Characterising heterogeneity and the role of attitudes in patient preferences: A case study in preferences for outpatient parenteral intravenous antimicrobial therapy (OPAT) services

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Abstract

Choice modelling techniques have established themselves as a key analysis tool in health economics and have been used to understand patient and practitioner preferences across a wide variety of settings. A key interest in recent years has been the incorporation of ever more flexible levels of heterogeneity in preferences across individual decision makers, and in particular a growing interest in the potential role that attitudes and perceptions might play in healthcare choices. This paper presents a novel application in this context, looking at preferences for outpatient parenteral intravenous antimicrobial therapy (OPAT). We adopt a state-of-the-art specification in our model and show very substantial levels of preference heterogeneity across patients. Crucially, a large share of this heterogeneity can be attributed to two key underlying attitudinal constructs, related to the attitude towards hospitals and perceptions on whether responsibility for healthcare should lie with the patient or the practitioner. These results may help design services that are suitable and appealing for a wide variety of patients as well as providing some insights into how a nudging of attitudes and perceptions could help drive patients towards safer and more cost-effective treatment options.

Keywords: *discrete choice; random heterogeneity; latent attitudes; outpatient parenteral intravenous antimicrobial therapy*

1. Introduction

Stated preference survey techniques are increasingly used in healthcare research, often using the term discrete choice experiment (DCE), for example to allow the incorporation of patient preferences into healthcare design and provision (see e.g. de Bekker-Grob et al., 2012). With this growth in application there has been an increase in the sophistication of the models used, again especially in the context of hypothetical choice data (cf. Clark et al., 2014).

Understanding patient preferences for healthcare provides valuable evidence for researchers, clinicians and policy makers. Results from such analyses may have important implications as they have the potential to influence clinical, commissioning and policy decisions relating to care provision and resource allocation. A key issue in understanding and modelling preferences is the treatment of heterogeneity across individual patients. Understanding average preferences for service or treatment attributes and levels is not sufficient alone and heterogeneity in preferences should be explored fully. Indeed, optimal healthcare decision making requires an understanding of, and the ability to account for, heterogeneity in preferences in any one population.

Understanding the source of heterogeneity may also be important as this may highlight a route through which a decision maker may seek to influence patient choices should they be deemed sub-optimal (for example, less beneficial treatment options chosen because they are perceived to be less risky). Behaviour change in this regard may be achieved through education in general or by targeting underlying attitudes relating to treatments and services.

The assessment of heterogeneity in health survey data has sometimes lagged behind methods applied routinely in other contexts such as transport, a field that is still very much at the forefront of developments in choice modelling (see Hess & Daly, 2014 for an overview of choice modelling). In the present paper, we address this by making use of an advanced modelling framework which seeks to allow for multiple sources of heterogeneity. We link some differences in preferences across individual decision makers to differences in the characteristics of those decision makers (e.g. gender, age). Further important improvements can be made by allowing for additional “random” heterogeneity; i.e. that which cannot be easily linked to observed characteristics of the decision makers. For both types of heterogeneity, deterministic and random, we explore what part of this can be attributed to the underlying attitudes of patients. This opens up substantial scope for policy interventions aimed at changing behaviour through nudging of attitudes (cf Voyer, 2015).

Using a stated choice (SC) survey (also regularly called DCE in health) conducted in the UK, our specific application looks at the preferences of patients who require intravenous antimicrobials (IVA) delivered by outpatient or community-based services – termed outpatient parenteral antimicrobial therapy (OPAT). OPAT services are used to treat short-term skin and soft tissue infections as well as chronic or longer-term infections such as joint and bone infections, bacteraemia, osteomyelitis, diabetic foot and tuberculosis. There is a wide range of OPAT service configurations but the most common are hospital/clinic outpatient appointments, nurse provision in the patient's home (general or specialist nurse), or patient self-administration after the receipt of training. Each has advantages and disadvantages; for example, being treated at home is convenient and has a lower risk of acquiring another infection than being treated in clinic but the treatment may take longer overall, if specific antimicrobials have to be used. While OPAT service provision is growing in the UK there is considerable variation in what is available geographically and a paucity of evidence to commend one particular service type over another.

We conducted a SC survey with (current or previous) patients who had either short or long term infections to understand their preferences for the four most common types of service as described above. In addition, we asked respondents to respond to other clinical questions and an attitudinal survey which was developed from our qualitative research (Twiddy et al., 2018).

2. Methods

2.1. Development of the survey

To understand what aspects of care are valued by patients, we followed best practice to design, develop and test the SC survey using three stages: attribute selection, attribute testing and development and pilot survey (Coast, Al-Janabi et al. 2011, Burton, Entwistle et al. 2017). To develop the initial corpus of possible attributes we drew on a systematic review of existing literature (Mitchell, Czoski Murray et al. 2017) and patient interviews (Twiddy, Czoski Murray et al. 2018). Our Patient and Public Involvement (PPI) group helped with the selection of preliminary attributes and development of the levels and then commented on draft versions of the questionnaire.

The literature identified a range of issues relating to OPAT treatment, such as risk of being treated at home (Bamford, Desai et al. 2011), quality of communication between staff (Hitchcock, Jepson et al. 2009, Bamford, Desai et al. 2011), lack of information and cost to the patient (Hitchcock, Jepson et al. 2009). We explored these and other ideas with 32 patients in qualitative interviews (Twiddy, Czoski Murray et al. 2018).

We carried out two cycles of development and testing of attributes and their associated levels. An initial pre-pilot version of the online survey was made available to clinical staff and PPI members and feedback sought. The second stage involved cognitive testing of the statements using a think aloud approach (Willis 2005, Ryan, Watson et al. 2009). The final SC survey included eight choice tasks per participant and each choice task had three alternatives:

- outpatient IVA administration;
- nurse at home IVA administration; and
- self-administration of IVA.

The order of the treatment options was varied across respondents. The characteristics of the models of care were described in the form of attributes (e.g. number of treatments per day) and levels within attributes (e.g. once daily, twice daily). Six attributes were selected to describe the individual models of care, namely:

- number of treatments each day;
- appointment times given;
- who gives the IVs?
- communication between patient and healthcare professionals (HCPs);
- aftercare from healthcare professionals after the end of treatment; and
- risk of a problem such as another infection or having to go into hospital.

