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PRACTICAL APPLICATION

Putting the Choice in Choice Tasks: Incorporating Preference Elicitation Tasks in Health Preference Research

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Abstract
Choice-based preference elicitation methods such as the discrete choice experiment (DCE) present hypothetical choices to respondents, with an expectation that these hypothetical choices accurately reflect a 'real world' health-related decision context and that consequently the choice data can be held to be a true representation of the respondent's health or treatment preferences. For this to be the case, careful consideration needs to be given to the format of the choice task in a choice experiment. The overarching aim of this paper is to highlight important aspects to consider when designing and 'setting up' the choice tasks to be presented to respondents in a DCE. This includes the importance of considering the potential impact of format (e.g. choice context, choice set presentation and size) as well as choice set content (e.g. labelled and unlabelled choice sets and inclusion of reference alternatives) and choice questions (stated choice versus additional questions designed to explore complete preference orders) on the preference estimates that are elicited from studies. We endeavoure to instil a holistic approach to choice task design that considers format alongside content, experimental design and analysis.

1 Introduction

Health preference research (HPR) provides important insights into the choices that health care decision makers, such as patients, caregivers and health care providers, would make regarding health and health care, and helps to build an understanding of what drives those choices. HPR studies are used for a range of purposes in healthcare, including to inform product design [1, 2], input to

Key Learnings/Points for HPR Researchers
The design and set-up of choice tasks in a choice experiment should mimic the real-world choice of interest if the discrete choice experiment is to be able to validly and accurately predict the actual decision behaviour of a wider group of individuals whom the respondents represent.
To achieve this, it is important to understand the implications of options available to the researcher in considering the following steps:
The choice context.
Choice set size and composition, including:
the impact of labelled vs. unlabelled alternatives.
inclusion of an opt-out alternative and appropriate specification.
Format for the 'choice' question (such as most preferred, most/least preferred, best/worst option).

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benefit-risk assessment and regulatory and HTA decisions [3–5], and for health state valuation [6].

There are many methods used to elicit preferences in HPR [7, 8]. Choice-based methods such as discrete choice experiments (DCEs) are arguably the best known and most commonly applied choice-based method in HPR, outside of the context of health state valuation (when indifference methods are commonly used). Choice-based methods such as DCEs elicit preferences by presenting hypothetical choices to respondents, with an expectation that these hypothetical choices accurately reflect a 'real world' health-related decision context and that consequently the choice data are driven by respondent's health or treatment preferences [9]. For this to be the case, careful consideration needs to be given to the format of the choice task in a choice experiment. Over the last 20 years, the question of how best to design and present the choice task has been the focus of methodological enquiry and debate [10, 11].

The overarching aim of this paper is to outline important aspects to consider when designing the content and presentation of choice tasks in a choice experiment and the impact of such decisions on resulting choice models, while drawing on the current knowledge and methodological insights available to inform this. By choice tasks we mean the alternatives presented in choice sets, the decisions respondents are asked to make and the description of the context in which those choices are made. Related to the presentation of choice tasks are key considerations of how attributes and levels are generated and framed, and subsequently inform an experimental design and analysis, and the overall survey design. These topics are not addressed directly by this paper but guidance is available from key methods guidance in the field (e.g., Bridges et al. [12], Lancsar and Louviere [13]).

The paper is organised around the three main components of a choice task: the choice context respondents are asked to place themselves in (Sect. 2); the choice sets containing alternatives respondents are asked to consider (Sect. 3); and the choice question(s) respondents are asked to make about each choice set (Sect. 4); as well as the discrete choice response type (Sect. 5).

2 Conceptualising the Choice Task—Setting the Scene

2.1 Engagement and Framing

When thinking about the design of surveys to elicit preferences, how information and choice questions are presented can influence the choices individuals make. In designing a choice task, we aim to present respondents with a task they are willing and able to engage with and that captures their preferences in a neutral and non-directed way.

