tackled by authors who have used evidence-support logic to negotiate, optimise the effectiveness of, and recently, model decisions.

In this paper, we propose the theoretical basis for a model that integrates: (a) the structuring of evidence that supports a group decision (represented here by the adoption of evidence-support logic); (b) the benefits of a decision outcome (represented by expected utility theory); and (c) that demonstrates the relevance of other influences in group decision making to practitioners, providing a model that increases the transparency of decision making influences. Representation of the combined approach is made here using TESLATM.

2. Methods

2.1 Selection of a model platform

TESLATM offers the user a means of improving the transparency of regulatory decisions, by recording the structure and sufficiency of the evidence that supports a risk decision. It has been successfully used in the context of safety cases for nuclear waste management (Seo *et al.*, 2004; Egan & Bowden, 2004) and is also proposed for building stakeholder confidence in the long term geological storage of carbon dioxide (Benbow *et al.*, 2006; Egan, undated). Lines of evidence are represented by a

structured cascade of logical ‘parent’ and ‘child’ hypotheses, each with its own supporting evidence. User inputs are combined to determine how ‘sufficient’, ‘dependent’ and ‘necessary’ each child hypotheses is for supporting its corresponding parent. TESLA™ does not account for the influence that personal preferences have on value judgements.

2.2 Integrating expected utility theory in evidence-support logic

Expected Utility Theory (EUT) can be incorporated within evidence-support logic to explore the integrity of TELSA™. This provides an indication of how subjective value-judgements bias the sufficiency of supporting evidence and the structure of the resulting framework.

The evidence-support logic, embodied within TESLA™, is an information propagation approach developed from Interval Probability Theory (IPT) (Feller, 1971; Cui & Blockley, 1990; Hall *et al.*, 1998a). It has been applied in several fields of risk-based decision-making to allow experts to characterise lines of evidence by expressing what they believe with regard to child hypotheses actively supporting, overlapping, or conflicting when considering a corresponding parent hypothesis (for examples, see Foley *et al.*, 1997; Hall *et al.*, 1998b).

Expert belief is expressed by a triple (p, u, q) , where p denotes the probability that an individual child hypothesis supports a corresponding parent hypothesis, q denotes the probability that it refutes the hypothesis, and u denotes the residual uncertainty attached to this belief. These values range between $0 \leq p, q \leq 1$ and $-1 \leq u \leq 1$; where $u = 1$ would denote a state of absolute ignorance, and $u < 0$ would denote a state of conflicting beliefs within the evidence.

Evidence-support logic has a simple algorithm to aggregate multiple beliefs about evidence. For example, if n beliefs about n child hypotheses are aggregated to form a belief about a single parent hypothesis, each belief for each child hypothesis will be expressed as (p_i, u_i, q_i) , $i = 1, \dots, n$. Each child hypothesis would then have p_i and q_i values from 0 to 1 and u_i value of -1 to 1 assigned to denote how much belief 'for' (p_i) and 'against' (q_i) and how much uncertainty (u_i) is related to the corresponding parent hypothesis' belief. Greater values of sufficiency will result in evidence being more influential, whilst greater values of dependency result in pertinent child hypotheses having a shared influence. The presence of a necessary child hypothesis determines whether beliefs assigned to child hypotheses can be aggregated to form a belief for the corresponding parent hypothesis.

If (p_A, u_A, q_A) denotes the aggregated belief for child hypothesis A . Then p_A can be computed as follows:

$$p_A = \sum_{i=1}^n w_i p_i - \sum_{\substack{i,j=1 \\ i < j}}^n \rho_{ij} \min(w_i p_i, w_j p_j) + \sum_{\substack{i,j,k=1 \\ i < j < k}}^n \rho_{ijk} \min(w_i p_i, w_j p_j, w_k p_k) \\ + \dots + (-1)^{n-1} \rho_{1,\dots,n} \min(w_1 p_1, \dots, w_n p_n) \quad (1)$$

Therefore, if $S = \{i, j, \dots\}$,

$$\rho_S = \frac{(1-D) \prod_{a \in S} w_a p_a}{\min(w_a p_a)_{a \in S}} + D$$

Where w_i is the weighting of the i^{th} line of evidence and D is the dependency between the evidence $p_i, p_j, \dots, p_n$. Then q_A can be computed similar to (1).