The possible values for each attribute depending on the alternative for which it is used are shown in Table 1. With the exception of the aftercare and risk attribute, the possible levels differed across the treatment options.

The specific combinations of values for the different characteristics to be shown in a given choice task were determined on the basis of an experimental design. We specifically made use of a D-efficient design (Rose and Bliemer, 2014), which seeks to create attribute combinations that will lead to reduced standard errors for the parameters estimated from the data collected with the design. In the absence of any meaningful evidence in the literature for many of our attributes, we decided to rely on uninformative (zero) priors, also as the sample of respondents available to us was too limited to develop priors based on the basis of a pilot survey. The full design included 24 rows, and orthogonal blocking was used to split this into three sets of eight choice tasks, with one block used for each respondent. An example of a single choice task is shown in Figure 1.

Table 1: Alternatives and possible attribute levels

		Service 1 **Nurse gives IVs in your home**	**Service 2** **You have your IVs in hospital**	**Service 3** **You give IVs to yourself at home**
Number of treatments each day	One	✓	✓	✓
	Two	✓	✓	✓
	Three			✓
	Pump provides continuous treatment	✓	✓	✓
Appointment times given	Daily appointment time given	✓	✓	
	Daily appointment time not given	✓	✓	
	No appointment needed			✓
	Specialist IV antibiotic nurse	✓	✓	

	General nurse	✓	✓	
	Doctor		✓	
Who gives the IVs?	You give the IVs yourself after half a day of training			✓
	You give the IVs yourself after one day of training			✓
Communication between you and healthcare professionals (HCPs)	See a HCP who knows you	✓	✓	
	See a HCP who does not know you	✓	✓	
	Speak on the phone with a HCP who knows you			✓
	Speak on the phone with a HCP who does not know you			✓
Aftercare from healthcare professionals after the end of treatment	None	✓	✓	✓
	Appointment at hospital with nurse	✓	✓	✓
	Appointment with your GP	✓	✓	✓
	Telephone appointment with nurse	✓	✓	✓
Risk of a problem such as another infection or having to go into hospital	1 in 6 chance	✓	✓	✓
	1 in 10 chance	✓	✓	✓
	1 in 25 chance	✓	✓	✓

An example of a single choice task is shown in Figure 1.

Please click on one box to indicate which service you would prefer

Type of service:	Nurse administers in your home	You attend hospital	You self administer at home
Number of treatments required per day	One	One	Two
Daily appointment time given	Daily appointment time given	Daily appointment time not given	No appointment needed
Who gives the IV's?	Specialist IV antibiotic nurse	Doctor	Self after one day of training
Communication between you and healthcare professionals (HCP)	Speak face-to-face with a HCP who knows you	Speak face-to-face with a HCP who does not know you	Speak on the phone with a HCP who knows you
Aftercare from healthcare professionals at end of treatment	Appointment at hospital with nurse	Appointment at hospital with nurse	Telephone appointment with nurse
Risk of a problem such as another infection or having to go into hospital	1 in 10 chance	1 in 6 chance	1 in 10 chance
Please tick which service you would prefer to receive:	❑	❑	❑

Figure 1: Example SC survey choice task

In addition to the answers to the hypothetical choice scenarios, the survey collected detailed socio-demographic and past treatment data. Recent work has shown that when patients are in a situation in which they have to make a decision about treatments, their attitudes and perceptions play a part in shaping these decisions (e.g. Klojgaard and Hess 2014). In the absence of pre-existing literature, a measure of patient attitudes was developed from the qualitative data. Questions were phrased as positive or negative statements and scored on a five-point Likert scale.(Edwards and Kenney 1946). A large number of such questions were included, with full details in Minton et al. (2017).

2.2. *Participants and delivery of the survey*

Participants were recruited through six NHS acute hospital trusts in the North of England if they fulfilled the following criteria: 18 years or over; OPAT experience in previous 2 years; and able to consent. The SC surveys were conducted between September 2014 and May 2015. Eligible patients were consented by a research nurse and the questionnaire delivered to patients face to face by a researcher using a laptop or iPad. See Minton et al (2017) for further details on sampling and data collection.

2.3. *Ethical Approval*

Ethical approval was sought and obtained from NRES Committee South West – Frenchay (13/SW/0060).

2.4. *Patient involvement*

A patient advisory group was formed to support the project comprising five OPAT patients. They were involved in the development of participant information sheets, and development and initial testing of the SC survey, including review of the qualitative data to select the initial corpus of potential attributes. One PPI member was a co-applicant on the grant and remained involved throughout, but has not been able to maintain involvement post completion.

2.5. *Model specification*

Data on choices, whether these be real world choices or those coming from a stated choice (SC) survey, are typically analysed using discrete choice models, a family of mathematical structures of varying levels of complexity. Our analysis specifically made use of an advanced hybrid choice model (see Abou-Zeid & Ben-Akiva, 2014, with an example of a health application in Klojgaard & Hess, 2014), which like the more widely used Multinomial Logit (MNL) or Mixed Logit (MMNL) models, is based on the notion of utility maximisation, but which uses a more flexible specification of heterogeneity in sensitivities/preferences across patients, namely:

- differences that can be linked to the socio-demographic and infection characteristics of the participant (including whether they had short term or long term infections);
- idiosyncratic differences across participants in their preferences that cannot be linked to the characteristics of the participant; and
- differences in preferences that can be linked to underlying attitudes, namely attitudes towards hospitals and towards healthcare responsibility.

With a view to accommodating the role of attitudes, factor analysis was used on the answers to attitudinal statements to identify two latent attitudes (see Table 1): attitude towards hospitals (five items) and attitude towards health care being a doctor's responsibility (four items). Together, these two latent attitudes accounted for 41% of the variance explained in the attitudinal data.