Respondent engagement with the choice tasks varies with many features of a survey and this can impact the accuracy and speed of data collection. In an interview setting, task engagement can be positively influenced, although differences between interviewers in this regard give rise to interviewer effects [14]; yet, preference surveys are typically offered to respondents in the form of a self-complete paper-based or, more usually, online survey. In this context, it is important to consider in advance how the presentation of choice tasks may influence participant engagement. This may include minimising task complexity and enhancing their relevance to respondents (through, for example, supporting acceptance of the premise of the choice task, enhancing the attractiveness of the task layout, and carefully considering the number of attributes included in the tasks) [15].

The quality of the data arising from a choice task will also be affected by the respondent's ability to process the information provided. Processing the information involves distinct cognitive steps by respondents: (1) interpreting the provided information in a concrete way, relying on imagination and experience; and (2) judging how the available options would affect one's life, given that person's preferences and circumstances [16]. Careful pretesting of the preference elicitation instrument including the choice task should be undertaken to ensure respondents are able to process the information provided [17]. If respondents are asked to process too much information simultaneously, they may be overwhelmed and less likely to complete the choice tasks, or to use decision short cuts (heuristics), opt out of the choice tasks, or complete the tasks half-heartedly to finish and receive payment. Deciding whether too much information is being presented is nuanced and includes consideration of whether the choice task includes too many attributes, descriptor levels that are too long, or too many alternatives. Eye-tracking technology has shown that attribute and alternative non-attendance increases with the number of attributes or alternatives presented in the choice tasks [18]. How many is 'too many' attributes or alternatives is an important topic and not one for which there is a strict answer since it will depend on the choice at hand and respondent familiarity with making that choice and the decision context. One review reports the median number of attributes in a health-related DCE study is five, with most (> 80%) including between four and nine attributes and only two alternatives (not including any opt-out or status quo option) [19]. Non-completion of choice tasks or the application of decision heuristics is not a trivial issue for DCEs [20–22] because it may violate the assumptions underpinning DCE modelling and increase error variance and the risk that biased results will be obtained.

Nonetheless, there is a limit to how much any task can be simplified, for instance by reducing the number of alternatives. Some decisions in real life require deliberation and consideration of many issues. If choice tasks in a DCE ignore alternatives or attributes that have relevance to the decision maker in a real-world context, the results obtained will have low external validity and the stated preferences are less likely to predict behaviour. In this situation, the initial DCE design should be revisited to ensure that all relevant alternatives are appropriately captured.

In making choices, individuals adopt a frame that depends partly on how the choice problem is presented, as well as their innate norms, habits and characteristics [23, 24]. If the way in which a choice is presented does not match a person's view, that can induce bias in subtle ways. Framing can influence the choices individuals make in two ways: (1) through cues that present information/the situation as positive or negative [25, 26]; and (2) through priming, where the information presented may result in individuals using pre-existing information to draw unintended meaning, or it establishes 'rules' for how later information is to be processed, thereby affecting their choices [25, 27].

The impact of framing effects in choice tasks has been investigated empirically, for example by looking at the influence of contextual cues—whether attributes are framed as gains or losses [28–32], how attributes are presented [30, 33], and priming effects in terms of the information included within a choice context or attribute [34, 35]. Taking framing into account, when considering the information to present in a DCE it is important to ask whether information is being presented in a way that would bias the respondent or presents some choice options in a 'more positive light' relative to others. Whether potential framing effects can be addressed *a priori* in the study design phase (potentially through qualitative studies for the development of DCE surveys) or in the analysis of subsequent results is open to further research [31].

