Journal of Environmental Economics and Management 131 (2025) 103148

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

The value of a value: The benefits of improved decision making informed by non-market valuation

David J. Pannell [a,*], Robert J. Johnston [b], Michael P. Burton [a], Md Sayed Iftekhar [a,c], Abbie A. Rogers [a], Cheryl Day [a]

[a] Centre for Environmental Economics and Policy, University of Western Australia, Perth 6009, Australia
[b] George Perkins Marsh Institute and Department of Economics, Clark University, Worcester, MA 01610, USA
[c] Department of Accounting, Finance and Economics, Griffith Business School, Griffith University, Australia

ARTICLE INFO

Keywords:
Value of information
Uncertainty
Cost-benefit analysis
Revealed preference
Stated preference
Benefit transfer

ABSTRACT

Information on non-market values has the potential to improve decision making but approaches to measure these values are costly and may be inaccurate. This study develops a Bayesian value of information (VOI) model to evaluate when and if the benefit of conducting a non-market valuation (NMV) study exceeds the cost, and which method of those considered delivers the highest expected net benefit. The approach is illustrated using a water quality improvement decision, with VOI estimated for stated preference, revealed preference and benefit transfer methods, the first two implemented at varying degrees of best practice. Information on the anticipated accuracy of each valuation method is derived via structured expert-elicitation. Results show that the net VOI from NMV studies varies widely and depends on multiple factors, including project scale, the quality of existing knowledge, the accuracy of NMV methods, the type of values measured (e.g., use versus nonuse values) and the costs of applying each method. Findings suggest that familiar narratives regarding the value of NMV estimates may be too simplistic, suggesting that a more nuanced approach to study application is warranted. Although demonstrated for one case study, the approach can be adapted to many decision settings.

3. Introduction

The importance of non-market valuation (NMV) is often asserted on the basis that the resulting information can support environmental decisions that increase social welfare (e.g., Laurans et al., 2013; Hanley and Czajkowski, 2019; Bateman and Kling, 2020). The literature frequently comments on the lack of adequate NMV studies to inform decisions directly or support future benefit transfers (e.g., Lovell et al., 2004; Loomis and Rosenberger, 2006; Moeltner and Woodward, 2009; Johnston et al., 2015; Newbold et al., 2018; Newbold and Johnston, 2020). These claims are buttressed by evidence from multiple policy areas that use NMV information (e.g., Bateman and Kling, 2020; Griffiths et al., 2012; Hanley et al., 2006; Hanley and Czajkowski, 2019; Metcalfe et al., 2012; Newbold et al., 2018; Wheeler, 2015). Notwithstanding these arguments, the literature provides little rigorous evidence that the Value of Information (VOI) from a typical NMV study exceeds the cost of conducting the study, as noted by Newbold and Johnston (2020).

Rigorous evidence is also lacking to inform choices over *which types* of NMV methods should be applied and under what circumstances. Depending on the values to be measured, analysts can choose among a variety of revealed preference (RP), stated

* Corresponding author.
E-mail address: David.Pannell@uwa.edu.au (D.J. Pannell).

https://doi.org/10.1016/j.jeem.2025.103148
Received 12 May 2024; Received in revised form 20 February 2025; Accepted 21 February 2025
Available online 26 February 2025

preference (SP) and benefit transfer (BT) methods (Freeman et al., 2014). These approaches may have different degrees of accuracy, different costs, and estimate different components of value (e.g., use versus nonuse values). Arguments that RP methods are generally superior to SP methods (as noted in reviews such as Kling et al. (2012), Banzhaf (2017) and Bateman and Kling (2020)), or that either are generally superior to BT methods,[1] tend to overlook trade-off between the potential costs and benefits of these studies and that the trade-off may vary over alternative decision settings.

Another aspect of the debate is the degree to which these NMV studies should be of "high quality" (e.g., Loomis and Rosenberger, 2006; Johnston and Rosenberger, 2010), typically meaning that they are consistent with consensus best practices (e.g., Johnston et al., 2017; Bishop and Boyle, 2019; Lupi et al., 2020; Bishop et al., 2020; Johnston et al., 2021). This discussion, too, is typically conducted in the absence of evidence on the benefits and costs of different degrees of compliance with best practice, and the degree to which the cost of greater study accuracy might be warranted for low-stakes decisions. It also overlooks relationships between study type and design dimensions that can influence accuracy—for example the possibility that a best-practice BT could be more accurate than a low-quality primary study.

In summary, there is a paucity of rigorous evidence to support assertions in the literature regarding the high value of NMV studies, along with a corresponding lack of insight into which methods should be used to support decisions and under what conditions. Only three prior studies formally assess the VOI provided by environmental NMV information. No existing work either evaluates the VOI of alternative types of NMV at different levels of best practice or considers implications for whether and how these methods should be used to inform decisions.

To address this lack of insight into the VOI of environmental valuation (cf., Newbold and Johnston, 2020), this article develops a formal VOI framework and model to evaluate whether and when the benefit of conducting a non-market valuation (NMV) study exceeds the cost, and which method of those considered delivers the highest expected net benefit under alternative circumstances. The approach is grounded in Bayesian Decision Theory, which provides a systematic approach for calculating gross and net VOI related to policy and program decisions (Hammitt and Shlyakhter, 1999; Yakota and Thompson, 2004; Wilson, 2015; Newbold and Marten, 2014; Newbold and Johnston, 2020). The model is adaptable to a wide array of NMV methods and is illustrated here for five: an SP study (at two different levels of best-practice), BT (at two different levels of best practice), and a best-practice hedonic property value analysis. The demonstration illustrates how VOI approaches can be used to evaluate the relative and absolute benefits of alternative NMV methods and the type of results that emerge in a realistic case.

Information on the accuracy of each NMV method for the policy setting was derived via systematic expert-elicitation and combined with other information as determined by the Bayesian VOI framework. Results yield insight into the circumstances in which NMV should be applied to inform decisions, which methods are expected to provide the greatest net benefit, and how the relative values and net benefits of different valuation studies vary with the decision context. Although the presented numerical results are specific to the case study, along with the details and assumptions of the analysis, the methods and more general insights are broadly applicable.

4. Background—Understanding the value of information for decision-making

Estimation of the VOI from proposed research is supported by a mature body of literature, theory and empirical methods (Conrad, 1980; Feltham, 1968; Hammitt and Shlyakhter, 1999; Laxminarayan and Macauley, 2012; Newbold and Johnston, 2020; Newbold and Marten, 2014; Phillips, 2001; Pratt et al., 1995; Yakota and Thompson, 2004; Rein, 2012). VOI theory recognizes that decisions are made under uncertainty and that new study information can reduce that uncertainty, enabling decisions with greater expected net benefits (Wilson, 2015; Maxwell et al., 2015). VOI modeling has been applied across diverse fields (Keisler et al., 2014), including medicine (e.g., Sadatsafavi et al., 2023), agriculture (e.g., Pannell, 1994), natural hazards (e.g., Tebib et al., 2023), engineering (e.g., Giordano et al., 2023), climate forecasting services (e.g., Delpiazzo et al., 2022), risk assessment (Hammitt and Shlyakhter, 1999), and the environment (e.g., Pannell and Glenn, 2000; Polasky and Solow, 2001). It is often used to determine whether new information collection, such as through research, monitoring, surveying or sensors, is likely to generate sufficiently valuable information (through improved decision making) to outweigh the costs of obtaining that information.

We are aware of only three published applications of VOI to NMV. Allen and Loomis (2008) compare the VOI provided by BT and an archetypal, primary-data NMV study, assuming a counterfactual situation in which the latter provides perfect information (i.e., the true value known with certainty). Newbold and Johnston (2020), in contrast, quantify the VOI from alterative SP study designs, where these studies expand the body of value estimates available to support future BTs. Strand and Siddiqui (2020) estimate the value of perfect information about NMVs for forest protection, sidestepping the challenges of estimating the benefits and costs of specific NMV methods. No study of which we are aware provides a rigorous means to compare VOI over multiple types of NMV that might be applied to inform the same decision, considering variations in study quality, accuracy and the types of values to be estimated.

The presented model addresses this knowledge gap in two complementary ways. First, we develop generalizable theory and a broadly applicable empirical approach that may be adapted to inform choices over NMV methods in many different settings for which these studies could inform environmental decisions made via a benefit-cost criterion. Second, we illustrate the results of such as model for a realistic-but-simplified setting, in similar vein to Newbold and Johnston (2020). The numerical application is illustrated for a case in which decision-makers face a binary choice on whether or not to implement a prototype water-quality improvement project, for

[1] For example, US EPA's Guidelines for Preparing Economic Analysis (US EPA, 2014, 7–44) argue that "benefit transfer should only be used as a last resort" but also note that the "advantages of benefit transfer in terms of time and cost savings must be weighed against the disadvantages in terms of potential reduced reliability of the final benefit estimates."

which we assume that the decision will be made based on a benefit-cost criterion. The following section outlines the theory that underpins the presented analysis of VOI for NMV. This is followed by a description of the numerical methods used to operationalize the theory for an illustrative case study, with study accuracy estimated via a systematic expert-elicitation procedure. We then discuss results of the model and implications for the use of NMV to inform decisions. In doing so, we distinguish between numerical results that are specific to the presented case study and more general insights with broader applicability.

5. Theory

The presented approach applies VOI theory to the case of environmental decisions potentially informed by NMV, as in Newbold and Johnston (2020).[2] We consider an archetypical case in which a decision-maker must determine whether to implement a costly water-quality-improvement project. Although decisions of this type are made subject to uncertainty regarding many relevant factors, the presented analysis mirrors common approaches for VOI modeling that address uncertainties related to a key parameter of interest (here environmental values), while assuming other information is known with certainty (Wilson, 2015; Newbold and Johnston, 2020).[3] We assume that the decision maker has the option of investing in additional information collection via an NMV study, with a goal of reducing uncertainty about per capita non-market values prior to the decision. We recognize that there can also be uncertainty about other variables that are important in the decision (e.g., the size of the population over which the benefits will be realized, the technical effectiveness of the project at delivering environmental benefits, and the trajectory of environmental conditions in the base case), and that new information may or may not be collected about those as well. Although the presented model can be adapted to accommodate additional types of uncertainty, we focus here solely on uncertainty regarding these per capita values.

VOI modeling relies on a Bayesian approach to decision theory, wherein uncertainty is represented as the probabilities that different possible states of the world are true. Here, this uncertainty applies to the benefits of a proposed environmental project which has known costs, C. Benefits are represented as an aggregation of mean willingness to pay (WTP) per person over a population of size J, with estimated mean WTP over the population given by $\overline{WTP}$. Aggregate benefits are hence represented $B = J \times \overline{WTP}$, with uncertainty emerging from lack of perfect knowledge on $\overline{WTP}$.[4] This may be formalized as a prior probability distribution over benefits, $p(B)$, derived from underlying uncertainty over WTP.

All VOI applications require a decision rule. Here, the decision maker is presumed to follow a deterministic benefit-cost criterion when determining whether to proceed with the project, with the project implemented if and only if expected benefits exceed costs, such that expected net benefits are positive, $\mathbb{E}(\pi) = \mathbb{E}(B) - C > 0$. The prior expected net benefit of the project option, given prior information K_0 and no new NMV study, may thus be represented

$$\mathbb{E}(\pi, K_0) = \max\left\{0, \int_{-\infty}^{\infty} (B - C)p(B)dB\right\}. \tag{1}$$

Equation (1) may be interpreted as anticipated benefits under the prior optimal act, i.e., the decision that maximizes net benefits absent new information (Hammitt and Shlyakhter, 1999; Pannell and Glenn, 2000). The decision maker with only prior knowledge (K_0) makes the decision based on the *ex ante*, expected net benefit of the project over all possible states of the world, as reflected in $p(B)$. The project is implemented if this *ex ante* expected value is positive, yielding expected net benefits as shown by the second term in brackets. The project is *not* implemented if the second term is zero or negative, yielding a net benefit of zero. If the project is implemented, the *ex post* or true net benefit to society is determined by the realized value of B, once uncertainty is resolved, where these net benefits could be positive, zero, or negative.

