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. At the same time however, many applications simply apply these new tools without then investigating the resulting richness in the results. This paper not only presents a novel application of hybrid choice modelling in health, by looking at preferences for outpatient parenteral intravenous antimicrobial therapy (OPAT), but also carefully explores the findings in terms of sources of heterogeneity, disentangling the role of attitudes from other heterogeneity. We find that a large share of the heterogeneity can be attributed to two key underlying attitudinal constructs, related to the general attitude towards hospitals and whether responsibility for healthcare should lie with the patient or the practitioner. Especially the latter accounts for more than 60% of the overall heterogeneity in preferences for the type of treatment. 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 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

The use of choice modelling in health research is growing in popularity, with an increasing breadth of application areas and growing sophistication of the models used (see e.g. de Bekker-Grob et al., 2012; Clark et al., 2014; Hole, 2018; Soekhai et al., 2019). A key focus in choice modelling, and increasingly also in health research, has been the recognition that preferences vary across individual decision makers. Such work recognises that 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. Given that preference data could be used to inform service provision, ignoring heterogeneity in preferences may result in sub-optimal services. These may have a negative impact on patient satisfaction, patient uptake and adherence, which in turn will likely impact on health outcomes and costs. Even in those cases where customisation of services is not possible and only a uniform treatment can be delivered, insights from a model recognising heterogeneity in preferences are still valuable. Indeed, given likely asymmetries in the distribution of preferences in a population, the results from a model not recognising the presence of such heterogeneity are likely to give a biased estimate of the mean sensitivities, a point well rehearsed in other fields (cf. Hess et al., 2015). Understanding the sources of heterogeneity is also important as this can highlight a route through which a health care professional may be able to better communicate the advantages or disadvantages of specific treatments to patients, and identify types of patients most likely to find a particular model of healthcare challenging, so tailored support can be offered.

The assessment of heterogeneity in preferences is a key topic in choice modelling across disciplines (see Hess & Daly, 2014 for an overview of choice modelling). In recent years, the has been increasing focus on incorporating the role of attitudes and perceptions as key drivers of preference heterogeneity. While the interest in attitudes for choice modelling goes back at least to McFadden (1986), it is only thanks to more recent improvements in estimation capability that analysts have been able to include such approaches in their analyses. A key recognition in that more recent stream of research has been that attitudes cannot be observed by an analyst, and that the treatment of answers to attitudinal questions as if they were error free measures of attitudes will thus likely lead to biased results. This has led to the development of hybrid choice models. These structures treat the attitudes themselves as latent (i.e. unobserved) variables, and use them to help explain the heterogeneity in preferences. The models are "hybrid" structures as the latent attitudes not only act as an explanator of the choice behaviour but are also used in measurement models that explain the answers to attitudinal questions. For an overview of the development of such models, see Abou-Zeid & Ben-Akiva (2014).

The easy access to powerful software has led to a growing number of health applications using hybrid choice models across areas, including in health (going back to Klojgaard and Hess 2014). However, such work has often been characterised by two shortcomings. First, there has been a tendency to apply the models without then exploiting their full potential when it comes to the analysis of the results and the additional insights that can be gained into behaviour. Second, many studies (which out of respect for the authors we do not cite here) have failed the heed the warnings in Vij & Walker (2016) when it comes to the specification of the models. Vij & Walker show that if an analyst allows for random heterogeneity only through the latent attitudes, then this will invariably lead to improvements in fit over a model without these latent constructs. This comparison however is misguided as it is based on the assumption that all random heterogeneity can indeed be linked to the attitudinal constructs. In reality, there will almost surely be a partial misattribution of the source of the heterogeneity, with heterogeneity not related to attitudes being attributed to attitudes. This point can be understood most easily by noting that, if heterogeneity across individuals exists in the data, then a model will use any mechanism available to capture that heterogeneity. This issue can be avoided by allowing at the same time for heterogeneity not linked to attitudes. As Vij & Walker (2016) show, any advantages in terms of prediction capability over a model without attitudinal constructs then disappear - a hybrid choice model <u>cannot</u> offer a better fit to the choice data than a model with a correspondingly flexible specification that only explains the choices (and not the answers to attitudinal questions). At first, this may seem a disappointing finding and reduce the interest in applying hybrid choice models. On the contrary however, it opens the possibility to use a hybrid choice model to dissect the sources of heterogeneity and allow us to understand what part of the variation in preferences can be linked back to attitudes. This is the aim of the present paper.