2.2 Choice Context

As with any survey, DCE respondents must be oriented to not only how to complete the survey in a technical way, outlining what they are expected to do (e.g. choose their preferred treatment/health state etc.; see Sect. 5 for discussion of response type), but, importantly, the context in which they are being asked to make decisions. The choice context is the scenario in which respondents are asked to consider themselves to be in and from which they are asked to make discrete choices. For example, respondents could be asked to imagine 'your doctor tells you that your current risk of stroke is 4% and your current risk of a bleed is 2%. Suppose you have the following options' [36], or imagine 'you are entering a convenience store to purchase a beverage', etc. [37]. To support a respondent to make their choice, information on all aspects of the context needs to be provided. In the example above, what is meant by risk of stroke or a bleed needs to be clearly defined.

The importance of constructing the choice context in a way that mimics the reality which the research aims to model is emphasised by Lancsar and Swait [9], who note that external validity (encompassing the choice context, choice process, task design and modelling) should be an objective pursued from the initial conceptualisation and design of any DCE as a preference elicitation design philosophy.

Being able to accurately represent a 'real-life' decision context is influenced by whether the information can be understood by respondents. This will depend on the type of language used and the quantity of information that respondents are asked to process. While it is possible to include definitions for technical terms, this can complicate the choice task (the inclusion of definitions can be facilitated by using 'hover' functions with computer-based surveys) and requires that the language used in definitions is sufficiently accessible to respondents. Similarly, it is recommended that surveys also include upfront information about the range of attributes and their levels. Whether or not the information can be understood also depends on the characteristics of the respondent; however, this is not amenable to addressing though the representation of the choice context and therefore is not discussed further here.

3 How to Compose the Choice Task

Presenting the choice task to be as close to reality as possible enhances the internal and external validity of the choice task (and subsequently the results). Moreover, respondents will be more likely to understand and engage in a task if it is familiar to or well understood by them. To help decide how to present the choice task, researchers must understand which aspects individuals include in their decision-making process, because failure to include relevant aspects will limit the possibility to predict respondent behaviour based on the experiment.

Researchers need to make several important decisions regarding the structure of the alternatives presented within a choice set, to inform how the choice tasks are presented to respondents.

3.1 Forced Choice Versus Non-forced Choice

An important decision required to formulate a choice task is to consider whether to make each choice task a 'forced choice' or whether to provide an 'opt-out' alternative [38]. A forced choice is when each choice set asks (i.e. 'forces') a respondent to choose one of the alternative profiles on offer in the choice set; for example, in a choice between treatment A or treatment B. The choice task does not allow the respondent to select 'neither' alternative. An advantage of forced choice questions is that respondents have to provide a response, and this will offer the analysts a clear differentiation of the preferences for all attribute levels.

The preferences estimated from a forced choice model are conditional on making a choice [39] and will lead to a conditional demand model. This has consequences for how the results may be interpreted or used. In effect, a conditional demand model assigns a zero probability to not making a choice, even when the probability may be non-zero.

The decision whether to use a forced choice scenario or to include an opt-out should reflect the options that are available to respondents and can be informed by qualitative insights. As noted in the literature (e.g. Viney et al. [40], Lancsar and Louviere [13]), forcing respondents to choose between two alternatives when neither of which would be chosen in the real world will simply reveal 'the best of a bad bunch'. If the alternatives presented are all unattractive, being forced to choose one of them represents a utility loss (since choosing none or 'opting out' has higher value or utility for the respondent). Here, we may lose the ability to learn whether the options on offer enhance welfare or not. If not choosing either alternative is a realistic option in real life, then using a forced choice design will potentially bias both attribute level trade-offs and lead to an overestimate of demand for the commodity being valued [41]. It can also increase randomness in responses [42]. Where predicting demand/uptake is important, a non-forced choice (unconditional demand) should be considered. Note that if a forced choice is realistic in the market (i.e. there is no feasible 'opt out' option), then the probability of making no choice is, in reality, zero, and the conditional and unconditional demand model are equivalent [39]. Forced choice may be relevant if the focus is on the attribute level trade-offs based on conditional demand rather than when the focus is on prediction of demand/uptake or welfare analysis where unconditional demand (and non-forced choice) is relevant.

