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Applying discrete choice experiments (DCEs) in social care research

ABSTRACT

Discrete choice experiments (DCEs) have been widely used by economists to elicit people's values in a number of areas, including market, transport and environmental issues. The last two decades have seen an increasing use of the technique in health economics, and it is beginning to be applied in social care and related research. This review aims to help social care researchers, policymakers and practitioners make the best use of DCEs to value preferences in social care settings. It discusses what DCE is, what you can do with it, and its use to incorporate informal care in economic evaluations. It also describes the key stages of developing a DCE for social care and presents a comprehensive search of the literature to identify and describe DCE applications to social care. Some of the important challenges of applying DCEs to social care are identified, and the need for further methodological development is discussed.

RECOMMENDATIONS

- DCE can be used within social care as a useful tool to inform the evaluation of social care interventions and social-care related quality of life and wellbeing measures.
- Different methods of data collection (such as face-to-face interviews) in different settings and/or with different client groups should be explored as potential means to improve the utility of the approach in this setting.
- The benefit of using pictorial representations of choice sets (to reduce cognitive burden) should be explored further with respondents.
- Careful attention should be placed on the determination of choice sets and selection and levels of attributes within DCE design to reduce the potential of bias in the estimates produced.
- The cognitive burden to respondents should be reduced when using DCE within social care to help respondents choose options that reflect their true preferences.
- Using conditional logit modelling for analysis could improve insights about variation of responses with clear relevance for policymakers.
- Further research is needed to test the external validity of DCE responses in a social care setting which can improve and inform best practice guidance.
- Further comparative research of DCE with best-worst scaling (an alternative stated preference approach) is needed to determine which is the superior approach.

KEYWORDS

discrete choice experiment, stated preferences, social care research

ACKNOWLEDGEMENTS

The author is grateful to Mike Clark and Martin Knapp within NIHR SSCR for their edits on earlier drafts of this review, and for the external reviewers for their comments. f t

Contents

Introduction

An economic evaluation in social care should adopt a broad societal perspective to consider the impact of an intervention on all relevant stakeholders, including not only the provider(s) but also people who use services and their carers (Drummond *et al*. 2005, NICE 2013, SCIE *et al*. 2011, van den Berg *et al*. 2005) and other societal impacts.

In the context of this paper social care refers to the system of care and support for a range of practical help that people need arising from, for example, an illness or disability, rather than to the immediate health care needs arising from a condition. In England this may be funded by the state or, increasingly, from people's own finances (referred to as self-funded care). Support may be delivered in communities, people's homes, or in institutional care, and can be delivered by people working in the statutory, independent (for profit) or third (charity) sectors of the economy. Unpaid carers, usually relatives of the person needing support but not always, are a key component of this care system.

Service users and their carers, then, are at the centre of the social care system, and it is therefore critical that evaluation and planning of social care services should include their costs and that the outcomes of interventions should be valued from their perspective. Different approaches have been employed to value social care and carer support and have been extensively described and discussed elsewhere (Faria *et al*. 2012, Flynn *et al*. 2007, Koopmanschap *et al*. 2008, Marley *et al*. 2008, Netten 2011, Oremus and Tarride 2008, van den Berg *et al*. 2008, 2005, 2004).

The focus of this review is on the discrete choice experiment (DCE) approach, an economics tool that has been widely used to elicit people's values in a number of areas, including market, transport and environmental

DCE and measuring benefits in the delivery of social care

The discrete choice experiment (DCE) approach seeks to establish the relative importance to people of different characteristics in the provision of a good or service (de Bekker-Grob *et al.* 2012). It assumes that any good/service can be defined as a combination of levels of a given set of attributes and the total utility (satisfaction or preference) that an individual derives from that product is determined by those attributes.

In the example shown in figure 1, the choice of renting alternative accommodation to that currently occupied may depend on different factors, including type of accommodation (flat, semi-detached house, detached house), number of rooms, facilities available in the accommodation (such as gas/electric heating), closeness to work (miles), facilities available nearby (shops, schools, pubs), availability for moving in (weeks), and monthly rent (£).

