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SYSTEMATIC REVIEW

Discrete Choice Experiments in Health Economics: A Review of the Literature

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Abstract

Background Discrete choice experiments (DCEs) are increasingly used in health economics to address a wide range of health policy-related concerns.

Objective Broadly adopting the methodology of an earlier systematic review of health-related DCEs, which covered the period 2001–2008, we report whether earlier trends continued during 2009–2012.

Methods This paper systematically reviews health-related DCEs published between 2009 and 2012, using the same database as the earlier published review (PubMed) to obtain citations, and the same range of search terms.

Results A total of 179 health-related DCEs for 2009–2012 met the inclusion criteria for the review. We found a continuing trend towards conducting DCEs across a broader range of countries. However, the trend towards including fewer attributes was reversed, whilst the trend towards interview-based DCEs reversed because of increased computer administration. The trend towards using more flexible econometric models, including mixed logit and latent class, has also continued. Reporting of monetary values has fallen compared with earlier periods, but the proportion of studies estimating trade-offs between health outcomes and experience factors, or valuing outcomes in terms of utility scores, has increased, although use of odds ratios and probabilities has declined. The reassuring trend towards the use of more flexible and appropriate DCE designs and econometric methods has been reinforced by the increased use of qualitative methods to inform DCE processes and results. However, qualitative research methods are being used less often to inform attribute selection, which may make DCEs more susceptible to omitted variable bias if the decision framework is not known prior to the research project.

Conclusions The use of DCEs in healthcare continues to grow dramatically, as does the scope of applications across an expanding range of countries. There is increasing evidence that more sophisticated approaches to DCE design and analytical techniques are improving the quality of final outputs. That said, recent evidence that the use of qualitative methods to inform attribute selection has declined is of concern.

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Key Points for Decision Makers

There has been an ongoing increase in the publication of health-related discrete choice experiments (DCEs), which can inform policy making: during 1990–2000 there were 34 health-related DCEs meeting reviewer inclusion criteria (approximately 3 per year); for 2001–2008, the figure was 114 health-related DCEs (approximately 14 per year); whilst for 2009–2012, 179 health-related DCEs met our inclusion criteria (approximately 45 per year).

For 2009–2012, we found a continuing trend towards conducting DCEs across a broader range of countries. Consequently, DCE results can influence decisions in a wider range of geographical settings.

There is evidence of improvement in DCE design and analysis. For example, an increasing proportion of DCEs take interactions as well as main effects into consideration as part of their designs. Also, the econometric models used to analyze DCE data increasingly cater for preference heterogeneity using either mixed logit, latent class models, or hierarchical Bayesian models.

1 Introduction

Discrete choice experiments (DCEs) are increasingly used in health economics to address a wide range of health policy-related concerns. The approach draws its micro-economic foundations from the characteristics theory of demand [1] and random utility theory (RUT) [2]. The characteristics theory of demand assumes that goods, services, or types of healthcare provision can be valued in terms of their constituent characteristics (otherwise known as attributes). DCEs involve respondents making a number of stated preference choices in response to DCE questions. According to RUT, respondents are assumed to act in a utility maximizing manner and make choices contingent upon the levels of attributes in DCE scenarios. Therefore, choice data obtained from respondents' stated preferences can be analyzed using econometric methods compatible with RUT. If the specified attributes are significantly related to respondent choices, findings from data analysis should confer information relating to how the average respondent's utility (or willingness to pay) is affected by changes in the levels of attributes. RUT assumes that respondent utility can be decomposed into a systematic component, which is a function of attributes and their levels, and a random component, which is an error term in the regression equation related to unmeasured preference variation. Published DCEs in healthcare are usually compatible with RUT [3–5], in the sense that they adopt a methodology consistent with RUT.

Although reviews and commentaries have been published of healthcare-related DCEs for specific clinical contexts or health-related concerns [6–8], and conjoint analyses more broadly [9], the most comprehensive reviews of the healthcare DCE literature cover the periods 1990–2000 [4] and 2001–2008 [3]. This paper updates those earlier systematic reviews to cover the period 2009–2012, and considers how key aspects of the design and application of DCEs have changed across the three periods.

2 Literature Review

2.1 Methods

This review builds upon the earlier systematic reviews [3, 4]. It focuses on the 2009–2012 literature, and was derived from the literature in the sense that it replicates the methodology of the most recent review [3]. Although further checklists or commentaries on best practice [10–16] have been developed in recent years, these did not require fundamental changes to the approach to reviewing the DCE literature. Moreover, some of these checklists or commentaries [12–14] had already informed the development of the criteria deployed in the 2001–2008 review, whilst others served to confirm that our review encompassed appropriate criteria [11, 15, 16]. However, we did feel that the range of information extracted in relation to preference heterogeneity models such as mixed logit could be improved upon, and so we also gathered additional information on the distributional assumptions deployed when mixed logit was applied, and the number of Halton draws that were specified for replications. Searches were restricted to the PubMed search engine, replicating the approach of the most recent review [3], and used the same search terms, including 'conjoint', 'conjoint analysis', 'conjoint measurement', 'conjoint studies', 'conjoint choice experiment', 'part-worth utilities', 'functional measurement', 'paired comparisons', 'pairwise choices', 'discrete choice experiment', 'dce', 'discrete choice mode(l)ling', 'discrete choice conjoint experiment', and 'stated preference'. Initial searches were conducted in September 2011, and then updated in March 2012 and August 2013 to ensure that all 2011 and 2012 papers were included. Moreover, for the period 2009–2012, we also allowed for the inclusion criteria to include a small number of best–worst scaling (BWS) DCEs/technical theoretical

papers, as long as they generated health-related DCE results alongside BWS results. We included case 3 type BWS studies [17, 18] in the main review because, unlike case 1 and 2 BWS studies, these involve a comparison between two or more profiles [17]. This is despite the fact that case 3 BWS studies do differ from mainstream DCEs, because respondents choose the least attractive profile in addition to the most attractive one [17].

At the request of one of the peer reviewers, we also reviewed health-related adaptive conjoint analysis (ACA) and adaptive choice-based conjoint (ACBC) studies, and any menu-based conjoint analyses that had been published between 1990 and 2012. Such analyses had been excluded from the previous reviews [3, 4].

3 Search Results

Following the PubMed searches using the aforementioned search terms, we sourced 12 ACA/ACBC analyses for the period 2009–2012 [19–30]; 14 ACA/ACBC analyses for the period 2001–2008 [31–44], and no analyses of these types for the period 1990–2000. However, we reviewed these separately and deposited the data in an electronic supplement (see the Electronic Supplementary Material) because these analyses adopt a fundamentally different approach to valuing attributes to mainstream DCE analyses, and we wanted to ensure that data in the main body of the paper were in step with inclusion criteria adopted for the previous reviews [3, 4], which had excluded such analyses.

Overall, 179 analyses were identified as meeting the inclusion criteria for the main review, i.e. health-related DCEs or case 3 BWS analyses published in the English language. Each paper was read carefully and key data extracted systematically in the sense of evaluating them against a checklist of pre-established criteria, which largely corresponded to those used in the most recent of the previous reviews [3]. The data are summarized in the following Sects. 3.1–7.2. In Table 1, we provide further information relating to the definitions and other details of analyses in each of the categories.