Table 1: Attitudinal items

Attitude towards hospitals	**Attitudes towards healthcare responsibility**
People get better more quickly treated at home (.664)	*Giving own IV would worry me (.58)*
I do not like hospitals (.664)	*Doctors not patients best to decide where patients cared for (.752)*
Hospitals increased risk contracting new infection (.623)	*Would prefer monitoring by doctor than by nurse (.742)*
Would have IV at home even if waiting hours for nurse (.522)	*I want to be responsible for own treatment (-.51)*
Being in hospital would make things difficult for family (.679)	

*factor loading in brackets

To include these effects in the hybrid choice model, we formulate two latent attitudes. In particular, we have the latent variables α_l, with *l=1,2*, hereafter referred to as:

- attitude towards hospitals;
- attitude towards healthcare being a doctor's responsibility

Each of these latent attitudes is defined to have a deterministic and a random component, with latent attitude *l* for person *n* being:

$$\alpha_{l,n} = \gamma_l z_n + \xi_{l,n} \qquad [1]$$

where the estimates of γ_l capture the impact of a range of sociodemographic characteristics of person n (z_n) on the latent attitude, and where ξ_l is a standard Normal variate (mean of 0, standard deviation of 1), distributed across respondents, capturing the random element of the latent attitude.

An important shortcoming in many applications of hybrid choice models is that analysts often attribute all heterogeneity to the latent variables instead of allowing for additional unrelated heterogeneity. This means that, as discussed at length by Vij & Walker (2016), such studies may overstate the share of heterogeneity that can actually be linked to attitudes. We avoid this issue by allowing for both deterministic and random heterogeneity that is not linked to the attitudinal constructs. In particular, the preference for the type of treatment for respondent *n*, is given by:

$$\beta_{hospital,n} = \beta_{hospital} + \gamma_{hospital} z_n + \sigma_{hospital} \xi_{hospital,n} + \sum_{l=1}^{L} \tau_{hospital,l} \alpha_{l,n} \qquad [5]$$

In the above specification, we have that $\beta_{hospital}$ is an estimated mean preference, $\gamma_{hospital}$ relates to socio-demographic impacts on this preference not related to the latent attitude, $\sigma_{hospital}$ is an estimated standard deviation for the random variation across respondents not related to the latent attitude, $\xi_{hospital,n}$ is a standard Normal variate (mean of 0, standard deviation of 1) distributed across respondents, and $\tau_{hospital,l}$ measures the impact of the latent attitude $\alpha_{l,n}$ on the preference by respondent n for hospital treatment. A corresponding specification is used for $\beta_{nurse\ home}$. The sociodemographic terms tested for effects on the latent attitudes were the same as those used in the above direct interactions with coefficients, allowing for a direct and indirect impact on preferences. These included age, gender, race, living status, education, employment status, number of past infections and a distinction between long term and short term infections. We chose not to segment the analysis by infection type (short term vs. long term) but instead included this variable as a respondent covariate in the modelling, testing for impacts on the preference for treatment types as well as the valuation of treatment characteristics. This provides greater sample sizes and acknowledges that time to infection resolution is on a continuum.

The estimation of a discrete choice model is reliant on appropriate normalisation as only differences in utilities across alternatives (rather than absolute levels) can influences choices. With this in mind, base levels were chosen for each of the attributes, including treatment type, and the associated coefficients were fixed to zero. We chose self-treatment as the base for the treatment type, continuous treatment as the base for the treatment frequency, daily appointment as the base for appointment frequency, doctor as the base for health care professional, an unknown contact as the base for communication, telephone appointment as the base for aftercare, and 1 in 25 as the base for risk. This type of normalisation is known as dummy coding, which, despite some confusion in the literature, is just as consistent as effects coding (Daly et al., 2016). Finally, the δ_i term captures ordering effects given concerns about an underlying propensity for respondents to choose options on the left, where, for normalisation, we set $\delta_3 = 0$.

Net of the inclusion of the extreme value error disturbance for logit models, the utility of alternative *i* (with *i=1,…,3*) for respondent *n* in choice task *t* is then given by:

$$
\begin{aligned}
V_{i,n,t} = \delta_i \\
&+\beta_{hospital,n} hospital_{i,n,t} + \beta_{nurse\ home,n} nurse\ home_{i,n,t} \\
&+\beta_{one\ treatment} one\ treatment_{i,n,t} + \beta_{two\ treatments} two\ treatments_{i,n,t} \\
&\qquad + \beta_{three\ treatments} three\ treatments_{i,n,t} \\
&+\beta_{no\ appointment} no\ appointment_{i,n,t} + \beta_{specialist\ nurse} specialist\ nurse_{i,n,t} \\
&+\beta_{general\ nurse} general\ nurse_{i,n,t} + \beta_{half\ day\ training} half\ day\ training_{i,n,t} \\
&+\beta_{see\ known} see\ known_{i,n,t} + \beta_{speak\ known} speak\ known_{i,n,t} \\
&+\beta_{after\ none} after\ none_{i,n,t} + \beta_{after\ nurse} after\ nurse_{i,n,t} + \beta_{after\ GP} after\ GP_{i,n,t} \\
&+\beta_{risk\ 6} risk\ 6_{i,n,t} + \beta_{risk\ 10} risk\ 10_{i,n,t} \qquad [2]
\end{aligned}
$$

In Equation [2], parameters that are to be estimated (δ and β) multiply the attributes of the alternatives, where these take on values of 1 or 0 depending on whether a given level applies for that alternative. For example, $hospital_{i,n,t}$ will take a value of 1 if and only if alternative *i* for respondent *n* in choice situation *t* is the hospital alternative. All parameters are generic across respondents with the exception of $\beta_{hospital,n}$ and $\beta_{nurse\ home,n}$, which are individual-specific (highlighted by the subscript *n*) owing to the inclusion of deterministic and random heterogeneity, including that linked to the latent attitudes.

Our model now incorporates extensive heterogeneity across individual respondents, where some of this is attributed to underlying, latent, attitudes. The parameters from the model are calibrated jointly on the answers to the stated choice scenarios and the answers to the attitudinal questions, where the latent attitude part of the model is used for both types of data, creating a link between choices and attitudinal responses. This use of answers to attitudinal questions as dependent rather than explanatory variables is more theoretically correct and can avoid some endogeneity bias and measurement error (cf. Abou-Zeid et al., 2014).