The outcomes of a DCE provide an alternative measure of benefit, where weights can be attached to a range of outcomes (e.g. the level of pain accepted during rehabilitation in a healthcare study), and to process attributes (e.g. location of care, frequency of care) (de Bekker-Grob *et al.* 2012). For example a DCE provides opportunities to evaluate whether or not a given additional services and/or cash benefits are important to caregivers to support their caregiving role; the relative importance of these various attributes; and the trade-offs individuals are willing to make between them. It presents respondents with a set of choices between hypothetical scenarios (i.e. combinations of attributes) picked from all possible choices determined according to statistical design properties. Each choice includes two or more alternatives which vary in the levels of the attributes of interest, and individuals are asked to choose one alternative (see example in Figure 1). Usually each respondent is asked to make a number of choices within a single survey questionnaire.

Example of a DCE choice question from [illegible]

	PROPERTY A	PROPERTY B	
Type of property	Flat	Semi-detached house	
Number of rooms	2	4	
Fully furnished	Yes	No	
Closeness to work (miles)	1	2	
Facilities available nearby	Only shops	Shops, schools and bars	
Monthly rent (£)	450	750	
Please place a tick on the property you would choose	Property A ✔	Property B ☐	Current* ☐

* Information on current property to be collected from each individual within the DCE questionnaire

A DCE's usefulness is that it will identify what characteristics of the service respondents value. For example, in Figure 1, they could value 'rent', 'closeness to work', 'whether it is already furbished', 'number of rooms', 'facilities available nearby' rather than 'type of accommodation' and 'availability for moving in'. It can also identify the relative values that they attach to these characteristics (for example, they could value 'rent' and 'closeness to work' more than other aspects) and the trade-offs they are willing to make (e.g. how much extra time they are willing to wait in order to rent a place within one mile of work).

DCEs allow estimation of a utility (or satisfaction) function which specifies the relationship between the service attributes and consumer preferences. From this function it is possible to estimate utility or satisfaction scores for alternative accommodation on offer. Such utility scores can be combined with costing data to make recommendations concerning the most 'efficient' way of providing the good/service (Drummond *et al.* 2005).

When a cost is included, we can calculate how much respondents are willing to pay (WTP) for changes in attributes levels (for example, how much they are willing to pay to rent a flat closer to work), or for an overall change in the service (how much they are willing to pay to move out from their present property (wi

Conducting a DCE exercise

Identifying the decision to be made is the most important stage of the study. The researchers seek to characterise the decision problem in terms that the decision-maker understands. The researchers need to: define the choice situation (e.g. care services available to people with long-term care needs); search for information on alternatives (e.g. care packages), attributes (e.g. transportation services) and their levels (e.g. available, not available); and construct choice sets (see figure 2). These items are crucial- [illegible]

This possible restriction on the number of attributes refers to an assumption of the DCE approach that individuals consider all the attributes, and make trade-offs (e.g. how much money an individual would be willing to give up to have ‘facilities available nearby’). The number of feasible choice sets will also restrict the number of attributes and levels if the full survey is used in a single sample. Previous studies have demonstrated that respondents are able to manage up to 16 choices (de Bekker-Grob *et al*. 2012).

There are alternative approaches to be applied when framing the choice set if it is important to use a higher number of attributes and levels than is feasible in a single survey. When there is a relatively large number of attributes one option reported in the social care literature is to split them across two or more separate DCE sets to allow the full set of domains to be examined (Burge *et al*. 2010, Hall *et al*. 2013). Rather than conducting this as two separate studies, each looking at one of the subset of domains, Netten *et al*. (2012) set up a single experiment in which each respondent was asked to consider both subsets, with the associated advantage that the samples for the two sub-studies were matched. Another possible approach to reduce the number of choices to a manageable number would involve splitting subsets of choices into separate surveys (see the blocking approach below).