Category A covers 25 separate analyses in 24 papers [45–67]; Category B includes 13 analyses in 13 papers [68–80]; Category C encompasses 81 analyses in 81 papers [81–162]; Category D relates to four analyses in four papers [163–166]; Category E covers 11 different analyses in eight papers [167–174]; Category F encompasses 24 analyses in 23 papers [47, 71, 72, 82, 86, 107, 119, 161, 175–189]; Category G includes 24 analyses in 23 papers [53, 62, 70, 72, 103, 122, 133, 139, 141, 143, 145, 190–201]; and Category H relates to 'other' analyses, and there are 21 'other' analyses in 21 papers [63, 90, 103, 137, 145, 158, 159, 197, 202–214]. In Sects. 3.1–7.2, key findings are summarized in graphs. In the following text, we highlight changes that are of a reasonable magnitude and may be regarded as of significance.

3.1 Number of Discrete Choice Experiment (DCE) Analyses per Year

Figure 1 summarizes the average number of DCEs published per year across the three review periods. The 2001–2008 review [3] noted that the number of published applications of DCEs in healthcare rose from a mean of 3 per year (1990–2000) to a mean of 14 per year (2001–2008). Our review for 2009–2012 showed that the average number of analyses rose again to 45 per year (2009–2012), a marked increase, and peaked at 74 in 2012.

3.2 DCE Studies Country of Origin

Figure 2 indicates the proportion of analyses emanating from different countries during the three time periods. The 2001–2008 review noted that the UK remained the main source of DCEs in healthcare. However, UK dominance has been eroded considerably since then (see Fig. 2). The proportion of analyses emanating from the UK has continued to fall, from 59 % in 1990–2000 to 48 % in 2001–2008, and to 22 % during 2009–2012. Moreover, the proportion of analyses emanating from Australia (AUS) has fallen from 18 % in 1990–2000 to 11 % in 2001–2008, and to 7 % in 2009–2012.

Comparing 2001–2008 with 2009–2012, an increased proportion of analyses now originate in the USA, Canada (CAN), Denmark (DNK), the Netherlands (NLD), and Germany (DEU). There was also an increase in analyses coming from 'other' countries (11 % in 2001–2008 compared with 25 % in 2009–2012), reflecting an increasing trend towards applying DCEs across a range of high-, middle-, and low-income countries[1].

3.3 The Number of Attributes Included in DCE Studies

Figure 3 provides information on the number of attributes included in DCE analyses across the three time periods. The most noteworthy change includes the fact that the proportion of analyses with four or five attributes rose from 29 % in 1990–2000 to 44 % in 2001–2008, but fell back to 32 % in 2009–2012. There was also an increase in the number of DCEs with between seven and nine attributes: 12 % in 1990–2000, 13 % in 2001–2008, increasing to 22 % in 2009–2012.

[1] Lower income countries in 2008–2012 included Kenya, South Africa, Thailand, China, Ghana, Vietnam, Ethiopia, Peru, Ukraine, India, Cuba, Nepal, Turkey, and Burkina Faso.

Table 1 Definitions, and details of total number of analyses in each category

Category	Definition of category	Number of analyses, and number of papers the analyses are contained in	Number of papers per category also covered by other categories and citation details	Other explanatory information
A	Patient or consumer experience factors	25 (24)	3 [47, 53, 62]	Within this category, a paper by Damman et al. [46] contains two analyses, one relating to knees, and another relating to cataracts; an analysis by Goodall et al. [51] contains two analyses, one relating to patient preferences and another relating to carer preferences. There are also two papers cited for one analysis by Naik-Panvelkar et al. [60, 61]
B	Valuing health outcomes	13 (13)	2 [70, 72]	Not applicable
C	Investigating trade-offs between health outcomes and patient or consumer experience factors	81 (81)	13 [82, 90, 103, 107, 119, 133, 137, 139, 141, 143, 146, 158, 161]	Within this category there are two papers by Morton et al. [131, 132], which have been reviewed as one analysis. However, a paper by Regier et al. [143] contained two analyses (one relating to fungal treatment, and the other relating to bacterial issues)
D	Estimating utility weights within the quality-adjusted life-year framework	4 (4)	Not applicable	Not applicable
E	Job choices	11 (8)	Not applicable	Within this category, a paper by Rockers et al. [173] contains four analyses, one relating to medical student preferences, another relating to nursing student preferences, another relating to pharmacy student preferences, and another relating to science student preferences
F	Developing priority setting mechanism	24 (23)	8 [47, 71, 72, 82, 86, 107, 119, 161]	Within this category, the paper by Promberger et al. [184] contains two separate analyses for evaluation
G	Health professionals preferences for treatment and screening options	24 (23)	10 [53, 62, 70, 72, 103, 133, 139, 141, 143, 145]	Within this category, the paper by Regier et al. [143] contains two separate analyses for evaluation. One of these relates to fungal infection and the other relates to bacterial infection
H	Other	21 (21)	8 [63, 90, 103, 137, 145, 158, 159, 197]	Not applicable

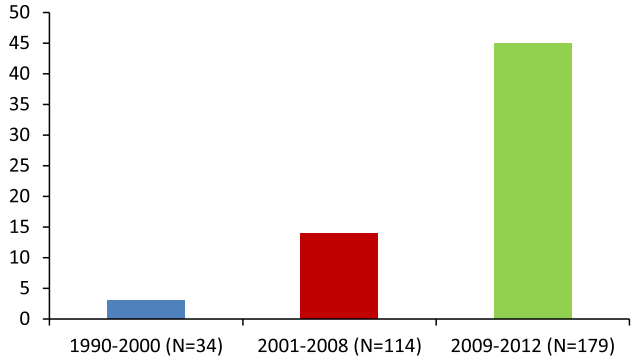

Fig. 1 Average number of DCE studies/year. *DCE* discrete choice experiment

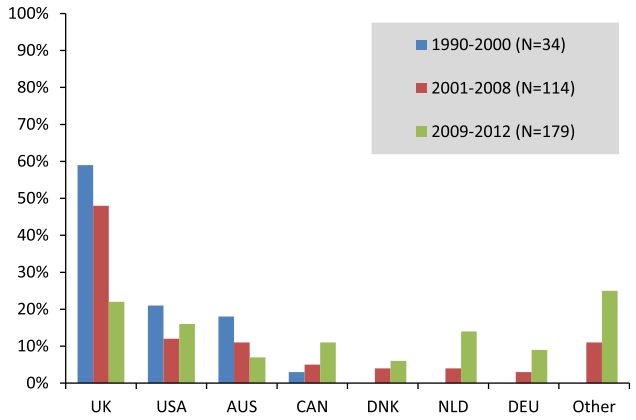

Fig. 2 Country of origin. *AUS* Australia, *CAN* Canada, *DEU* Germany, *DNK* Denmark, *NLD* the Netherlands

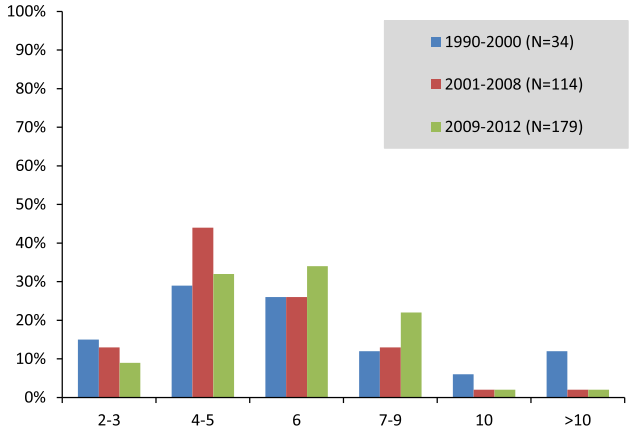

Fig. 3 Number of attributes

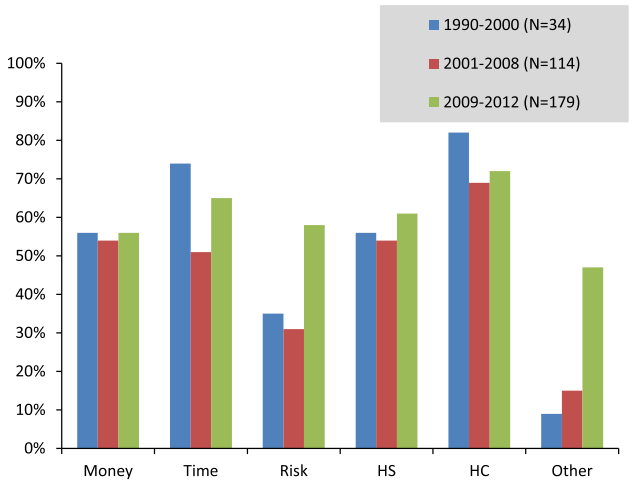

Fig. 4 Attribute domains. *HC* healthcare, *HS* health status

The proportion of analyses with more than ten attributes fell from 12 % in 1990–2000 to 2 % in 2001–2008, and remained at that level in 2009–2012.