Now assume that the decision maker commissions a new NMV study of type $s = \{1, 2 \ldots S\}$ relevant to the prospective project, where type s reflects the set of methodological and design dimensions that determines how the value is estimated, e.g., using a best-practice SP study. The study provides a new estimate of $\overline{WTP}$, given by w_s. Importantly, the decision maker does *not* simply assume that $B = J \times (w_s)$ is the true non-market benefit. Instead, she uses the new study estimate to update the prior benefit distribution $p(B)$ to a better-informed posterior distribution $p(B|w_s)$. The study type, s, influences the potential bias and variance of the new estimate, which determines the relationship between $p(B)$ and $p(B|w_s)$ via Bayesian updating, as detailed below.

The decision maker's enhanced state of information after the new study is denoted K_1, leading to a potentially new posterior optimal act and associated net benefits (Hammitt and Shlyakhter, 1999; Pannell and Glenn, 2000). How much better is the decision as a result of having conducted the NMV study? This may be quantified as the anticipated improvement in the net benefit of the decision made possible by the new information. To illustrate, we first present the expected net benefit of the project option, assuming that a new study has been conducted before making the decision. The expected benefit of this posterior optimal act is given by:

$$\mathbb{E}(\pi, K_1) = \int_{-\infty}^{\infty} \max\left\{0, \int_{-\infty}^{\infty} (B - C)p(B|w_s)dB\right\} p(w_s)dw_s. \tag{2}$$

[2] Newbold and Johnston (2020) address a case in which data for VOI estimation are derived from metadata on WTP for water quality changes and new NMV studies support BT through expansions to the metadata. Here we consider a case in which new studies inform the environmental decision directly. These distinct objectives require different though related methods and theoretical foundations.

[3] Effects of other potentially uncertain dimensions, such as program costs, are typically accommodated via sensitivity analysis, as shown below.

[4] This formulation incorporates heterogeneity in WTP over individuals $j = 1 \ldots J$ but we assume that of the distribution, only mean WTP is utilized in decision making.

Here, the inner integral, $\int_{-\infty}^{\infty}(B-C)p(B|w_s)dB$, is the expected net benefit of the project given NMV study outcome w_s, as determined by the updated posterior benefit distribution $p(B|w_s)$. This expected net benefit could be positive, zero, or negative. The surrounding integrand, $\max\{0, \int_{-\infty}^{\infty}(B-C)p(B|w_s)dB\}$, has the same intuition as equation (1), but with posterior $p(B|w_s)$ replacing prior $p(B)$. That is, the project is implemented if and only if expected benefits exceed costs (i.e., $\int_{-\infty}^{\infty}(B-C)p(B|w_s)dB > 0$), yielding expected net benefits $\int_{-\infty}^{\infty}(B-C)p(B|w_s)dB$. If the project is not implemented, net benefits are zero. The complete expression in (2) represents the sum of these pre-posterior expected values[5] weighted by the unconditional probability of all possible study outcomes w_s between $-\infty$ and ∞, given by $p(w_s)$. The subscript s clarifies that this distribution may vary over different study types, reflecting alternative levels of study accuracy.

The gross value of information from study type s, $GVOI_s$, is represented as the difference between the expected value of the project option with and without study information (Hammitt and Shlyakhter, 1999; Yakota and Thompson, 2004; Newbold and Johnston, 2020):

$$GVOI_s = \int_{-\infty}^{\infty} \max\left\{0, \int_{-\infty}^{\infty}(B-C)p(B|w_s)dB\right\}p(w_s)dw_s - \max\left\{0, \int_{-\infty}^{\infty}(B-C)p(B)dB\right\}. \tag{3}$$

In simple terms, $GVOI_s$ reflects the difference between (a) the expected net benefit of making the decision informed by the posterior distribution of B given study information and (b) the expected net benefit of making the decision given only prior information on B.[6]

As reflected in the subscript on $GVOI_s$, study value is expected to vary with study type due to variations in study accuracy, as reflected in $p(B|w_s)$ and $p(w_s)$. In the numerical application that follows, we illustrate differences in $GVOI_s$ over alternative NMV study types, characterized by the method (i.e., SP, RP, BT) and methodological quality (i.e., following best practices or not). Study type also influences the cost of the NMV study. For example, the cost of a best-practice SP study is likely to exceed the cost of a low-budget BT. Calculation of the net VOI from each study type ($NVOI_s$) must therefore consider not only $GVOI_s$ but also the anticipated study cost (C_s), where $NVOI_s = GVOI_s - C_s$.

Following prior VOI applications in the literature, $p(B)$, $p(B|w_s)$ and $p(w_s)$ are related via Bayesian updating (cf., Munro and Hanley, 2001). Applying Bayes' Rule, the posterior probability of B conditional on NMV study estimate w_s is given by

$$p(B|w_s) = p(B)p(w_s|B)/_{p(w_s)}, \tag{4}$$

where $p(w_s|B)$ represents the "likelihoods" of any possible valuation outcome from a new study of type s. This term represents the anticipated probability that the new study will produce particular estimates of mean WTP, conditional on certain values being objectively true (as implicit in B). For example, if true mean WTP for an environmental improvement is \$40 (implicit in aggregate benefit $B = J \times \$40$), the likelihood $p(w_s|B)$ specifies the anticipated probability that a new NMV study of type s would generate a result indicating that the mean WTP was \$30, \$40, \$50 or any other possible value. The likelihoods thus capture the perceived bias and variance of the NMV study when prior probabilities are updated to posteriors.

To facilitate the expert elicitation process described below, we follow common practice and discretize study outcomes (Yakota and Thompson, 2004; Newbold and Johnston, 2020).[7] We assume that priors are binned into $n = \{1...N\}$ possible values for B_n (each with a corresponding probability) with the same bins representing the set of feasible posterior values (but with potentially different corresponding probabilities). Hence, what is updated via study information is the assumed probability that each of these possible binned values is true. We further assume that there are $k = \{1...K\}$ possible levels of w_s, where $p(w_{sk})$ represents the subjective anticipated probability of observing value $w_s = w_{sk}$ from study type s. As described under the numerical application below, we do not impose the constraint that the number of bins for the priors (N) is identical to the number of bins for possible study values (K). Corresponding prior and posterior probabilities for B_n are given by $p(B_n)$ and $p(B_n|w_{sk})$, respectively.

The analysis proceeds as above with summations replacing the integrals, such that,

$$GVOI_s = \sum_{k=1}^{K} \max\left\{0, \sum_{n=1}^{N}(B_n - C)p(B_n|w_{sk})\right\}p(w_{sk}) - \max\left\{0, \sum_{n=1}^{N}(B_n - C)p(B_n)\right\}. \tag{5}$$

Following a parallel transformation to that shown by Newbold and Johnston (2020), we can substitute Bayes' Rule into the top line of equation (5), yielding the equivalent relationship

$$GVOI_s = \sum_{k=1}^{K} \max\left\{0, \sum_{n=1}^{N}(B_n - C)p(B_n)p(w_{sk}|B_n)\right\} - \max\left\{0, \sum_{n=1}^{N}(B_n - C)p(B_n)\right\}. \tag{6}$$

[5] This is denoted as "pre-posterior" because it reflects the posterior benefit distribution evaluated before the study outcome is known (Yakota and Thompson, 2004).

[6] Parallel theory may be used to derive the value of perfect information, often used as a theoretical upper bound to study information. This relatively standard derivation is suppressed for conciseness, but may be found in prior work such as Yakota and Thompson (2004) and Newbold and Johnston (2020), among others.

[7] Discretizing possible outcomes is an artificial but common simplification in VOI modeling, with numerical approximations used for integrals (Yakota and Thompson, 2004; Newbold and Johnston, 2020). Among other advantages, this approach obviates the need for simulation methods to derive solutions (as closed-form solutions are available) and facilitates elicitation of likelihoods via expert elicitation, as described below.

Equation (6) demonstrates the calculation of $GVOI_s$ as a function of priors $p(B_n)$ and likelihoods $p(w_{sk}|B_n)$. Operationally, $GVOI_s$ may be calculated via either (5) or (6), with Bayes' Rule and basic rules of probability used to derive relationships between $p(B_n)$, $p(w_{sk})$, $p(B_n|w_{sk})$, and $p(w_{sk}|B_n)$. For example, $p(w_{sk})$ may be calculated as the combination of priors $p(B_n)$ and likelihoods $p(w_{sk}|B_n)$.

Further details are found under the numerical application below. When interpreting the results, it is important to recognize that all VOI models presume that decisions are made in a systematic, evidence-based way—here assuming a deterministic benefit-cost criterion (similar, e.g., to Wilson (2015) and Newbold and Johnston (2020)). We recognize that many policy and management decisions are not made in this manner (e.g., Gibson et al., 2017) and that formal use of NMV to support decisions may or may not occur (e.g., Laurans et al., 2013; Rogers et al., 2015; Dehnhardt, 2013; Newbold et al., 2018; Welling et al., 2023). Therefore, our study demonstrates the estimation of *potential* benefits from utilizing non-market values in decision making within a range of contexts, *conditional* on the study being used to inform a single decision with the objective of maximizing public net benefits, guided by Benefit-Cost Analysis.[8] Although this context is admittedly stylized, it allows us to implement a systematic exploration of key questions such as: (1) the type of circumstances under which NMV should be conducted, i.e., anticipated VOI outweighs study cost, (2) which type of NMV is expected to provide the greatest net benefit, and (3) the circumstances under which particular types of NMV are optimal. We also illustrate a generalizable framework that can be used to examine similar questions for other policy contexts and different sources of information on NMV study accuracy. As such, the primary contribution of this study is not one "universally correct answer" on the value of NMV, but rather a systematic approach to analyze such values when determining whether and how NMV might be warranted within particular policy settings.

6. Numerical application

We demonstrate application of the framework using an illustrative water-quality-improvement project (see below),[9] where decisions about the project can be informed by a prospective NMV study. Note that in the analysis that follows there are two decisions in play. First, there is a decision about which NMV method to use (if any), depending on the VOI it generates. This value depends on the use of the NMV information in a second decision about whether to undertake the environmental project.

Information on the anticipated validity and reliability of each NMV method under consideration (i.e., the "likelihoods") is produced via a multi-step expert elicitation process. To narrow the dimensionality of the analysis, we limit the choice of method to five possible options: SP (best practice), SP (time and budget constrained), BT (best practice), BT (time and budget constrained), and Hedonic pricing (best practice). We did not include Hedonic pricing (time and budget constrained) or other common NMV methods to limit the burden placed on the panel of experts who provided critical information used in the analysis. Moreover, the goal of the analysis is to demonstrate a method that may be applied to characterize VOI for a range of valuation approaches and circumstances, not to produce an encyclopedic set of all possible VOI estimates for the present case study. Table 1 provides brief descriptions of the included methods. Supplementary Appendix Aprovides further detail, which was also provided to the experts during likelihood elicitation. Other dimensions of the problem (e.g., project size, priors on net benefits) are varied to provide insight on the sensitivity of VOI to the decision context.