Attribute development has to be rigorous, systematic, and transparently reported (Coast *et al*. 2012). Various methods have been applied to the development of DCE attributes. These include literature reviews, existing conceptual and policy-relevant outcome measures, theoretical arguments, panel of experts, patient surveys, and qualitative research methods. Coast *et al*. (2012) argue that qualitative studies are best suited to derive attributes, since they reflect the perspective and experiences of the potential beneficiaries. However, a recent review of the healthcare literature reported that 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 (Clark *et al*. 2014).

Creating a choice set and the role of efficiency measures

When creating a choice set, careful consideration needs to be applied in deciding which combinations of attribute levels to present in the questionnaire so attributes can be identified and estimated as precisely as possible. The exact number of questions will depend on the complexity of the particular experiment and the survey approach used. The number of feasible choices will also have an impact on the number of attributes and levels if the full set of combinations is used in a single sample included in the experimental design.

Full factorial and fractional factorial designs

A full factorial design includes all possible combinations of attributes and levels for making profiles or choice sets. Generally, the number of possible profiles is a^n where a is the number of levels and n is the number of possible attributes. If the number of levels varies across attributes then the number of possible hypothetical profiles is a^n x b^m where a and b are the different attributes levels and n and m are the different attributes.

A full factorial design is likely to yield a very large number of possible choices. For example, in an experiment with two attributes at two levels and four attributes at four levels we have a full factorial of 1204 choices (44*22). Rather than using all the possible combinations, a researcher can opt to use only a fraction of the treatment combinations in what is called a fractional factorial design (FFD) (Louviere *et al*. 2000). FFDs are used to reduce the number of profiles that have to be evaluated, while ensuring enough data are available for statistical analysis, resulting in a carefully controlled set of ‘profiles’ for the respondent to consider. This often results in a large number and experimental design methods are used to create smaller fractional factorial designs. They are extensively documented elsewhere, for example by Reed Johnson *et al*. (2013), and briefly discussed in the paragraphs on orthogonal and D-efficient designs below. If a binary choice DCE is employed (a binary choice is where respondents are presented with a number of profiles (one at a time) and asked how they would choose, with possible responses being ‘yes’ or ‘no’), then the binary c status quo option in such a study risks misrepresenting respondents' choice, because individuals may be 'forced' to choose between plans of support services that do not account for their current services.

The inclusion of the opt-out or status quo option can compromise the statistical design properties of the study. Where the levels for the opt-out or status quo are known in advance the implications for the efficiency of the design can be estimated before collecting data. Where the opt-out or status quo levels are constant across respondents, the effect on design efficiency is smaller. Where information is collected from individuals within the study on their opt out or status quo, and this varies across respondents, the effect on the statistical efficiency of the design is likely to be greater and cannot be estimated in advance of data collection (Ryan 2011).

Constructing and conducting the survey

At the start of the questionnaire the DCE choice set needs to be introduced to the respondent by providing information on the project and the experiment itself, explaining the different attributes and levels and presenting an example of a possible answer to a choice. Respondents are presented with a hypothetical situation where they have to imagine the hypothetical services on offer. A general example of such a choice in the social care setting is presented in figure 2.

After completion of the choice task it is possible to include questions to collect information on the respondents' reasons for answering the choice set in the way they did and the degree of difficulty they experienced in answering. These questions can help in identifying possible misunderstandings (Bennett [illegible]

- the data collection method to be used – self-completion questionnaires are often cheaper compared with other collection methods such as interviews, but their response rates tend to be lower, so the sample size should be larger; and
- the level of variability between responses – the less variable the responses are the smaller is the sample size required to achieve the same level of accuracy (Ryan et al. ; [illegible]

Interpretation of results

Raw preferences can be presented to see how choices are split between different alternatives. The total number of raw preferences is calculated from the number of choices per set multiplied by the number of respondents. Percentages of preferences across alternatives can be calculated from the frequencies of choice for each alternative (Tinelli *et al*. 2009).