Work in a health context has long highlighted the possible role of attitudes in driving patients' preferences (Mosnier-Pudar et al., 2010; Russo et al., 2019). The specific focus of our application is to look 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 may involve the use of once or twice-a-day broader spectrum antibiotics rather than targeted antibiotics . 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, with care pathway decisions often made on the basis of funding or clinician preference. This motivates the focus on understanding patients' preferences for the different services, how these preferences vary across patients, and how this heterogeneity links back to underlying attitudes. These findings can be used to inform the development of new, tailored and patient-centred OPAT services (e.g. e-opat.com; Chapman et al., 2019).

We collected data via a stated choice (SC) survey (also regularly called DCE in health) in the UK, sampling (current or previous) patients who had either short or long term infections. The SC component looked at choices between the key three delivery methods outlined above (outpatient, nurse visit at home, self-administration), while the survey also collected extensive socio-demographic and other clinical data in addition to answers to attitudinal questions. We then specified a flexible hybrid choice model which allowed for two main sources of heterogeneity, one linked to underlying attitudes and one independent of those attitudes. For both sources, we incorporate both deterministic variation (i.e. linked to patient characteristics) as well as remaining random variation. Our findings show a substantial role for two underlying attitudes, one that captures a broad attitude towards hospital while the other relates to the attitude towards responsibility of healthcare. We see that these two attitudes together account for the vast majority of the heterogeneity in preferences towards the three types of treatment. This work thus highlights that a carefully specified model can disentangle the sources of heterogeneity and provide insights into the role of psychological constructs in driving preferences. This opens up substantial scope for policy interventions aimed at changing behaviour through nudging of attitudes (cf Voyer, 2015).

The remainder of this paper is organised as follows. Section 2 presents the survey design, sampling, and preliminary analysis of the attitudinal data. This is followed in Section 3 by the modelling methodology. Section 4 presents the results of the analysis, with conclusions in Section 5.

2. Survey work and initial data analysis

This section of the paper first presents an overview of the survey before looking at data collection and a preliminary analysis of the data.

2.1. Survey components

The data used in this paper comes from a large study and full details of the survey work are presented in Czoski Murray et al. (2015) and Minton et al. (2017). In what follows, we focus on the stated choice component and the attitudinal questions. The survey additionally collected detailed socio-demographic and health data relevant for the context of the study.

2.1.1. Stated choice scenarios

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 was 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 by six attributes, namely:

- number of treatments each day;
- appointment times given;
- person who administers 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 are shown in Table 1, where, with the exception of the aftercare and risk attribute, the possible levels differed across the treatment options.

Table 1: Alternatives and possible attribute levels

		Nurse gives IVs in your home	You have your IVs in hospital	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			✓
Who gives the IVs?	Specialist IV antibiotic nurse	✓	✓	
	General nurse	✓	✓	
	Doctor		✓	
	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	✓	✓	✓

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 made use of a D-efficient design (cf. Rose and Bliemer, 2014), but, in the absence of any meaningful evidence in the literature for many of our attributes, we decided to rely on uninformative (zero) priors. 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 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

2.1.2. Attitudinal component

With a view to developing a model that incorporates attitudinal constructs, we collected answers as to the level of agreement with a number of attitudinal statements. 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), going from "strongly agree" to "strongly disagree". A total of 12 such questions were included, as follows:

- People get better more quickly if they are treated at home.
- I do not like hospitals.
- If you are treated in hospital, there is an increased risk of contracting a new infection.
- Giving my own intravenous antibiotics would worry me.
- Doctors, not patients, are in the best position to decide where patients should be cared for.
- I would choose to have intravenous antibiotics in my own home even if this meant waiting several hours for a nurse to visit.
- I prefer that my recovery is monitored by a doctor rather than by a nurse.
- Being in hospital would have made things difficult for my family.
- I want to be responsible for making decisions about my own treatment.
- I did not know if my illness was cured when my intravenous treatment finished.
- There is a significant health risk if the intravenous treatment is not given properly.
- Intravenous antibiotics are more effective than oral antibiotics.

2.2. Data collection and sample overview

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 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 (cf. Minton et al, 2017, for further details on sampling and data collection).

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 summarised in Table 2.

Table 2: Sample characteristics

	Number (% of sample)
Mean age (range; SD)	56.76 (20-94; 13.7)
Male	118 (50.9%)
Has 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

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

2.4. Preliminary analysis of choices and answers to attitudinal questions

As a first step in analysing the data, we looked at the choice shares for the three alternatives in the SC scenarios. Overall, the nurse at home option obtains the largest share, at 52.5%, ahead of self-administration at 24% and hospital attendance with 23.5%.