$$q_A = \sum_{i=1}^n w_i q_i - \sum_{\substack{i,j=1 \\ i < j}}^n \rho_{ij} \min(w_i q_i, w_j q_j) + \sum_{\substack{i,j,k=1 \\ i < j < k}}^n \rho_{ijk} \min(w_i q_i, w_j q_j, w_k q_k) \\ + \dots + (-1)^{n-1} \rho_{1,\dots,n} \min(w_1 q_1, \dots, w_n q_n) \quad (2)$$

Where,

$$\rho_S = \frac{(1-D) \prod_{a \in S} w_a q_a}{\min_{a \in S} (w_a q_a)} + D.$$

Once we have the values of p_A and q_A , u_A can be determined by means of

$p_A + q_A + u_A = 1$ For example, when $n = 2$ and beliefs 1 and 2 are independent, we have,

$$\begin{cases} p_A = w_1 p_1 + w_2 p_2 - \max(w_1 p_1, w_2 p_2) \min(w_1 p_1, w_2 p_2) \\ q_A = w_1 q_1 + w_2 q_2 - \max(w_1 q_1, w_2 q_2) \min(w_1 q_1, w_2 q_2) \end{cases} \quad (3)$$

2.3. Incorporating expected utility

Expected utility theory is widely adopted for addressing risk and uncertainty in economics (Hey & Orme, 1994; Starmer, 2000) and has applications in regulatory decision-making (Li et al. 2009). It can be traced back to the work of Daniel Bernoulli (1738) and has been further promoted through the ‘theory of games and economic behaviour’ (Von Neumann & Morgenstern, 1944). The underlying principle is that the decision-maker has prior knowledge of the probabilities of all activities occurring and can assign a value representing a sum of money or similar against each alternative. This assumes that the decision-maker has a complete, reflexive, transitive, and continuous evaluation over monetary outcomes, or in other words, s/he possesses a von Neumann-Morgenstern utility function.

Expected utility over a set of outcomes can be expressed as,

$$U(X) = \sum_{i=1}^n u(x_i) p(x_i) \quad (4)$$

Where X is the utility of all the set of possible outcomes; x is the utility of an outcome; p is the probability of X as $p = (p(x_1), p(x_2), \dots, p(x_n))$, $p(x_i)$ is the

189 probabilities of outcome $x_i \in X$ ($i = 1, \dots, n$) occurring with finite elements $x \in X$
 190 for which $p(x) > 0$, and that $p(x_i) \geq 0$ for all $i = 1, \dots, n$ and $\sum_{i=1}^n p(x_i) = 1$ (all
 191 probabilities must add up to 1).

192 Expected utility theory may also be applied for considering costs and benefits in
 193 risk-based regulation, where the public (or environmental) health is a benefit arising
 194 from preventative risk management decisions. If we consider a scenario of decision
 195 making under risk (for example, the disposal of nuclear waste; Pape, 1997) where
 196 there is a risk of an environmental hazard being realised, the hazard may lead to a loss
 197 of utility (e.g. wealth, ecosystem function, environmental quality), $w_N - w_A$
 198 (expressed for illustrative purposes by a monetary value); where w_N denotes the
 199 value of the hazard not being realised and w_A the reduced value of the hazard being
 200 realised. In the case where the utility is purely financial, the decision maker can
 201 quantify the cost (loss of utility) of a hazard being realised ($w_N - w_A$) and envisage
 202 the value of making an investment to manage the risk. The challenge that practitioners
 203 face, however, is the ability to optimise the amount of money (C) that they invest
 204 along with the extent to which they are able to minimise the risk of the hazard being
 205 realised (often referred to in regulatory circles as ‘optimisation’). For this, let γ
 206 denote the possibility of a hazard being realised. We assume the existence of a state-
 207 independent utility function of the regulator $u(w)$ defined over payoffs, thus:

$$208 \quad U(\gamma, C) = \gamma u(w_A - C) + (1 - \gamma)u(w_N - C) \quad (5)$$