6.1. *Prospective water-quality improvement project*

A project context is required for VOI estimation and associated likelihood elicitation. Following prior examples (e.g., Allen and Loomis, 2008; Newbold and Johnston, 2020), we calculate VOI for an illustrative, prototype environmental decision grounded in a realistic context, allowing exploration of the sensitivity of VOI to changes in the project context. The illustrative case-study project is a prospective improvement in water quality in hypothetical "Lake Balance". Details are provided in Supplementary Information Appendix B. To summarize briefly, the lake covers an area of 85 km^2 (21,000 acres) adjacent to the hypothetical town of "Benting". The population of the town is 25,000 (>18 years), including surrounding rural communities. Benefits generated by the lake include recreation (fishing and water sports), aesthetics, and provision of ecosystems that support biodiversity. Water quality in the lake has declined in the past 15 years and this decline has negatively affected the social and ecological values supported by the lake. The project being considered would return water quality to its condition of 15 years ago.

6.2. *Structured elicitation of likelihoods*

VOI models are grounded in decisions, benefits, costs and uncertainties as understood by a decision maker (or decision-making body). The relevant likelihoods for VOI estimation, representing the perceived accuracy of each NMV method, are those held by the decision maker. In practice, few decision makers in environmental agencies are likely to have sufficient knowledge to specify likelihoods for NMV methods. For the purposes of our analysis, we therefore assumed that the decision maker would be informed about these likelihoods by a panel of NMV experts. This mirrors the setting for many types of environmental decisions, wherein external panels of experts (or advisory boards) are used to provide insight into key dimensions that require targeted scientific expertise (Drummond et al., 2020). Although this expert advice might be incorporated in a variety of ways, our analysis assumes that the

[8] If a study is not used, it has no value in terms of improving the consequences of decision making.

[9] In principle, we could generalize further by integrating results over a probability distribution of many different possible policy and program contexts (e.g., air quality, biodiversity, etc.), although this would greatly increase the complexity of our application.

Table 1
Summary definitions of non-market valuation methods used for value of information estimation.

Method	Description	Assumed cost of conducting a study
Stated Preference (best practice)	A top-quality, high-budget stated-preference study following all elements of best-practice, following Johnston et al. (2017). Extensive pretesting and development. A large, representative sample (2000 respondents). Supported by a battery of validity and robustness tests.	US$500,000
Stated Preference (time and budget constrained)	A stated-preference study, conducted with a restricted budget in a relatively short time frame. Experimental design follows good practice. Some validity tests possible. Sample size is smaller (300 respondents).	US$100,000
Benefit Transfer (best practice)	Best-practice benefit transfer following Johnston et al. (2021). Benefits estimated using benefit function from a large-sample meta-regression analysis of prior stated preference studies (e.g., 200 study observations on WTP).	US$150,000
Benefit Transfer (time and budget constrained)	An income-adjusted, unit-value benefit transfer based on a good quality somewhat recent (e.g., five years old) stated-preference study that was conducted at a generally similar site in the same country.	US$15,000
Hedonic Pricing (best practice)	A best-practice hedonic property-value analysis, following recommendations of Bishop et al. (2020) for market definitions, data collection and preparation, econometric analysis and identification, and mitigation of omitted variable bias.	US$100,000

See Supplementary Appendix A for detailed descriptions of these methods.

decision makers use the average of likelihoods elicited from the experts to update priors. Mathematical aggregation of expert judgements in this way is practiced in several of the expert elicitation protocols described by Soares et al. (2024). For comparison and as a sensitivity analysis, however, we also implement an alternative variant of the model in which separate VOIs are derived for each expert and then averaged; this alternative model is shown in Appendix D.

Likelihoods were obtained using a structured elicitation process.[10] Prospective members of the panel were identified through our knowledge of their expertise and experience, supported by measures such as publications, citations, experience implementing applied valuation projects related to water quality and general reputation within the field (as represented by positions such as editorships of journals, recognition by scholarly organizations, etc.). The requirement for experience was high, given the difficult judgments that these experts were asked to make. Most invitees were researchers based in universities, but we also sought to include some experts who work in policy institutions. Invitations were sent to 30 experts (10 females,[11] 20 males; 24 in universities, 6 in policy agencies; 13 in Europe, 13 in North America, 4 in Australia) in August 2023. The 30 invitees were selected from a longer list of experts judged to have sufficient knowledge and experience, and likely to have sufficient interest to accept an invitation to participate. The number of invitations was further influenced by consideration of an effective group size for the expert elicitation process, allowing for non-acceptances.

There were 17 acceptances (3 females, 14 males; 14 in universities, 3 in policy agencies; 7 in Europe, 7 in North America, 3 in Australia). As indicators of their research experience, the academic participants had between 3000 and 37,000 citations on Google Scholar, with an average of 9,300, and H-indices of between 22 and 95, with an average of 43. The three participants from policy agencies were all from the USA, including two national and one state-level. All 17 had participated in multiple NMV studies, with averages of at least 19 SP studies, 8 hedonic pricing studies, and 12 BT exercises.[12]

From this expert panel, valuation likelihoods were elicited via an adaptation of the IDEA protocol, where “IDEA” is an acronym for “Investigate, Discuss, Estimate and Aggregate” (Burgman, 2015; Hemming et al., 2017). Other protocols for expert elicitation are available, including modified Delphi (e.g., Keeney et al., 2021) and SHELF (Gosling, 2018). The various protocols have much in common (Soares et al., 2024). We chose IDEA because it was designed to facilitate remote (i.e., online) elicitation. Given that our experts were distributed across multiple countries (Canada, the United States, the United Kingdom, Denmark, Germany, Poland, Australia), this was an important feature. The five steps of the IDEA protocol (Burgman, 2015) were implemented as follows. (A more complete description of the process is provided in Appendix C.[13]).

1. **Pre-elicitation.** Prior to contacting the experts, background information on the proposed project and expert-elicitation tasks was compiled. Experts were then contacted and briefed on the elicitation process. This was followed by initial, live (but online) workshops at which the project and required tasks were described in detail.
2. **Investigate.** Each expert was asked to provide likelihood distributions for each of the five NMV methods (Table 1), for each of five true non-market values ($10 to $50) for the project scenario provided (25 distributions in total). To avoid problems of anchoring,

[10] This step is comparable to the stage in Bayesian statistics of specifying likelihoods based on sample counts or proportions observed for each “state” in an empirical sample. The lack of empirical evidence that could be used in this way to identify the likelihoods for each NMV method led to our use of an expert elicitation approach.

[11] Gender balance was a goal of the research team with respect to the composition of the panel, but this was challenged by the need for a high level of experience and the gender imbalance that persists at senior levels in the field.

[12] The numbers of studies reported here are conservative as many experts responded to our survey questions on this topic with the top, open-ended response category.

[13] University of Western Australia Human Research Ethics approval number was #2022/ET000552.

this was done individually and independently. To facilitate the process, a spreadsheet was provided (Supplementary Information Appendix F) that gave structure and clarity to the elicitation process and provided visualizations of their responses. The range of values included in the likelihood distribution (−US$20 to US$150) is wider than the range of potential true values to allow for inaccuracy of the NMV methods.
3. **Discuss.** In the second set of online workshops, experts were shown the anonymous likelihood responses from each participant and visual summaries of aggregate responses. They then discussed the motivation for their answers and reasons for differences among the individual responses. As a result, some experts were prompted to consider additional factors and some differences in interpretation of the questions were identified, promoting further deliberation and a small amount of convergence between the experts.
4. **Estimate.** Following the second-round workshops, experts could modify their individual answers, if desired. All experts made at least one change for at least one of the NMV methods. On average, the experts made changes to 3.8 of the 5 methods. The number of experts making changes for each of the NMV methods were 11 for Stated Preference (best practice), 14 for Stated Preference (time and budget constrained), 12 for Benefit Transfer (best practice), 13 for Benefit Transfer (time and budget constrained), and 15 for Hedonic Pricing (best practice).
5. **Aggregate.** Aggregate likelihood distributions were calculated as averages across the 17 experts. Individual and aggregate distributions were provided to each expert for checking and approval. The elicited likelihood distributions were used to inform subsequent VOI calculations following equations (2) and (3), as described in greater detail below.

6.3. Prior information (benefits)

VOI analysis begins with decision-makers' perceptions about the uncertain variable(s) prior to collecting additional information. In Bayesian Decision Theory, the relevant priors are those held by the decision maker. In past studies, prior perceptions have been estimated using available data (e.g., Newbold and Johnston, 2020), from modeling (e.g., Maxwell et al., 2015) or assumed (e.g., Pannell, 1994; Tebib et al., 2023) and a further option would be to use a formal elicitation process with the decision maker(s).[14] Here we utilize assumed priors that vary systematically to explore their influence on VOI. Prior probabilities are required for each potential value that might be the true value. We assume that the true value for mean WTP lies between US$10 and US$50 per head[15] and represent priors as a discrete distribution with five levels. Various distributions of priors, reflecting different degrees of uncertainty, are analyzed (Table 2). Note that these distributions sum to 1.0 across each row.

The decision to simplify the distribution of priors to five discrete levels was made after considering the trade-off between obtaining precise results and the cost and feasibility of providing the required inputs to the analysis. Full likelihood distributions are required for each potential true value, so increasing the number of levels would increase the already considerable burden on our expert panelists. Moreover, a distribution with five levels (at least arguably) provides sufficient precision to illustrate VOI modeling and explore variations in VOI under alternative decision settings. In cases where greater precision is desired, increasing the number of levels in the discrete distribution would be conceptually straightforward, though more burdensome for the expert elicitation process.

The range chosen for the distribution of priors (US$10 to US$50 in this case) imposes a constraint on the results of the analysis, in that no values outside that range are considered possible. Bayesian updating in response to the results of a study modifies the probabilities of different possible true values within that range. While this generally results in a different mean and standard deviation, it cannot broaden the range set by the specification of priors.

As noted above, the distributions of likelihoods encompass a wider range of values (−$20 to $150) than the distributions of priors (10 to $50). This allows for potential inaccuracy in the NMV methods. For example, even if it is judged that the highest plausible (true) average non-market value for the environmental benefits in question is US$50, an NMV method may give a result above (or below) US $50. The expert panel members were not required to use the full range of possible values for their likelihoods but could do so if they judged it to be appropriate.

6.4. Project costs

The costs of implementing the hypothetical water-quality project are assumed to be known with certainty. The assumed cost levels vary in different parts of the analysis; the specific cost assumptions are given with each set of results discussed below.

[14] Using a distribution such as the Dirichlet distribution for the priors, common in Bayesian statistics given its statistical properties (Ng et al., 2011), is not necessarily applicable for VOI modeling *unless* one assumes that such a distribution represents subjective decision-maker beliefs.

[15] Several considerations informed this assumed range of values. WTP estimates in the metadata of Johnston et al. (2019, Table 1) span the range from $0.49 to $57.41 (2016 USD), per standardized unit of water-quality change on a 100-point scale. These estimates are drawn from 148 observations over 53 S P studies, implemented in heterogeneous sites and populations across the US. For this analysis, the illustrative water-quality project would deliver several units of water-quality change, but it is at one site and for one population, for which extensive background information is available. In addition, we assume that past NMV research at the site has already informed the decision makers to some extent. Therefore, it was considered reasonable to assume that the distribution of priors for mean WTP would have a range of US$10 to US$50. Using a different range would be straightforward but would require a new expert elicitation process.

Table 2
Assumed Distributions of Priors used in the VOI Analysis.

Non-Market Value					Standard Deviation
US$10	US$20	US$30	US$40	US$50	
0	0	1	0	0	0
0	0.05	0.9	0.05	0	3.16
0	0.1	0.8	0.1	0	4.47
0.025	0.125	0.7	0.125	0.025	6.7
0.05	0.15	0.6	0.15	0.05	8.37
0.075	0.175	0.5	0.175	0.075	9.75
0.1	0.2	0.4	0.2	0.1	10.95*
0.15	0.2	0.3	0.2	0.15	12.65
0.2	0.2	0.2	0.2	0.2	14.14

* Baseline distribution assumed in VOI estimations below.