In health, historically there are many examples of decision contexts where researchers have used a forced choice format, particularly where the focus was on attribute level trade-offs, but this has changed over time with increasing reporting of use of status quo and opt-out alternatives [19]. An area where forced choice has received attention is health state valuation literature, where the approach to anchoring to 0 has been widely discussed and investigated [6]. In health state valuation, non-forced choice is also explored, including via the use of death as an opt-out, while full health may also be included as a reference state [43–45].

Instead of giving respondents an alternative of 'none of these', it is possible to present a reference case alternative. The most common is the 'status quo', that is the current or existing alternative (or usual treatment). The status quo or reference case may be described using none, some, or all of the attributes and levels that are used to describe other alternatives in the choice task, but the levels are typically held constant across choice tasks. In addition, the status quo alternative can be fixed across all respondents, or fixed within any one respondent but vary between respondents (Box 1).

Box 1: Defining the Status Quo or Reference Case

Fixed across all respondents

The status quo alternative may be the same (fixed) across all choice sets for all respondents. The status quo alternative might be presented this way when the usual care offered to people is the same for all individuals or when all choices are being compared with a constant reference case, e.g. full health.

Respondent-specific

The status quo alternative may be the same (fixed) across all choice sets for any one respondent but allowed to differ between respondents. For example, 'usual care' may differ between people.

While including a status quo or reference alternative has the advantage of increasing the realism of a choice situation, there is the potential for respondents to consistently choose the status quo alternative. For some respondents, the status quo is simply their preferred alternative. However, choice of status quo can also be driven by decision heuristics such as the endowment effect, status quo bias, loss aversion, or task avoidance, particularly if the task is cognitively demanding [46].

3.2 Dual Response Questions

Some researchers have suggested using a dual response design to overcome some of the limitations associated with forced choice and opt-out formats [42]. In a dual response design, respondents are asked a two-stage choice question; in one stage they are asked to make a forced choice between the alternatives on offer, and in another stage, they are asked to indicate if they would like to opt-out of the choice. Thus, a dual response design enables the estimation of both conditional and unconditional choice models and may reduce the risk of losing data due to respondents avoiding the task to minimise cognitive effort [42]. However, this format also requires the researcher to select whether to analyse the data using a forced or non-forced choice specification, with the latter collapsing the dual response into a single three alternative choice task, with little guidance on rationale for doing so. Alternatively, choice data from both datasets could be jointly modelled, but this complicates the technical specification of the model and the extent to which it adheres to theories (such as random utility theory [RUT]) that underpin DCE analysis. Examples of DCEs that have used a dual response design in health include Veldwijk et al. [42], Brazell et al. [47], Laba et al. [48], and Marshall et al. [49, 50].

4 Format of Discrete Alternatives

Regardless of the topic, the alternatives described in the choice sets can be presented in various ways, each of which is informed by the research questions at hand and will in turn have implications for the experimental design, the analysis of the resulting choice data, and the conclusions that can be drawn.

4.1 Size of the Choice Set

A key decision to address is how many alternatives will be presented within a given choice task. In some choice tasks, respondents will be shown a single alternative and asked if they would choose/accept that alternative. In this case, researchers and respondents would need to know what non-choice/non-acceptance means; e.g. for Lancsar et al. [51], in the context of a hypothetical asthma medication, not choosing the alternative offered meant staying on their current real-world medication, which the respondent had already been asked to describe (in a 'report card') using the attributes used in the hypothetical alternatives.