With a view to accommodating the role of attitudes, factor analysis was used on the answers to attitudinal statements. This revealed two factors (see Table 3) loading onto 9 out of the 12 statements. We interpret these as an attitude towards hospitals (five items) and an attitude towards health care being a doctor's responsibility (four items). Together, these two factors accounted for 41% of the variance explained in the attitudinal data.

Table 3: Results of factor analysis

Attitude towards hospitals	Attitudes towards healthcare responsibility
People get better more quickly if they are treated at home (0.664)	Giving my own intravenous antibiotics would worry me (0.58)
I do not like hospitals (0.664)	Doctors, not patients, are in the best position to decide where patients should be cared for (0.752)
If you are treated in hospital, there is an increased risk of contracting a new infection (0.623)	I prefer that my recovery is monitored by a doctor rather than by a nurse (0.742)
I would choose to have intravenous antibiotics in my own home even if this meant waiting several hours for a nurse to visit (0.522)	I want to be responsible for making decisions about my own treatment (-0.51)
Being in hospital would have made things difficult for my family (0.679)	

*factor loading in brackets

3. Model specification

As discussed in the introduction, our analysis 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). Like the more widely used Multinomial Logit (MNL) or Mixed Logit (MMNL) models, the choice component of the hybrid model is based on the notion of utility maximisation, but the model incorporates additional dependent variables, in our case in the form of answers to attitudinal questions. This allows us to use a more flexible specification of heterogeneity in sensitivities/preferences across patients, through linking some of the variations to differences in underlying attitudes.

We specifically incorporate the following layers of heterogeneity in the model:

- differences that can be linked to the socio-demographic and infection characteristics of the participant;
- idiosyncratic ("random") 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, where these are driven in part (but not entirely) by socio-demographic characteristics.

We now look at the model specification and estimation in detail, where we start our discussion by looking at the latent attitudes, given that they create the link between the different model components.

3.1. Specification of latent attitudes

A key component of a hybrid choice model is the definition of one or more latent variables that represent unobserved underlying constructs such as attitudes and perceptions. The work in Section 2.4 has highlighted the potential for two such constructs with the present data. To include these effects in the hybrid choice model, we formulate two latent attitudes, hereafter referred to as:

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

In particular, we have the latent variables $\alpha_{l,n}$ for respondent *n*, with *l=1,2*, and *n=1,…,N*. The latent variables have a deterministic and a random component, with:

$$\alpha_{l,n} = \gamma_{\alpha_l} z_n + \eta_{l,n} \qquad [1]$$

where γ_{α_l} is a vector of parameters (to be estimated) and z_n is a vector of socio-demographic and infection characteristics of respondent *n*. The component $\gamma_{\alpha_l} z_n$ thus represents the deterministic variation in the latent attitude across individual characteristics. As attitudes cannot be fully explained through observed effects, we include an error term, where $\eta_{l,n}$ is a standard Normal variate (mean of 0, standard deviation of 1), distributed across respondents, capturing the random element of the latent attitude. No additional mean parameter is included in the specification of the latent variables given that means are estimated in the choice model for any effects that vary as a function of the latent variables (see Section 3.2), while a full set of thresholds is used in the measurement models for the answers to attitudinal questions (see Section 3.3).

3.2. Specification of choice model component

The choice model component of our hybrid structure relies on an underlying random utility model, with a utility function specified for each of the three alternatives. A key decision to make in the specification of a hybrid choice model relates to which components of the utility function are to be interacted with the latent variables. In our model, we chose the service delivery attribute (i.e. hospital, nurse at home, self-delivery) as the attribute of interest, given that this is the key focus of the study and the attribute most directly related to the attitudinal constructs uncovered in Section 2.4. A normalisation is required, and we set the self-delivery attribute as the base (fixing its parameter to zero).

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. As discussed at length by Vij & Walker (2016), such studies may thus overstate the share of heterogeneity that can actually be linked to attitudes. We avoid this issue by allowing for additional heterogeneity that is not linked to the attitudinal constructs, both deterministic and random. In particular, the utility parameters for the type of treatment varies across individuals, and is given by (for person *n*):

$$\begin{aligned}
\beta_{hospital,n} &= \beta_{hospital} + \gamma_{hospital} z_n + \sigma_{hospital} \xi_{hospital,n} + \textstyle\sum_{l=1}^{2} \tau_{hospital,l} \alpha_{l,n} \\
\beta_{nurse@home,n} &= \beta_{nurse@home} + \gamma_{nurse@home} z_n + \sigma_{nurse@home} \xi_{nurse@home,n} + \textstyle\sum_{l=1}^{2} \tau_{nurse@home,l} \alpha_{l,n} \\
\beta_{self@home,n} &= 0
\end{aligned} \qquad [2]$$