6.5. *Study costs*

Although researchers may have expectations regarding the cost of applying each NMV method, costs are likely to vary across policy contexts, in different countries, and for different research teams. For example, the cost of a best-practice BT could vary depending on whether researchers have access to a high-quality, previously estimated meta-analysis that can be used for the purpose or must develop an entirely new meta-regression (and set of underlying metadata) to support the analysis. For this reason, the cost estimates used in the analysis should be viewed as illustrative.

Study costs were specified by the project team based on experience in providing high-quality results to environmental agencies in the United States. These illustrative costs were assumed to be US$500,000 (Stated Preference (best practice)), $100,000 (Stated Preference (time and budget constrained)), $150,000 (Benefit Transfer (best practice)), $15,000 (Benefit Transfer (time and budget constrained)) and $100,000 (Hedonic Pricing (best practice)). These assumed study costs serve to illustrate that there can be a trade-off between the benefits of a higher-quality NMV study and the cost of delivering it, such that the optimal decision regarding NMV methods is not necessarily obvious. However, these assumed costs can easily be adapted to illustrate the sensitivity of results to alternative estimates of research costs.

6.6. *Integrated VOI estimation*

Model implementation integrates priors, likelihoods, project benefits and project costs to derive both gross and net VOIs for each of the five NMV methods, following the theoretical model above. Model implementation is illustrated in a numerical example in Appendix G. For SP and BT methods, updating is assumed to occur for total WTP, including both use and nonuse values. For the Hedonic Pricing method, updating is only assumed to occur for use values, with perceptions of nonuse values assumed to remain unchanged from the priors. We illustrate VOI estimates both for a case where total WTP includes use and nonuse values and for a case consisting only of use values. Sensitivity analyses include variations in project net benefits, the distribution of priors (as per Table 2), the proportions of use and nonuse values, the scale of the project, and the likelihoods. In all cases, VOI measures assume a yes/no decision on whether to implement the project at a given project cost.

7. Results

We present results for a selected set of scenarios to illustrate how VOI—and implications for the optimal choice of NMV studies to inform the decision—vary over different circumstances.

7.1. Expert-elicited likelihoods

Fig. 1 shows the five likelihood distributions for an assumed true value of \$30, averaged across the 17 experts.[16] Results show that none of the NMV methods is viewed as being highly precise. Standard deviations of the WTP distributions range from \$14 for SP (best practice) to \$24 for BT (time and budget constrained) and Hedonic Pricing (best practice). Even for the most precise method, the bounds of the 95% confidence interval are \$10 and \$60. For BT (time and budget constrained), the 95% confidence interval ranges from \$0 to \$80. All of these anticipated likelihood distributions are positively biased (their means are greater than the assumed true value of \$30) to at least some degree. The long upper tail for Hedonic Pricing (best practice) results from different perceptions among the experts. One expert, in particular, believed that Hedonic Pricing provides results that are highly biased in an upward direction, and this had a noticeable impact on the distribution. Later we present sensitivity analysis results that exclude this expert.

7.2. Gross value of information across NMV methods and project assumptions

Fig. 2 shows how $GVOI_s$ estimates compare across the five different NMV methods and how these estimates compare to the value of perfect information. With perfect information, the decision maker knows the true value of B with certainty prior to making the decision and implements the project only when true net benefits are positive; perfect information thus precludes the possibility of an inadvertently welfare-reducing decision. We first illustrate these results for the baseline priors (from Table 2) and project costs of \$30, 000, 000. We also assume, for now, that all project benefits arise from use values, so that Hedonic Pricing and the other NMV methods are assumed to estimate the same true benefits. This assumption is relaxed below. The horizontal axis is the prior expected net benefit of the project, meaning the Net Present Value from a Benefit-Cost Analysis (BCA) of the project conducted using the baseline priors in Table 2.

Despite their lack of precision, the NMV methods can perform reasonably well relative to perfect information. For example, at its peak, a best-practice SP study yields an estimated $GVOI_s$ that is over 70% of that provided by perfect information. The relatively high value of valuation studies compared to perfect information parallels prior findings of Newbold and Johnston (2020) for SP studies that inform meta-analytic BT. SP (best practice) has the highest $GVOI_s$, BT (time and budget constrained) has the lowest, and of the others, the rank order is Hedonic Pricing (best practice), SP (Time and Budget Constrained), and BT (best practice). This ranking reflects the distributions of the likelihoods shown in Fig. 1.

In all cases (including perfect information), $GVOI_s$ estimates are sensitive to the prior expected net benefit of the project, $\mathbb{E}(B) - C$. Study value is maximized when the project's expected benefits and costs are equal (i.e., the prior expected Net Present Value of the project is zero). At this point, the decision on whether to invest in the environmental project is evenly balanced, so new information is most likely to influence the decision. In contrast, if the prior expected net benefit is highly negative or highly positive, the optimal project decision is relatively obvious even in the absence of new information, so collecting further information is unlikely to change the decision. If there is no prospect of influencing the decision, then the information has no value for decision-making. For this example, where the project cost is \$30, 000, 000 and the baseline priors are used, if the prior expected net benefit lies below −\$10, 000, 000 or above \$25, 000, 000, the $GVOI_s$ is zero for all NMV methods.

To illustrate the impact of project scale on VOI, assumptions must be made about the effect of scale on benefits (B) and project costs (C). Here, we assume that B and C are proportional to the number of beneficiaries J—with a "scaled-up" project providing the same per head value ($\overline{WTP}$) to a proportionally greater number of people.[17] This structure implies that $GVOI_s$ is perfectly proportional to the scale of the project and its associated gross benefits. Thus, for an equivalent project costing \$3,000,000, the range outside of which NMV $GVOI_s$ equal zero is −\$1,000,000 to \$2,500,000. So, for a case where there is some not-very-precise prior knowledge of values (see the baseline priors in Table 2), if the initially estimated Benefit-Cost Ratio (BCR) of the project is above 2 or below 0.5, it appears unlikely that collecting additional information about non-market values would provide value in terms of improving a yes/no decision about an environmental project. Given the range of BCRs that occur in practice, this is a relatively narrow range.

Within the "sweet spot" for high value of information, however, $GVOI_s$ for an NMV can be substantial. For example, considering the project in Fig. 2 (with project cost of \$30, 000, 000) and baseline priors (Table 2), the maximum $GVOI_s$ from the alternative NMV methods varies from roughly \$1.8 to \$2.9 million. Hence, when there is somewhat high uncertainty about non-market benefits (implied by the assumed baseline distribution of priors underlying Fig. 2) and expected benefits are similar to costs (i.e., prior expected net benefits are close to zero), the $GVOI_s$ from an NMV study can far exceed study cost.

Fig. 3 shows that $GVOI_s$ is also sensitive to the standard deviation of the distribution of assumed priors. These results are for the distributions in Table 2, with standard deviations ranging from zero (perfect prior knowledge) to 14.14 (a uniform distribution, indicating no prior knowledge other than that the value lies between \$10 and \$50, inclusive). For this illustration, we assume a scenario wherein prior $\mathbb{E}(B) = C$, so $GVOI_s$ is maximized for each set of priors. All other parameters are assumed identical to those underlying Fig. 2.

As expected, improved prior knowledge, reflected by a smaller standard deviation of the priors, reduces $GVOI_s$. Comparing the baseline priors, which imply a modest level of knowledge about the non-market values (standard deviation 10.95), with priors that

[16] To illustrate the variation in likelihood distributions elicited from the experts, the distributions are shown for all 17 experts for one true non-market value in Appendix D. This reveals that there is considerable heterogeneity among the experts.

[17] Other assumptions regarding relationships between project scale, costs and benefits are possible, leading to corresponding changes in the responsiveness of VOI to scale.

Estimates of population mean willingness to pay ($/head)	Stated Preference (best practice)	Stated Preference (time & budget constrained)	Benefit Transfer (best practice)	Benefit Transfer (time & budget constrained)	Hedonic Pricing (best practice)
-$10	0.00	0.00	0.00	0.01	0.01
$0	0.01	0.03	0.03	0.03	0.03
$10	0.05	0.07	0.09	0.09	0.08
$20	0.14	0.13	0.14	0.14	0.19
$30	0.35	0.22	0.22	0.19	0.30
$40	0.23	0.20	0.19	0.16	0.17
$50	0.12	0.15	0.14	0.14	0.08
$60	0.06	0.10	0.09	0.09	0.04
$70	0.02	0.07	0.06	0.07	0.02
$80	0.01	0.03	0.03	0.05	0.01
$90	0.00	0.01	0.01	0.02	0.01
$100	0.00	0.00	0.01	0.01	0.02
$110	0.00	0.00	0.00	0.01	0.02
$120	0.00	0.00	0.00	0.00	0.01
$130	0.00	0.00	0.00	0.00	0.01
Distribution mean	$35.28	$39.47	$39.07	$41.31	$36.55
Standard deviation	$14.43	$19.63	$21.13	$23.97	$24.44

Fig. 1. Likelihood distributions elicited from expert panels and aggregated across experts. Likelihoods are shown for the case in which true mean WTP is assumed to be $30 per head (single lump sum payment).

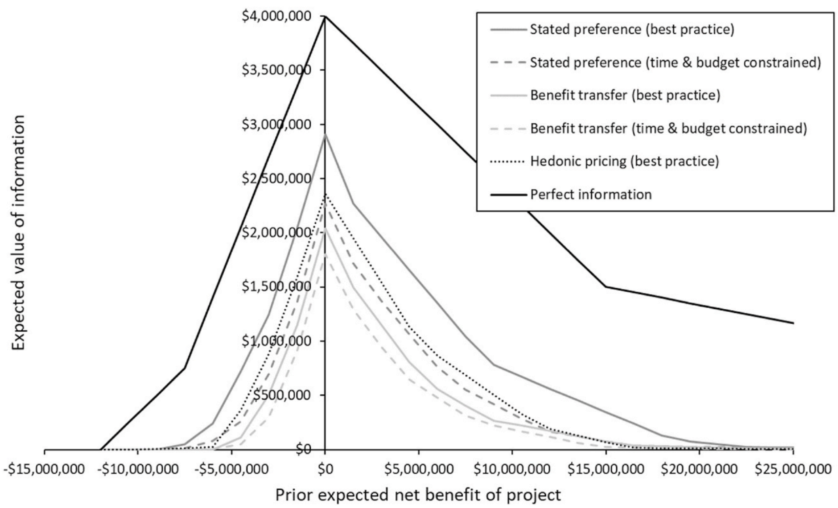

Fig. 2. Expected gross value of perfect and imperfect information for five NMV methods. Based on $30, 000, 000 project cost, baseline priors, and assumes that all benefits are from use values. Study costs are not represented.

represent less prior knowledge (standard deviation 14.14), the increase in $GVOI_s$ is disproportionally large: around a 60% increase for each NMV method. The differences between the estimated $GVOI_s$ of the methods also increase. However, the $GVOI_s$ rankings of the methods remain unchanged, with the greatest $GVOI_s$ produced by a best-practice SP study and the lowest by a time-and-budget-constrained BT. This consistency of ranking is expected given that only the priors are changing and the priors are not specific to an NMV method.

The above results are from the perspective of the environmental decision maker, using likelihoods that are assumed to be formed from an average of the distributions elicited from the 17 experts. It may also be of interest to examine parallel $GVOI_s$ results for individual experts. Table D.2 in Appendix D shows the variation in these results between the experts, and that, in this case study, the average of their individual VOI results is slightly higher than the results based on average likelihoods (Fig. 2).