Consideration can be given here to whether or not any individual always chooses a given option. First, respondents could always choose option A over B (or vice versa), or the first option rather than the second in each choice set. Secondly, they could also present constant preferences for a particular option on offer, e.g. opt-out (current situation/no service) versus alternative services on offer. In such circumstances, it would be unclear if they were still trading across alternatives when facing each choice of the DCE experiment. Subgroup analysis across respondents could be employed to compare preferences across groups of subjects with or without constant preferences (Tinelli *et al*. 2009).

A third case of constant preferences occurs when only one attribute matters to the choice (lexicographic preferences). Some respondents (respondents with 'dominant preferences') consistently chose the scenario with the 'best' level of a particular dimension. This may arise both from the complexity of the DCE choices but also an individual's past experiences or expectations (Scott 2002).

From the coefficient estimates it is possible to identify whether the attribute influences the preferences for that particular good or service, the relative importance of individual attributes, the trade-offs or marginal rates of substitution between these attributes and the overall utility from a scenario.

The sign, relative size and significance level of the regression coefficients show the relative importance of the different attributes to individual preferences. A positive sign on the coefficient indicates that the higher that attribute level, the higher the level of utility derived. The relative size of the coefficients indicates the relative importance of that attribute in determining the overall utility, taking into account the different units of measurement considered. However, it gives no indication of the strength of preferences, which is why the marginal rate of substitution (MRS) is calculated, this being the rate at which respondents are willing to give up one attribute for another (where all the rest are constant). It is worth noting that estimation of trade-offs can only be conducted when a continuous variable is included. This continuous variable is most commonly price (e.g. monetary compensation to conduct carer support tasks (see Mentzakis *et al*. (2011)), but risk and time have also been used in social care applications of DCE (e.g. risk of falling and the duration of effort required in the rehabilitation session) (Milte *et al*. 2013).

Another objective might be estimating how preferences vary by individual respondent characteristics. For policy analysis, researchers may calculate how choice probabilities vary with changes in attributes or attribute levels or calculate secondary estimates of money equivalence (willingness to be compensated for caregiver task (Mentzakis *et al*. 2011)), risk equivalence (maximum acceptable risk of falling) or time equivalence (maximum acceptable duration of effort required in the rehabilitation session) for changes in scenarios (Milte *et al*. 2013).

DCEs and their application to social care

Discrete choice experiments have been widely applied to health care settings in different contexts. These include: eliciting patient/community preferences in the delivery of health services; establishing consultants' preferences when setting priorities across interventions; developing outcome measures; eliciting patient preferences in the doctor-patient relationship; and evaluating alternati

Creating a choice set and the role of efficiency measures

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Table [illegible]: Summary of the literature search: creating the choice sets

	Number of papers	%	References
Design type			
Fractional factorial	12	100	Burge et al. (2010), Burton et al. (2014), Dixon et al. (2013), Hall et al. (2013), Hoefman et al. (2014), Mentzakis et al. (2011), Milte et al. (2013), Negrín et al. (2008), Netten et al. (2012), Nieboer et al. (2010), Potoglou et al. (2011), Ryan et al. (2006)
Design method			
Orthogonal designs (catalogues or derived from software)	6	50	Burge et al. (2010), Burton et al. (2014), Dixon et al. (2013), Hoefman et al. (2014), Nieboer et al. (2010), Ryan et al. (2006)
Optimal designs ('Huber and Zwerina designs' or 'Street and Burgess designs')	6	50	Hall et al. (2013), Mentzakis et al. (2011), Milte et al. (2013), Negrín et al. (2008), Netten et al. (2012), Potoglou et al. (2011)
Number of choices			
2	3	25	[illegible]

Constructing and conducting the survey

In the majority of the cases the development of the questionnaire was informed by piloting with a subset of respondents before starting data collection (7/12; see Table 4). Similar results were reported elsewhere in the healthcare research literature (Mandeville *et al.* 2014). Unfortunately, there is no clear guidance available on sample size nor sampling strategy for DCEs, and half of the social care studies did not report any specification on their calculation for these. The remaining studies referred to: simple random sampling approach (2); stratified random sampling approach (2) ; and previous cases from the literature (2). The target samples included: general adult population (5/12), older people (3/12), patients/service users (2/12), or carer (3/12). Burton *et al.* (2014) compared preferences results between different groups of patients and their carers.