Using $\beta_{hospital,n}$ as our example (with a corresponding specification for $\beta_{nurse@home,n}$), we have that:

- $\beta_{hospital}$ is the utility for the hospital option for an individual in the base category of all socio-demographic characteristics;
- $\gamma_{hospital}$ is a vector of estimated parameters that capture the impact of socio-demographics and infection characteristics (included in z_n) on $\beta_{hospital,n}$, i.e. explaining the shift away from $\beta_{hospital}$ for individuals that are not in the base category;
- $\sigma_{hospital}$ is an estimated standard deviation for the random variation across respondents not related to the latent attitude, with $\xi_{hospital,n}$ being 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 $\beta_{hospital,n}$, where the sum is across the two latent attitudes, with *l=1,…,2*.

The sociodemographic variables included in the specification search for the latent attitudes (i.e. the z_n in $\gamma_{\alpha_l} z_n$ included in Equation [1]) were the same as those used in $\gamma_{hospital} z_n$ and $\gamma_{nurse@home} z_n$ in Equation [2]. This thus means that we are able to disentangle the direct impact of respondent characteristics on choices (through $\gamma_{hospital}$ and $\gamma_{nurse@home}$) from the "indirect" impact of respondent characteristics through the attitudes (through γ_{α_1} and γ_{α_2}), reducing the risk of misattributing sources of heterogeneity. Similarly, $\beta_{hospital,n}$ and $\beta_{nurse@home,n}$ incorporate random heterogeneity both through the two latent attitudes (given the inclusion of $\xi_{l,n}$ in Equation [1] and the incorporation of $\sum_{l=1}^{2} \tau_{hospital,l} \alpha_{l,n}$ and $\sum_{l=1}^{2} \tau_{nurse@home,l} \alpha_{l,n}$ in Equation [2]), and random heterogeneity not linked to the latent attitudes (through $\sigma_{hospital} \xi_{hospital,n}$ and $\sigma_{nurse@home} \xi_{nurse@home,n}$), similarly reducing the risk of misattributing the source of random heterogeneity.

The terms in Equation [2] relate solely to the type of service, and the utility of an alternative clearly also depends on the other attributes included in the survey (cf. Table 1 and Figure 1). For each of these attributes, we again tested the influence of socio-demographic and infection characteristics on the sensitivities, but do not additionally allow for random heterogeneity or an impact by the latent attitudes.

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. Dummy coding was used throughout. We have already mentioned above that self-administration at home was used as the base for the treatment type, and the associated coefficients were fixed to zero. We chose 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. Finally, we included alternative specific constants (ASC) to captures ordering effects given concerns about an underlying propensity for respondents to choose options on the left, where δ_i is the estimated ASC for alternative *i (i=1,...,3),* where, for normalisation, we set $\delta_3 = 0$.

Not showing the omitted base levels for each attribute, the representative utility of alternative *i* (with *i=1,...,3*) for respondent *n* in choice task *t* is then given by:

$$
\begin{aligned}
V_{i,n,t} = \delta_i \\
&+ \left[\beta_{hospital} + \gamma_{hospital} z_n + \sigma_{hospital}\xi_{hospital,n} + \sum_{l=1}^{2} \tau_{hospital,l}\alpha_{l,n})\right] x_{hospital_{i,n,t}} \\
&+ \left[\beta_{nurse@home} + \gamma_{nurse@home} z_n + \sigma_{nurse@home}\xi_{nurse@home,n} \right. \\
&\qquad \left. + \sum_{l=1}^{2} \tau_{nurse@home,l}\alpha_{l,n})\right] x_{nurse@home_{i,n,t}} \\
&+ (\beta_{one\ treatment} + \gamma_{one\ treatment} z_n) x_{one\ treatment_{i,n,t}} \\
&+ (\beta_{two\ treatments} + \gamma_{two\ treatments} z_n) x_{two\ treatments_{i,n,t}} \\
&+ (\beta_{three\ treatments} + \gamma_{three\ treatments} z_n) x_{three\ treatments_{i,n,t}} \\
&+ (\beta_{no\ appointment} + \gamma_{no\ appointment} z_n) x_{no\ appointment_{i,n,t}} \\
&+ (\beta_{specialist\ nurse} + \gamma_{specialist\ nurse} z_n) x_{specialist\ nurse_{i,n,t}} \\
&+ (\beta_{general\ nurse} + \gamma_{general\ nurse} z_n) x_{general\ nurse_{i,n,t}} \\
&+ (\beta_{half\ day\ training} + \gamma_{half\ day\ training} z_n) x_{half\ day\ training_{i,n,t}} \\
&+ (\beta_{see\ known} + \gamma_{see\ known} z_n) x_{see\ known_{i,n,t}} \\
&+ (\beta_{speak\ known} + \gamma_{speak\ known} z_n) x_{speak\ known_{i,n,t}} \\
&+ (\beta_{after\ none} + \gamma_{after\ none} z_n) x_{after\ none_{i,n,t}} \\
&+ (\beta_{after\ nurse} + \gamma_{after\ nurse} z_n) x_{after\ nurse_{i,n,t}} \\
&+ (\beta_{after\ GP} + \gamma_{after\ GP} z_n) x_{after\ GP_{i,n,t}} \\
&+ (\beta_{risk\ 6} + \gamma_{risk\ 6} z_n) x_{risk\ 6_{i,n,t}} \\
&+ (\beta_{risk\ 10} + \gamma_{risk\ 10} z_n) x_{risk\ 10_{i,n,t}}
\end{aligned}
\qquad [3]
$$