With $i_{n,t}$ being the alternative chosen by respondent *n* in task *t* (out of *T=8*), and with $x_{I_{s,n},p}$=1 if and only if respondent *n* chooses answer *p* for attitudinal question *s*, we have that the likelihood of the 8 observed choices and 9 answers to attitudinal questions for respondent *n* is given by:

$$L_n = \int_\alpha \int_\beta \left[\prod_{t=1}^{8} \frac{e^{V_{i_{n,t}}}}{\sum_{j=1}^{4} e^{V_{j,t}}}\right] \left[\prod_{s=1}^{9} \left(\sum_{p=1}^{5} x_{I_{s,n},p} \left(\frac{e^{t_{I_s,p}-\zeta_{l,s}\alpha_{l,n}}}{1+e^{t_{I_s,p}-\zeta_{l,s}\alpha_{l,n}}} - \frac{e^{t_{I_s,p-1}-\zeta_{l,s}\alpha_{l,n}}}{1+e^{t_{I_s,p-1}-\zeta_{l,s}\alpha_{l,n}}}\right)\right)\right] f(\alpha) f(\beta) d\beta d\alpha \qquad [3]$$

The use of an extreme value error term in the utilities leads to a logit kernel for the choice model, while we make use of an ordered logit model for the measurement model for the answers to attitudinal questions, where the $t_{I_s,p}$ parameters are thresholds that are to be estimated, with the normalisation that $t_{I_s,0} = -\infty$ and $t_{I_s,5} = +\infty$. The estimated parameter $\zeta_{l,s}$ measures the impact of the latent variable α_l on I_s. A significant estimate for $\zeta_{l,s}$ thus shows us that the latent attitude α_l has a statistically significant impact on the answers provided to the attitudinal question I_s, with the same applying for an impact on the utilities in the choice model, if e.g. $\tau_{hospital,l}$ is significant.

Both the component relating to the choices (i.e. the Logit kernel) and the component relating to the attitudinal questions are a function of the vector of latent variables α, while the choice model component is also a function of the random components used in the marginal utility coefficients (β). This is why the entire likelihood function is integrated over the distribution of α and β, leading to an integrated choice and latent variable (ICLV) or hybrid choice model. For estimation, we work with the log-likelihood function (the logarithm of Equation [3]) and approximate this using numerical simulation, i.e. maximizing the simulated log-likelihood. In this process, we need to take draws (where we rely on 200 MLHS draws per person, see Hess et al., 2006) for 4 normally distributed random terms. All models were coded in Ox (Doornik, 2001), and the standard errors reported in the results are obtained with the sandwich method (Huber, 1967). Finally, we estimate choice share (uptake) between alternatives based on models with different levels of heterogeneity incorporated.

5. Results

A total of 512 people were approached to complete the survey, of whom 254 consented. Data were collected from 197 participants (20 participants could not be contacted post recruitment, 15 were too ill to participate, 17 refused post consent and 5 were removed due to missing data). The sample characteristics are included in Table 3.

Table 3: Sample characteristics

	N (%)
Mean age (range; SD)	56.76 (20-94; 13.7)
Gender (male)	118 (50.9%)
Children under 18	43 (21.8%)
Ethnicity	
White	178 (90%)
Asian/Black British	15 (7.6%)
Other	4 (2%)
Education	
University or College	88 (44.7%)
Technical	27 (13.7%)
Secondary	77 (39.1%)
Primary	5 (2.5%)
Working status	
Full time	61 (30.9%)
Part time	21 (10.7%)
Retired	74 (37.6%)
Unable to work due to illness	31 (15.7%)
Other	10 (5.1%)
Previous IV antibiotic experience	
1 current/previous infection	156 (79%)
2 previous infections	20 (10.2%)
3 or more previous infections	21 (10.7%)
Type of infection**	
Short term	80 (40.7%)

Long term	117 (59.3%)
Model of care experienced*	
Hospital attendance	119
Nurse at home	81
Self- administration	13

*>1 is possible; **Based on response to time to heal question where ≤7 days = short and >7 days = long

Our analysis made use of a complex model, with a very large number of parameters. We thus present the results across a number of separate tables. We start by looking at the estimates for the choice model component, summarised in Table 4. Alternative specific constants are estimated for the first and second alternative, with the third serving as the base. From the estimates, we observe a slight preference for left most alternative (positive effect compared to the base), but this is not statistically significant, while the middle alternative is the least preferred, all else being equal, but this is also not highly significant.

For treatment type, self-administration is used as the base, and we estimate effects for the two other treatment types. We observe that, for a respondent in the base socio-demographic category, there is no statistically significant difference in preference between hospital and self-administration, with a preference, albeit with low statistical significance, for nurse treatment at home. For patients aged under 50, the preference for hospital treatment increases and becomes close to that for nurse at home, while, for those aged 65 and over, there is a very strong preference for the nurse at home option.

There is however extensive additional heterogeneity. We see a highly significant estimate for the standard deviation for the hospital treatment, where this is much larger in absolute value than the mean. For the nurse at home option, the standard deviation has a lower level of statistical significance but remains large, indicating again high level of variation across individuals in their treatment preferences. Indeed, ignoring for now the additional heterogeneity from the attitudinal construct, a 95% confidence interval for the utility for hospital treatment would range from -4.55 to 4.25, while, for the nurse option, it would range from -0.87 to 3.78. This shows that while, at the average for a respondent in the base socio-demographic groups, nurse at home would be preferred to self-administration and in turn to hospital, all other orderings of preferences are similarly possible in the sample population.

Additional heterogeneity is introduced by the latent attitudes. Before analysing the impact of the latent variables in the choice model, we need to understand their directionality. For this purpose, Table 5 shows the results for the structural model for the two latent variables, i.e. explaining the latent attitudes on the basis of patient characteristics, as well as the results of the measurement model, showing the role of the latent attitudes in explaining the answers to attitudinal questions. The results show a positive impact (see ζ) of the first latent variable on all five associated statements in the measurement model. This means that a higher value for the first latent variable would lead to a higher value for the answer to these statements, where higher values mean stronger disagreement. This identifies the first latent variable as a ***pro-hospital attitude***, as people with a more positive latent variable disagree more with statements such as "People get better more quickly treated at home". These respondents are less likely to be female or non-white and more likely to live at alone, albeit that this latter effect is not significant at high levels.