Face-to-face interview was the preferred data collection method (8/12) followed by mailed questionnaire (4/12). Again, the proportions are similar in healthcare research (de Bekker-Grob *et al.* 2012). Two articles included pictorial representations of the attributes rather than written

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[redacted]	References
[redacted]	Burge et al. (2010), Hall et al. (2013), Mentzakis et al. (2011), Milte et al. (2013), Negrín et al. (2008), Netten et al. (2012), Potoglou et al. (2011), Ryan et al. (2006[8]

descriptions, which were used in the remaining ten papers. The review by de Bekker-Grob *et al.* (2012) reported little progress on this matter in healthcare research, with only two studies in their review using pictures/figures to help respondents' understanding of risk.

Analysis of data and interpretation of findings

In the literature included here, responses from choices were modelled using random utility framework (Ryan *et al.* 2008). Random effect logit/probit models were employed for binary choice models (3/12). Multinomial logit/conditional logit were the preferred models of analysis for multiple choice experiments (5/12). More advanced models for analysis were also used to relax multinomial logit restrictions, including nested logit (1/12), mixed logit (3/12) or latent class (1/12) models (see Table 5). One article used both multinomial logit and nested logit models to inform the analysis framework (Burge *et al.* 2010). The trend towards using more flexible econometric models in DCE evaluations, including mixed logit and latent class, remains stronger in the healthcare research literature (Clark *et al.* 2014).

Table 5 Summary of the literature search: analysis of data and interpretation of findings

	Number of papers	References
Model of analysis		
multinomial logit/conditional logit	5	Burge et al. (2010), Hall et al. (2013), Hoefman et al. (2014), Milte et al. (2013), Nieboer et al. (2010)
nested logit	1	Burge et al. (2010)
random effect logit/probit models	3	Burton et al. (2014), Dixon et al. (2013), Ryan et al. (2006)
mixed logit	3	Negrín et al. (2008), Netten et al. (2012), Potoglou et al. (2011)
latent class	1	Mentzakis et al. (2011)
S		
cost	4	Burge et al. (2010), Mentzakis et al. (2011); Negrín et al. (2008), Nieboer et al. (2010)
time	2	Burton et al. (2014), Milte et al. (2013)
risk	1	Milte et al. (2013)
Validity of results		
rationality (dominance) test	1	Ryan et al. (2006)
reliability test	2	Burge et al. (2010), Ryan et al. (2006)
convergent validity test	1	Ryan et al. (2006)
theoretical test	1	Mentzakis et al. (2011)

All papers in this review reported on the parameter estimates from the regression analysis, and commented on which attributes influenced the respondent preferences for the service considered and their relative importance. In line with current trends in healthcare research, where reporting of monetary values has fallen compared with earlier periods of research (Clark *et al*. 2014), only a few papers (4/12) included a cost attribute and calculated respondent willingness to be compensated for unit increases in a particular attribute. For example, Mentzakis *et al*. (2011) reported that caregivers were willing to accept a payment of £0.38 to £0.83 per hour for the personal care service they provided. Additional studies calculated MRS between attributes and time or attribute and risk. For example, Milte *et al*. (2013) reported that respondents were prepared to accept an increase in the duration of the rehabilitation programme of over two hours in a two-month period (132 minutes) in order to achieve the highest mobility outcome of walking with a stick unaided; or a 22% increase in the risk of falling and breaking another bone to avoid enduring severe pain from participating in a rehabilitation programme.