209 Notice that $U(\gamma, C)$ represents the expected utility of the regulator and that γ is a
 210 function of C . For illustrative purposes, we assume that when the decision maker is
 211 risk-neutral, the condition of optimal expenditure against risk is:

$$\gamma' = 1/(w_N - w_A) \quad (6)$$

Under (6), a risk is reduced to the extent that further investment would be disproportionate to the benefits received. Note that the optimal expenditure is independent of individual utility in (6). If the parameters of w_N , w_A and $\gamma(C)$ are from unique sources and remain the same among all stakeholders, (6) then holds for different risk-neutral decision makers. Arrow and Lind (1970) indicated that decision makers should behave in a risk-neutral fashion when public welfare is concerned. For this, it is possible for the decision to be unanimous within a group of stakeholders. However, if the stakeholders are not all risk-neutral or cost and benefit are not evenly shared, (6) will not hold.

By incorporating expected-utility theory within evidence-support logic we provide a greater level of transparency that facilitates optimisation being achieved. The output from TESLATM provides a decision maker with an informed, evidence-based, decision that they can use to decide the level of resource to invest in managing the risk. However, before this can happen, experts (or a group of experts) must come together to map out the cascades of parent and child hypotheses that form different lines of supporting evidence. Then experts must determine how sufficient, dependent and necessary each child hypothesis is for answering its corresponding parent. Sufficiency, in this context, becomes the expert's best guess and is, of course, a value-based judgement. However, in group decisions, risk and benefit may be unevenly shared and the decision makers may have their own utilities towards risk and uncertainty.

2.4 Application to group decision-making

When multiple agents are involved in group decision making, there is also a need to determine the group decision based on individual utilities and evidence-support logic. If there are m agents faced with n alternatives $\{x_1, x_2, \dots, x_n\}$ each agent will have a von Neumann-Morgenstern utility and a monetary cost-benefit estimation for all alternatives. Here, the von Neumann-Morgenstern utility is not necessarily the evaluation of his/her own individual benefit; rather the value of the decision expressed in terms of public health or environmental benefit (though monetised here for illustrative purposes). If $U_i(x_j)$ denotes agent i 's expected utility of an alternative x_j where $i = \{1, \dots, m\}$ and $j = \{1, \dots, n\}$, for each agent we are able to establish a set of beliefs, each of which denotes the comparison between two different alternatives. Therefore agent i 's belief can be represented by the triple $(p_{jk}^i, u_{jk}^i, q_{jk}^i)$ which denotes the belief where $j, k = 1, \dots, n$ and $j \neq k$. For all n alternatives, every agent has a complete set of beliefs that contains $\frac{1}{2}n(n-1)$ items, each of which denotes a comparison between two different alternatives. For example, when $n = 2$, there is only one belief with respect to the hypothesis that 'alternative x_j is preferred to alternative x_k '. When $n = 3$, each agent has three beliefs. Each agent assigns a set of values (between 0 and 1) to each belief, which denotes how much sufficiency the agent assigns each belief. The relationship between individual beliefs and their utilities of alternatives can be expressed as:

$$p_{jk}^i - q_{jk}^i = \frac{U_i(x_j) - U_i(x_k)}{D_i}$$

where $D_i = \text{Max}\{U_i(x_1), \dots, U_i(x_n)\} - \text{Min}\{U_i(x_1), \dots, U_i(x_n)\}$.

257 Note that $p_{jk}^i + u_{jk}^i + q_{jk}^i = 1$ and $0 \leq p_{jk}^i, q_{jk}^i \leq 1$, p_{jk}^i and q_{jk}^i can be uniquely
 258 determined by the following, when:

$$\begin{aligned}
 259 \quad & -(1 - u_{jk}^i) \leq \frac{U_i(x_j) - U_i(x_k)}{D_i} \leq 1 - u_{jk}^i, \\
 260 \quad & \left\{ \begin{aligned} p_{jk}^i &= \frac{1 - u_{jk}^i}{2} + \frac{U_i(x_j) - U_i(x_k)}{2D_i} \\ q_{jk}^i &= \frac{1 - u_{jk}^i}{2} - \frac{U_i(x_j) - U_i(x_k)}{2D_i} \end{aligned} \right. \quad (7)
 \end{aligned}$$