7.3. Accounting for the cost of an NMV study

When considering which NMV method to apply, if any, the costs of these prospective studies can be as important as their benefits (i.e., their $GVOI_s$). Because our assumed study costs are correlated with the quality of the information generated, there is a trade-off between the benefits and costs of the alternative methods. The increase in $GVOI_s$ made possible by a higher-quality study may or

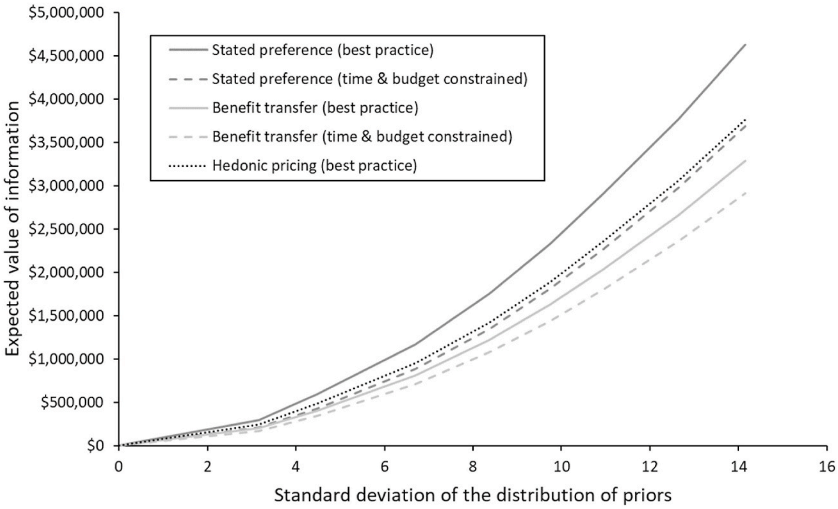

Fig. 3. Expected gross value of imperfect information for five NMV methods depending on the level of uncertainty of prior knowledge about the non-market values. Based on \$30, 000, 000 cost of project, expected benefits of \$30, 000, 000, and symmetrical distribution of priors, and assumes that all benefits are from use values. Study costs are not represented.

may not outweigh the additional study cost, depending on the decision context.

To illustrate these trade-offs, Fig. 4 shows $NVOI_s$ for each NMV method, for a range of project scales, using the illustrative study costs presented earlier (i.e., SP (best practice) \$500,000; SP (time and budget constrained) \$100,000; BT (best practice) \$150,000; BT (time and budget constrained) \$15,000; Hedonic pricing (best practice) \$100,000). We again assume baseline priors and that prior $\mathbb{E}(B) = C$. Results demonstrate the potentially decisive importance of project scale when considering trade-offs between $GVOI_s$ and study cost, and that no study type is universally preferred.[18] The valuation method with the highest $NVOI_s$ changes from BT (time and budget constrained) to Hedonic Pricing (best practice) to SP (best practice) as project scale (reflecting both cost and beneficiaries) increases from \$0 to \$30, 000, 000. For example, SP (best practice) generates the highest $NVOI_s$ for projects costing roughly \$20, 000, 000 or more. However, it has the lowest net benefit out of the five NMV methods for project scales below roughly \$12, 000, 000. For project scales below \$5,000,000 it has *negative* $NVOI_s$.

At the other end of the spectrum, the low cost of BT (time and budget constrained) leads to the highest $NVOI_s$ for project scales below roughly \$5,000,000. Even though the other NMV methods are more accurate and reliable (Fig. 1) and generate higher $GVOI_s$ (Figs. 2 and 3), their higher cost means that they have lower net benefits for small projects. Of course, the successful use of BT depends on there being suitable existing studies from which benefits can be transferred (Johnston et al., 2021). In the absence of suitable studies to support BT, the next best methods in Fig. 4 for small projects are SP (time and budget constrained) or Hedonic Pricing (best practice). The elicited likelihoods for SP (time and budget constrained) and BT (best practice) are similar (Fig. 1), so their ranking relative to other methods in Fig. 4 depends primarily on their assumed costs.

Another result that stands out in Fig. 4 is that the $NVOI_s$ of the five methods are not greatly different. At a project scale of \$15, 000, 000, the difference in $NVOI_s$ between the highest and lowest ranked NMV methods was \$193,000, which is only 1.3% of the project scale, while at a scale of \$30, 000, 000 the equivalent range is 2.1%. Although BT (time and budget constrained) has the lowest net benefit for projects above a scale of about \$17, 000, 000, it can still generate substantial $NVOI_s$ and is a far better option than basing decisions solely on the decision maker's priors (for the baseline priors). In sum, for the illustrated case, for situations where the expected benefits of the environmental project are similar to its costs, some information on non-market values is very often better than no information, provided that the project scale is large enough.

Fig. 4 reflects a case of high decision uncertainty (prior to obtaining additional NMV information) for an environmental project whose prior expected net benefit is zero, and thus show arguably optimistic results for the $NVOI_s$. If the prior BCR departs from 1.0, the $GVOI_s$ is lower at all project scales, and the ranges of project net benefits over which $NVOI_s$ would be negative are correspondingly larger. This is consistent with prior findings of Newbold and Johnston (2020) for the case of new studies designed to support BT.

7.4. Partial value estimation (use versus nonuse values)

Hedonic Pricing produces relatively high gross and net VOI estimates in the above simulations (Figs. 2–4), reflecting the expert-elicited likelihoods for this method (e.g., Fig. 1).

However, these results are based on a strong assumption that all five NMV methods estimate an identical set of underlying benefits comprised solely of use values. Many environmental projects generate a mix of use and nonuse values, and one of the arguments

[18] Similar conclusions emerge under alternative (but realistic) assumptions on study cost.

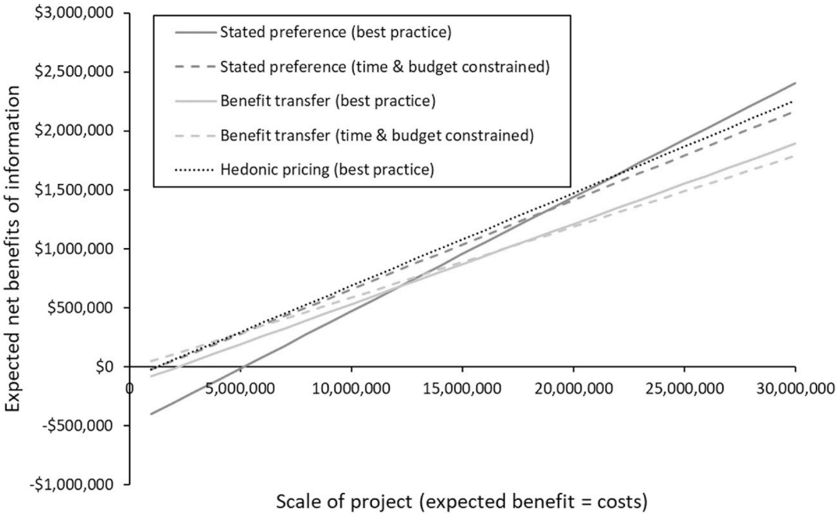

Fig. 4. Expected net value of imperfect information from each NMV method for different project scales. Assumes baseline distribution of priors and prior expected net benefit of project = 0. Assumes NMV study costs $500,000, $100,000, $150,000, $15,000, or $100,000, respectively. Assumes that all benefits are from use values.

supporting the use of SP methods is the capacity of these methods to estimate total values, including both use and nonuse components (Johnston et al., 2017). In such cases, RP methods such as Hedonic Pricing would estimate only a subset of the benefits, reflecting use values only.

To illustrate the implications of partial value estimation of this type, we re-estimate $NVOI_s$ for scenarios wherein use values represent varying proportions of total project benefit, assuming that Hedonic Pricing methods only provide insight on these use values. When Hedonic Pricing is applied, decision-makers are unable to update priors for the non-use portion of project benefit (i.e., non-use values are not assumed to be zero by the decision maker; they simply remain at the prior distribution). We derive $NVOI_s$ for an illustrative case with project gross benefits of $30, 000, 000 and a prior expected project net value of $0.

Fig. 5 illustrates how variations in the proportion of benefits derived from use values affect the $NVOI_s$ of Hedonic Pricing (best practice) and how this affects the ranking of this method relative to others. As anticipated, the ranking of Hedonic Pricing (best practice) according to $NVOI_s$ is highly sensitive to the proportion of benefits derived from use values, with the rank varying from second best (if use values comprise over ~96% of total value) to worst (if use values comprise less than ~76% of total value).

7.5. *Favorable versus unfavorable perceptions of non-market valuations*

Professional opinions on the reliability of valuation methods differ. This pattern may be seen most clearly for SP methods, for which strongly divergent perspectives have been presented in the literature (Kling et al., 2012; Banzhaf, 2017). However, differences in opinion also exist for other methods. How do these differences impact anticipated $GVOI_s$? The likelihoods estimated for each NMV method provide direct and comparable measures of reliability. Hence, sensitivity analysis over these likelihoods can provide insight into how estimated $GVOI_s$ varies with different experts' perceptions of NMV quality. To illustrate these patterns, we first identify the five experts whose elicited likelihood distributions had the lowest standard deviations for each NMV method, and the five with the highest standard deviations (i.e., those experts who are most and least favorable about reliability for each method, respectively).[19] We then calculate average likelihood distributions for those two groups of five experts, for each method. Examples for SP (best practice) are shown in Fig. 6 for a true WTP of $30.

Figs. 7 and 8 show results that are equivalent to Fig. 2 but with results limited to the most favorable and most unfavorable likelihood distributions, respectively. The results are intuitive. Comparing these results to Fig. 2 (reflecting the composite likelihoods of all experts), it can be seen that the $GVOI_s$ increases for all methods (closer to the value of perfect information) when likelihoods are drawn from the five most favorable experts for each NMV method. The opposite occurs when likelihoods are drawn from the least favorable experts.

For both favorable and unfavorable cases, $GVOI_s$ estimates continue to show a pronounced peak at zero prior expected net benefit of the project, and mostly have similar rankings to those found previously. The exception is Hedonic Pricing (best practice). The results for favorable likelihood distributions have Hedonic Pricing (best practice) performing about as well as State Preference (best practice),

[19] The selection of five experts in each group were based on the variances of their elicited likelihood distributions, rather than their judgments about the bias of each method. We noted earlier that one expert was an extreme outlier on the likelihoods for Hedonic Pricing (best practice), viewing this method as highly biased. However, the likelihood variance for this expert was not among the five largest or smallest, so the expert was not included in either group.

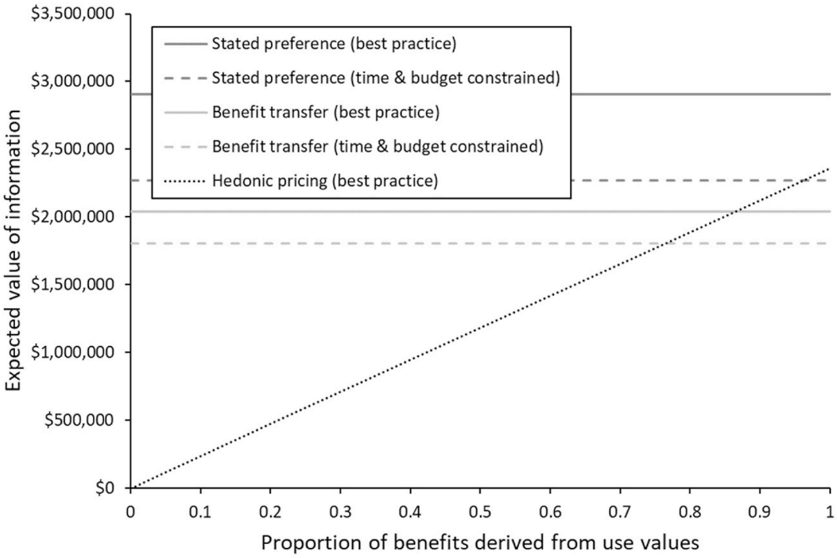

Fig. 5. Expected net value of imperfect information for each non-market valuation method allowing for hedonic pricing only capturing use values. Based on symmetrical distribution of priors, expected project benefits of $30, 000, 000, and prior expected value of project of $0.

