Internal Medicine: Open Access

Perard and Orme, Intern Med 2014, S6:008
DOI: 10.4172/2165-8048.S6-008

Review Article Open Access

# A Discrete Choice Experiment to Evaluate Blood Glucose Meter Preferences in People with Type 1 and Type 2 Diabetes in the UK

**Rodolphe Perard**[1] **and Michelle E Orme**[2*]

[1]*Merck Serono, UK*

[2]*ICERA Consulting Ltd., UK*

[*]**Corresponding author:** Dr. ME Orme, ICERA Consulting Ltd, 17 Redbridge Close, Swindon, SN5 8ZL, UK, Tel: 01793 876761; E-mail: michelle.orme@iceraconsulting.com

**Received date:** August 18, 2014; **Accepted date:** October 24, 2014; **Published date:** October 29, 2014

**Copyright:** © 2014 Perard R, et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

## Abstract

**Background:** Self-monitoring of blood glucose helps diabetic patients adjust their management strategies proactively, thus avoiding complications which place a burden on healthcare resources. It is hypothesised that some blood glucose meter attributes may influence patients' choice.

**Objective:** The aim of this study is to elicit diabetic patients' preferences for attributes associated with blood glucose meters.

**Methods:** A cross-sectional, web-based survey of UK patients with Type 1 and type 2 diabetes was conducted and preferences for attributes associated with blood glucose meters were estimated using a discrete choice experiment (DCE) framework.

**Results:** Type 1 respondents considered 'time to test' to be the most critical factor and were willing to trade a compact device (2.61 units), or convenience (1.37 units) for a device that could produce test results in under 30 seconds. Type 2 respondents preferred the low maintenance attribute and were most willing to trade a compact device (2.72 units) or convenience (1.37 units) for this attribute.

**Conclusions:** The DCE has elicited preference weightings for five key glucose meter attributes for both Type 1 and Type 2 diabetic patients. Devices that provide value added features such as offline storage of data and additional data analysis will be valued by both Type 1 and Type 2 patients whereas a compact device is less valued.

**Keywords:** Discrete choice experiment; Diabetes; Patient preferences; Glucose meters

## Introduction

Diabetes mellitus is a disease characterised by a chronic abnormal blood glucose level caused by the failure of the pancreatic insulin secretion or tissues' resistance to insulin action (i.e. glucose absorption). Potential long-term complications of diabetes include retinopathy, myocardial infarction, stroke, renal failure, and amputation [1].

The worldwide prevalent diabetic population was 171 million in 2000 [2] but is predicted to rise to 328-552 million by 2030 [2-4]. Due to its significant morbidity, the increasing prevalence of diabetes, mostly Type 2 patients, represents a significant burden to health services. Current estimates for the UK are that there are three million people diagnosed with diabetes (85%-95% being Type 2 diabetics) with a further 850,000 undiagnosed cases [5]. In England, the National Health Service (NHS) spends at least £3.9 billion treating diabetes and its complications (2009/10 estimates [6]). Other estimates put the direct cost of diabetes in the UK at around £9.8bn (2010/2011) and this is forecast to reach £16.9 billion by 2035 [7]. Given this trend, the cost of treating diabetes is likely to be unsustainable considering the overall NHS budget in the short term (£98.7 billion in 2010 to £109.8 billion in 2015; [8]).

Type 1 diabetes is usually diagnosed at a relatively young age [5] and is due to a constant insulin deficiency which requires daily administration of insulin or insulin analogues and self-monitoring of blood glucose levels. Type 2 diabetes is associated with a gradual resistance to insulin action or a deficient secretion of insulin and, in the initial stages, can be managed by lifestyle changes (diet and exercise) and oral anti-diabetic medications, though eventually insulin may be required for uncontrolled disease.

The aim of the therapy is to maintain glycaemic control which can be assessed by monitoring HbA1c concentration in the blood. Glucose molecules attach to the haemoglobin when blood glucose levels are high, such that a single HbA1c measurement reflects the propensity of hyperglycaemia in the last few months, though it is not precisely indicative of the glycaemic peak over the past few days [9]. In order to achieve tighter control, regular daily glycaemia tests would be required to observe whether HbA1c levels stay within the therapeutic range. Hence self-monitoring of blood glucose provides diabetes patients with tangible feedback on their glycaemic control to help them adjust their management strategies proactively.

For Type 1 patients, on-going long-term self-monitoring of blood glucose is essential to guide the administration of insulin. Newly

diagnosed Type 2 patients should have a period of self-monitoring of blood glucose as part of their self-management programme [1]. In practice there may be a wide variation in the NHS offering of blood glucose meters for this purpose. However, it seems prudent to encourage patients to adopt self-monitoring of blood glucose as routine, even though insulin therapy is potentially avoidable for well-controlled Type 2 diabetics, and that the escalating costs of managing complications in uncontrolled patients is avoidable.

A patient will need to be well-informed and highly motivated in order to adhere to regular self-monitoring. It is hypothesised that some glucose meter attributes may influence patients' choice, and thus, their willingness to adhere to a self-monitoring of blood glucose regimen.

The aim of this study is to elicit and quantify UK diabetic patients' preferences for attributes associated with blood glucose meters. The research question and the hypothesis that we are testing follows: Is a patient's choice of glucose meter influenced by the time taken to administer the test, discreteness of use in public, or another attribute [Null hypothesis: In the discrete choice model, the parameter estimate for the attributes is not statistically significantly different from zero]? Do Type 1 diabetes patients have different preferences to Type 2 diabetes patients [Null hypothesis: The difference between Type 1 and Type 2 patient preference weightings is not statistically significantly different from zero]?

## Methods

A cross-sectional, web-based survey of UK patients with Type 1 and Type 2 diabetes was conducted and preferences for attributes associated with blood glucose meters were estimated using a discrete choice experiment (DCE) framework. A discrete choice experiment is used as an appropriate method to estimate the relative importance of each attribute. In a discrete choice experiment, respondents are shown a scenario consisting of two or more choices and are asked to select the option they prefer. By repeating this across a series of different scenarios, we can estimate a preference weighting for each level of an attribute and a marginal rate of substitution which measures the extent to which patients are willing to trade off one glucose meter attribute for another. The methodology was guided using the ISPOR Conjoint Analysis Task Force checklist [10] and, retrospectively, the methodology concurs with recently published recommendations [11].