3.4 Domains of DCE Attributes

Figure 4 provides information on the proportion of DCEs encompassing different domains. The main noteworthy changes include the fact that the proportion of analyses with a domain related to time fluctuated; it was 74 % in 1990–2000, in 2001–2008 it fell to 51 %, before rising again to 65 % in 2009–2012.

The proportion of DCEs including a measure of risk rose in the most recent period from 35 % in 1990–2000 and 31 % in 2001–2008, to 57 % in 2009–2012.

The proportion of analyses with a healthcare (HC) domain also fluctuated: 82 % in 1990–2000, falling to 69 % during 2001–2008, and increasing to 72 % in 2009–2012. At the same time, the proportion of analyses with attributes relating to 'other' domains, not encompassed by existing categories, increased from 9 % in 1990–2000 to 15 % in 2001–2008, and 47 % in 2009–2012. Additional categories in Fig. 4 include a monetary domain (Money) and a health status domain (HS).

3.5 The Number of Questions Posed by DCEs

Figure 5 provides information on the number of choice tasks posed by DCEs. The main noteworthy trends are as follows. The proportion of DCE analyses posing eight or fewer choices (<9) was 38 % in 1990–2000, 39 % in 2001–2008, but fell back to 22 % in 2009–2012. In contrast, the proportion of analyses with 9–16 choices was 53 % in 1990–2000, falling to 38 % during 2001–2008, and rising to 62 % during 2009–2012. The proportion of analyses with more than 16 choices (>16) rose initially and then stabilized (6 % in 1990–2000, 18 % in 2001–2008, and 15 % in 2009–2012).

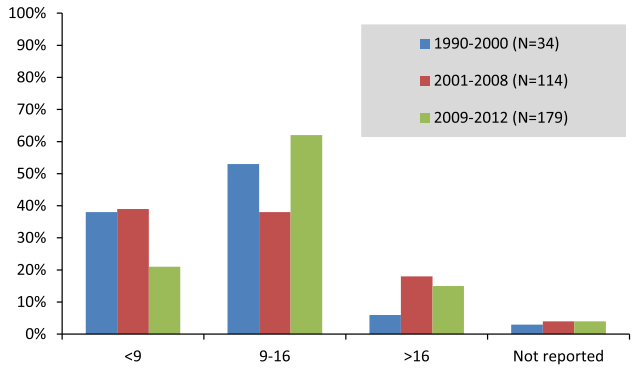

Fig. 5 Number of choice tasks

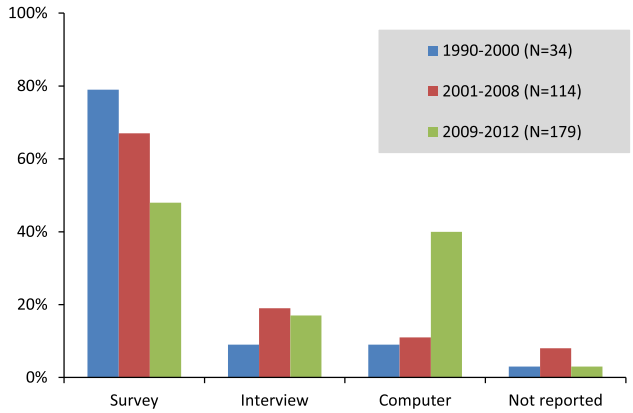

Fig. 6 Survey administration

3.6 DCE Survey Administration

Figure 6 provides information on the different modes of administering DCEs. Since 1990, there has been a trend away from self-completed pen/paper questionnaires. The proportion of analyses using self-completed questionnaires (Survey) was 79 % in 1990–2000, falling to 67 % in 2001–2008, and then further to 48 % in 2009–2012. The proportion of interviewer-administered DCEs (Interview) was 9 % in 1990–2000, rising to 19 % in 2001–2008, and was 17 % in 2009–2012.

Overall, there has been a trend towards DCEs involving computerized administration (Computer), sometimes involving internet surveys, over the last 20 years. There have been improvements in computer technology, combined with the increased use of computers by the wider population. This has made accessing DCE respondent samples using computers easier. Moreover, the ease with which DCE samples can be accessed using computers and the internet partly explains the trend towards increased use of DCEs since 1990. During 1990–2000, 9 % of analyses involved computerized administration; the figure was 11 % in 2001–2008 and then rose sharply to 40 % during 2009–2012. As depicted in Fig. 6, a small proportion of analyses failed to report (Not reported) the form of survey administration in each period.

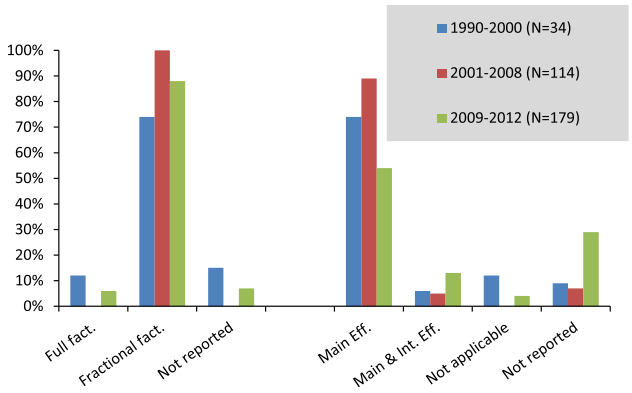

Fig. 7 Design plan. *Eff.* effects, *fact.* factorial, *Int.* interaction

4 DCE Experimental Design and Choice Set Construction

A good discussion of some of the relevant issues relating to DCE design is contained in the review by de Bekker-Grob et al. [3], so in the interests of brevity, we refer the reader to that paper and to another key citation [11].

4.1 Design Plan

Figure 7 depicts information on the different types of design plans. The most noteworthy trends are as follows. The proportion of analyses involving full factorial (Full fact.) DCE designs fell from 12 % in 1990–2000 to 0 % in 2001–2008, and then rose again to 6 % during 2009–2012. In the period 1990–2000, 74 % of analyses adopted a fractional factorial design (Fractional fact.), a proportion that rose to 100 % in 2001–2008, but then decreased to 88 % in 2009–2012. Overall, 15 % of analyses did not clearly report their design type (Not reported) in 1990–2000, a proportion that fell to 0 % in 2001–2008, but then rose again to 7 % during 2009–2012.

Overall in 1990–2000, 74 % of DCE analyses involved a 'main effects' design (Main Eff.), and this proportion rose to 89 % during 2001–2008, but then fell back to 54 % in 2009–2012. Therefore, as with the baseline and 2001–2008 reviews, 'main effects' designs remain the dominant type of design in published DCE studies. In 1990–2000, 6 % of analyses catered for interaction effects alongside main effects (Main & Int. Eff.); the proportion was 5 % in 2001–2008, and increased to 13 % in 2009–2012. In some cases, a design plan was not applicable, whilst in others, it was not reported.