For the second latent variable, we see a negative impact on the first three statements and a positive (though no significant) impact on the last. This implies that the second latent variable relates to ***people seeing healthcare as a doctor's responsibility***, with those with a more positive latent variable agreeing for example with “Giving own IV would worry me”. The socio-demographic influences suggest that people over 65 see healthcare more as a doctor's responsibility, as do non-white respondents, while this is reduced for people with a university degree (though not statistically significant). While some of the socio-demographic effects included in the structural equations were not significant at usual levels of confidence, they were retained as they made behavioural sense, and also as they aid identification of the model. The remaining set of 36 threshold parameters (t) in Table 5 simply capture the distribution of answers to attitudinal questions in the data.

Returning now to the impact of the latent variables in the choice model, as captured by the τ parameters in Table 4, we see that respondents with a more positive pro-hospital attitude (i.e. more positive latent variable) have a stronger preference for in hospital treatment in the choice model (positive impact of first latent variable) while the baseline preference for nurse treatment at home is reduced (negative impact of first latent variable). Respondents who are more of the view that healthcare is a doctor’s responsibility have a stronger preference for in hospital treatment in the choice model (positive impact of second latent variable) but the preference for nurse treatment at home is increased even further (positive impact of second latent variable).

Table 4: Estimates for choice model component

		estimate	**robust t-ratio**
constants for three alternatives (option 3 as base)	option 1 (left)	0.2129	0.88
	option 2 (middle)	-0.4938	-1.47
treatment type (self administration as base)	hospital (main effect)	-0.1508	-0.23
	standard deviation (pure random heterogeneity, σ)	2.2462	4.10
	impact of first latent variable (τ)	1.1159	3.16
	impact of second latent variable (τ)	3.4171	5.12
	… shift for hospital for under 50	1.2314	1.72
	nurse at home (main effect)	1.4585	1.57
	standard deviation (pure random heterogeneity, σ)	1.1869	1.74
	impact of first latent variable (τ)	-0.8918	-1.87
	impact of second latent variable (τ)	4.0320	9.25
	… shift for nurse at home for over 65	1.5504	2.48
treatment frequency (continuous as base)	one per day	0.7074	5.14
	two per day	0.1819	0.7
	three per day	-0.2956	-1.04
appointment (daily appointment time as base)	main effect for no appointment	-0.5688	-3.51
	… shift for no appointment for patients with long term infections	0.4548	2.09
treatment administered by (doctor as base)	specialist IV nurse (main effect)	0.6091	1.91
	… shift for specialist IV nurse for patients living alone	-0.6479	-1.54

	general nurse (main effect)	0.2237	0.59
	… shift for general nurse for patients living alone	-0.7355	-1.53
training for self administration (full day as base)	half day training (main effect)	-0.3578	-0.72
	… shift for half day training for patients aged under 50	1.1833	2.47
	… shift for half day training for patients living alone	-1.0338	-1.85
	… shift for half day training for patients with long term infections	0.7676	1.58
in person communication between patient and health-care professionals (unknown person as base)	known person (main effect)	0.0166	0.12
	… shift for known person for patients aged under 50	0.4776	2.33
	… shift for known person for patients with long term infections	0.3991	2.34
telephone communication between patient and health-care professionals (unknown person as base)	known person (main effect)	0.8155	1.47
	… shift for known person for patients aged over 65	-1.2197	-3
	… shift for known person for patients living alone	-1.0737	-2.04
	… shift for known person for patients with long term infections	0.4771	1.03
aftercare (telephone appointment as base)	no appointment	-0.1562	-1.13
	appointment at hospital with nurse	0.1578	1.05
	appointment with own GP	0.0153	0.09
Risk of adverse reactions (1 in 25 as base)	1 in 6 or 1 in 10 (main effect)	-0.988	-6.22
	… shift for 1 in 10 for patients aged over 65	0.7145	2.85
	… shift for 1 in 10 for patients in employment	0.3493	1.98

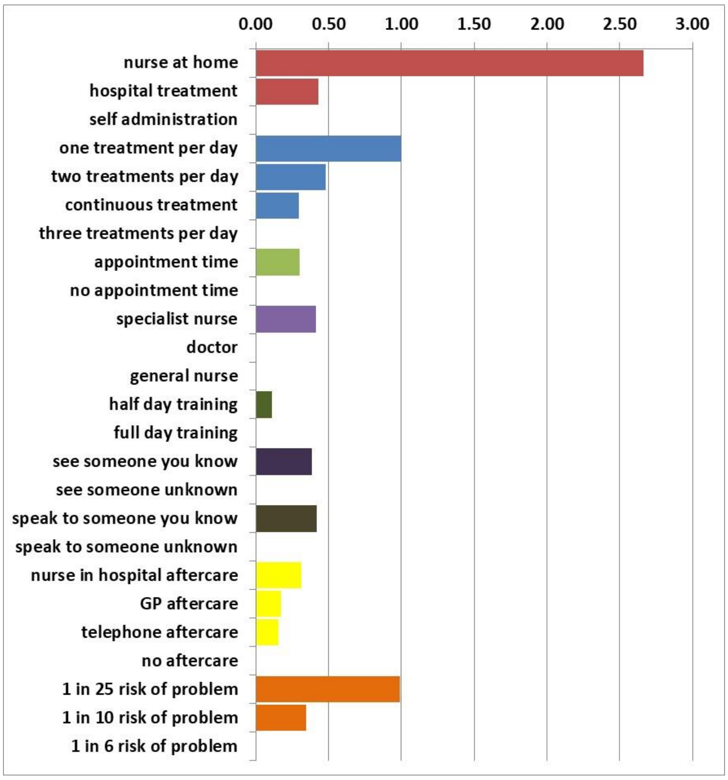
Table 5: Results for structural and measurement models for latent variables