### DCE design

The design of the questionnaire is crucial to ensure the viability of the analysis. The attributes used in the choice scenarios must be non-overlapping, measurable and meaningful to the respondent. A series of choices sets must be generated that maximises statistical efficiency whilst ensuring all parameters estimates are identifiable and a number of candidate designs should be considered. The choice set design must not be too complicated, otherwise patients will find the questionnaire too difficult to complete. Therefore we conducted the design phase with a view to balancing these issues.

An ad-hoc PubMed (National Library of Medicine) literature review was conducted in September 2012 to assess the extent of the current literature for DCE in blood glucose meters for diabetic patients and to inform the study design. As there were no DCE publications in this specific setting, the review was extended to 'discrete choice experiment' and 'diabetes'. After removing duplications, and non-relevant papers, 10 publications remained [12-21]. Two papers [16,17] were found to be secondary publications and one paper was not a discrete choice experiment [13], leaving seven publications of interest [12,14,15,18-21]. The review of the DCE papers can be summarised as follows: most DCEs covered 4-6 attributes and the design had 8-10 paired choice sets; the DCEs were a mix of online surveys, in-person questionnaires and face-to-face interviews; included a small pilot study prior to main data collection phase; number of usable responses for analysis ~160-280 respondents; collected demographic data such as age, gender and in some studies race, educational level, and income, health status, last HbA1c level (as categories), type of diabetes, duration of diabetes, insulin status/treatments. None of the studies included attribute interactions explicitly. Survey design was either based on orthogonal designs or 'level-balance'. The use of an orthogonal design in some of the DCEs led to a large set of alternatives, and therefore block designs were used (note that unless the blocks are distributed evenly amongst respondents then orthogonality would not hold). None of the DCEs retrieved from the systematic literature review related to the use of blood glucose meters.

In addition to the literature review, internal market research [22], which included interviews with nurses and patients, was also used to inform the development of the attributes and levels for this DCE (Figure 1). After considering various glucose meter features, five key attributes were selected on the basis that these would differentiate between blood glucose meters, were measurable, were meaningful to the respondent, and were attributes that could be 'traded'. For example 'test accuracy' was not included as an attribute in this DCE as it is an essential feature of any glucose meter and something respondents would not be willing to trade (a dominant attribute). One attribute (time to test) is a three-level attribute (under 30 seconds, 30 to 60 seconds, over 60 seconds), the remaining four attributes (convenience, data management, maintenance, size) having two (dichotomous) levels. 'Willingness-to-pay' and social economic characteristics were also not included, as in the UK the cost of the blood glucose meters is usually funded by the NHS.

| | | Glucose meter A | Glucose meter B |
|---|---|---|---|
| **Time to test:** | Total time to administer test including assembly | Over 60 seconds | 30 to 60 seconds |
| **Convenience:** | Glucose meter is easy to use discreetly in public | No | Yes |
| **Data management/ conncetivity:** | Storage and analysis of blood glucose reading | Data management on device only | Data transfer for additional data storage and analysis |
| **Maintenance:** | Frequency of manual coding of test papers, base level reset, replacement of batteries/ cartridges/cassetters/lancet or cleaning the device | High (at least twice a week) | Low (less than twice a week) |
| **Size:** | Size of glucose meter | Standard size | Compact size |
| **Which glucose meter would you chooseA?** *(Tick one)* | | ☐ | ☐ |

**Figure 1:** Test question for glucose meter discrete choice experiment.

The choice experiment consisted of a series of unlabelled, paired choice sets. For each choice set, the respondent chose between one of two hypothetical blood glucose meters based on the levels of attributes listed. By varying the attribute levels in each choice set, the respondent is forced to trade between attributes and an analysis of preferences across all the choice sets allows for an estimation of the relative importance of each attribute, and preference weights, for each level of an attribute. A main effects analysis does not include interactions between attributes, i.e. the preference for each attribute is assumed to be independent of the preference for any of the other attributes. This simplifies the experimental design and interpretation of the marginal rate of substitution.

The software package Ngene 1.1.1 (ChoiceMetrics Ltd) [23] was used to generate choice sets and assess each set for statistical efficiency. If we impose level balance (a desirable design property where each level appears the same number of times across all scenarios), then the minimum number of choice sets will be six, with potential level balanced designs of size 12 and 18. We did not consider larger choice sets as they are likely to be inefficient and/or impractical for use in a patient survey without implementing a block design.

Three candidate designs were considered [11].

**Design 1)** Main-Effects Near-Optimised Design using Foldover: An initial design of 12 choice sets was created by hand by using an 'off-the-shelf' orthogonal design for the design of alternative A [24], and 'folded over' to create alternative B. As the initial design contained one dominant choice set, this choice set was removed from the design and replaced with a similar non-dominant choice set. This resulted in a near optimal design (D-optimality=95.7%). The discarded dominant choice set could be used as the screening question.

**Design 2)** Main-Effects Optimised Orthogonal Differences (OOD): The methods proposed by Street et al. were used to develop a design where differences in attribute levels are orthogonal [11,25] and the draft design was created using Ngene 1.1.1 with D-optimality=100%. One potential issue with OOD designs arises, if there is potential for one attribute level to dominate, as respondents may not trade if their preferred attribute level appears in all choice sets. As per design 1, design 2 contained a dominant choice set.

**Design 3)** Main-Effects D-efficient Design: D-efficient designs [11,26] use assumptions for the parameters to generate parameter estimates with as small as possible standard errors. These designs make use of any prior information about the parameters (e.g. estimates available in literature, from pilot studies, or vague information such as the sign that the parameters may take) to determine the asymptotic standard errors. For our DCE, it is assumed that for each attribute, respondents would prefer a higher level to a lower level (the higher levels being an improvement on the previous level), i.e. vague priors where all parameters are close to zero but positive. The resultant design was D-optimal (100%) and had a D-error of 0.277695 which indicates a reasonably efficient design.

Design 3 was chosen on the basis of efficiency and the dominant choice set from design 1 was used as a screening question (Figure 1). The choice set design was such that either A or B could be preferred and responders would be expected to choose a mix of As and Bs across the twelve choice sets.

As is good practice, the survey included an introductory/ informed consent section and collected patient demographic data and information about the respondent's diabetes. This data was used to screen patients and for examining potential confounding factors in the results. Demographic and other respondent characteristics collected include: number of blood glucose tests per day, age, gender, type of diabetes, years since diagnosis, diabetes treatments used (general), insulin regimen, co-morbidities, most recent HbA1c level.

