Available online at www.sciencedirect.com

ScienceDirect

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

Conducting a Discrete Choice Experiment Study Following Recommendations for Good Research Practices: An Application for Eliciting Patient Preferences for Diabetes Treatments

Ellen M. Janssen, BA[1,*], *A. Brett Hauber, PhD*[2], *John F.P. Bridges, PhD*[1]

[1]*Department of Health Policy and Management, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA;* [2]*RTI Health Solutions, Research Triangle Park, NC, USA*

ABSTRACT

Objectives: To consolidate and illustrate good research practices in health care to the application and reporting of a study measuring patient preferences for type 2 diabetes mellitus medications, given recent methodological advances in stated-preference methods. **Methods:** The International Society for Pharmacoeconomics and Outcomes Research good research practices and other recommendations were used to conduct a discrete choice experiment. Members of a US online panel with type 2 diabetes mellitus completed a Web-enabled, self-administered survey that elicited choices between treatment pairs with six attributes at three possible levels each. A D-efficient experimental design blocked 48 choice tasks into three 16-task surveys. Preference estimates were obtained using mixed logit estimation and were used to calculate choice probabilities. **Results:** A total of 552 participants (51% males) completed the survey. Avoiding 90 minutes of nausea was valued the highest (mean −10.00; 95% confidence interval [CI] −10.53 to −9.47). Participants wanted to avoid low blood glucose during the day and/or night (mean −3.87; 95% CI −4.32 to −3.42) or one pill and one injection per day (mean −7.04; 95% CI −7.63 to −6.45). Participants preferred stable blood glucose 6 d/wk (mean 4.63; 95% CI 4.15 to 5.12) and a 1% decrease in glycated hemoglobin (mean 5.74; 95% CI 5.22 to 6.25). If cost increased by $1, the probability that a treatment profile would be chosen decreased by 1%. **Conclusions:** These results are consistent with the idea that people have strong preferences for immediate consequences of medication. Despite efforts to produce recommendations, ambiguity surrounding good practices remains and various judgments need to be made when conducting stated-preference studies. To ensure transparency, these judgments should be described and justified.

Keywords: diabetes mellitus, discrete choice experiment, patient preferences.

Introduction

Patient-centered outcomes research aims to elicit patients' viewpoints to inform health care decision making [1]. The value of patients' experiential knowledge about living with their health condition to health care decision making is increasingly being recognized [2–4]. Several countries have initiated patient-centered approaches to regulatory decision making [5–7].

There are several approaches to evaluating patient preferences [2,8,9]. Qualitative information may be sufficient for relatively straightforward decisions, but stated-preference methods help to quantify preferences in support of more difficult assessments [10]. Many stated-preference methods have the advantage of measuring preferences in a controlled experimental setting [11]. They can also be used to estimate specific trade-offs people are willing to make in treatment choices [12].

The increased role of patient preference information in patient-centered decision making requires preference studies that meet standards of transparency consistent with clinical evidence [13]. Because of a lack of thoroughness and transparency in reporting, it is often not clear how good research practices are implemented [14]. Therefore, we sought to quantify patient preferences following good research practices and to demonstrate the application of good research practices to the development, implementation, analysis, and dissemination of this study.

This study applied recommendations on stated-preference studies in a health care setting as part of a study that measured treatment preferences of people with type 2 diabetes mellitus [15]. By choosing a disease area for which a preference research base exists [16–19], the study could be placed in the context of the existing diabetes preference literature. In the Methods section, choices that were made in each step of conducting the stated-preference study are reported. In the Results section, preference results are presented according to good research practices. In the Discussion section, limitations of this stated-preference study and gaps in stated-preference recommendations are discussed. This study will aid researchers in considering the choices that need to be made when conducting a stated-preference study

*Address correspondence to: Ellen M. Janssen, Department of Health Policy and Management, Johns Hopkins Bloomberg School of Public Health, 624 N. Broadway, Baltimore, MD 21205.

E-mail: ejansse1@jhu.edu.

1098-3015$36.00 – see front matter

http://dx.doi.org/10.1016/j.jval.2017.07.001

and in transparently reporting their stated-preference studies. Although this study focuses on people with type 2 diabetes mellitus, this research will advance methods that should have broad generalizability across diseases and stakeholder groups.

Methods

A discrete choice experiment (DCE) survey was developed following good research practices for stated-preference studies. This study followed the framework of the International Society for Pharmacoeconomics and Outcomes Research Conjoint Analysis Task Force checklist for good research practices [20] because it provides consensus-based recommendations for the reporting of different steps of a stated-preference study. The task force's checklist contains 10 study steps that contain three items each for consideration. To address each of the 10 steps of the checklist, various recommendations on the development, implementation, analysis, and dissemination of stated-preference studies [2,8,12–14,17,21–31] were consolidated and applied to this study. Table 1 presents how the items for each step in this checklist were addressed and which recommendations can be referenced for additional information on each checklist step. This study used the task force's recommendations on experimental design [11] and also used statistical analysis [32].