In Equation [3], the utility parameters 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, $x_{hospital_{i,n,t}}$ will take a value of 1 if and only if alternative *i* for respondent *n* in choice situation *t* is the hospital alternative. We test for socio-demographic and infection impacts for all parameters, hence the γ terms, though random heterogeneity and the impact of latent attitudes are only included for treatment type, as discussed above.

Equation [3] already incorporates random variations across individuals through the inclusion of $\xi_{hospital,n}$, $\xi_{nurse@home,n}$, $\alpha_{1,n}$, and $\alpha_{2,n}$. We now in addition include the typical type I extreme value error term, such that we have that the total utility of alternative i (with $i=1,...,3$) for respondent n in choice task t is given by:

$$U_{i,n,t} = V_{i,n,t} + \varepsilon_{i,n,t} \qquad [4]$$

With this error assumption, the probabilities are given by a Logit formula. In particular, let $i^*_{n,t}$ be the alternative chosen by individual n in choice task t. We then have that:

$$P_{i^*_{n,t}}(\Omega_{\mathrm{C}}, \Omega_\alpha, \xi_n, \eta_n) = \frac{e^{V_{i^*_{n,t}}}}{\sum_{j=1}^{3} e^{V_{j,n,t}}} \qquad [5]$$

This is conditional on the vector of parameters of the choice model Ω_{C}, which groups together the various β, γ, τ and σ parameters in Equation [3], the values of the parameters of the structural equation model in Equation [1], where $\Omega_\alpha =< \gamma_{\alpha_1}, \gamma_{\alpha_2} >$, as well as the values of the unobserved components $\xi_n =< \xi_{hospital,n}, \xi_{nurse@home,n} >$ (cf. Equation [2]) and $\eta_n =< \eta_{1,n}, \eta_{2,n} >$ (cf. Equation [1]). We will return later to the impact of this on estimation.

3.3. Specification of measurement model component

The final component of our hybrid structure is the set of measurement models used to explain the answers to attitudinal questions, i.e. the level of agreement on a Likert scale to the nine questions retained during the factor analysis (cf. Table 3). We use an ordered logit model structure for this purpose. We have two groups of attitudinal indicators, with the five statements in the first column in Table 3 relating to the first latent variable (attitude towards hospitals), and the four statements in the second column relating to the second latent variable (attitude towards healthcare responsibility). Let us represent the answers given to these two sets by person n as $I^*_{h,n} =< I^*_{h,1,n}, \dots, I^*_{h,5,n} >$ and $I_{r,n} =< I_{r,1,n}, \dots, I_{r,4,n} >$. We then have that the probability of the observed level of agreement for given attitudinal statement (say $I_{h,s,n}$ and $I_{r,s,n}$) in the two groups is given by:

$$P_{I^*_{h,s,n}}\left(\Omega_{I_{h,s}}, \gamma_{\alpha_1}, \eta_{1,n}\right) = \sum_{p=1}^{5} [I^*_{h,s,n} == \mathrm{p}] \left(\frac{e^{t_{I_{h,s},p} - \zeta_{h,s}\alpha_{1,n}}}{1 + e^{t_{I_{h,s},p} - \zeta_{h,s}\alpha_{1,n}}} - \frac{e^{t_{I_{h,s},p-1} - \zeta_{h,s}\alpha_{1,n}}}{1 + e^{t_{I_{h,s},p-1} - \zeta_{h,s}\alpha_{1,n}}} \right)$$

$$P_{I^*_{r,s,n}}\left(\Omega_{I_{r,s}}, \gamma_{\alpha_2}, \eta_{2,n}\right) = \sum_{p=1}^{5} [I^*_{r,s,n} == \mathrm{p}] \left(\frac{e^{t_{I_{r,s},p} - \zeta_{r,s}\alpha_{2,n}}}{1 + e^{t_{I_{r,s},p} - \zeta_{r,s}\alpha_{2,n}}} - \frac{e^{t_{I_{r,s},p-1} - \zeta_{r,s}\alpha_{2,n}}}{1 + e^{t_{I_{r,s},p-1} - \zeta_{r,s}\alpha_{2,n}}} \right)$$