## Data collection

Responders were recruited via a short advert in the 9th of January 2013 edition of the Diabetes UK e-newsletter which has approximately 65,000 subscribers [27-29]. The survey was online from 8th January 2013 and was closed on 30th January 2013 prior to the publication of the next Diabetes UK e-newsletter.

The online survey was developed and hosted using Snap 10 Professional software [30]. The software allowed for some degree of control over responses. For example, the responder was not shown the blood glucose meter choice sets if the responder indicated they did not use a glucose meter. For multiple choice questions, the number of responses that could be chosen was controlled, i.e. choose one/choose any that apply. Numerical fields were restricted to positive integers and certain questions were mandatory. Short descriptions were provided to describe the differences between different attribute levels.

The survey was tested by a small sample of non-diabetics and a draft online survey was reviewed and tested prior to the publication of the live survey.

Response data were censored to exclude responders who did not select 'yes' in the informed consent section, or were under 18. Respondents who failed the screening question (Figure 1) were censored from the DCE analysis along with any non-traders (responders who always provided the same answer regardless of the choices shown: the rationale for exclusion being that these responses indicate non-participation). Some data were censored from the relevant part of the analysis if the response was illogical, e.g. duration of disease>age of responder.

For type of insulin treatment, categories were stratified by the six main types of insulin as defined by Diabetes UK [31]; however some of the category descriptions were ambiguous, such that some respondents used the 'other' treatments field to qualify the insulin combination used. These responses were cleaned before being used in the analysis. The responses in the 'other' co-morbidity and 'other' diabetes treatments were combined into more general categories to reduce the number of variables.

## Statistical analysis

Descriptive statistics using MS Excel 2010 summarise the demographics and other characteristics of the respondents. Differences between groups were tested using the two-sided Student's t-test for continuous variables or $\chi 2$ test of independence for dichotomous variables. The discrete choice experiment analysis was conducted using STATA 12.1 [32] and conditional logit models [33]. Where needed, the data was clustered by respondent, to take into account correlations within the 12 choice sets when calculating standard errors. The main effects are included in the basecase analysis and if p is the probability of choosing an alternative, then the model takes the form:

$$Z=\text{Logit}(p)=\beta 1med^{*}x1med+\beta 1quick^{*}x1quick+\beta 2^{*}x2+\beta 3^{*}x3+\beta 4^{*}x4+\beta 5^{*}x5 \quad (1)$$

Where:

Time to test: x1med=1 if 30 to 60 seconds, x1quick=1 if under 30 seconds; 0 otherwise

Convenience: x2=1 if glucose meter is easy to use discreetly in public; 0 otherwise,

Data management/Connectivity: x3=1 if data transfer (by Bluetooth/Wi-Fi) for additional data storage and analysis; 0 otherwise,

Maintenance: x4=1 if low maintenance (less than twice a week); 0 otherwise,

Size of glucose meter: x5=1 if compact size; 0 otherwise.

The marginal rate of substitution is the ratio of the coefficients (βi/βj) and 500 bootstrapped samples were generated to calculate the standard error and confidence intervals around the mean marginal rate of substitution. Statistically significant differences between different marginal rates of substitution are assumed if the 95% confidence intervals do not overlap.

We also looked at responder characteristics to determine whether these have an impact on attribute preferences. The covariate model, including both alternative-specific and case-specific variables, takes the form:

$$Z=\text{Logit}(p)=\beta 1med^{*}x1med+\beta 1quick^{*}x1quick+\beta 2^{*}x2+\beta 3^{*}x3+\beta 4^{*}x4+\beta 5^{*}x5+\gamma 1^{*}y_{age}+\gamma 2^{*}y_{male\_cat}+\gamma 3^{*}y_{yearsd}+\gamma 4^{*}y_{tests}+\gamma 5^{*}y_{comorb}+\gamma 6^{*}y_{HbA1c3}+\gamma 7^{*}y_{HbA1c2}+\gamma 8^{*}y_{othertx} \quad (2)$$

Where, the $x_i$ are as specified for equation 1 and:

Age of respondent in years: $y_{age}$

Gender: $y_{male\_cat}$=1 if respondent male; 0 otherwise,

Years since diagnosis: $y_{yearsd}$

Tests per day: $y_{tests}$

Number of comorbidities: $y_{comorb}$

Recent HbA1c result: yHbA1c3=1 if recent HbA1c result more than 10%, $y_{HbA1c2}$=1 if recent HbA1c result is 7.1% to 10%; 0 otherwise

Number of other treatments: $y_{othertx}$

## Results

There were 447 responses to the survey and after removing non-qualifying responders there were 406 (90.83%) responses available for the DCE analysis (3 opted-out, 3 under 18s, 24 do not use glucose meters, 8 failed DCE screening question, 3 non-traders). See Figure 2 below for a summary of the survey attrition.