4.2 Use of Software Packages to Design DCEs

Figure 8 summarizes information on the use of different software packages for the design of the DCEs. The most noteworthy trends are that the use of a software package to design DCEs remained steady throughout the years (Fig. 9).

Figure 8 shows there seems to have been a general trend away from using SPEED over the period as new software has become available. In 1990–2000, 38 % of analyses used SPEED; this proportion fell to 19 % in 2001–2008, and to 4 % in 2009–2012.

The SAS package (which can provide D-efficient designs) has become increasingly popular. Recorded use rose from 0 % in 1990–2000 to 12 % in 2001–2008, and 21 % in 2009–2012. Use of SPSS did not change that much. The use of Sawtooth software fluctuated; 6 % of analyses used this software in 1990–2000, 4 % used it in 2001–2008, and 13 % used it in 2009–2012. The use of 'other' software was also low (6 % in 1990–2000, 0 % in 2001–2008, and 7 % in 2009–2012[2]), and only a small proportion of analyses in each period failed to provide information on type of software (No details).

4.3 Use of Design Catalogues, Websites, and Expert Advice to Design DCE Questionnaires

Figure 9 depicts information on the use of software, design catalogues, websites, and experts to inform DCE design and whether this was not reported. Figure 9 shows that there have not been any particularly large changes in the use of these over the three periods.

4.4 Methods Used to Create Choice Sets

Figure 10 depicts information on the use of different methods to create choice sets. The most noteworthy trends are as follows. In 1990–2000, 9 % of analyses reported designs that involved orthogonal arrays with single profiles, i.e. binary choices (Single profiles); the proportion was 11 % in 2001–2008, but fell to 1 % in 2009–2012. Use of orthogonal arrays with random pairing (RP) was more common, but has fallen over time; in 1990–2000 it was applied in 53 % of analyses, falling to 17 % in 2001–2008 and 10 % in 2009–2012.

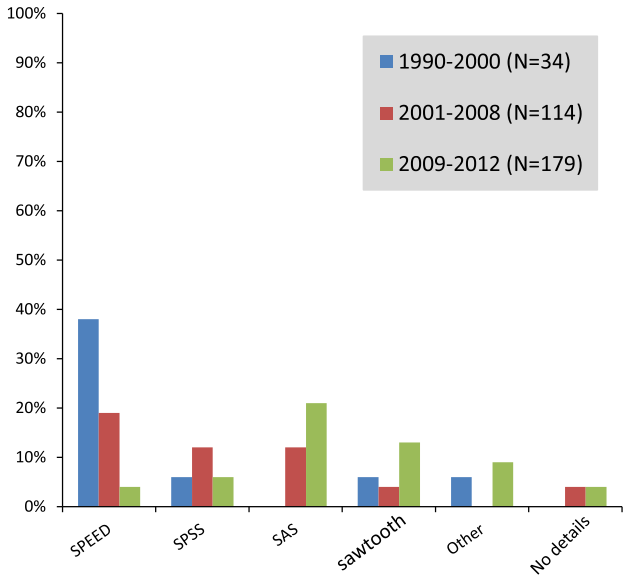

Fig. 8 Software packages

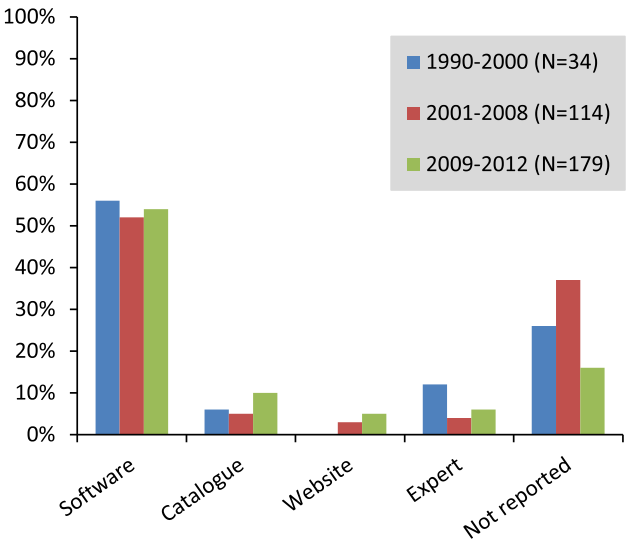

Fig. 9 Design source

Analyses involving orthogonal arrays with pairing with a constant comparator constituted approximately one in five designs in earlier periods, 18 % in 1990–2000 and 20 % in 2001–2008, before falling to 3 % in 2009–2012. In 1990–2000, none of the analyses involved orthogonal arrays with a foldover design, but this proportion rose to 10 % in 2001–2008 and 17 % in 2009–2012. Very few analyses in each period used a foldover design with random pairing (Foldover RP), or pragmatically chosen designs. Similarly, there has been a general trend towards D-efficient designs (D-efficiency), rising from 0 % in 1990–2000 to 12 % of studies in 2001–2008, and 30 % of studies in 2009–2012. The proportion of analyses that did not clearly report (Not reported) the methods used to create choice sets

[2] 'Other' packages used included Gauss for two analyses; nGene (a Bayesian efficient design) for four analyses; and the statistical design procedure Gosset for one analysis; a D-efficient design advocated by Rose and Bliemer for one analysis; STATA for one design; a design described as "an experimental design algorithm optimizing orthogonality, attribute balance, and efficiency" for one design; and Street and Burgess Software for one design.

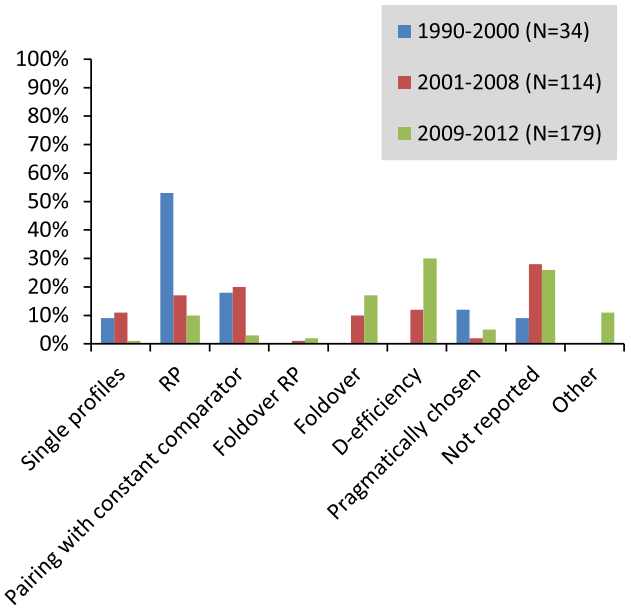

Fig. 10 Methods to create choice sets. *RP* random pairing

rose from 9 % in 1990–2000 to 28 % in 2001–2008 and stabilized at 26 % in 2009–2012, whilst in one period (2009–2012), 11 % of analyses used 'other' methods to create choice sets.

5 Estimation Procedures

As there is a good explanation of RUT, alternative DCE econometric models, and the appropriateness of different models for different DCE applications in the earlier review paper, we refer readers to Sects. 5.1–5.3 of that paper in the interests of brevity [3]. Figure 11 depicts information on the different estimation methods. The most noteworthy trends are described in the sections below. In Fig. 11 details of the econometric estimation methods used are depicted.