[6]

Using the first equation as our example (with corresponding notation for the second), we have that $\Omega_{I_{h,s}}$ is a vector grouping together the following parameters:

- $t_{I_{h,s},0}, \dots, t_{I_{h,s},5}$ is a set of 5 threshold parameters, where $t_{I_{h,s},0} = -\infty$, $t_{I_{h,s},5} = +\infty$, and $< t_{I_{h,s},1}, \dots, t_{I_{h,s},4} >$ are estimated, where these need to be monotonically increasing
- $\zeta_{h,s}$ is an estimated parameter that captures the impact of the latent variable $\alpha_{1,n}$ on the attitudinal indicator utility $I_{h,s,n}$, with a positive estimate indicating the higher values for $I_{h,s,n}$ are more likely as the latent variable increases.

In the ordered logit models, the probability of a given observed outcome is given by the probability of the latent variable (rescaled by the appropriate ζ term) falling between the relevant two thresholds. Which thresholds to use depends on the observed outcome, and this is the reason for the summation across the five possible outcomes (using the index $p=1,...,5$), where the term $I^*_{h,s,n} ==$ p will be equal to 1 if level p is chosen as the answer to the s[th] statement in the hospital category for person n, and 0 otherwise.

For each of the 9 attitudinal indicators, we thus estimate five parameters, namely four thresholds and one ζ parameter to capture the impact of the latent attitude. The probabilities in Equation [6] are again a function of the latent variables, and we will return to the impact on estimation below.

3.4. Overall model likelihood function

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).

The contribution by person n to the overall likelihood of the model is thus given by the probability of the sequence of eight choices in the SC component and the probability of the answers to the two sets of attitudinal questions. The former depends on the values of two sets of random variables, namely ξ_n and α_n, while the latter depends on α_n, with one latent variable used in each of the two sets of indicators. The log-likelihood is then a multi-dimensional integral over the distribution of these random terms, with:

$$\mathrm{LL}(\Omega) = \sum_{n=1}^{N} log\left(\int_{\alpha_n}\int_{\xi_n}\prod_{t=1}^{8} P_{i_{n,t}^*}(\Omega_{\mathrm{C}},\Omega_\alpha,\xi_n,\alpha_n)\prod_{s=1}^{5} P_{I_{h,s,n}^*}\left(\Omega_{I_{h,s}},\gamma_{\alpha_1},\alpha_{1,n}\right)\prod_{s=1}^{4} P_{I_{r,s,n}^*}\left(\Omega_{I_{r,s}},\gamma_{\alpha_2},\alpha_{2,n}\right) f(\xi_n)f(\alpha_n)d\xi_n d\alpha_n\right) \quad [7]$$

In Equation [7], the new vector Ω now groups together the parameters from all model components previously defined, as well as the parameters of the structural equation for the latent variable, i.e. $\Omega = <\Omega_\alpha, \Omega_{\mathrm{C}}, \Omega_{I_h}, \Omega_{I_r}>$, where Ω_{I_h} and Ω_{I_r} group together the parameters for their relevant measurement models from Equation [6].

In estimation, we approximate Equation [7] using numerical simulation, i.e. maximizing the simulated log-likelihood, where we use 200 MLHS draws (cf. Hess et al., 2006) per person and for each of the four normally distributed random terms. All models were estimated using Apollo v0.1.1 (Hess & Palma, 2019), and the standard errors reported in the results are obtained with the sandwich method (Huber, 1967).

3.5. Specification search

We undertook a detailed specification search to understand the role of respondent characteristics in explaining the heterogeneity in the model. For all characteristics, we tested for direct impact on choices, i.e. through the γ terms shown in Equation [3], and indirect impact through the latent attitudes, i.e. through the γ terms shown in Equation [1]. The characteristics we used in this process 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. A large number of models were estimated, gradually removing socio-demographic effects that were not statistically significant and/or where the parameter estimates were too small to have a major behavioural influence. Statistical tests were used throughout to investigate the losses in fit resulting from the removal of parameters. Some socio-demographic effects with lower levels of significance where retained in the model if they gave interesting behavioural insights – this is good practice rather than blindly following arbitrary thresholds for parameter significance.