Estimates of population mean willingness to pay ($/head)	Favourable (5 experts with lowest variance)	Aggregate (all 17 experts)	Unfavourable (5 experts with highest variance)
-$10	0.00	0.00	0.00
$0	0.00	0.01	0.03
$10	0.02	0.05	0.07
$20	0.09	0.14	0.16
$30	0.44	0.35	0.28
$40	0.32	0.23	0.17
$50	0.10	0.12	0.12
$60	0.03	0.06	0.08
$70	0.00	0.02	0.05
$80	0.00	0.01	0.03
$90	0.00	0.00	0.01
$100	0.00	0.00	0.00
$110	0.00	0.00	0.00
$120	0.00	0.00	0.00
$130	0.00	0.00	0.00
Distribution mean	$35.28	$39.47	$39.07
Standard deviation	$14.43	$19.63	$21.13

Fig. 6. Favorable, aggregate and unfavorable likelihood distributions for Stated Preference (best practice) elicited from expert panels. True mean WTP is $30 per head (single lump sum payment) in each case.

assuming that 100% of the benefits are derived from use values (Fig. 7). In contrast, where unfavorable likelihoods are assumed, Hedonic Pricing (best practice) performs worse than previously. Its VOIs are lower than those of SP (time and budget constrained) at all levels of project net benefit, and in some cases are below the results for BT (time and budget constrained). This reflects a pronounced divergence in expert opinions regarding the reliability of hedonic methods, with some viewing the method as highly reliable (relative to other methods) and others viewing it as highly unreliable.

7.6. Sensitivity analysis and general findings

As implied by the theoretical model and illustrated numerically, the VOI from NMV methods varies as a function of the decision context. These variations can affect $NVOI_s$ and associated decisions on whether and how to optimally apply NMV methods. Given these

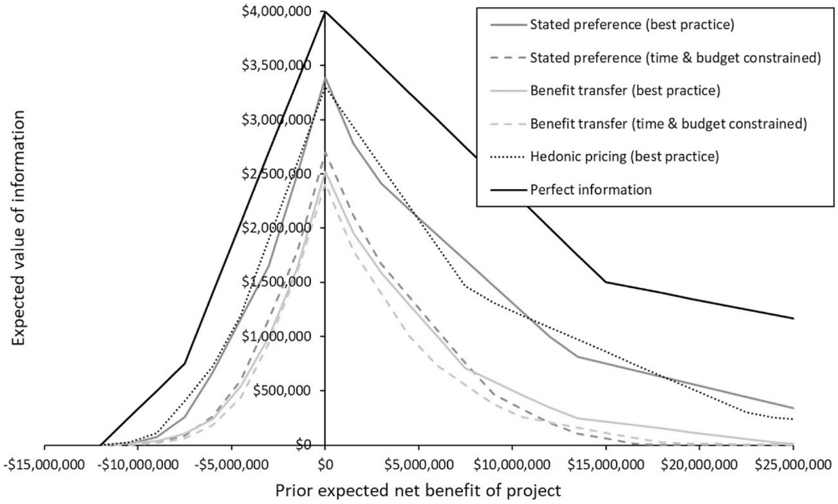

Fig. 7. Expected gross value of imperfect information for five NMV methods, for favorable likelihoods (based on the five experts with the most favorable perceptions for this NMV method). Assumes $30, 000, 000 cost of the project, baseline priors, and that all benefits are from use values.

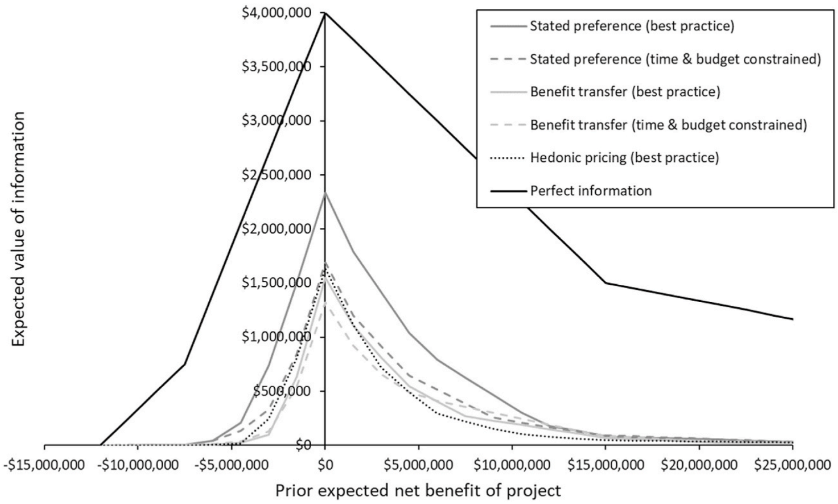

Fig. 8. Expected gross value of imperfect information for five NMV methods, for unfavorable likelihoods (based on the five experts with the most unfavorable perceptions for this NMV method). Assumes $30, 000, 000 cost of the project, baseline priors, and that all benefits are from use values.

variations, is it possible to draw generalizable conclusions? To gain a perspective on how frequently different results may occur across a wide range of contexts (e.g., when the value of NMV outweighs the cost; what method has the highest $NVOI_s$), we conducted a detailed sensitivity analysis that combined: five sets of priors, three levels of project cost, two levels of NMV study cost, five use-value percentages, three sets of likelihoods, and 30 prior BCRs ranging from 0.1 to 5.0. Other variables were unchanged, and results depend on the default values used for those variables. Details of factors included are provided in Appendix E. We conducted a full-factorial experiment, leading to a total of 13,500 results for both $GVOI_s$ and $NVOI_s$, for each method.

Summarizing these results, $GVOI_s$ was greater than the study cost of at least one NMV method in 2308 of the 13,500 solutions (i.e., $NVOI_s$ was greater than zero for at least one method). Hence, the net value of NMV information was positive in 17% of the considered circumstances. Out of the 2308 solutions for which $NVOI_s > 0$, Benefit Transfer (time and budget constrained) had the highest net VOI in 47% of cases, Stated Preference (best practice) in 32% of cases, Stated Preference (time and budget constrained) in 12% of cases and Hedonic Pricing in 10% of cases. Benefit Transfer (best practice) was not ranked highest in any scenario. These results are broadly consistent with the regular use of approaches similar to Benefit Transfer (time and budget constrained) within governmental Benefit-Cost Analyses (Griffiths et al., 2012; Newbold et al., 2018).

Note that the result that 17% of results in the sensitivity analysis had at least one net VOI greater than zero is not necessarily indicative of how frequently a positive net VOI would be encountered in practice. Among the reasons are that the sensitivity analysis derives VOI under a range of possible contexts but the relative likelihood that each of these contexts might occur in reality is unknown (some might be more likely to occur than others) and that not all possible valuation contexts are considered. However, the sensitivity analysis results do serve to reinforce the finding that, in each project scenario, the net VOI is only likely to be positive in certain circumstances.

Results also provide insights into the width of the "sweet spot": the range of prior BCRs with high VOIs. There were 450 scenarios over which we simulated 30 prior BCRs. For each scenario we identified the range of prior BCRs between which the best NMV method had $NVOI_s > 0$. The average lower bound for this range was 0.86 and the average upper bound was 1.55. These bounds did not vary greatly between the scenarios (0.7–1.0 for the lower bound and 1.0 to 2.4 for the upper bound). These results confirm that the proximity of prior expected benefits to zero (or the BCR to 1.0) has an important influence in whether $NVOI_s > 0$ (i.e., on whether the benefit of NMV information is worth the cost). If prior expected net benefits are close to zero (hence there is considerable ambiguity on whether the benefits of the project will outweigh the costs), $NVOI_s$ is greater than zero under a fairly wide range of circumstances. In contrast, when prior expected net benefits are far from zero, it is unlikely that new NMV information will change the decision (regardless of other circumstances), and hence $NVOI_s$ is typically negative.

8. Discussion

Despite common assertions in the valuation literature concerning the "need" for further information on environmental values to inform decisions, the value of NMV for decision support is context- and method-specific. Considering this contextual dependence, the goal of this article is to develop and illustrate a rigorous approach—grounded in Bayesian value of information (VOI) theory—that may be used to evaluate when and if the benefit of conducting a non-market valuation (NMV) study exceeds the cost, and which method of those considered delivers the highest expected net benefit under alternative circumstances. Using this approach, we illustrate general patterns in VOI that may occur over a range of realistic situations wherein valuation results might be used to inform decisions. Results provide a number of insights on the value of valuation, the circumstances within which $GVOI_s$ from NMV methods outweigh the costs, and which methods tend to be preferred on the basis of $NVOI_s$.

As in any model of this type, several caveats and limitations should be noted. Among these, the presented findings assume that NMV results are used to inform a dispositive BCA. Although this is a ubiquitous assumption within VOI modeling and there are cases where it may be a reasonable approximation (e.g., Griffiths et al., 2012; Wheeler, 2015; Newbold et al., 2018; Hanley and Czajkowski, 2019; Newbold and Johnston, 2020), there are many cases in which NMV plays little direct role in decisions (e.g., Laurans et al., 2013; Rogers et al., 2015; Welling et al., 2023). In cases where policy makers do *not* make decisions using BCA that includes NMV, our results are best interpreted as identifying *potential* VOI if they were to do so.

The presented $NVOI_s$ estimates may also understate the true value of NMV studies if results are used for additional purposes, such as supporting future BTs for other decisions. For example, if a study is used *both* to support an immediate environmental decision and then later contributes to a meta-analysis that informs a second decision, VOI results such as those shown here may be considered additive to VOIs due to BT (as estimated in Newbold and Johnston (2020)). Naturally, any additional benefits of research—such as those related to methodological development or education—will further add to potential study value.

The analysis is limited to an illustration over only five potential NMV methods. This simplification is imposed to maintain tractability, particularly for the expert elicitation. However, the proposed approach can be readily extended to additional methods and/or methodological variations. Variations in the details of each method, such as in sample size, can be captured by representing each variation as a different "method," each with its own likelihoods and study costs. Further research on how likelihoods and study costs vary with study design, including sample size, would help to facilitate future analysis.

Likelihoods are also likely to differ for different environmental management contexts. For example, if the environmental values relevant to the decision have not previously been well studied, the ability to apply BT will be inhibited, and the likelihoods for BT will need to reflect that. Greater experience with valuation for certain types of resources or environmental changes may also improve the accuracy of methods applied to those areas, potentially affecting the likelihoods. The imbalance in topics covered by the valuation literature has been long recognized, with someg areas (such as water quality and big game hunting) addressed by reasonably robust bodies of work and others (such as non-lethal effects on wild species) rarely considered (Loomis and Rosenberger, 2006; Newbold et al., 2018; Johnston et al., 2024).

While the results provide direct estimates of $GVOI_s$ only for the studied methods, they can support at least some insight into potential $GVOI_s$ that might apply to others. For example, results suggest that a capacity to update a larger proportion of total benefits (e.g., use values vs. total values) plays an important role in determining $GVOI_s$. Here, if NMV methods are ranked by $GVOI_s$, the proportion of use values substantially influences the ranking of hedonic pricing relative to other methods (Fig. 5). Following the same logic, it seems likely that the $GVOI_s$ of other RP methods—such as recreation demand models (Lupi et al., 2020)—will depend similarly on the proportion of total benefits comprised of use values that can be measured by those methods. The reliability of valuation (reflected in the standard deviation of the likelihoods) also impacts $GVOI_s$, as it influences the degree to which the anticipated posteriors depart from the priors via equation (4).