261 When,

$$\begin{aligned}
 262 \quad & \frac{U_i(x_j) - U_i(x_k)}{D_i} < -(1 - u_{jk}^i), \\
 263 \quad & \left\{ \begin{aligned} p_{jk}^i &= 0 \\ q_{jk}^i &= 1 - u_{jk}^i \end{aligned} \right. \quad (8)
 \end{aligned}$$

264 When,

$$\begin{aligned}
 265 \quad & \frac{U_i(x_j) - U_i(x_k)}{D_i} > (1 - u_{jk}^i), \\
 266 \quad & \left\{ \begin{aligned} p_{jk}^i &= 1 - u_{jk}^i \\ q_{jk}^i &= 0 \end{aligned} \right. \quad (9)
 \end{aligned}$$

267 Equations 7 to 9 are conditional functions; the value of the belief, p_j and q_k are

268 dependent on where the utility functions, $\frac{U_i(x_j) - U_i(x_k)}{D_i}$, lie, in relation to the

269 uncertainty, $u_j \frac{U_i(x_j) - U_i(x_k)}{D_i}$.

270 Each agent can be assigned a weight (w_i) range from 0 to 1 that denotes her/his
 271 power in the group decision. This acts as the sufficiency of belief in the process of
 272 aggregation of multiple beliefs. Multiple agents' beliefs can then be aggregated. The
 273 aggregated beliefs denote a group preference over all alternatives. This can be
 274 illustrated using a hypothetical example, in this case the decision over disposal

options of animal carcasses produced during exotic disease outbreaks, which we have previously described the international policy context and implications of these types of decision and the benefits of having an established hierarchy of options for carcass disposal (Delgado *et al.*, 2010).

3. Results and discussion

With exotic animal disease, the policy officials (in any country) must consider the differential merits of various carcass disposal options and the ensuing implications for public health, animal health and welfare and environmental protection. Consider a grossly simplified and hypothetical case whereby policy advice is informed by a stakeholder group on whether to restrict (or not) certain disposal methods. We assume that five agent representatives are involved: (1) a policy official; (2) a government regulator; (3) an environmental expert; (4) an industrial representative; and (5) a public interest representative. For ease of illustration, 3 alternatives (A1, A2, A3) are considered: A1, the on-farm burial of carcasses; A2, burial in permitted, constructed landfills; and A3, controlled incineration. A1 poses hazards to animal and human health and a high potential for groundwater contamination from pathogens and nutrients. A2 reduces this risk but retains a long term risk to groundwater and poses a significant odour nuisance, especially during the operational phase. A3 reduces animal health, public health and environmental risks to the minimum, but has the disadvantages of higher construction and maintenance costs. The benefit each agent perceives from each of the options in this illustrative example can be represented by either expected utilities (not shown here) or monetised values (Table 1).

Table 1 Benefits of the agents

There are three hypotheses: H_1 : Alternative A_1 is preferred to A_2 ; H_2 : Alternative A_1 is preferred to A_3 ; H_3 : Alternative A_2 is preferred to A_3 . With respect to these hypotheses, each agent i has three beliefs $(p_{12}^i, u_{12}^i, q_{12}^i)$, $(p_{13}^i, u_{13}^i, q_{13}^i)$ and $(p_{23}^i, u_{23}^i, q_{23}^i)$. According to (7), the values of the beliefs can be calculated for each hypothesis (Tables 2 to 4).

Table 2 Individual beliefs on H_1

Table 3 Individual beliefs on H_2

Table 4 Individual beliefs on H_3

By assigning each agent a weight of 0.2, the aggregated belief, can be computed by means of (1) and (2). TESLA™ provides a graphical interface on which to present these outcomes (Egan, undated; <http://www.quintessa-online.com/TESLA/ESLGuide.pdf>).

Figure 1 Interface of TESLA™.

The aggregated beliefs are computed as: $(p_{12}^A, u_{12}^A, q_{12}^A) = (0.16, 0.22, 0.62)$; $(p_{23}^A, u_{23}^A, q_{23}^A) = (0.39, 0.2, 0.41)$; and $(p_{13}^A, u_{13}^A, q_{13}^A) = (0.18, 0.14, 0.68)$. These beliefs infer that alternatives A_2 and A_3 are preferred to alternative A_1 , and alternative A_3 is slightly preferred to alternative A_2 . Ratio plots, in which both individual beliefs and the aggregated beliefs are illustrated, can be produced for each hypothesis (Figures 2 to 4), where the horizontal axis indicates the percentage uncertainty in the evidence, and the vertical axis indicates the ratio of “evidence for” to the “evidence against”. In Figure 2, all beliefs lie below the horizontal axis, which shows a consensus that ‘ A_2 is better than A_1 ’.