4. Estimation results

This section first presents the "raw" estimation results before presenting some further analysis that investigates the amount and sources of heterogeneity in preferences.

4.1. Model fit statistics

The model fit statistics are summarised in Table 4. With just a single model presented in this paper, the only measure of comparative interest relates to the ρ^2 and average probability of correct prediction

($\overline{P_{chosen}}$, which is the average in the sample of the probability of the chosen alternative). These figures suggest relatively good performance of the model in terms of explaining the stated choices.

Table 4: Model fit statistics

Final log-likelihood (whole model)	-3,399.68
Final log-likelihood (choice component)	-978.25
Parameters	89
Bayesian information criterion (whole model)	7,454.64
$\boldsymbol{\rho^2}$ **(choice component)**	0.43
$\overline{\boldsymbol{P_{chosen}}}$ **(choice component)**	0.54

4.2. Parameter estimates

Our analysis made use of a complex model, with a several different model components and a very large number of parameters. We thus present the results across a number of separate tables.

Given the central role played by the latent variables in the model, we start the discussion with the estimation results for the structural model for the latent attitude (Equation [1]) and interpret the directionality of the latent variables by looking at the estimates from the measurement model components (Equation [6]). These results are shown Table 5, divided into two groups, for the two different latent variables. For all parameters, we show the maximum likelihood estimate (*est.*), along with the robust t-ratio (*rob t*).

The results show a positive impact (see $\zeta_{h,s}$) 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. The threshold parameters ($\tau_{I_{h,s},p}$) show the required monotonic increase across levels, where the different ranges and gaps highlight the different distributions of answers across the five statements.

For the second latent variable, we see a negative impact (see $\zeta_{r,s}$) 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). The threshold parameters ($\tau_{I_{r,s},p}$) again show the expected patterns.

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 with a view to our interest in disentangling sources of heterogeneity.

Table 5: Estimation results for structural models and measurement models

Latent variable $\alpha_{1,n}$: attitude towards hospitals

Structural model				Measurement models									
				"People get better more quickly if they are treated at home"		*"I do not like hospitals"*		*"If you are treated in hospital there is an increased risk of contracting a new infection"*		*"I would choose to have intravenous antibiotics in my own home even if this meant waiting several hours for a nurse to visit"*		*"Being in hospital would have made things difficult for my family"*	
	est.	*rob. t*		*est.*	*rob. t*	*est.*	*rob. t*	*est.*	*rob. t*	*est.*	*rob. t*	*est.*	*rob. t*
$\gamma_{\alpha_1,female}$	-0.4954	-2.31	$\zeta_{h,s}$	1.2866	4.17	0.8945	4.28	0.8606	3.21	1.8487	3.89	1.1457	4.19
$\gamma_{\alpha_1,\text{non-white}}$	-0.3323	-1.42	$t_{I_{h,s},1}$	-1.177	-3.77	-1.6936	-7.92	-0.8715	-4.25	-2.0871	-3.64	-0.6502	-2.64
$\gamma_{\alpha_1,\text{living alone}}$	0.1887	0.9	$t_{I_{h,s},2}$	0.3912	1.67	-0.2661	-1.44	0.9017	4.19	0.6702	2.32	0.6962	2.88
			$t_{I_{h,s},3}$	2.0141	5.55	0.6429	3.17	1.6472	6.91	1.0196	3.42	1.5152	4.58
			$t_{I_{h,s},4}$	4.1935	6.69	2.7464	8.35	3.4597	8.22	3.2735	5.58	4.3082	5.8

Latent variable $\alpha_{2,n}$: attitude towards responsibility for healthcare

Structural model				Measurement models							
				"Giving my own intravenous antibiotics would worry me"		*"Doctors, not patients, are in the best position to decide where patients should be cared for"*		*"I prefer that my recovery is monitored by a doctor rather than by a nurse"*		*"I want to be responsible for making decisions about my own treatment"*	
	est.	*rob. t*		*est.*	*rob. t*	*est.*	*rob. t*	*est.*	*rob. t*	*est.*	*rob. t*
$\gamma_{\alpha_2,\text{aged over 65}}$	0.37	1.44	$\zeta_{r,s}$	-2.2614	-4.91	-0.4332	-2.43	-0.5798	-2.82	0.1699	0.99
$\gamma_{\alpha_2,\text{non-white}}$	0.8505	4.51	$t_{I_{r,s},1}$	-1.6471	-0.75	-1.8055	-4.31	-2.6319	-4.81	-0.9482	-4.34
$\gamma_{\alpha_2,\text{university educ.}}$	-0.0933	-0.7	$t_{I_{r,s},2}$	-0.3395	-0.17	-0.1547	-0.41	-1.4832	-2.84	0.4399	1.97
			$t_{I_{r,s},3}$	0.0544	0.03	0.788	2.04	0.4947	0.97	1.1794	4.9
			$t_{I_{r,s},4}$	1.961	1.18	2.2158	4.99	2.3679	4.59	2.786	7.8

We next look at the estimates for the choice model component, summarised in Table 6. 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.