5.1 Use of Probit, Random Effects Probit, Logit, and Random Effects Logit

As previously reported, early DCE studies, i.e. those published in 1990–2000, seemed to focus upon applying either binary choice or 'forced choice' DCEs [4]. So, for example, in 1990–2000, 18 % of analyses used probit; this proportion fell to 7 % in 2001–2008, and fell further to 2 % in 2009–2012. Similarly, in 1990–2000, 53 % of analyses used random effects probit (RE probit), falling to 41 % in 2001–2008, and then further to 10 % in 2009–2012. The proportion of logit analyses was 3 % in 1990–2000, rising to 11 % in 2001–2008, and was 10 % in 2009–2012, and relatively few analyses used random effects logit (RE Logit) in each time period.

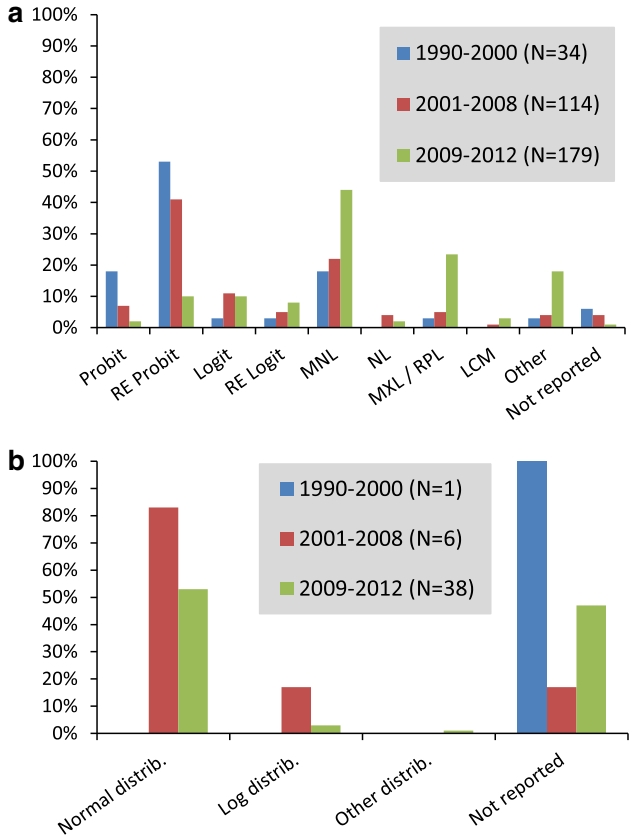

Fig. 11 **a** Estimation procedures. **b** Distributional assumptions. *Distrib.* distributions, *LCM* latent class model, *MNL* multinomial logit, *MXL/RPL* mixed logit/random parameters logit, *NL* nested logit, *RE* random effects

5.2 Use of Multinomial Logit

The overall decline in the use of logit, probit and random effects probit reported above has been offset by an increased use of multinomial logit (MNL) analyses, which are sometimes otherwise known as conditional logit analyses. These analyses have the advantage that they can cater for more than two response options, and they can also allow respondents to 'opt-out' from making a decision. Sometimes such models may also be associated with better 'goodness of fit' than some other econometric models. During 1990–2000, 18 % of studies used MNL, 22 % used it during 2001–2008, rising to 44 % during 2009–2012.

5.3 Use of Nested Logit

During the period 2001–2008, a small shift towards use of nested logit (NL), a technique that relaxes the independence of irrelevant alternatives (IIA), was observed [3]. It was applied in 4 % of studies during 2001–2008, up from 0 % in 1990–2000. For the period 2009–2012, the proportion remained low at 2 % of studies.

5.4 Models Applicable When There is Preference Heterogeneity

During 1990–2000, only 3 % of studies used mixed logit/random parameters logit (MXL/RPL); by 2001–2008, 5 % of analyses used MXL/RPL. During the period 2009–2012, there was a clear trend towards increased use of MXL/RPL, and 21 % of analyses utilized the technique. All the analyses involving MXL/RPL found evidence of preference heterogeneity. Ideally, when MXL/RPL analyses are submitted for publication, details of the number of replications (sometimes described as 'Halton draws') should be provided, as results can be sensitive to the number of replications. This occurred in 0 % of MXL/RPL analyses in 1990–2000, 67 % in 2001–2008, and 47 % in 2009–2012.

Unlike latent class models (LCM), MXL/RPL analyses make distributional assumptions for random parameters (Fig. 11b). Not all MXL/RPL analyses indicate what these are. Indeed, in 1990–2000, 100 % of analyses failed to indicate them. In 2001–2008, 17 % failed to provide this information, and in 2009–2012, 47 % failed to provide this information. When such information was provided, analyses usually indicated they had assumed normal distributions for random parameters: 0 % in 1990–2000, 83 % in 2001–2008, and 53 % in 2009–2012. However, in 17 % of cases in 2001–2008, and 8 % in 2009–2012, models assuming logarithmic distributions for random parameters were also reported alongside results from models assuming normal distributions for random parameters. Also, one study [115] used a mixed logit hierarchical Bayesian model (MLHB), an extension of mixed logit modeling. Another analysis used what it described as a Bayesian-like approach similar to mixed logit [80]. Sometimes hierarchical Bayesian analysis has also been used without mixed logit [48, 70, 114, 204]. A small proportion of analyses did not report the estimation procedure used.

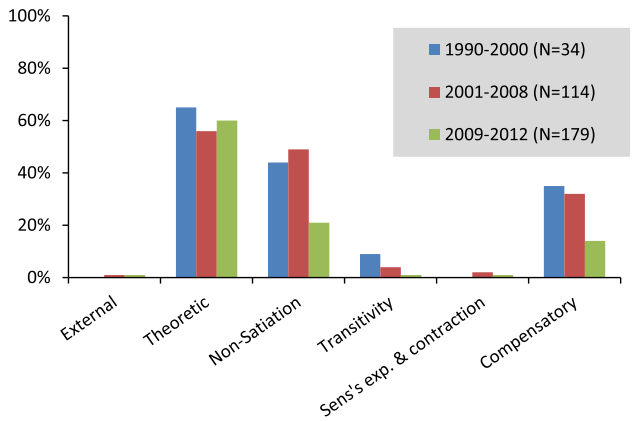

Fig. 12 Validity checks. *Exp.* expansion

During the early period (1990–2000), no study used LCM. During the period 2001–2008, one study (1 %) used LCM, and the study also found evidence of preference heterogeneity [216]. During 2009–2012, five analyses (3 %) [57, 61, 129, 168, 204] used LCM, and they all identified evidence of preference heterogeneity.

A few analyses used 'other' estimation procedures. In 1990–2000, this was the case for 3 % of analyses; the proportion was 4 % of analyses in 2001–2008 and 17 % of analyses in 2009–2012[3].

6 Validity

6.1 Validity Checks

The proportions of studies that used different validity tests are depicted in Fig. 12.

The most noteworthy trends are as follows. Tests of external validity (External) are particularly valuable because stated preferences from DCEs can then be compared with revealed preferences. However, there is often little scope to conduct tests of external validity (particularly if DCEs are applied in the context of state funded healthcare provision). This may explain why none of the analyses contained a test for external validity during 1990–2000. The proportion rose to 1/114 analyses (1 %) in 2001–2008 as there was a study [217] that compared doctors' prescribing decisions in relation to prescriptions for alcoholism with the preferences they expressed in a DCE. For the most recent period (2009–2011), only one [144] analysis (<1 %) contained a test of external validity.