In this project, we elicited likelihoods for five potential true values. We observe in the results that, while the means of the elicited likelihood distributions changed for different true values, the variances and general shapes of the distributions did not change greatly and did so in a smooth manner. As a result, it may be possible to extrapolate likelihoods to true values outside the elicited range. However, we have not evaluated the possible errors in VOI estimation that would occur, and further research would be helpful to understand the safe limits to this extrapolation.

While the presented theory is broadly applicable, the numerical results are conditional on a particular application (water quality) for which NMV methods are well-developed and there is an extensive prior literature (Newbold and Johnston, 2020; Moeltner et al., 2023). Results could vary for settings in which there is less experience and prior work to draw upon. Wherever possible, modeling assumptions were grounded in available evidence or varied as part of the analysis to evaluate implications for VOI, in an attempt to distinguish results with greater generality from those specific to the case study illustration. Nonetheless, the presented numerical results should be interpreted in context.

For example, project costs are assumed to be certain and, in many cases, equal to the expected value of benefits. These assumptions tend to increase estimated $GVOI_s$. The priors used in the analysis were also set by assumption and varied as part of the numerical illustration. If applying the approach in a specific application, priors could be elicited from the decision-makers in the relevant agency.[20] The corresponding likelihoods (i.e., that determine how priors are updated given study outcomes) were elicited from a group of experts. Although experts were invited based on their NMV experience (as they would often be by a government agency seeking input), the experience of this group may reflect a favorable disposition towards NMV. We did not elicit likelihoods from those who have voiced strong skepticism to the use of particular methods and rarely if ever use them, although Fig. 8 shows results for experts with less favorable perceptions. Further research could elicit likelihoods for a more diverse expert sample.

Alternatively, at least in concept, one could seek to derive information on priors and likelihoods from valuation metadata, adapting the approach shown in Newbold and Johnston (2020) for one valuation method (SP). However, extending such an approach to multiple methods and levels of best practice is not straightforward. For example, one would require comparable, commodity- and welfare-consistent valuation metadata (Bergstrom and Taylor, 2006) for all NMV methods under consideration, while allowing systematic adjustments for alternative levels of best practice. Analysts often struggle to produce consistent metadata even for one valuation method (Vedogbeton and Johnston 2020)—such as SP and hedonic methods considered in isolation—without considering the added challenge of compiling sufficiently comparable metadata for multiple NMV methods simultaneously (cf. Londoño and Johnston, 2012; Moeltner and Rosenberger, 2014).

It is also important to consider the ways in which perceived bias in NMV influences $GVOI_s$. Unlike reliability (which impacts $GVOI_s$), *biased likelihoods within the model do not affect* $GVOI_s$. This is anticipated based on model structure and verified via additional sensitivity analyses (omitted here for conciseness). The reason is that, within VOI models, study information is not used directly and naively to provide a "true" value for BCA. Instead, this information is used to update priors. Implicit in this standard theory is an assumption that *any bias in valuation results is anticipated by decision-makers* when updating priors. Intuitively, if a bias is recognized in the likelihood distribution, then it can be accommodated when determining what a new NMV result implies about what the true value is likely to be.

In practice, of course, NMV study results are often used directly *without* adjusting for bias, in which case the results presented here would overstate $GVOI_s$. This raises the question of whether adjusting for assumed bias within BCA should be a general practice and, if so, how it should be done. The VOI framework presented here provides a logical and rigorous method for doing so, contingent on analysts being able to access information about likelihoods for the particular NMV methods they are considering. Even if the framework is not used explicitly, an understanding of it can inform thinking about how adjustment for bias could be made in principle, considering that true values can never be observed (Bishop and Boyle, 2019).

We also emphasize that real-world legal and regulatory frameworks may lead to additional ramifications of anticipated study validity (bias) and reliability (variance), beyond those captured by the presented model. For example, within the US, agency BCAs may be subject to legal challenge, and the general acceptance of a study technique (e.g., as sufficiently valid and reliable) by the scientific community is among the criteria considered for the admissibility of expert testimony under the Daubert standard (Bishop and Boyle, 2017).

Finally, we acknowledge that potential VOI is only one of many factors that might influence the feasible or beneficial use of NMV to inform decisions. For example, time and resource constraints may preclude the use of primary studies (Newbold et al., 2018; Johnston et al., 2021), even if preferred based on VOI. Regulatory requirements facing government agencies may also require lengthy approval processes for certain types of data collection, such as SP survey data (U.S. Office of Management and Budget, 2016), discouraging the use of such methods. More generally, data availability (or ability to obtain data) can impact the feasibility of any valuation method, regardless of the VOI it might provide. For example, RP methods are only feasible when considering values that emerge within the context of currently observable situations—beyond such observable situations SP methods are generally required (Johnston et al., 2017).

9. Conclusion

This article provides insights that are relevant to a number of longstanding debates about NMV. For example, while some advocate the use of SP methods to support decision (e.g., Hanley and Czajkowski, 2019), others argue that SP methods should be eschewed (e.g., Hausman, 2012). Methods and findings presented here suggest that greater nuance is warranted when making assertions such as these. The $NVOI_s$ from NMV studies can vary widely, even within the bounds of a similar set of projects or policy proposals. Moreover, as emphasized above, relative study accuracy is not necessarily a decisive factor in $GVOI_s$ or $NVOI_s$, at least within the ranges of the likelihoods elicited from the current expert panel. Study accuracy does, of course, affect $GVOI_s$, but it is one of several factors that do so, and the other factors may be more influential.

Results also suggest a number of general conclusions relevant to when and how valuation should optimally be used to inform decisions (subject to the caveats noted above). Among these, $GVOI_s$ is highly sensitive to prior expected net benefits (Strand and

[20] Decision-makers might seek advice from experts to establish these benefit priors, as we have assumed for the likelihoods.

Siddiqui, 2020). There is a "sweet spot," with high $GVOI_s$, where net benefits are initially estimated to be close to zero. In contrast, if prior information suggests that net benefits are likely to be far from zero (positive or negative), a new study is likely to have negligible value to decision makers, regardless of type or accuracy. The preliminary BCRs at which this happens will be case-study-specific, although further research to test possible rules of thumb would be informative. Our sensitivity analysis suggests that a BCR range from 0.8 to 1.6 could be a useful starting point in the search for a robust rule of thumb.

Although none of the considered NMV methods were perceived by the panel of experts to highly accurate, estimated $GVOI_s$ was nonetheless high under some circumstances—sometimes approaching the value of perfect information. The circumstances that favor high $GVOI_s$ include: a large project, prior estimate of net benefit close to zero, and high prior uncertainty about non-market values. Within circumstances such as these, even an inaccurate estimate of value can be more valuable to decision-makers than no number. This stands in juxtaposition to debates in the literature emphasizing the validity and reliability of alternative NMV methods. For example, low-cost BTs can provide sufficient VOI to justify their use to support decisions, particularly for small-scale policies and projects, provided that the initial BCR for the environmental project (prior to collecting any additional NMV information) is sufficiently close to 1. Indeed, in circumstances that favor high informational values, $GVOI_s$ results for alternative methods are not so different from each other as one might expect based on assertions in the literature.

Perhaps the principal insight that may be drawn from the presented results is the importance of systematic consideration of informational benefits and costs when considering the use of alternative NMV methods to inform policy decisions. Like the environmental decisions they are meant to inform, choices over NMV methods (or whether to use NMV at all) are essentially *economic decisions* but are rarely considered as such in the literature. When adopting this economic lens, we can see that, under realistic conditions, common assertions appearing in the literature may be questionable. For example, under some conditions low-budget BTs can provide $NVOI_s$ that is greater than that of more accurate methods (e.g., for informing decisions about smaller-budget projects). Within our illustration, we also find that SP methods often produce higher gross and/or net VOI than RP methods (here, hedonic pricing), in large part due to the inability of RP methods to support updating of nonuse values.[21] Results such as these demonstrate the hazards in making universal arguments about the superiority or inferiority of particular approaches. Although results suggest a number of general conclusions on conditions under which certain types of studies are likely to have high or low $NVOI_s$, the value of valuation studies is an empirical question and context-specific.

Strand and Siddiqui (2020) proposed that VOI analysis "ought to become a much more standard tool and procedure in the science and practice of valuation of public goods" (p. 434). We concur and encourage further work along the lines demonstrated here, as a means to draw broader insights into the value of valuation for decision support. While we expect the high-level insights described above to be broadly applicable, repeating the analysis for other environmental decision contexts, deriving priors from decision makers, and eliciting likelihoods from a larger, more diverse group of experts will likely prove valuable. The presented framework and illustration provide a foundation from which work of this type can proceed.

CRediT authorship contribution statement

David J. Pannell: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Robert J. Johnston:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Michael P. Burton:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Md Sayed Iftekhar:** Writing – review & editing, Methodology, Conceptualization. **Abbie A. Rogers:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Cheryl Day:** Software, Project administration, Data curation.

Ethics approval

University of Western Australia Human Research Ethics approval number was #2022/ET000552.

2. Use of AI

Nil.

Conflicts of interest

Nil.

Acknowledgements

The authors are especially grateful to the members of our expert panel, who generously shared their time and expertise in the

[21] We note that the expert panel produced likelihoods for Hedonic Pricing (best practice) that represented a lower accuracy than for Stated Preference (best practice), and some may disagree with this assessment. However, even if RP studies are believed to be more accurate, SP methods can still be favored if the proportion of use benefits is sufficiently low.

elicitation of likelihoods. The panelists were Ian Bateman, Vic Adamowicz, Daniel Phaneuf, Jette Bredahl Jacobsen, Dan Lew, George Parsons, Mark Morrison, Mikolaj Czajkowski, Klaus Glenk, Jeff Kline, Chris Moore, Frank Lupi, Darla Hatton MacDonald, John Rolfe, Søren Bøye Olsen, Tobias Börger, and Silvia Ferrini. The project was funded by the Australian Research Council, Project ID DP200102877. We are also grateful to Dan Rigby, Alaya Spencer-Cotton, Claire Doll, and Maksym Polyakov for pre-testing our preliminary survey for the expert panelists and the spreadsheet used in the elicitation process. The editor and reviewers provided exceptionally helpful advice on how to improve the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2025.103148.