| | **Type 1 Diabetes** | | | **Type 2 Diabetes** | | | **All respondents** | | | **Type 1 vs. Type 2** |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | N | Mean | SD | N | Mean | SD | N | p-value‡ |
| Age | 47.98 | 13.68 | 188 | 57.99 | 9.83 | 218 | 53.35 | 12.77 | 406 | <0.0001 |
| Years since diagnosis | 23.34 | 15.65 | 188 | 8.62 | 6.99 | 218 | 15.44 | 13.90 | 406 | <0.0001 |
| Glucose tests per day | 5.26 | 2.25 | 188 | 2.47 | 1.78 | 218 | 3.76 | 2.45 | 406 | <0.0001 |
| Average number of co-morbidities | 0.99 | 1.46 | 188 | 1.24 | 1.28 | 218 | 1.13 | 1.37 | 406 | 0.0644 |
| Gender | n | % | N | n | % | N | n | % | N | p-value* |
| Male | 79 | 42.0 | 188 | 140 | 64.2 | 218 | 219 | 53.9 | 406 | <0.0001 |
| Most recent HbA1c | n | % | N | n | % | N | n | % | N | p-value* |
| 4% to 7% (20 to 53 mmol/mol) | 68 | 37.4 | 182 | 93 | 47.9 | 194 | 161 | 42.8 | 376 | 0.0420 |
| 7.1% to 10% (54 to 86 mmol/mol) | 103 | 56.6 | 182 | 86 | 44.3 | 194 | 189 | 50.3 | 376 | |
| More than 10% (more than 86 mmol/mol) | 11 | 6.0 | 182 | 15 | 7.7 | 194 | 26 | 6.9 | 376 | |
| Don't know | 6 | 3.2 | 188 | 24 | 11.0 | 218 | 30 | 7.4 | 406 | - |
| Number of co-morbidities | n | % | N | n | % | N | n | % | N | p-value* |
| None reported | 100 | 53.2 | 188 | 75 | 34.4 | 218 | 175 | 43.1 | 406 | 0.00001 |
| 1 | 44 | 23.4 | 188 | 72 | 33.0 | 218 | 116 | 28.6 | 406 | |
| 2 | 20 | 10.6 | 188 | 31 | 14.2 | 218 | 51 | 12.6 | 406 | |
| 3 | 6 | 3.2 | 188 | 30 | 13.8 | 218 | 36 | 8.9 | 406 | |
| More than 3 | 18 | 9.6 | 188 | 10 | 4.6 | 218 | 28 | 6.9 | 406 | |
| Most common co-morbidities | n | % | N | n | % | N | n | % | N | p-value* |
| Hypertension | 56 | 29.8 | 188 | 107 | 49.1 | 218 | 163 | 40.1 | 406 | 0.0001 |
| Hyperlipidaemia | 11 | 5.9 | 188 | 21 | 9.6 | 218 | 32 | 7.9 | 406 | 0.1585 |
| Cardiovascular disease | 11 | 5.9 | 188 | 23 | 10.6 | 218 | 34 | 8.4 | 406 | 0.0883 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Retinopathy | 39 | 20.7 | 188 | 30 | 13.8 | 218 | 69 | 17.0 | 406 | 0.0618 |
| Nephropathy | 12 | 6.4 | 188 | 3 | 1.4 | 218 | 15 | 3.7 | 406 | 0.0077 |
| Diabetic foot disease | 3 | 1.6 | 188 | 3 | 1.4 | 218 | 6 | 1.5 | 406 | 0.8549 |
| Diabetic neuropathy | 37 | 19.7 | 188 | 38 | 17.4 | 218 | 75 | 18.5 | 406 | 0.5603 |

**Table 1:** Summary of responder characteristics: all 406 patients qualifying for DCE analysis.

‡Using two-sided Student's t-test.

*Using $\chi 2$ test of independence.

†Excluding missing or partially completed EQ5D responses.

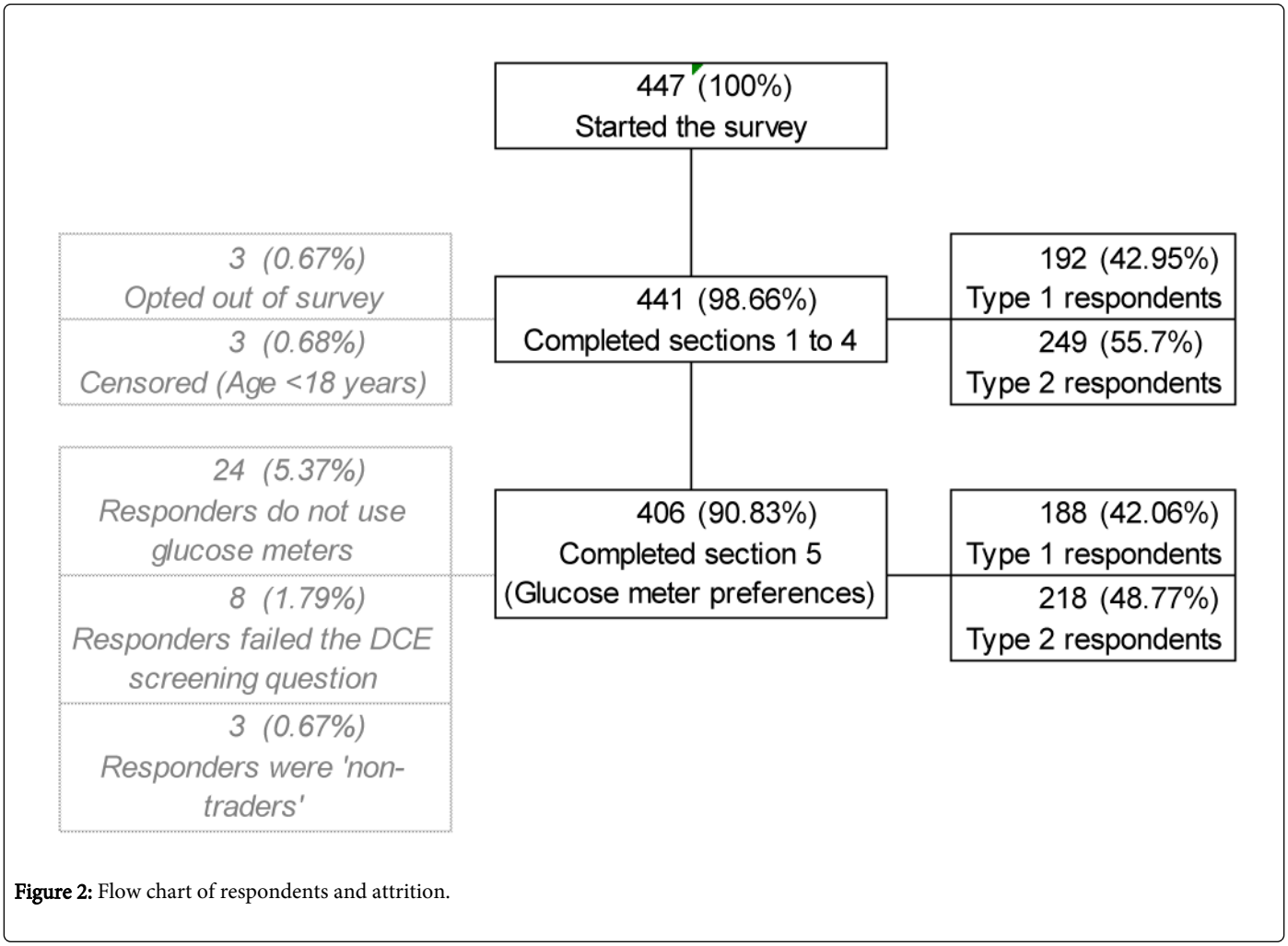


**Figure 2:** Flow chart of respondents and attrition.

## Demographics

Statistically significant differences ($p<0.05$) were found between the Type 1 and Type 2 subgroups when comparing responder characteristics (Table 1). The Type 1 responder subgroups were younger (~10 years younger; $p<0.0001$), had been diagnosed with diabetes for longer (14.72 years longer; $p<0.0001$) and tested HbA1c more frequently compared to Type 2 patients (2.79 more tests per day; $p<0.0001$).