				estimate	robust t-ratio
First latent variable	Structural model (socio-demographic impacts on first latent variable)		female (vs male)	-0.4954	-2.31
			non-white (vs white)	-0.3323	-1.42
			living alone (vs not alone)	0.1887	0.9
	Measurement models (role of first latent variable in explaining answers to attitudinal questions)	"People get better more quickly treated at home" (positive means disagree)	impact of first latent variable ($\zeta_{1,1}$)	1.2866	4.17
			threshold 1 ($t_{I_1,1}$)	-1.177	-3.77
			threshold 2 ($t_{I_1,2}$)	0.3912	1.67
			threshold 3 ($t_{I_1,3}$)	2.0141	5.55
			threshold 4 ($t_{I_1,4}$)	4.1935	6.69
		"I do not like hospitals" (positive means disagree)	impact of first latent variable ($\zeta_{1,2}$)	0.8945	4.28
			threshold 1 ($t_{I_2,1}$)	-1.6936	-7.92
			threshold 2 ($t_{I_2,2}$)	-0.2661	-1.44
			threshold 3 ($t_{I_2,3}$)	0.6429	3.17
			threshold 4 ($t_{I_2,4}$)	2.7464	8.35
		"Hospitals increased risk contracting new infection" (positive means disagree)	impact of first latent variable ($\zeta_{1,3}$)	0.8606	3.21
			threshold 1 ($t_{I_3,1}$)	-0.8715	-4.25
			threshold 2 ($t_{I_3,2}$)	0.9017	4.19
			threshold 3 ($t_{I_3,3}$)	1.6472	6.91
			threshold 4 ($t_{I_3,4}$)	3.4597	8.22
		"Would have IV at home even if waiting hours for nurse"	impact of first latent variable ($\zeta_{1,4}$)	1.8487	3.89
			threshold 1 ($t_{I_4,1}$)	-2.0871	-3.64
			threshold 2 ($t_{I_4,2}$)	0.6702	2.32
			threshold 3 ($t_{I_4,3}$)	1.0196	3.42

		(positive means disagree)	threshold 4 ($t_{I_4,4}$)	3.2735	5.58
		"Being in hospital would make things difficult for family" (positive means disagree)	impact of first latent variable ($\zeta_{1,5}$)	1.1457	4.19
			threshold 1 ($t_{I_5,1}$)	-0.6502	-2.64
			threshold 2 ($t_{I_5,2}$)	0.6962	2.88
			threshold 3 ($t_{I_5,3}$)	1.5152	4.58
			threshold 4 ($t_{I_5,4}$)	4.3082	5.8
Second latent variable	Structural model (socio-demographic impacts on second latent variable)		aged over 65 (vs under 65)	0.37	1.44
			non-white (vs white)	0.8505	4.51
			university educated (vs non-university)	-0.0933	-0.7
	Measurement models (role of second latent variable in explaining answers to attitudinal	"Giving own IV would worry me" (positive means disagree)	impact of first second variable ($\zeta_{2,6}$)	-2.2614	-4.91
			threshold 1 ($t_{I_6,1}$)	-1.6471	-0.75
			threshold 2 ($t_{I_6,2}$)	-0.3395	-0.17
			threshold 3 ($t_{I_6,3}$)	0.0544	0.03
			threshold 4 ($t_{I_6,4}$)	1.961	1.18
		"Doctors not patients best to decide where patients cared for" (positive means disagree)	impact of first second variable ($\zeta_{2,7}$)	-0.4332	-2.43
			threshold 1 ($t_{I_7,1}$)	-1.8055	-4.31
			threshold 2 ($t_{I_7,2}$)	-0.1547	-0.41
			threshold 3 ($t_{I_7,3}$)	0.788	2.04
			threshold 4 ($t_{I_7,4}$)	2.2158	4.99
		"Would prefer monitoring by doctor than by nurse" (positive means disagree)	impact of first second variable ($\zeta_{2,8}$)	-0.5798	-2.82
			threshold 1 ($t_{I_8,1}$)	-2.6319	-4.81
			threshold 2 ($t_{I_8,2}$)	-1.4832	-2.84
			threshold 3 ($t_{I_8,3}$)	0.4947	0.97
			threshold 4 ($t_{I_8,4}$)	2.3679	4.59

		"I want to be responsible for own treatment" (positive means disagree)	impact of first second variable ($\zeta_{2,9}$)	0.1699	0.99
			threshold 1 ($t_{I_9,1}$)	-0.9482	-4.34
			threshold 2 ($t_{I_9,2}$)	0.4399	1.97
			threshold 3 ($t_{I_9,3}$)	1.1794	4.9
			threshold 4 ($t_{I_9,4}$)	2.786	7.8

As we can see from Tables 4 and 5 and the above discussion, there is extensive heterogeneity across individuals in the value they obtain from the different attribute levels, with for example a lower importance assigned to appointment times for those with long term infections, a preference for half-day training for younger patients, and reduced importance for knowing the person for telephone communication for those patients living alone. To get a first sample level overview of sensitivities, Figure 2 shows the values at the sample level mean for the different attribute levels. We see that overall, the service delivery attribute has the biggest range of values for its levels, with a very strong preference for the nurse at home model. The gap at the sample average between the nurse at home level and the self-administration levels is almost as large as the sum across all other attributes of the differences between the best and worst levels. We see that on average, one treatment is preferred to two treatments, continuous treatments and three treatments per day. Having an appointment is preferred to not having an appointment, while specialist nurses are preferred to doctors and general nurses. A half day training is preferred to a full day for self-administration, while patients prefer interacting with someone they know, whether in person or in the phone. Nurses are preferred to GPs or telephone appointments for aftercare, which are preferred to no aftercare. Finally, we see strong non-linearity in the response to risk, where, on average, the benefit of a reduction in risk is twice as high per percent point in the space from 1 in 10 to 1 in 25 as in the space from 1 in 6 to 1 in 10. This suggests that, at least with the present data, changes in risk at are valued more highly when the current risk level is low than when the current risk level is high. This non-linearity, and the fact that only three levels of risk were used, prevents the treatment of risk sensitivity as continuous and we hence also avoid the calculation of marginal rates of substitution which would require assumptions about the shape of the sensitivities outside the range of the three presented levels.