In contrast with current practice in healthcare research (Clark *et al*. 2014), only a few articles tested the validity of results (3/12). The tests adopted by Ryan *et al*. (2006) included dominance tests (inconsistent responses were dropped), test–retest reliability (a subsample completed a second DCE interview) and convergent validity of quality weights (respondents' rating of 16 vignettes). In another application Burge *et al*. (2010) deleted responses if they did not pass accuracy checks. One additional paper considered the theoretical validity of the results (Mentzakis *et al*. 2011). When testing for irrational/inconsistent responses none of the applications included comparison between all responses and subsets without irrational/inconsistent responses in the final analysis, as suggested by current guidance (Lancsar and Louviere 2008), but instead they deleted all irrational/inconsistent responses from their analysis (Burge *et al*. 2010, Ryan *et al*. 2006).

Recommendations

for further development of DCEs to support their use in social care research

DCEs have a strong history of use in health economics and in recent years they have supported the evaluation of social care interventions as well as the development of social care-related quality of life and wellbeing measures. However, the application of DCEs to social care is far from straightforward and a number of challenges have been raised in the literature.

The cognitive burden to respondents

There is discussion around the fact that DCE designs could put too much cognitive burden on some respondents, and participants could react by opting for decisions that do not reflect their true preferences (Bilger *et al*. 2013, Burton *et al*. 2014, Negrín *et al*. 2008, Netten *et al*. 2012, Whitty *et al*. 2013). This is particularly challenging when dealing with social care evaluations, where the target sample of the research is more likely to include individuals in need or at risk, or individuals with needs arising from illness, disability, old age or poverty. A few related recommendations for future research are presented below.

Selecting the attributes and levels

The construction of the choice sets included in an experiment requires a careful selection of the attributes and levels to be used. When respondents are asked to trade-off between a large number of attributes

Using pictorial representations of the subject

Different formats are available to the researchers when presenting the choice sets to the respondents, including pictorial representations versus written format (de Bekker-Grob *et al*. 2

Using alternative stated preference approaches. When creating the choice set a focus of attention in the literature is the inclusion of a base-case scenario (status quo or no service) as an added comparator within the choice set if the current situation and/or non-participation is a relevant alternative (Bridges *et al*. 2011, Reed Johnson *et al*. 2013). However, keeping two or more alternatives in mind at once may be a difficult task, particularly for people with some cognitive problems (if not assisted in the choice process, see above). An alternative stated preferences approach, best–worst scaling (BWS), has been already introduced to social care research (Flynn *et al*. 2007, Koopmanschap *et al*. 2008, Marley *et al*. 2008, Potoglou *et al*. 2011, van den Berg *et al*. 2004). Instead of respondents making choices between alternatives, they are presented with alternatives one at a time and make choices within each of them. BWS appears to facilitate collection of preference data from service users as it is likely to secure lower cognitive burden compared with DCE, where keeping two or more profiles in mind is likely to be a harder task.

Using BWS in social care research has had success but it remains a relatively new method, and more comparative research is needed to demonstrate the superiority of BWS over DCE in terms of respondents' fatigue and responses, and the robustness of the resulting modelling estimates acc[illegible]

References

Bech M, Kjaer T, Lauridsen J (2011) Does the number of choice sets matter? Results from a web survey applying a discrete choice experiment, *Health Economics*, 20, 3, 273–286.

Bennett J, Blamey R (eds) (2001) *The Choice Modelling Approach to Environmental Valuation*, Edward Elgar, Cheltenham.

Bilger M, Flynn T, Farooqui A, Malhotra C, Finkelstein E (2013) Cognitive burden in discrete choice experiments: the case of preferences for end-of-life in Singapore, presentation at Inter[illegible]

Flynn TN, Louviere JJ, Peters TJ, Coast J (2007) Best-worst scaling: what it can do for health care research and how to do it, *Journal of Health Economics*, 26, 1, 171–189.