More often, the focus of DCEs is on problems that involve choices among many alternatives, raising the question of how many alternatives to show in a single choice task. The number of alternatives in each choice set increases the amount of information that respondents need to consider. Two competing considerations need to be balanced: task complexity versus precision. Choice sets that include more alternatives produce more information, and thus are more efficient from a statistical point of view, implying that for a design of a given size a smaller sample size could suffice, or that respondents need to answer fewer questions. However, the inclusion of more alternatives within a choice may make it harder for respondents to choose and that might affect choice consistency or reduce the number of choice tasks that a single respondent can complete. Striving for maximal efficiency thus comes at a price [52]. The statistical properties of the design need to be considered in relation to (and possibly balanced against) respondent efficiency. The number of alternatives per choice set should also be informed by qualitative work and pretesting. Although choice sets of larger size are more common in other areas of applied economics beyond health, choice sets in health have tended to include two to three alternatives (one of which may be a fixed reference alternative) [19].

4.2 Labelled versus Unlabelled Alternatives

The alternatives presented in each choice set can either be unlabelled (also called generic) or labelled. Unlabelled alternatives in a choice carry non-informative descriptors, such as Test A, Test B, Test C, etc. Labelled alternative presentation involves assigning labels (or descriptors) to each alternative that are in some way informative. In health, this might include generic names of medicines, or specific tests (e.g. colonoscopy, computed tomography colonography) or treatments (e.g. surgery, medication).

One advantage of using labels is that it can help make the alternatives more realistic, and as discussed above, this can help improve respondent engagement and understanding of the task and improve validity of results. Labels convey information about the alternatives themselves that is not already captured in the attributes and levels. The use of labels also allows preferences specific to those labelled alternatives to be captured in the analysis via the use of alternative specific constants and interactions between the labels and attributes of the alternatives. However, the interpretation of and preference for the label may differ over respondents and such inferences may be correlated with the random component [39, 53]. Consequently, if labels are included, there is a risk that respondents will draw on their previous experience with a labelled alternative and the researcher may not be able to disentangle and interpret the impact of this experience when analysing the choice data. Therefore, if using labels, it is important to consider their description carefully, to try to ensure (as far as is possible) that all respondents interpret them the same way and to appropriately model preferences for the labels in the analysis. Unlabelled alternatives may be appropriate if the focus is solely on the attributes. A number of studies have compared the use of labelled and unlabelled alternatives (e.g. de Bekker-Grob et al. [54] and Jin et al. [55]).

5 Discrete Choice Response Types

When designing choice tasks, a key consideration and decision faced by researchers is the choice question respondents will be asked to address under each choice set, or put differently, the type of response they are asked to make. By far the most common choice question is a single choice (described below). However, other response types that elicit a preference order over some or all alternatives presented in each choice set are gaining attention. This section outlines various response types, advantages and disadvantages of each, and the circumstances in which such a response type might be appropriate.

5.1 Single Choice of Most Preferred, Best and Variations

The most common response type in DCEs is a single choice, to choose the best or most preferred alternative from those on offer in the choice set. This discrete choice grounds the analysis of data generated from choice experiments in RUT and leads to the estimation of limited dependent variable models [56]. A key axiom of RUT is that the alternative chosen from a choice set is the alternative that provides at least as much or more utility than any other alternative on offer. This elicitation format also has high external validity as individuals are very familiar with making choices between alternatives in all facets of life. Variations on this single response per choice set include which would you choose/recommend/accept/avoid.

5.2 Full Preference Rank

A number of authors (e.g. Beggs et al. [57] and Chapman and Staelin [58]) have noted potential efficiency gains from eliciting a full preference order across the alternatives in choice sets containing three or more alternatives (choice sets of size 3 or more is increasingly the norm in health economics [59] and is the norm in other disciplines in which DCEs are undertaken (e.g. transport, environment, marketing). Below we set out three approaches to eliciting a full preference order (see Lancsar et al. [60] for the model equations and practical guide to estimation of each of these, including data and Stata code). We note that for each of the three approaches, partial preference orders can also be obtained by asking respondents to only rank a subset of alternatives, or only make a subset of possible best-worst or best-best choices, respectively. The advantages of a complete preference order may be particularly relevant where sample sizes are small, e.g. due to budget constraints or if the population from which researchers are sampling is itself small [61].