mean	sd
2.66	4.60
0.43	4.35
0.00	
1.00	0.00
0.48	0.00
0.30	0.00
0.00	
0.30	0.22
0.00	
0.41	0.04
0.00	0.34
0.00	
0.11	0.76
0.00	
0.39	0.28
0.00	
0.42	0.76
0.00	
0.31	0.00
0.17	0.00
0.16	0.00
0.00	
0.99	0.00
0.35	0.30
0.00	

Figure 2: Sample level utility values for different attribute levels

With the different socio-demographic interactions used in the model, a total of 48 different socio-demographic groups exist in our model, and we note strong variations in the mean preferences relative to self-administration across these groups, as highlighted in the standard deviations shown in Figure 2. As shown above, there is an overall preference for nurse at home treatment ahead of hospital treatment and ahead of self-administration, where this ordering applies to 39 out of 48 groups at the mean sensitivities (i.e. mean of random variations). Additionally, nurse at home treatment is always preferred to self-administration at the mean preferences, while only white males under 50 living alone marginally prefer hospital treatment to nurse at home treatment. Some groups of patients prefer self-administration to hospital treatment, namely white respondents aged between 50 & 65 that either do not live alone (male or female), are female and live alone, or are male, live alone and have a university degree. Importantly, the gaps between preferences for the different treatment types differ across groups as a result of the different socio-demographic interactions, both directly and through the latent attitudes. Of course, due to random heterogeneity, a significant probability of reversal of preferences exists. To illustrate this, we look at the probability for the three services for a base scenario with the following attributes:

- one treatment per day for each type of service;
- specialist IV nurse for in hospital and nurse at home deliver;
- half-day training for self-administration;
- communication with somebody known to the patient (in person/on phone);
- hospital follow-up appointment with a nurse; and
- 1 in 25 risk.

The treatment frequency and risk attributes have no impact in this case as they are equal across alternatives. With these settings, we obtain mean probabilities as follows:

- Hospital: mean of 24.2%
- Nurse at home: mean of 61.7%
- Self-administration: mean of 14.1%

The extent of heterogeneity is such that for all options, the lower limit of 95% confidence approaches 0, while the upper limit approaches 1 for the nurse option, 94% for the hospital option, and 88% for the self-administration option. We illustrate this heterogeneity in Figure 3, which shows that, despite strong mean preferences, the extent of heterogeneity is such that extensive scope for order reversal exists. We also see that the mean (indicated by a dot) is above the median for hospital and self-administration, while the opposite applies for the nurse at home option.

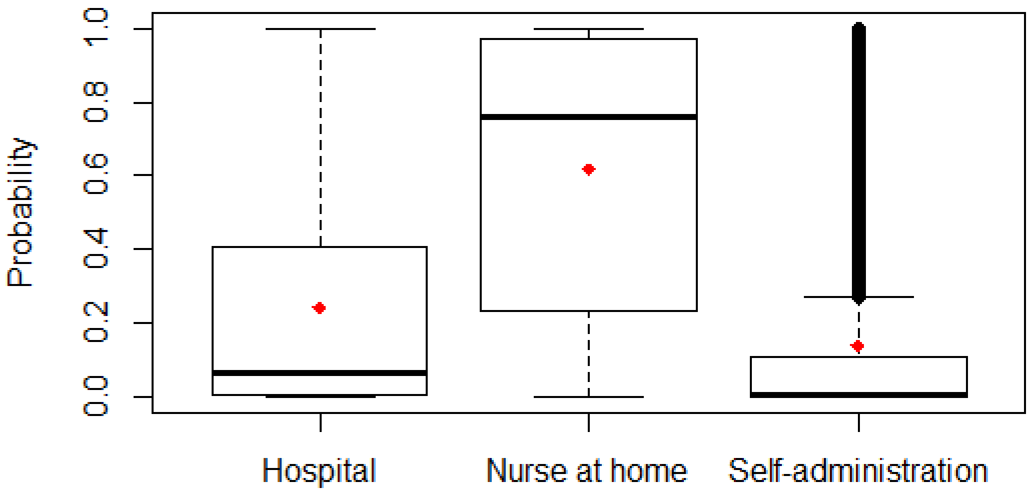


Figure 3: Heterogeneity in probabilities for base scenario

The incorporation of attitudes in the model allows us to investigate possible changes in preferences if attitudes were to change. In particular, we can predict that, if all patients took on the "healthcare responsibility" attitude of younger, white and university educated patients, we would see a small shift in the probabilities from the nurse at home option to self-administration (and to a lesser extent the hospital option), with:

- Hospital: mean of 25.3%
- Nurse at home: mean of 56.5%
- Self-administration: mean of 18.2%

We have looked at the role of attitudes in the model before, but as a final step, we now investigate what share of the overall heterogeneity that we retrieve in the model can be attributed to these attitudinal constructs. Remember that the preference for hospital and nurse at home deliver (with self-administration as the base) varies across respondents both randomly and as a function of patient characteristics. For both types of heterogeneity, part of this comes through the two latent attitudes, while a remainder is independent of the latent attitudes, i.e. directly enters the utility function. Table 6 first looks at the random components of heterogeneity. We see that the total amount of random heterogeneity is fairly similar for both services. However, for the nurse at home service, the random heterogeneity is almost entirely linked to the attitude relating to whose responsibility healthcare is. For the hospital service, roughly two thirds of the random heterogeneity can be linked to that attitude, while over a quarter remains unexplained differences across patients that cannot be linked to the two attitudinal constructs. For either service option, the attitude towards hospital does not drive a large share of the overall heterogeneity, as reflected in the estimates for ζ in Table 5.

We can also study the impact of patient characteristics on heterogeneity. Here, we see that a much larger number of effects are picked up through the latent attitudes than directly in the utility functions. This is a direct benefit of the hybrid choice framework, where gains in efficiency are obtained by making use of more information per respondent, combining the stated choice data with the answers to attitudinal questions. This approach also allows for given patient characteristics to play different roles depending on the "mechanism" through which they enter the utility function. We see this in our case for ethnicity, where non-white respondents have a reduced utility for the hospital option through the pro-hospital latent variable (albeit with low significance) where this is counteracted by a much increased utility through the healthcare responsibility latent attitude.