References

Allen, B., Loomis, J., 2008. The decision to use benefit transfer or conduct original valuation research for benefit-cost and policy analysis. Contemp. Econ. Policy 26, 1–12.
Banzhaf, H.S., 2017. Constructing markets: environmental economics and the contingent valuation controversy. Hist. Polit. Econ. 49 (Suppl. ment), 213–239.
Bateman, I.J., Kling, C.L., 2020. Revealed preference methods for nonmarket valuation: an introduction to best practices. Rev. Environ. Econ. Pol. 14 (2), 240–259.
Bergstrom, J.C., Taylor, L.O., 2006. Using meta-analysis for benefits transfer: theory and practice. Ecol. Econ. 60 (2), 351–360.
Bishop, R.C., Boyle, K.J., 2017. Reliability and validity in nonmarket valuation. In: Champ, P.A., Boyle, K.J., Brown, T.C. (Eds.), A Primer on Nonmarket Valuation. Kluwer Academic Publishers chapter 12 in.
Bishop, R.C., Boyle, K.J., 2019. Reliability and validity in nonmarket valuation. Environ. Resour. Econ. 72 (2), 559–582.
Bishop, K.C., Kuminoff, N.V., Banzhaf, H.S., Boyle, K.J., von Gravenitz, K., Pope, J.C., Smith, V.K., Timmins, C.D., 2020. Best practices for using hedonic property value models to measure willingness to pay for environmental quality. Rev. Environ. Econ. Pol. 14 (2), 260–281.
Burgman, M.A., 2015. Trusting Judgements: How to Get the Best Out of Experts. Cambridge University Press.
Conrad, J., 1980. Quasi-option value and the expected value of information. Q. J. Econ. 94, 812–820.
Dehnhardt, A., 2013. Decision-makers' attitudes towards economic valuation – a case study of German water management authorities. Journal of Environmental Economics and Policy 2 (2), 201–221.
Delpiazzo, E., Bosello, F., Mazzoli, P., Bagli, S., Luzzi, V., Dalla Valle, F., 2022. Co-evaluation of climate services. A case study for hydropower generation. Climate Services 28, 100335.
Drummond, C., Gray, S.G., Raimi, K.T., Wilson, R., Arvai, J., 2020. Public perceptions of federal science advisory boards depend on their composition. PNAS 117 (37), 22668–22670.
Feltham, G., 1968. The value of information. Environment Systems and Decisions 43, 684–696.
Freeman, A.M., Herriges, J.A., Kling, C.L., 2014. The Measurement of Environmental and Resource Values: Theory and Methods, third ed. Resources for the Future.
Gibson, F.L., Rogers, A.A., Smith, A.D.M., Roberts, A., Possingham, H., McCarthy, M., Pannell, D.J., 2017. Factors influencing the use of decision support tools in the development and design of conservation policy. Environmental Science and Policy 70 (1), 1–8.
Giordano, P.F., Prendergast, L.J., Limongelli, M.P., 2023. Quantifying the value of SHM information for bridges under flood-induced scour. Structure and Infrastructure Engineering 19 (11), 1616–1632.
Gosling, J.P., 2018. SHELF: the Sheffield elicitation framework. In: Dias, L.C., Morton, A., Quigley, J. (Eds.), Elicitation: the Science and Art of Structuring Judgement. Springer, Cham, pp. 61–93.
Griffiths, C., Klemick, H., Massey, M., Moore, C., Newbold, S., Simpson, D., Walsh, P., Wheeler, W., 2012. US Environmental Protection Agency valuation of surface water quality improvements. Rev. Environ. Econ. Pol. 6, 130–146.
Hanley, N., Czajkowski, M., 2019. The role of stated preference valuation methods in understanding choices and informing policy. Rev. Environ. Econ. Pol. 13 (2), 248–266.
Hammitt, J.K., Shlyakhter, A.I., 1999. The expected value of information and the probability of surprise. Risk Analysis 19 (1), 135–152.
Hanley, N., Colombo, S., Tinch, D., Black, A., Aftab, A., 2006. Estimating the benefits of water quality improvements under the Water Framework Directive: are benefits transferable? Eur. Rev. Agric. Econ. 33, 391–413.
Hausman, J., 2012. Contingent valuation: from dubious to hopeless. J. Econ. Perspect. 26 (4), 43–56.
Hemming, V., Burgman, M.A., Hanea, A.M., McBride, M.F., Wintle, B.C., 2017. A practical guide to structured expert elicitation using the IDEA protocol. Methods Ecol. Evol. 9, 169–180.
Johnston, R., Rosenberger, R., 2010. Methods, trends and controversies in contemporary benefit transfer. J. Econ. Surv. 24, 479–510.
Johnston, R.J., Rolfe, J., Rosenberger, R., Brouwer, R., 2015. Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners. Springer.
Johnston, R., Boyle, K., Adamowicz, W.L., Bennett, J., Brouwer, R., Cameron, T.A., Hanemann, W.M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., Vossler, C., 2017. Contemporary guidance for stated preference studies. Journal of the Association of Environmental and Resource Economists 4 (2), 319–405.
Johnston, R.J., Besedin, E., Holland, B., 2019. Modeling distance decay with valuation meta-analysis. Environ. Resour. Econ. 72, 657–690.
Johnston, R.J., Boyle, K.J., Loureiro, M.L., Navrud, S., Rolfe, J., 2021. Guidance to enhance the validity and credibility of environmental benefit transfers. Environ. Resour. Econ. 79 (3), 575–624.
Johnston, R.J., Börger, T., Hanley, N., Meginnis, K., Ndebele, T., Ali Siyal, G.E., Beaumont, N., de Vries, F.P., 2024. Consequences of omitting non-lethal wildlife impacts from stated preference scenarios. J. Environ. Econ. Manag. 126, 103011.
Keeney, E., Thom, H., Turner, E., Martin, R.M., Sanghera, S., 2021. Using a modified Delphi approach to gain consensus on relevant Comparators in a cost-effectiveness model: application to Prostate Cancer Screening. Pharmacoeconomics 39 (5), 589–600.
Keisler, J.M., Collier, Z.A., Chu, E., Sinatra, N., Linkov, I., 2014. Value of information analysis: the state of application. Environmental Systems and Decisions 34, 3–23.
Kling, C.L., Phaneuf, D.J., Zhao, J., 2012. From Exxon to BP: has some number become better than no number? J. Econ. Perspect. 26, 3–26.
Laurans, Y., Rankovic, A., Billé, R., Pirard, R., Mermet, L., 2013. Use of ecosystem services economic valuation for decision making: questioning a literature blindspot. J. Environ. Manag. 119, 208–219.
Laxminarayan, R., Macauley, M. (Eds.), 2012. The Value of Information: Methodological Frontiers and New Applications in Environment and Health. Springer.
Londoño, L.M., Johnston, R.J., 2012. Enhancing the reliability of benefit transfer over heterogeneous sites: a meta-analysis of international coral reef values. Ecol. Econ. 78, 80–89.
Loomis, J., Rosenberger, R., 2006. Reducing barriers in future benefit transfers: needed improvements in primary study design and reporting. Ecol. Econ. 60, 343–350.
Lovell, S., Newbold, S., Owens, N., Wyatt, T., 2004. How Academic Economists Can Improve Benefit Transfers at EPA. Association of Environmental and Resource Economists (AERE) Newsletter, vol. 24, pp. 25–28.
Lupi, F., Phaneuf, D.J., von Haefen, R.H., 2020. Best practices for implementing recreation demand models. Rev. Environ. Econ. Pol. 14 (2), 302–323.

Maxwell, S.L., Rhodes, J.R., Runge, M.C., Possingham, H.P., Ng, C.F., McDonald-Madden, E., 2015. How much is new information worth? Evaluating the financial benefit of resolving management uncertainty. J. Appl. Ecol. 52 (1), 12–20.
Metcalfe, P.J., Baker, W., Andrews, K., Atkinson, G., Bateman, I.J., Butler, S., Carson, R.T., East, J., Gueron, Y., Sheldon, R., Train, K., 2012. An assessment of the nonmarket benefits of the Water Framework Directive for households in England and Wales. Water Resources Research 48, W03526.
Moeltner, K., Puri, R., Johnston, R.J., Besedin, E., Balukas, J.A., Le, A., 2023. Locally-weighted meta-regression and benefit transfer. J. Environ. Econ. Manag. 121, 102871.
Moeltner, K., Rosenberger, R.S., 2014. Cross-context benefit transfer: a Bayesian search for information pools. Am. J. Agric. Econ. 96 (2), 469–488.
Moeltner, K., Woodward, R., 2009. Meta-functional benefit transfer for wetland valuation: making the most of small samples. Environ. Resour. Econ. 42, 89–108.
Munro, A., Hanley, N.D., 2001. Information, uncertainty, and contingent valuation. In: Bateman, I.J., Willis, K.G. (Eds.), Valuing Environmental Preferences: Theory and Practice of the Contingent Valuation Method in the US, EU, and Developing Countries. Oxford University Press, Oxford, pp. 258–279.
Newbold, S.C., Johnston, R.J., 2020. Valuing non-market valuation studies using meta-analysis: a demonstration using estimates of willingness-to-pay for water quality improvements. J. Environ. Econ. Manag. 104, 102379.
Newbold, S., Marten, A., 2014. The value of information for integrated assessment models of climate change. J. Environ. Econ. Manag. 68, 111–123.
Newbold, S., Simpson, R.D., Massey, D.M., Heberling, M.T., Wheeler, W., Corona, J., Hewitt, J., 2018. Benefit transfer challenges: perspectives from U.S. practitioners. Environ. Resour. Econ. 69, 467–482.
Ng, K.W., Tian, G.L., Tang, M.L., 2011. Dirichlet and Related Distributions: Theory, Methods and Applications. Wiley.
Pannell, D.J., 1994. The value of information in herbicide decision making for weed control in Australian wheat crops. J. Agric. Resour. Econ. 19 (2), 366–381.
Pannell, D.J., Glenn, N.A., 2000. A framework for economic evaluation and selection of sustainability indicators in agriculture. Ecol. Econ. 33 (1), 135–149.
Phillips, C., 2001. The economics of 'more research is needed'. Int. J. Epidemiol. 30, 771–776.
Polasky, S., Solow, A.R., 2001. The value of information in reserve site selection. Biodivers. Conserv. 10, 1051–1058.
Pratt, J.W., Raiffa, H., Schlaifer, R., 1995. Introduction to Statistical Decision Theory. MIT Press.
Rein, D., 2012. Value of information and research prioritization. PCORI white paper. https://www.pcori.org/assets/Value-of-Information-and-Research-Prioritization2.pdf. (Accessed 20 November 2024).
Rogers, A.A., Kragt, M.E., Gibson, F.L., Burton, M.P., Petersen, E.H., Pannell, D.J., 2015. Non-market valuation: usage and impacts in environmental policy and management in Australia. Aust. J. Agric. Resour. Econ. 59 (1), 1–15.
Sadatsafavi, M., Lee, T.Y., Wynants, L., Vickers, A.J., Gustafson, P., 2023. Value-of-information analysis for external validation of risk prediction models. Med. Decis. Mak. 43 (5), 564–575.
Soares, M., Colson, A., Bojke, L., Ghabri, S., Ulises Garay, O., Felli, J.K., Lee, K., Molsen-David, E., Morales-Napoles, O., Shaffer, V.A., Ijzerman, M.J., 2024. Recommendations on the use of structured expert elicitation protocols for healthcare decision making: a good practices report of an ISPOR task force. Value Health 27 (11), 1469–1478.
Strand, J., Siddiqui, S., 2020. Value of improved information about environmental protection values: toward a benefit–cost analysis of public-good valuation studies. J. Benefit-Cost Anal. 11 (3), 418–440.
Tebib, H., Douglas, J., Roberts, J.J., 2023. Using the value of information to decide when to collect additional data on near-surface site conditions. Soil Dynam. Earthq. Eng. 165, 107654.
U.S. Environmental Protection Agency (US EPA), 2014. Guidance for preparing economic analyses. National Center for Environmental Economics, Office of Policy. U. S. Environmental Protection Agency, Washington, DC.
U.S. Office of Management and Budget (US OMB), 2016. Questions and answers when designing surveys for information collections. https://obamawhitehouse.archives.gov/sites/default/files/omb/inforeg/pmc_survey_guidance_2006.pdf. (Accessed 20 November 2024).
Vedogbeton, H., Johnston, R.J., 2020. Commodity consistent meta-analysis of wetland values: an illustration for coastal marsh habitat. Environ. Resour. Econ. 75 (4), 835–865.
Welling, M., Dehnhardt, A., Aß, S.M., 2023. Does validity matter for policymakers? Evidence from choice experiments on urban green. Journal of Environmental Economics and Policy 12 (4), 524–538. https://doi.org/10.1080/21606544.2023.2186954.
Wheeler, W., 2015. Benefit transfer for water quality regulatory rulemaking in the United States. In: Johnston, R.J., Rolfe, J., Rosenberger, R., Brouwer, R. (Eds.), Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners. Springer.
Wilson, E.C.F., 2015. A practical guide to value of information analysis. Pharmacoeconomics 33, 105–121.
Yakota, F., Thompson, K., 2004. Value of information analysis in environmental health risk management decisions: past, present, and future. Risk Anal. 24, 635–650.