Grutters JPC, Kessels AGH, Dirksen CD, van Helvoort-Postulart D, Anteunis LJC, Joore MA (2008) Willingness to accept versus willingness to pay in a discrete choice experiment, *Value in Health*, 11, 7, 1110–1119.

Hall J, Kenny P, Hossain I, Street DJ, Knox SA (2013) Providing informal care in terminal illness: an analysis of preferences for support using a discrete choice experiment, *Medical Decision Making*, 34, 6, 731–745.

Hensher DA, Rose JM, Greene WH (2005) *Applied Choice Analysis Primer*, Cambridge University Press, Cambridge.

Hoefman RJ, van Exel J, Rose JM, van de Wetering EJ, Brouwer WBF (2014) A discrete choice experiment to obtain a tariff for valuing informal care situations measured with the CarerQol instrument, *Medical Decision Making*, 34, 1, 84–96.

Koopmanschap MA, van Exel JNA, van den Berg B, Brouwer WBF (2008) An overview of methods and applications to value informal care in economic evaluations of healthcare, *PharmacoEconomics*, 26, 4, 269–280.

Lancsar E, Louviere J (2008) Conducting discrete choice experiments to inform healthcare decision making: a user's guide, *PharmacoEconomics*, 26, 8, 661–677.

Lancsar E, Swait J (2014) Reconceptualising the external validity of discrete choice experiments, *PharmacoEconomics*, 32, 10, 951–965.

Louviere JJ, Flynn TN, Carson RT (2010) Discrete choice experiments are not conjoint analysis, *Journal of Choice Modelling*, 3, 3, 57–72.

Louviere JJ, Hensher DA, Swait JD (2000) *Stated Choice Methods: Analysis and Applications*, Cambridge University Press, Cambridge.

Mandeville KL, Lagarde M, Hanson K (2014) The use of discrete choice experiments to inform health workforce policy: a systematic review, *BMC Health Services Research*, 14, 1, 367.

Marley AAJ, Flynn TN, Louviere JJ (2008) Probabilistic models of set-dependent and attribute-level best–worst choice, *Journal of Mathematical Psychology*, 52, 5, 281–296.

Marshall D, Bridges JFP, Hauber B, Cameron R, Donnalley L, Fyie K, Reed Johnson F (2010) Conjoint analysis applications in health — how are studies being designed and reported? *The Patient: Patient-Centered Outcomes Research*, 3, 4, 249–256.

Mentzakis E, Ryan M, McNamee P (2011) Using discrete choice experiments to value informal care tasks: exploring preference heterogeneity, *Health Economics*, 20, 8, 930–944..

Milte R, Ratcliffe J, Miller M, Whitehead C, Cameron ID, Crotty M (2013) What are frail older people prepared to endure to achieve improved mobility following hip fracture? A discrete choice experiment, *Journal of Rehabilitation Medicine*, 45, 1, 81–86.

National Institute for Health and Care Excellence (2013) *The Social Care Guidance Manual*, NICE, Manchester, www.nice.org.uk/article/pmg10/resources/non-guidance-the-social-care-guidance-manual-pdf.

Negrín MA, Pinilla J, León CJ (2008) Willingness to pay for alternative policies for patients with Alzheimer's Disease, *Health Economics, Policy, and Law*, 3, 3, 257–275.

Netten A (2011) *Overview o*

van den Berg B, Brouwer WBF, Koopmanschap MA (2004) Economic valuation of informal care. An overview of methods and applications, *European Journal of Health Economics*, 5, 1, 36–45.

Whitty J, Ratcliffe J, Chen G, Scuffham P (2013) A comparison of discrete choice and best worst scaling methods to assess Australian public preferences for the funding of new health technologies, presentation at International Choice Modelling Conference, Sydney, www.icmconference.org.uk/index.php/icmc/ICMC2013/paper/viewFile/612/286.