Table 6: role of latent attitudes in shaping heterogeneity

		Utility for hospital (vs self-administration)			**Utility for nurse at home (vs self-administration)**		
		direct	through pro-hospital latent attitude	through responsibility latent attitude	direct	through pro-hospital latent attitude	through responsibility latent attitude
random heterogeneity	random variance	5.05	1.25	11.68	1.41	0.80	16.26
	share of random variance	28.08%	6.93%	64.99%	7.63%	4.31%	88.06%
impact of patient characteristics	female		-0.55			0.44	
	non-white		-0.37	2.91		0.30	3.43
	living alone		0.21			-0.17	
	aged under 50	1.23					

aged over 65	1.26	1.55	1.49
university degree	-0.32		-0.38

Discussion

Patient choice is becoming increasingly important in the provision of healthcare in England. Patients are being provided with information relating to health conditions and available treatments and being empowered to influence the care they receive. Given this, it is important to factor their preferences and demand for aspects of care in to the design of new services. The use of SC surveys to inform the design of health services is a well established approach. (Ryan 1996; Clark et al, 2014) This research is the first attempt to understand patients' preferences for OPAT services and one of the most in-depth explorations of the role of patient attitudes in influencing healthcare preferences.

The survey attributes of the service were selected on the basis that the qualitative interviews and/or systematic review literature showed these to be important to patients. They were mainly comprised of process aspects of care including the number of treatments per day, whether appointments were given, who delivers the treatment and the level of communication and aftercare provided. However, we did include a health outcome aspect which was the level of risk of an adverse event.

The main effects preferences averaged across the respondents indicated that the type of service was the most important factor with the nurse at home being strongly preferred over hospital treatment and self-administration. The next strongest preference was for once per day treatment vs. two or continuous treatments closely followed by the preference for the lowest level of adverse event risk. While other attribute levels were significant in determining respondent's choices, they were less important. People preferred a specialist nurse over a doctor and general nurse to deliver their IVA; preferred an appointment time (to not having one) and preferred to communicate with someone they know regarding their care. These sources of process utility are clearly important to patients and is a consistent finding of stated choice studies.(Higgins et al, 2014)

By quantifying patient preferences for attributes of care, commissioners may use the results of SC studies to inform changes to service provision so as to obtain the best outcomes within a given budget.

The results indicate that where one model of OPAT care is envisaged, a nurse at home model is likely to be preferred by patients. However, where possible, a range of options should be available. The most promising model would be one which offered a specialist nurse at home model, utilizing one-a-day treatment (where safely available). The service should have a dedicated team of staff caring for patients, to ensure patients receive continuity of care (i.e. good handover and communication between staff), and are followed up by a nurse at the end of treatment.

However, no one model was preferred by all patients, with strong heterogeneity across different patient types. The choices people make about their healthcare are influenced by a number of patient characteristics as well as more general attitudes towards healthcare. In this study, younger patients tended to prefer to come to hospital for their care, and older people tend towards a preference for a nurse at home model, compared to the alternative treatments. Although wide levels of preference heterogeneity were observed, certain trends were apparent. For example age and cohabitation circumstances were consistently important determinants of choices. The finding that older patients who live alone have a stronger preference for longer training sessions, face to face contact and with specialist nurses suggests that this group exhibits greater anxiety about IVA and requires greater support. On average, people preferred less risk but there were some groups that did not differentiate between the risk levels. We were unable to establish the marginal rates of substitution between risk and other service attributes as risk did not appear to be linear. This may reflect a real non-linear attitude to risk or be a function of the specific survey design employed here. (Harrison, et al, 2014)It is worth noting that the risks presented in the survey are higher than those likely to be faced in reality.

An important component in our work is the incorporation of underlying attitudes. Here, we see that the attitude towards responsibility of healthcare accounts for 65% of the random heterogeneity for the preference for hospital treatment, and 88% for the preference for nurse at home treatment. The attitude towards hospitals on the other hand accounts for only 6.9% of the heterogeneity for the preference for hospital treatment, and 4.3% for the preference for nurse at home treatment. The significance of attitudes in explaining heterogeneity in this study is greater than observed elsewhere (Kløjgaard and Hess, 2014). It is unclear why there are differences between studies but it may relate to the level of information on attitudes available which in the current case was quite extensive, as it was based both on literature and qualitative research (Twiddy, 2018; Mitchell, 2017), potentially leading to a more appropriate wording for the attitudinal questions.

A previous economic evaluation of these services concluded that, in those with long term infections, self-administration was the most cost-effective service and yet, on average, it was the least preferred service.(Vargas-Palacios et al, 2017) Thus, allowing choice in this context may result in a significant loss of net benefit to the health care system as a majority will choose lower value service options. Incorporating attitudinal factors into the choice share predictions highlighted how a change in attitudes may impact on choices. In particular, it is possible that any nudging of attitudes towards patients taking responsibility of healthcare could be helpful in influencing choices. This may be especially useful if a change in attitudes can encourage greater uptake of more cost-effective services. There are very few instances in health care where SC information has been used to inform resource allocation. Any future attempts to do this should acknowledge the level of heterogeneity in preferences and fully characterise this (which may mean incorporating attitudes). In doing so, the level of uncertainty in decision making will be greater but better characterised and thus decision making will be more informed.

The study had a number of limitations but most important to acknowledge may be the relatively modest sample size, especially considering the number of sub-groups we considered and the complexity of the models used. We did not have additional information that may have improved the model estimations such as choice certainty or revealed preference data. Our survey also did not have an opt-out which may improve external validity of predictions, however, in the clinical context, patients would not receive a ‘no treatment’ option. While the results may be useful for service commissioners in this area there are a number of caveats. The SC survey only provides information on stated preferences and may not accurately reflect the choices people would make if faced with the same options in reality. (Quaife et al, 2018) Additional research is required to understand if and how stated preferences in health could be calibrated to better reflect revealed preferences to facilitate service design and planning. Thirdly, the socio-demographic (especially age) effect we retrieve may relate to differences across people (coming from cross-sectional data) rather than variation in preferences for the same person over time, and it is thus difficult to predict how treatment preferences will evolve over time. For this, more longitudinal survey methods are needed.

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