5.2.1 Ranking

One way to elicit the full preference order is to ask respondents to rank the alternatives presented in each choice set from best to worst [57, 58]. It can also be considered (and indeed most estimation makes this assumption explicitly) that the complete rank order is obtained by choosing best in successively smaller choice sets—the top-ranked alternative is the best from the full choice set, the second ranked alternative is considered the best from the choice set after the top ranked alternative is removed, and so on. An advantage is a complete preference order is obtained from the presented choice options. A potential disadvantage is, without further guidance, simply asking respondents to rank several alternatives could be challenging as the number of alternatives increases and researchers will not know the way in which the ranking was arrived at. Respondent burden of such free ranking increases as the choice set size increases.

5.2.2 Best-Worst

An alternative way to arrive at a complete rank order is to ask respondents repeated best and worst questions [52, 61]: best from the full choice set, worst from the choice set excluding the alternative already chosen as best, and so on until a complete preference order is obtained. For example, “Please choose the best from all alternatives; from the remaining alternatives please choose the worst; from the remaining alternatives please choose the best…” and so on. This approach has been referred to as either best-worst DCE because it is the same as a standard DCE but more questions are asked per choice set, or as best-worst scaling type three [61]. Unlike a free ranking task, a best-worst DCE task puts structure on how respondents make choices to arrive at the rank, potentially reducing cognitive burden. This question type exploits the fact that people must consider all alternatives to identify the best option, and that a second question about the same set of alternatives is easier to answer than a question about a new set of alternatives. Lancsar et al. [61] demonstrate empirically the efficiency gains from such an elicitation process, but also note that there is ‘no free lunch’ in that respondents are completing more tasks per choice set compared with a standard DCE. Nevertheless, it is more efficient than presenting more choice sets and asking respondents to simply choose the best to achieve the same quantity of choice data, since in a best-worst task respondents have already considered all alternatives to make the choice of best. Flynn and colleagues [62] also suggested answering best-worst questions is easier for respondents, potentially improving respondent efficiency; however, some empirical evidence questions this [63, 64].

5.2.3 Best-Best

A key advantage of both ranking tasks and best-worst is the efficiency gains with which to elicit additional choice data and the resulting statistical efficiency gains (tighter standard errors). However, as noted by Ghijben et al. [36] and Lancsar et al. [60], a best-worst task requires respondents to change mental tasks—from choice of best to choice of worst. As noted above, using ranking data we assume when modelling those data that respondents arrived at the rank order by choosing best from successively smaller choice sets, which may or may not be how respondents rank. To collect the same amount of data but without asking respondents to change mental tasks, Ghijben et al. [36] introduced best-best DCEs in which respondents are asked to choose best from the full choice set, followed by best from the choice set without the alternative already chosen as best, and so on until a full rank order is obtained. The elicited data match the proposed data-generation process assumed in a rank order logit, namely choice of best from successively smaller choice sets and respondents remain in the single choice frame—choice of best. Recent research comparing different choice response formats suggests that best-best may be preferred to best-worst formats if going beyond a traditional single choice 'best' DCE [65].

6 Summary/Conclusions

This paper has focused on the presentation of choice sets into a choice elicitation task to be considered by respondents in a DCE. Choice experiments elicit preferences to help us understand and measure the comparative value associated with a number of alternatives and the attributes that describe those alternatives, and predict choice behaviour in a particular decision context. A key purpose of a preference elicitation task is to be able to validly and accurately predict the actual decision behaviour of a wider group of individuals whom the respondents represent in a real-life choice context. Given this, it is important to mimic the real-world choice of interest in the choice task, and the steps needed to do that include giving due consideration to the choice context presented to respondents; presentation of the choice sets, including choice set size, labelled and unlabelled alternatives; the importance of a reference alternative; and the choice question(s) respondents are asked to consider.

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