[3] 'Other' methods used in 2009–2012 included weighted probit [68]; OLS with a hetero-robust covariance matrix estimator [192]; a method described as "modelling including interaction effects" [45]; Cox's proportional hazards model with time-dependent covariate [105]; weighted least squares regression to estimate utility weights [105]; multivariate ordered probit to estimate conjoint utility parameters [76]; mixed logit with hierarchical Bayesian modeling and ordered probit [115]; generalized estimated equations [109, 125]; random parameter logit estimated using a hierarchical Bayesian algorithm [208]; conditional logit and parameter weighting functions [160]; a series of multivariate regressions [50, 65]; a method described as Bayesian-like for preference weights [80]; OLS [87]; hierarchical Bayesian analysis [48, 70, 114, 205, 212]; multinomial exploded logit [177]; Firth's unbiased estimator [193]; combined conditional logit and ranked logit model [127]; multivariate multilevel logistic regression [46]; generalized multinomial logit [119]; mixed effect logistic regression [184], error components mixed logit analysis [63]; a combination of Bayes theorem, Monte Carlo Markov chain procedure and the Metropolis Hastings algorithm [182]; and logistic and probit regression using cluster-robust standard error (SE), random effects and GEE and multinomial logistic and probit regressions with cluster-robust SE and random effects multinomial logistic model and probit model with cluster-robust SE treating the choices from two stages as two correlated binary outcomes [94].

Most analyses included tests for internal theoretical validity (Theoretic). Overall, 65 % of analyses in 1990–2000 included these tests, with the proportion falling to 56 % in 2001–2008, and it was 60 % in 2009–2012. Such tests involve an assessment of whether coefficients appear to move in line with prior expectations, and studies generally reported that this was the case.

Tests for non-satiation were less frequently reported. For the period 1990–2000, 44 % of analyses contained such a test; the proportion was 49 % in 2001–2008, before falling to 21 % in 2009–2012. The decline in the use of such tests probably reflects concerns that they tend to be passed, so that they are a relatively weak test of validity. Also, in an influential paper [218], it has been argued that preferences that may appear to be 'irrational' may in reality be compatible with some form of rationality. Therefore, to delete such responses may be inappropriate, so the decline in the use of such tests may reflect good practice.

If tests of transitivity could readily be applied using DCEs, the information yielded might be more useful. However, they cannot always be readily applied, which is presumably why over the period 1990–2000 only 9 % of analyses contained a transitivity test; in 2001–2008, 4 % of analyses contained such a test, and during 2009–2012, 1 % of analyses contained a transitivity test. During 1990–2000, none of the analyses contained a test relating to Sen's expansion and contraction properties (Sen's exp. & contraction); the proportion was 2 % of analyses during 2001–2008, and 1 % of analyses during 2009–2012. Use of a test for internal compensatory decision making (Compensatory) [3] was much more frequent. In 1990–2000, 35 % of analyses involved such a test; the value for 2001–2008 was 32 % of analyses, but in 2009–2012, this declined to 14 % of analyses.

6.2 Use of Qualitative Methods to Enhance DCE Processes and Results

Information on the use of qualitative methods to enhance DCE processes and results is depicted in Fig. 13. In 1990–2000, 18 % of analyses used qualitative methods to inform attribute selection (Attrib. selection), rising to 69 % of analyses in 2001–2008, before declining to 51 % of analyses in 2009–2012. This is potentially a worrying trend because if the selection of attributes is not properly grounded in qualitative research, then inappropriate attributes may be specified and appropriate attributes may be omitted (triggering omitted variable bias). It would be of little concern, however, if the recent reduction in the use of qualitative methods to inform attribute selection was triggered by the wider use of DCEs in contexts in which the decision framework is already known (for example, if DCEs are conducted alongside clinical trials).

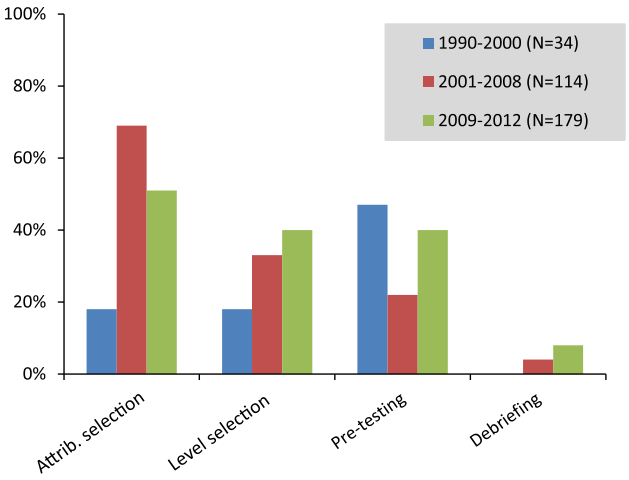

Fig. 13 Use of qualitative methods. *Attrib.* attribute.

In contrast, the use of qualitative methods to inform attribute level selection (Level selection) increased; the proportion was 18 % of analyses in 1990–2000, increasing to 33 % in 2001–2008, before increasing again to 40 % in 2009–2012. The use of a pre-testing questionnaire (Pre-testing) fluctuated over time; it was applied in 47 % of analyses in 1990–2000, just 32 % of analyses in 2001–2008, but was applied in 41 % of analyses in 2009–2012. The use of debriefing choices (Debriefing) to help strengthen understanding increased from 0 % of analyses in 1990–2000 to 4 % of analyses in 2001–2008, and 8 % of analyses during 2009–2012.

7 Areas of Application and Outcome Measures

7.1 Areas of Application

As indicated by de Bekker-Grob et al. [3], although DCEs had originally been introduced into health economics primarily in order to value patient experience [219], there was clear evidence that the application of DCEs had broadened considerably by 2000–2008 [3]. Moreover, this trend continued into 2009–2012. Figure 14 summarizes the relevant data (for the definitions of categories A, B, C, D, E, F, G, and H, refer to Table 1).

The main noteworthy trends are as follows. In 1990–2000, 35 % of analyses had a main study objective that involved valuing experience factors (Category A). The proportion was the same in 2001–2008, as 35 % of analyses had the same main study objective. However, during 2009–2012, this proportion fell to 12 % of analyses. In contrast, the proportion of DCEs exploring trade-offs between health outcomes and experience factors has risen steadily (Category C). In 1990–2000, 41 % of analyses had this as a primary objective; during 2001–2008, the

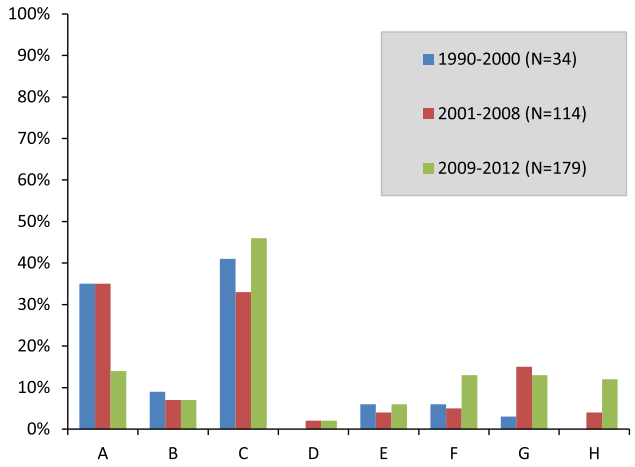

Fig. 14 Areas of application. For the definitions of categories A, B, C, D, E, F, G, and H, refer to Table 1

proportion was 33 % of analyses, increasing further to 44 % of analyses in 2009–2012. This reflects a shift from examining patient experience factors (Category A) in isolation (down from 35 % in 2001–2008 to 12 % in 2009–2012) towards estimating trade-offs between health outcomes and experience factors (Category C), which increased from 33 % of analyses in 2001–2008 to 41 % in 2009–2012. The latter category (Category C) also includes the estimation of trade-offs for non-patient groups, whereas the former (Category A) is specific to patient respondents.