The majority of Type 2 responders (65.6%) reported at least one comorbidity as well as diabetes, whereas 46.8% of Type 1 responders reported comorbidities ($p=0.006$). This may explain the difference in quality of life between the two diabetes subgroups. Hypertension was significantly more common in Type 2 responders than in Type 1 responders ($p=0.0001$) though Type 1 patients had significantly more nephropathy ($p=0.0077$). The other co-morbidities that were reported included respiratory disorders (n=7), hormone disorders (n=8), musculoskeletal disorders (n=14), glaucoma/eye problems (n=4), neurological disorders (n=5), and gastrointestinal disorders (n=5).

As expected, there was a significant difference in the use of insulin in Type 1 patients compared to Type 2 (98.4% v 36.2%; $p<0.001$. (Table 2)) and in particular the use of rapid-acting analogues with or without background long-acting treatment.

| | Type 1 Diabetes | | | Type 2 Diabetes | | | All respondents | | | Type 1 vs. Type 2 |
|---|---|---|---|---|---|---|---|---|---|---|
| Type of insulin treatment | n | % | N | n | % | N | n | % | N | p-value* |
| Rapid-acting insulin analogues | 87 | 46.3 | 188 | 13 | 6.0 | 218 | 100 | 24.6 | 406 | <0.001 |
| Long-acting insulin analogues | 14 | 7.4 | 188 | 14 | 6.4 | 218 | 28 | 6.9 | 406 | |
| Short-acting insulins | 15 | 8.0 | 188 | 3 | 1.4 | 218 | 18 | 4.4 | 406 | |
| Medium- and long-acting insulins | 16 | 8.5 | 188 | 18 | 8.3 | 218 | 34 | 8.4 | 406 | |
| Mixed insulin analogue | 40 | 21.3 | 188 | 18 | 8.3 | 218 | 58 | 14.3 | 406 | |
| Mixed insulin | 13 | 6.9 | 188 | 13 | 6.0 | 218 | 26 | 6.4 | 406 | |
| Don't use insulin or insulin analogues | 3 | 1.6 | 188 | 139 | 63.8 | 218 | 142 | 35.0 | 406 | <0.001 |
| Other diabetes treatments | n | % | N | n | % | N | n | % | N | p-value* |
| Metformin IR | 12 | 6.6 | 183 | 68 | 31.2 | 218 | 80 | 20.0 | 401 | <0.001 |
| Metformin PR | 10 | 5.5 | 183 | 68 | 31.2 | 218 | 78 | 19.5 | 401 | <0.001 |
| Gliclazide | 0 | 0.0 | 183 | 47 | 21.6 | 218 | 47 | 11.7 | 401 | <0.001 |
| Liraglutide | 1 | 0.5 | 183 | 20 | 9.2 | 218 | 21 | 5.2 | 401 | <0.001 |
| Sitagliptin | 1 | 0.5 | 183 | 16 | 7.3 | 218 | 17 | 4.2 | 401 | 0.001 |
| Gliclazide MR | 0 | 0.0 | 183 | 14 | 6.4 | 218 | 14 | 3.5 | 401 | <0.001 |
| Exenatide (twice daily) | 0 | 0.0 | 183 | 12 | 5.5 | 218 | 12 | 3.0 | 401 | 0.001 |
| Metformin+Pioglitazone | 1 | 0.5 | 183 | 10 | 4.6 | 218 | 11 | 2.7 | 401 | 0.014 |
| Diet/exercise | 2 | 1.1 | 183 | 8 | 3.7 | 218 | 10 | 2.5 | 401 | 0.099 |
| Pioglitazone | 0 | 0.0 | 183 | 8 | 3.7 | 218 | 8 | 2.0 | 401 | 0.009 |
| Glimepiride | 0 | 0.0 | 183 | 7 | 3.2 | 218 | 7 | 1.7 | 401 | 0.014 |
| Metformin+Sitagliptin | 0 | 0.0 | 183 | 6 | 2.8 | 218 | 6 | 1.5 | 401 | 0.024 |
| Saxagliptin | 0 | 0.0 | 183 | 5 | 2.3 | 218 | 5 | 1.2 | 401 | 0.039 |
| Acarbose | 0 | 0.0 | 183 | 2 | 0.9 | 218 | 2 | 0.5 | 401 | 0.194 |
| Exenatide (once daily) | 0 | 0.0 | 183 | 2 | 0.9 | 218 | 2 | 0.5 | 401 | 0.194 |
| Glipizide | 1 | 0.5 | 183 | 1 | 0.5 | 218 | 2 | 0.5 | 401 | 0.901 |
| Metformin+Vildagliptin | 1 | 0.5 | 183 | 1 | 0.5 | 218 | 2 | 0.5 | 401 | 0.901 |
| Glibenclamide | 1 | 0.5 | 183 | 0 | 0.0 | 218 | 1 | 0.2 | 401 | 0.274 |
| Repaglinide | 0 | 0.0 | 183 | 1 | 0.5 | 218 | 1 | 0.2 | 401 | 0.359 |
| Other treatments | 6 | 3.3 | 183 | 2 | 0.9 | 218 | 8 | 2.0 | 401 | 0.092 |
| No treatment reported | 0 | 0.0 | 183 | 8 | 3.7 | 218 | 8 | 2.0 | 401 | 0.009 |
| Don't Know | 5 | 2.7 | 188 | 0 | 0.0 | 218 | 5 | 1.2 | 406 | - |

**Table 2:** Summary of diabetes treatment: all 406 patients qualifying for DCE analysis.

†Stratified by the six main types of insulin [31]: Mixed insulin analogue=short/rapid-acting analogue+medium-long acting background; Mixed insulin=Short/rapid-acting insulin+medium-long acting insulin background

*Using $\chi 2$ test of independence; IR-immediate release; MR-modified release; PR-prolonged release.