Figure 2 Ratio plot with respect to H_1 .

Figure 3 Ratio plot with respect to H_2 .

Figure 4 Ratio plot with respect to H_3 .

In these examples, an equal weight was given to all agents to reflect their power to decide. Note that the scale of individual payoff or monetary values does not affect the group decision. Individual agents cannot manipulate the final decision by scaling up (or down) their benefits. This ensures that each agent cannot influence the group decision by more than his/her assigned weight, which provides a greater level of transparency to the model.

This work establishes the basis for integrating evidence support logic and utility for regulatory decisions on risk. It allows, albeit mechanistically and in practice probably for presentational and illustrative purposes alone, an exploration of the role experts value judgements might have on regulatory decision outcomes. Nevertheless, as Monticino and colleagues (2007) also illustrate for forest ecosystem decisions affected by various stakeholder interests, ‘unpacking’ the flow of information between the contributors to decisions has merit in communicating the evidential basis for complex environmental decisions. A further contribution of this work, which we seek to further explore in later work, will be in understanding the role of personality traits on decision outcomes as well as the affect that different amounts of power will have on a group decision.

4. Conclusions

We have attempted to develop the theoretical basis for a model that seeks to represent expert judgements and the impact this has on the impact of supporting evidence within regulatory decisions. What emerges is a rudimentary proof of concept, which we have illustrated, which has application to authentic regulatory

347 decision contexts. We have proposed a new decision support approach that can be
348 used to make group decisions when risk, uncertainty, and conflicts of interest among
349 stakeholders are involved. While this study makes a preliminary effort to link
350 evidence-support logic and economic analysis, it should be recognised that it has been
351 conducted using important simplifying assumptions; for example, individual utilities
352 with respect to decision outcomes and the independency of individual beliefs. So far
353 we deal with group decision making as a static process. However, it is of course a
354 dynamic process where individual beliefs may change along with interactions
355 between experts, and where uncertainty may be reduced through dialogue, negotiation
356 and the introduction of new information. Intelligent computer agents can learn in this
357 process and be adaptive to the dynamics. The benefit of this approach will be the
358 ability it will provide Government bodies and organisations to explore the influence
359 people in relative positions of power have on the weight assigned to different lines of
360 evidence. Future research will focus on the dynamics of this group decision making
361 process.

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463 Table headings

464 Table 1. Table showing the perceived benefits for Agents 1 to 5 (monetarised) for
465 three alternative scenarios for carcass disposal, where A_1 is the on-farm burial of
466 carcasses; A_2 is the burial in permitted, constructed landfills; and A_3 is controlled
467 incineration.

468 Table 2. Table showing the individual beliefs on H_1 (Alternative A_1 is preferred to A_2)

469 Table 3. Table showing the individual beliefs on H_2 (Alternative A_1 is preferred to A_3)

470 Table 4. Table showing the individual beliefs on H_3 (Alternative A_2 is preferred to A_3)

471

472

473 Figure legends

474 Figure 1. Graphic interface of TESLA demonstrating the aggregation of individual
475 agent's belief in a hypothesis (illustrated here with respect to H_1) using a calculated
476 weight.

477 Figure 2. Ratio plot of evidence ratio against the percentage uncertainty in the
478 evidence illustrating aggregated (1) and individual beliefs (2-6) with respect to H_1 .

479 Figure 3. Ratio plot of evidence ratio against the percentage uncertainty in the
480 evidence illustrating aggregated (1) and individual beliefs (2-6) with respect to H_2 .

481 Figure 4. Ratio plot of evidence ratio against the percentage uncertainty in the
482 evidence illustrating aggregated (1) and individual beliefs (2-6) with respect to H_3 .

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Evidence and belief in regulatory decisions - Incorporating expected utility into decision modelling

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