Research Question

Defining a specific research question is not only the first step in a stated-preference study, but it also guides all subsequent decisions [8]. This study measured the treatment preferences of people with type 2 diabetes mellitus. Like previous contributions [33–43], we estimated a set of preference weights for medication attributes. We then examined how each attribute level affected the probability that a treatment profile would be chosen. On the basis of stakeholder input [28], people with type 2 diabetes mellitus were asked to consider the perspective of a person who needed to start using an additional diabetes medicine. This is a common clinical occurrence in diabetes treatment [44,45] and it helped standardize the choice scenario for participants with different disease histories. We chose to use a choice-based conjoint analysis, or a DCE, to allow for the examination of trade-offs across treatment attributes [10].

Attributes and Levels

Identifying relevant preference attributes and levels is key to designing any stated-preference study [27]. All relevant attributes and levels for this study were identified from the diabetes preference literature [28] and supplemented with qualitative and quantitative data [8,12,22] obtained by engaging diverse stakeholders (clinicians and diabetes researchers, stated-preference and regulatory experts, and people with type 2 diabetes mellitus). We conducted qualitative pretest interviews with people with type 2 diabetes mellitus in the local community ($n = 25$) to refine the survey and to assess the salience of the attributes to the treatment decision. We conducted quantitative pilot testing with a national sample of people with type 2 diabetes mellitus ($n = 27$) to obtain priors for the attribute level. We selected six attributes that consisted of treatment benefits (glycated hemoglobin [HbA_{1c}] decrease, stability of blood glucose), harms (low blood glucose, nausea), and burdens (treatment burden, out-of-pocket cost) at three possible levels each (the range most reported in the literature [21]). Attributes and levels are presented in Table 3 (see also Fig. 2). Other recent development processes have placed more focus on community engagement [25,26]. Further details regarding survey development were previously reported [28].

Construction of Tasks

Construction of the choice tasks determines whether the generated data can be used to answer the research question [23]. We tested multiple-choice elicitation formats [28] and chose to use full-profile, forced-choice tasks between two treatment profiles in which participants indicated which treatment they would prefer to take. This setup allowed for the elicitation of acceptable trade-offs people were willing to make between different treatment attributes. In health care, full-profile, forced-choice, and paired treatment profiles are common and considered good research practice [20]. If the number of attributes is low enough that participants can reasonably complete a full-profile task, this maximizes information about trade-offs [24]. We did not allow participants to select an opt-out to maximize information obtained about trade-offs [24] and to reduce biases in how participants evaluate an opt-out option [23]. An example choice task with decision scenario is shown in Figure 1. Given that forced-choice scenarios might not be a realistic treatment scenario, another strategy would have been to include two steps in which the forced choice was followed by an opt-out option [46].

Experimental Design

Experimental design affects both statistical and response efficiency [11]. Ngene software (ChoiceMetrics, Sydney, Australia) [47] used row-based swapping to create a Bayesian D-efficient design [48]. D-efficient designs maximize the precision of the estimated parameters given a set number of choice tasks [49]. Priors for the Bayesian design were estimated from pilot results. To create the experimental design, cost was assumed to be continuous and fixed [50] and the other attribute levels were assumed to be categorical and uniformly distributed. This design was sufficient to estimate main preference effects without interactions between attributes and was sufficient to answer our research question. A more advanced design approach could have been to adjust the levels of the cost attribute until a predicted choice probability of 75% for one of the treatment profiles and 25% of the other profile was achieved [34]. This approach was not taken to minimize the time that the instrument was in the field.

The design contained 48 choice tasks. Attribute balance was achieved but cost levels overlapped for 14 tasks. The design was blocked into three 16-task survey versions. Versions were selected to minimize average correlation between the versions and attribute levels. Although blocking reduces response burden, other desirable properties of the experimental design may not hold for individual blocks [11]. Two additional tasks were added to each survey version. The first was a repeat task that tested choice consistency. The second was a holdout task that was the same across all the three survey versions and tested for equivalence in the choices across survey versions. In total, participants completed 18 choice tasks, which was slightly more than average [21], but was deemed appropriate on the basis of pilot results.

Preference Elicitation

Although the choice of preference elicitation technique is strongly related to the research question (step 1), other considerations such as the study population might also drive the choice of preference elicitation technique [2]. We conducted a DCE to meet our objective of applying good research practices because it is the most commonly used stated-preference method in health care [21] with good research practices recommendations available (Table 1). It allowed us to place preference results in the context of other diabetes DCEs [28,51]. The forced-choice DCE also