## Preferences

Given the differences between Type 1 and Type 2 responder characteristics, these subgroups were analysed separately. We also hypothesised that the preferences for Type 1 and Type 2 patients would be different. Table 3 shows the attribute coefficients and odds ratios from the main effects model by diabetes subgroup. As expected,

all attributes are viewed positively by responders. For Type 1 responders, time to test under 30 seconds is the most favoured attribute followed by data management options and low maintenance. For Type 2 responders, low maintenance is the most favoured attribute followed by data management options and time to test of under 30 seconds. Figure 3 below shows the average marginal effects, namely the impact of a change in attribute effect on the probability of choosing a glucose meter.

| **Attribute** | $X_i$ | **Type 1** | | | **Type 2** | | | **p-Value‡** |
|---|---|---|---|---|---|---|---|---|
| | | $\beta_i$ | 95% CI | | $\beta_i$ | 95% CI | | |
| Time to test: 30-60 s | $x_{1med}$ | 0.590 | 0.464 | 0.715 | 0.433 | 0.324 | 0.541 | 0.062 |
| Time to test: <30 s | $x_{1quick}$ | 0.906 | 0.712 | 1.101 | 0.609 | 0.462 | 0.757 | 0.016 |
| Convenience | $x_2$ | 0.572 | 0.454 | 0.691 | 0.528 | 0.424 | 0.631 | 0.577 |
| Data management | $x_3$ | 0.752 | 0.606 | 0.898 | 0.741 | 0.593 | 0.890 | 0.918 |
| Low maintenance | $x_4$ | 0.647 | 0.510 | 0.784 | 0.846 | 0.706 | 0.987 | 0.045 |
| Compact size | $x_5$ | 0.260 | 0.152 | 0.368 | 0.311 | 0.224 | 0.398 | 0.466 |
| Attribute | $X_i$ | OR† | 95% CI | | OR† | 95% CI | | |
| Time to test: 30-60 s | $x_{1med}$ | 1.803 | 1.591 | 2.044 | 1.541 | 1.383 | 1.718 | |
| Time to test: <30 s | $x_{1quick}$ | 2.475 | 2.038 | 3.007 | 1.839 | 1.587 | 2.131 | |
| Convenience | $x_2$ | 1.772 | 1.575 | 1.995 | 1.695 | 1.529 | 1.880 | |
| Data management | $x_3$ | 2.122 | 1.833 | 2.456 | 2.099 | 1.809 | 2.435 | |
| Low maintenance | $x_4$ | 1.910 | 1.666 | 2.191 | 2.331 | 2.026 | 2.683 | |
| Compact size | $x_5$ | 1.297 | 1.164 | 1.445 | 1.365 | 1.251 | 1.489 | |

**Table 3:** Attribute coefficients and odds ratios by type of diabetes: Preferences main effects model.

‡Type 1 vs. Type 2 using two-sided Student's t-test

†Compared with base level $X_i$=0.

OR: odds ratio; s: Seconds; CI: Confidence Interval.

| **Trade up to** | **Trade up from** | **Type 1** | | | **Type 2** | | |
|---|---|---|---|---|---|---|---|
| $X_i$ | $X_j$ | $\beta_i/\beta_j$ | 95% CI‡ | | $\beta_i/\beta_j$ | 95% CI‡ | |
| $x_{1quick}$ | $x_{1med}$ | 1.483 | 1.164 | 1.801 | 1.408 | 0.850 | 1.966 |
| $x_{1quick}$ | $x_2$ | 1.368 | 1.035 | 1.701 | 1.154 | 0.677 | 1.631 |
| $x_{1quick}$ | $x_3$ | 1.007 | 0.806 | 1.208 | - | - | - |
| $x_{1quick}$ | $x_4$ | 0.993 | 0.785 | 1.201 | - | - | - |
| $x_{1quick}$ | $x_5$ | 2.614 | 1.642 | 3.586 | 1.957 | 0.678 | 3.236 |
| $x_3$ | $x_{1med}$ | 1.275 | 0.804 | 1.747 | 1.714 | 0.940 | 2.488 |
| $x_3$ | $x_{1quick}$ | - | - | - | 1.217 | 0.780 | 1.654 |
| $x_3$ | $x_2$ | 1.314 | 0.903 | 1.726 | 1.404 | 1.006 | 1.803 |
| $x_3$ | $x_4$ | 1.162 | 0.860 | 1.464 | - | - | - |
| $x_3$ | $x_5$ | 2.895 | -0.472 | 6.261 | 2.382 | 1.177 | 3.587 |
| $x_4$ | $x_{1med}$ | 1.098 | 0.708 | 1.487 | 1.957 | 0.916 | 2.997 |
| $x_4$ | $x_{1quick}$ | - | - | - | 1.390 | 0.923 | 1.857 |
| $x_4$ | $x_2$ | 1.131 | 0.780 | 1.482 | 1.604 | 1.152 | 2.055 |
| $x_4$ | $x_3$ | - | - | - | 1.142 | 0.906 | 1.378 |
| $x_4$ | $x_5$ | 2.491 | 0.585 | 4.397 | 2.720 | 1.439 | 4.001 |
| $x_{1med}$ | $x_2$ | 1.030 | 0.597 | 1.464 | - | - | - |
| $x_{1med}$ | $x_5$ | 2.269 | 0.228 | 4.311 | 1.390 | 0.349 | 2.431 |
| $x_2$ | $x_{1med}$ | - | - | - | 1.220 | 0.582 | 1.858 |
| $x_2$ | $x_5$ | 2.202 | 0.436 | 3.969 | 1.696 | 0.865 | 2.527 |