In 1990–2000, no analysis included a main objective of estimating utility weights within a quality-adjusted life-year (QALY) framework (Category D). During 2001–2008, 2 % of analyses had this as the main objective. These two analyses used DCEs as an alternative to standard gamble (SG) and time trade-off (TTO) to estimate utility weights within a QALY framework [220, 221]. More recently, there has been some further work in this area. In 2009–2012, 2 % of analyses had this as their main objective, reflecting some interest in this research agenda. One of these analyses [165] looked at deriving distributional weights for QALYs using DCEs; another [164] used DCEs to quantify EQ-5D health states, whilst another [163] explored whether a DCE that resembles TTO exercises is able to estimate consistent values on the health utility scale for the EQ-5D. A further analysis compared case 3 BWS DCE analysis with WTP analysis [166].

A small proportion of DCEs have had a primary objective of evaluating job choices, human resource policy (Category E), or developing priority setting frameworks (Category F), and values for these categories did not exhibit much change (see Fig. 14).

During 1990–2000, 3 % of analyses had the main objective of establishing health professionals' preferences (Category G); this rose to 15 % in 2001–2008, before falling slightly to 12 % in 2009–2012. In 1990–2000, 0/34 analyses (0 %) had an 'other' (Category H) main objective; this rose to 4 % of analyses in 2001–2008, before rising again to 10 % of analyses in 2009–2012[4].

7.2 Outcome Measures

Information on trends relating to 'main outputs' is depicted in Fig. 15. In the past, DCEs often expressed outputs in terms of a primary outcome measure of 'per WTP unit' or 'per time unit'. In 1990–2000, 29 % of analyses used the 'per WTP unit' (WTP) outcome measure, increasing to 39 % of analyses in 2001–2008; however, in 2009–2012, the proportion was only 31 % of analyses. The use of 'per unit of time' (Time) as an outcome measure has also declined markedly over the period. During 1990–2000, 29 % of analyses used this outcome measure; in 2001–2008, the proportion was 20 % of analyses, and it declined further to 3 % of analyses in 2009–2012.

The proportion of DCEs using 'per risk unit' (Risk) as a primary outcome is low, and this has fluctuated little over the period (see Fig. 15). Only a minority of analyses use monetary welfare measures (Money) as the primary outcome measure, and this proportion has fallen in proportionate terms over time. During 1990–2000, 15 % of analyses involved a money welfare measure; during 2001–2008, the proportion was 12 % of analyses; and during 2009–2012, the proportion was 2 % of analyses.

[4] In 2009–2012, one study explored how changing the number of responses elicited from respondents might affect estimates of WTP [204]; another looked at parents' preferences for management of attention-deficit hyperactivity disorder [206]; one study looked at general public preferences for long-term care [137]; another two studies looked at preferences for human papillomavirus vaccine, one case looking a societal preferences [207] and the other [63] looking at mothers' preferences; another study looked at the valuation of diagnostic testing for idiopathic developmental disability by the general population [208]; another looked at various stakeholder groups' preferences for coagulation factor concentrates to treat hemophilia [145]; one study looked at general public preferences for tele-endocopy services [158]; another compared Dutch and German preferences for health insurance amongst their populations [214]; one paper looked at public and decision maker preferences for pharmaceutical subsidy decisions [215]; one study explored how individuals perceive various coronary heart disease factors [203], whilst another described the relative importance of major adverse cardiac and cerebrovascular events to be used when analyzing trials [212]. Two other DCEs were performed on the area of quality improvement; one investigated how to best disseminate evidence-based practices to addiction service providers and administrators [205], while the other was used to investigate which indicators had the greatest impact on the decisions of health service inspectors concerning the assessment of quality of mental health care [211]. Other applications included a study on preferences of health workers in Burkina Faso for health-insurance payment mechanisms [209]; a study on how respondents valued mortality risk attributable to climate change reductions [210]; and a study on the preferences for reducing contaminated sites to reduce the risk for cancer [213].

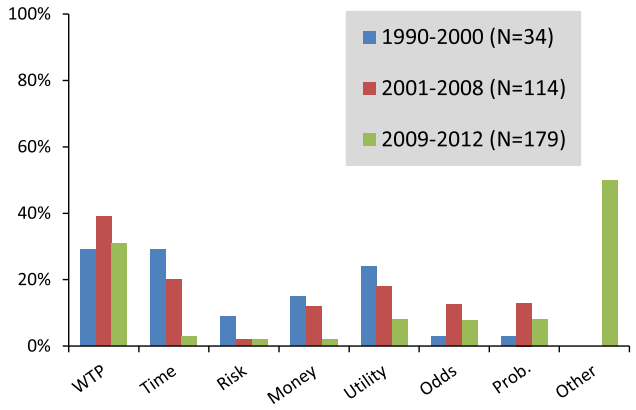

Fig. 15 Outcome measures. *Prob* probability, *WTP* willingness to pay

The use of utility scores (Utility) as the primary outcome measure is more common, and this has fluctuated over time. In 1990–2000, 24 % of analyses had utility scores as the primary outcome measure. The proportion was 18 % of analyses during 2001–2008, decreasing to 8 % of analyses during 2009–2012.

There is also evidence that the use of odds ratios (Odds) has fluctuated. In 1990–2000, only 3 % of analyses used odds ratios as the primary outcome measure. By 2001–2008, the proportion of had more than tripled to 11 % of analyses; the proportion was 8 % in 2009–2012. Likewise, the use of probability scores (Prob) increased from 3 % of analyses in 1990–2000 to 13 % of analyses in 2001–2008, before declining to 8 % of analyses during 2009–2012.

Finally, Fig. 15 presents information on 'other' outcome measures used. For the periods 1990–2000 and 2001–2008, the earlier review authors did not use an 'other' category for the main outcome measure used. However, for this review, we categorized a substantive number of analyses, 49 % of analyses, in the 'other' category. This was mainly because in 2009–2012 there was a trend to use importance scores or relative importance of attributes (25 % of analyses) or preference weights (6 % of analyses).

8 Review of Adaptive Conjoint Analysis/Adaptive Choice Based Conjoint Studies

Having summarized the ACA/ACBC studies in an electronic supplement (because they use a fundamentally different approach to DCEs), we concluded that it was difficult to discern major trends in relation to these analyses across study periods. This is because our PubMed search unearthed a total of only 26 analyses in 26 papers to review for the entire review period, 1990–2012. Nonetheless, for the interesting trends that have been discerned, the details have been provided in Appendix A of the Electronic Supplementary Material.

Our searches (Table AI; see the Electronic Supplementary Material for all appendix tables) unearthed no studies of this type for the period 1990–2000, 14 analyses for the period 2001–2008, and 12 analyses for the period 2009–2012. In contrast to the DCE literature, most of these analyses seemed to emanate from the USA, and the surveys were more likely to be computer administered. The analyses also tended to be designed using Sawtooth software (Table AII), and no analyses indicated the use of an alternative software package. Published analyses did not indicate whether they ever used the main estimation methods used for DCEs (Table AIII), and all of them either fell into the 'other' or 'not reported' categories. Moreover, validity checks were rarely incorporated into ACA/ACBC analyses (Table AIV).

9 Discussion

The number of published health-related DCEs has increased dramatically over the last 2 decades. There has also been a shift away from UK dominance of health-related DCEs, with a widening range of countries producing DCE studies.

The 2001–2008 review [3] noted a wide range of policy applications for DCEs; this continued during 2009–2012. In 2001–2008, the valuation of patient experience continued "to be the focus of the majority of studies" [3]. In contrast, this declined as the main focus during 2009–2012. Nevertheless, in 2009–2012, most DCEs continued to include attributes relating to patient experiences, but increasingly in order to examine trade-offs between health outcomes and experience factors. Also health outcomes and experience factors for respondents groups other than patients are encompassed by this category (e.g., Category C analyses).