**Table 4:** Marginal rate of substitution (trading up attributes) by type of diabetes: Preferences main effects model.

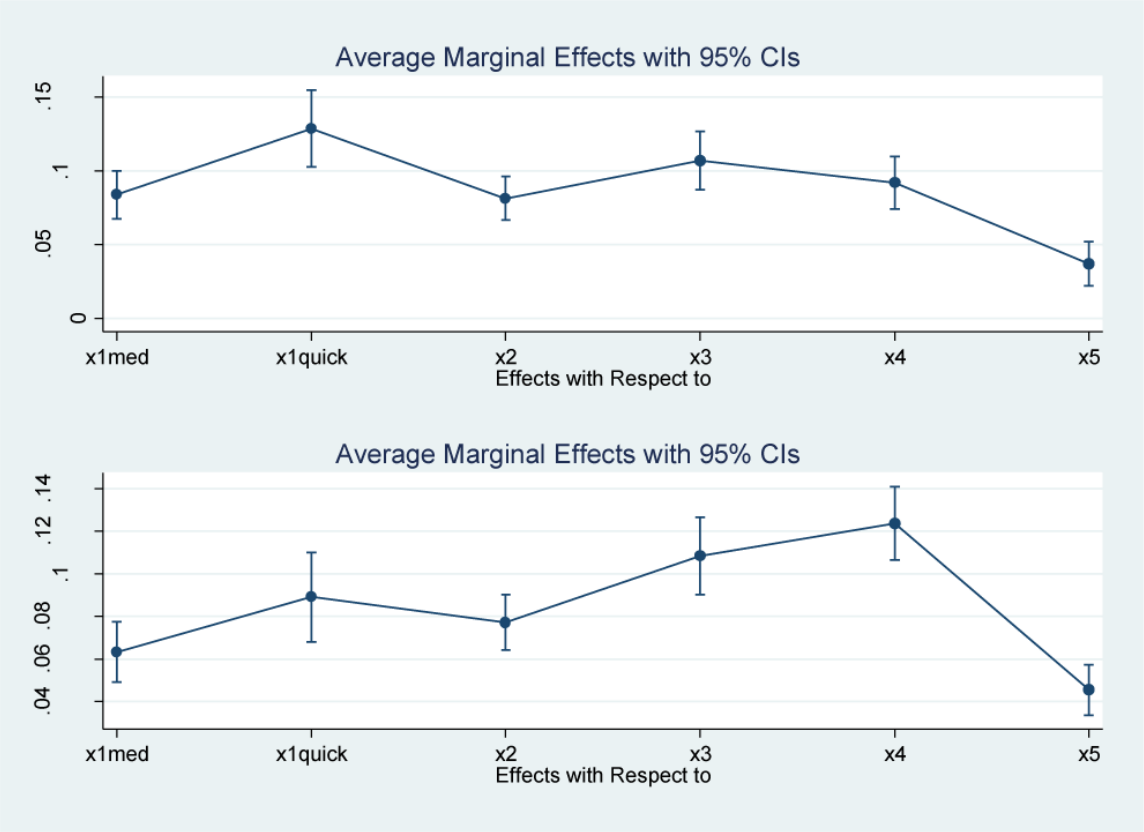


**Figure 3:** Plot of marginal effects on probability of glucose meter choice for main effects model: a) Type 1 diabetes; b) Type 2 diabetes.

Table 4 shows the marginal rate of substitution for trading from attribute $X_j$ to attribute $X_i$ with 95% confidence intervals calculated from the standard error obtained from 500 bootstrapping samples. Type 1 respondents were most willing to trade a compact device (2.61 units), time to test of 30 to 60 seconds (1.48 units) or convenience (1.37 units) for a device that could produce test results in under 30 seconds. Type 2 respondents were most willing to trade a compact device (2.72 units) or convenience (1.37 units) for a device that was low maintenance, or to trade a compact device (2.38 units) or convenience (1.40 units) for a device that had better data management options.

The covariate analysis was conducted using complete records only (394 respondents). None of the covariates are significant explanatory factors and inclusion of these covariates does not improve the model fit (Table 5). The main effects analysis does not include interactions between attributes, i.e. the preference for each attribute is independent of the preference for any of the other attributes. This simplifies the experimental design and interpretation of the marginal rate of substitution. However, a main effects only design assumes that interactions are not significant or do not account for a significant proportion of the explainable variance, and that the omission of interactions will not lead to undue bias in the results.

| | **Type 1** | | | | **Type 2** | | | |
|---|---|---|---|---|---|---|---|---|
| | Observations=4344;<br>Respondents=181<br>LR chi2(9)=3.27<br>Prob>chi2=0.9525 | | | | Observations=5112;<br>Respondents=213<br>LR chi2(9)=3.55<br>Prob>chi2=0.9384 | | | |
| Model | LL | df | AIC* | BIC* | LL | df | AIC* | BIC* |
| Main effects model | -1167.436 | 7 | 2348.873 | 2393.509 | -1376.064 | 7 | 2766.128 | 2811.904 |
| Covariate model | -1165.800 | 16 | 2363.600 | 2465.625 | -1374.289 | 16 | 2780.577 | 2885.207 |

**Table 5:** Comparison of preferences main effects model with main effects model with covariates.

AIC-Akaike Information Criterion [AIC=-2*ln(likelihood)+2*k]; BIC-Bayesian Information Criterion [BIC=-2*ln(likelihood)+ln(N)*k]; df-degrees of freedom; k=number of parameters estimated; LL-log likelihood; N=number of observations.

*Given two models fit on the same data, the model with the smaller value of the information criterion is considered to have a better fit.

## Conclusion

For this DCE, we considered three different designs using standard design methods [11]: orthogonal with foldover, optimal and orthogonal in the differences, and a Bayesian D-efficient design. It was unnecessary to limit the design to an orthogonal design, and in fact for this particular DCE, an orthogonal design resulted in a dominant choice set which would yield no information. The web-based data collection format enabled us to collect a sufficient number of responses in a short period of time. Our literature review of DCEs examining diabetes treatment preferences [12,14,15,18-21] indicated that 160-280 usable responses could produce robust results. Similarly, the ISPOR Task Force report indicated that, in general, precision flattens out at around 150 to 300 observations [11]. Given that statistical significance was achieved in the main effects model, we conclude that our final DCE design provided a good balance between response efficiency and statistical efficiency.

We had sufficient data to compare Type 1 and Type 2 respondents' characteristics. In our sample, the characteristics of the Type 1 respondents were significantly different to the Type 2 respondents and as such the preferences for these subgroups were analysed separately in the DCE. As anticipated, Type 1 respondents showed a preference for the shortest time to test, whereas Type 2 respondents showed a preference for low maintenance. The covariate analysis attempted to assess additional confounding factors within each diabetes subgroup. However this analysis was underpowered and no significant explanatory factors were detected.

It was evident post-data collection, that the insulin category section of the questionnaire was ambiguous [31]. This data was cleaned prior to analysis and used in the descriptive statistics section, but was not included in the covariate analysis because of potential misclassification.

In this DCE, it was necessary to present 12 choice sets with some sets being very similar (utility balanced sets) to each other and this task may have seemed monotonous to the respondent. DCEs have a high cognitive burden compared to a simple opinion survey and the cognitive burden may be even higher for respondents with chronic or multiple comorbid conditions. The respondents may find it hard, to appreciate the concept of trading, i.e. that they have to give up one or more attributes to receive another, particularly as the cost of the glucose meter may be funded by a third party. However, only eight responders were excluded for failing the screening question (1.79%) and we only excluded a further three responders (0.67%) who were non-traders, in that their attribute preferences did not have internal consistency, as they always gave the same answer (always answered A or always answered B). We considered the quality of responses to be good for the majority of respondents and no further respondents were excluded from the analysis.

In this analysis, we assumed attributes were independent, which may not be the case. A main effects only design assumes that interactions are not significant or do not account for a significant proportion of the explainable variance, and that the omission of interactions will not lead to undue bias in the results. We believe that these assumptions are reasonable for this DCE. The choice sets were unlabelled and the analysis restricted to five attributes, such that there would be unobserved factors associated with blood glucose meter choice that could not be measured by this analysis.

This is the first DCE to examine the impact of blood glucose meter attributes on blood glucose meter choice. We have elicited preference weightings for five key glucose meter attributes for both Type 1 and Type 2 diabetics. Type 1 respondents considered 'time to test' to be the most critical factor when choosing a blood glucose meter, and the preference weighting was significantly higher than Type 2 respondents who have a stronger preference for low maintenance. Devices that provide value added features such as offline storage of data and additional data analysis will be valued by both Type 1 and Type 2 patients whereas a compact device was not particularly favoured.

## Acknowledgement

This work was funded by Merck Serono, UK. MO was a paid consultant to Merck Serono, UK and RP was a paid employee of Merck Serono, UK.

## References

1. National Institute for Health and Clinical Excellence (2009) CG87: Type 2 Diabetes - newer agents (partial update of CG66).
2. Wild S, Roglic G, Green A, Sicree R, King H (2004) Global prevalence of diabetes: estimates for the year 2000 and projections for 2030. Diabetes Care 27: 1047-1053.
3. Mathers CD, Loncar D (2006) Projections of global mortality and burden of disease from 2002 to 2030. PLoS Med 3: e442.
4. International Diabetes Federation (2011) One adult in ten will have diabetes by 2030.
5. Diabetes UK (2013) What is diabetes?
6. Committee of Public Accounts (2012) Department of Health: The management of adult diabetes services in the NHS. Seventeenth Report of Session 2012–13, London, UK.
7. Hex N, Bartlett C, Wright D, Taylor M, Varley D (2012) Estimating the current and future costs of Type 1 and Type 2 diabetes in the UK, including direct health costs and indirect societal and productivity costs. Diabet Med 29: 855-862.
8. HM Treasury (2010) Spending Review 2010.
9. Koenig RJ, Peterson CM, Jones RL, Saudek C, Lehrman M, et al. (1976) Correlation of glucose regulation and hemoglobin AIc in diabetes mellitus. N Engl J Med 295: 417-420.
10. Bridges JF1, Hauber AB, Marshall D, Lloyd A, Prosser LA, et al. (2011) Conjoint analysis applications in health--a checklist: a report of the ISPOR Good Research Practices for Conjoint Analysis Task Force. Value 14: 403-413.
11. Reed Johnson F, Lancsar E, Marshall D, Kilambi V, Mühlbacher A, et al. (2013) Constructing experimental designs for discrete-choice experiments: report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. Value health 16: 3-13.
12. Casciano R, Malangone E, Ramachandran A, Gagliardino JJ (2011) A quantitative assessment of patient barriers to insulin. Int J Clin Pract 65: 408-414.
13. Sussman A, Taylor EJ, Patel M, Ward J, Alva S, et al. (2012) Performance of a glucose meter with a built-in automated bolus calculator versus manual bolus calculation in insulin-using subjects. J Diabetes Sci Technol 6: 339-344.
14. Aristides M, Weston AR, FitzGerald P, Le Reun C, Maniadakis N (2004) Patient preference and willingness-to-pay for Humalog Mix25 relative to

Humulin 30/70: a multicountry application of a discrete choice experiment. Value health 7: 442-454.

15. Bøgelund M, Vilsbøll T, Faber J, Henriksen JE, Gjesing RP, et al. (2011) Patient preferences for diabetes management among people with type 2 diabetes in Denmark - a discrete choice experiment. Curr Med Res Opin 27: 2175-2183.
16. Guimarães C, Marra CA, Colley L, Gill S, Simpson S, et al. (2009) Socioeconomic differences in preferences and willingness-to-pay for insulin delivery systems in type 1 and type 2 diabetes. Diabetes Technol Ther 11: 567-573.
17. Guimarães C, Marra CA, Colley L, Gill S, Simpson SH, et al. (2009) A valuation of patients' willingness-to-pay for insulin delivery in diabetes. Int J Technol Assess Health Care 25: 359-366.
18. Guimaraes C, Marra CA, Gill S, Simpson S, Meneilly G, et al. (2010) A discrete choice experiment evaluation of patients' preferences for different risk, benefit, and delivery attributes of insulin therapy for diabetes management. Patient Prefer Adherence 4: 433-440.
19. Hauber AB, Mohamed AF, Johnson FR, Falvey H (2009) Treatment preferences and medication adherence of people with Type 2 diabetes using oral glucose-lowering agents. Diabet Med 26: 416-424.
20. Lloyd A, Nafees B, Barnett AH, Heller S, Ploug UJ, et al. (2011) Willingness to pay for improvements in chronic long-acting insulin therapy in individuals with type 1 or type 2 diabetes mellitus. Clin Ther 33: 1258-1267.
21. Yeo ST, Edwards RT, Fargher EA, Luzio SD, Thomas RL, et al. (2012) Preferences of people with diabetes for diabetic retinopathy screening: a discrete choice experiment. Diabet Med 29: 869-877.
22. CEGEDIM. Blood Glucose Meters Zoom UK. Market Research with Diabetes Specialist Nurses/Practice Nurses Wave 1: March - May 2012.
23. ChoiceMetrics (2012) Ngene 1.1.1 16/02/2012 ed.
24. Sloane NJA (2005) Tables of orthogonal arrays.
25. Street DJ, Burgess L, Viney R, Louviere j (2010) Designing discrete choice experiments for health care. The Netherlands: Springer.
26. ChoiceMetrics (2012) Efficient Designs. Ngene 111 User Manual and Reference Guide.
27. Dolan P (1997) Modeling valuations for EuroQol health states. Med Care 35: 1095-1108.
28. Rabin R, Oemar M, Oppe M (2011) EQ-5D-3L User Guide: Version 4.
29. Diabetes UK (2010) E-newsletter.
30. Snap Surveys (2010) Snap 10 Professional.
31. Diabetes UK (2012) Guide to diabetes. Insulin.
32. StataCorp LP (2011) Stata IC 12.1.
33. Ryan M, Watson V, Gerard K (2010) Practical issues in conducting a discrete choice experiment. The Netherlands: Springer, 2010.

This article was originally published in a special issue, entitled: **"Obesity & Diabetes",** Edited by Prof. Ouliana Ziouzenkova, Ohio State University, USA