The 2001–2008 review [3] reported that "willingness to pay continued to be a commonly used output from DCEs" over that period. However, the present review found evidence that the proportion of DCE studies using either a 'per WTP unit' or a 'monetary welfare measure' as their primary outcome has fallen. This could in part be attributable to concerns that have been raised in relation to the use of DCEs to elicit WTP. These include whether estimated WTP obtained via DCEs may be sensitive to the range specified for the monetary attribute or the presence or absence of payment per se [222], or the presence or absence of a non-zero cost, rather than the level of cost indicated by the monetary attribute [223]. Other evidence suggests that the way attributes are 'framed' in a DCE questionnaire may impact upon estimated WTP [113].

Furthermore, the hypothetical nature of DCEs can hinder correct estimates of WTP because respondents will not be bound by the choices they make [143].

Another issue arises because when estimating marginal willingness to pay (MWTP), it is commonly assumed that marginal utility of money is constant and the cost function is therefore continuous and linear. However, there is reason to believe that the cost gradient may not be continuous and linear [115]. Therefore, if WTP is calculated there is a need to proceed with econometric analysis that assumes more complex indirect utility functions [123, 124], for example, using interaction terms between attributes [224], or using non-linear attribute transformations, such as the squaring of attributes [225], or taking natural logarithms [226].

In addition to using methods that can be used to identify unobserved preference heterogeneity, which we discussed in detail in Sect. 5.4, the issue of segmenting DCE data to examine the preferences of defined subgroups is sometimes important. One early analysis [227] segmented the DCE data according to the severity of symptoms associated with osteoarthritis, and the importance of a joint ache attribute was seen to increase in respondents with more severe symptoms. Other analyses relating to establishing priority criteria for allocating cadaveric kidney transplants [71, 72] have provided evidence of statistically significant differences in preferences between different stakeholder groups. A major finding to emerge from this research was that whilst non-ethnic minority patients would prefer to allocate kidney transplants to recipients with a good tissue match, ethnic minorities (who would be disadvantaged by use of such priority criteria) would not. Another interesting analysis relating to segmentation used segmentation because "health organizations need to understand whether the same health treatments, prevention programs, services, and products should be applied to everyone in the relevant population or whether different treatments need to be provided to each of several segments that are relatively homogeneous internally but heterogeneous among segments" [228]. Segmenting the data to facilitate subgroup analysis is particularly appropriate if policy-relevant differences in preferences between defined subgroups might be applicable.

The use of simulation may be important, when DCEs are applied, because simulation may enable you to do something useful with DCE data. For example, in a DCE relating to junior doctors' preferences for specialty choice, it was found that increasing general practitioners (GPs) wages by $AUS50,000, or increasing opportunities for procedural or academic work, can increase the number of junior doctors choosing general practice by between 8 and 13 % [174]. Another example of how useful simulation of DCE data can be is an analysis that was designed to predict the place of out-of-hours care. Using DCE data to predict market shares, it was predicted that a new GP cooperative could capture about a third of the market, ahead of the emergency department, the second most preferred service [183].

In Sect. 5.2, we pointed out that econometric methods are increasingly being used which can facilitate allowing respondents to 'opt-out' from registering a preference. An example of why this might be important is apparent from an analysis relating to colorectal cancer screening [110]. This is because when screening for colorectal cancer, it was important to give people an 'opt-out' response in order to ensure that the choices respondents faced were realistic. Similarly, when evaluating two hypothetical smoking cessation mechanisms, it was important to provide respondents with an 'opt-out' option [128].

This review for 2009–2012 found an increasing trend towards presenting respondents with more DCE choice scenarios. Some evidence suggests [203] that later DCE responses might be more thought through, so this may be a welcome development. However, the optimal number of choices presented should ideally be established through piloting, because it is likely to be a function of the complexity of choices presented. There has also been an interest in developing approaches to cater for the inclusion of increased numbers of attributes within DCE designs [161, 198]. Another development has been a shift away from self-administered pen/pencil-response DCE questionnaires towards either interviewer-administered or, more particularly, computer-administered questionnaires and the use of internet panels.

The trend towards the increased use of D-efficient DCE designs noted by de Bekker-Grob et al. [3] has continued. Although there has been an increase in the proportion of analyses catering for interactions, main effects designs remain dominant. Trends away from the use of probit and random effects probit towards greater use of MNL reflect the increased use of DCEs incorporating more than two choices, or two choices plus an opt-out. Recent interest in the use of models catering for preference heterogeneity is welcome because when mixed logit or LCM is applied, it invariably identifies preference heterogeneity, which otherwise would have been overlooked. That said, one limitation of the mixed logit approach is that it requires the imposition of assumptions about the distribution of the random coefficients. If the distributional assumptions are not valid, then this can undermine the validity of findings about preference heterogeneity. LCM has the advantage over mixed logit that it does not involve the imposition of such distributional assumptions, but can have the disadvantage that it may be more time consuming to implement.

There appears to have been a decline in the use of most validity tests during 2009–2012, including tests of non-satiation, transitivity, Sen's expansion and contraction

properties, and tests of compensatory decision making. We might have anticipated a decline in the use of such validity checks, because the usefulness of the results they yield has increasingly been called into question [144, 218, 229]. Reassuringly, however, during 2009–2012, there has been an improvement in the proportion of analyses using qualitative methods to enhance DCE processes and results, in some respects, including the use of qualitative methods to inform level selection; use of pilot pre-testing questionnaires; and the use of qualitative methods to strengthen understanding of responses (including debriefing choices). A remaining cause for concern, however, is that the use of qualitative methods to inform attribute selection has declined since 2001–2008. This could lead to increased likelihood of omitted variable bias affecting DCE results.

The main limitation of this study was that, like the published review for 2001–2008 [3], we only used PubMed to source literature. However, as that review noted [3], when additional searches are conducted on other databases, it does not markedly affect review findings. So in the interests of ensuring comparability with data from that earlier review, we also restricted our searches to the PubMed database.

10 Conclusions

The use of DCEs in healthcare continues to grow dramatically, as does the scope of applications across an expanding range of countries. There is increasing evidence that more sophisticated approaches to DCE design and analytical techniques are improving the quality of final outputs. That said, recent evidence that the use of qualitative methods to inform attribute selection has declined is of concern.

Conflict of interest Dr. Michael D. Clark: no conflict of interest. Mr. Clark wrote the drafts of the paper, and then took on board feedback from co-authors and peer reviewers in order to further refine it. He will act as overall guarantor for this work. He also evaluated many of the analyses relating to the new review period (2009–2012), and conducted some of the literature searches. Dr. Domino Determann: no conflict of interest. Determann MD reviewed a significant proportion of DCE papers relating to the period 2009–2012, and conducted many of the literature searches. She also provided feedback on early drafts of the paper and suggested some amendments.

Professor Stavros Petrou: no conflict of interest. Professor Petrou supervised this new DCE review from the outset, and commented on drafts of the paper, suggesting edits.

Dr. Domenico Moro: no conflict of interest. Dr. Moro reviewed some papers involving the use of mixed logit or latent class models. He was part of the review team from the onset, and commented on drafts of the paper when appropriate.

Dr. Esther de Bekker-Grob: no conflict of interest. As the first author of a high-profile published review of the DCE literature [3] which reviewed the DCE literature for the period 2001–2008, this co-author helped to ensure consistency with the earlier published review in terms of application of review criteria. She also commented on drafts of the paper, and made some valuable contributions to the points raised by the paper in Sects. 9 and 10.

Ethics committee approval Not required.

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