Table 6: Estimates for choice model component

				est.	*rob. t*
constants (option 3 as base)		option 1 (left)	δ_1	0.2129	0.88
		option 2 (middle)	δ_2	-0.4938	-1.47
treatment type (self administration as base)	hospital	main effect	$\beta_{hospital}$	-0.1508	-0.23
		standard deviation (pure random het.)	$\sigma_{hospital}$	2.2462	4.10
		impact of pro-hospital latent variable	$\tau_{hospital,1}$	1.1159	3.16
		impact of healthcare resp. latent variable	$\tau_{hospital,2}$	3.4171	5.12
		… shift for patients under 50	$\gamma_{hospital,under\ 50}$	1.2314	1.72
	nurse at home	main effect	$\beta_{nurse@home}$	1.4585	1.57
		standard deviation (pure random het.)	$\sigma_{nurse@home}$	1.1869	1.74
		impact of pro-hospital latent variable	$\tau_{nurse@home,1}$	-0.8918	-1.87
		impact of healthcare resp. latent variable	$\tau_{nurse@home,2}$	4.0320	9.25
		… shift for patients over 65	$\gamma_{nurse@home,over\ 65}$	1.5504	2.48
treatment frequency (continuous as base)		one per day	$\beta_{one\ treatment}$	0.7074	5.14
		two per day	$\beta_{two\ treatments}$	0.1819	0.7
		three per day	$\beta_{three\ treatments}$	-0.2956	-1.04
no appointment (daily appointment time as base)		main effect	$\beta_{no\ appointment}$	-0.5688	-3.51
		… shift for for patients with long term infections	$\gamma_{no\ appt,long-term}$	0.4548	2.09
treatment administered by (doctor as base)	spec. IV nurse	main effect	$\beta_{specialist\ nurse}$	0.6091	1.91
		… shift for patients living alone	$\gamma_{spec.nurse,live\ alone}$	-0.6479	-1.54
	gen. nurse	main effect	$\beta_{general\ nurse}$	0.2237	0.59
		… shift for patients living alone	$\gamma_{gen.nurse,live\ alone}$	-0.7355	-1.53
half-day training for self administration (full day as base)		main effect	$\beta_{half\ day\ training}$	-0.3578	-0.72
		… shift for patients aged under 50	$\gamma_{half\ day,over\ 50}$	1.1833	2.47
		… shift for patients living alone	$\gamma_{half\ day,live\ alone}$	-1.0338	-1.85
		… shift for patients with long term infections	$\gamma_{half\ day,long-term}$	0.7676	1.58
in person communication with known health-care professional (unknown person as base)		main effect	$\beta_{see\ known}$	0.0166	0.12
		… shift for patients aged under 50	$\gamma_{see\ kn.,under\ 50}$	0.4776	2.33
		… shift for patients with long term infections	$\gamma_{see\ kn.,long-term}$	0.3991	2.34
telephone communication with known health-care professional (unknown person as base)		main effect	$\beta_{speak\ known}$	0.8155	1.47
		… shift for known person for patients aged over 65	$\gamma_{speak\ kn.,over\ 65}$	-1.2197	-3
		… shift for known person for patients living alone	$\gamma_{speak\ kn.,live\ alone}$	-1.0737	-2.04
		… shift for known person for patients with long term infections	$\gamma_{speak\ kn.,long-term}$	0.4771	1.03
aftercare (telephone appointment as base)		no aftercare	$\beta_{after\ none}$	-0.1562	-1.13
		appointment at hospital with nurse	$\beta_{after\ nurse}$	0.1578	1.05
		appointment with own GP	$\beta_{after\ GP}$	0.0153	0.09
Risk of adverse reactions (1 in 25 as base)	1 in 6	main effect	$\beta_{risk\ 6}$	-0.988	-6.22
	1 in 10	main effect	$\beta_{risk\ 10}$		
		… shift for patients aged over 65	$\gamma_{risk\ 10,over\ 65}$	0.7145	2.85
		… shift for patients in employment	$\gamma_{risk\ 10,employed}$	0.3493	1.98

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.

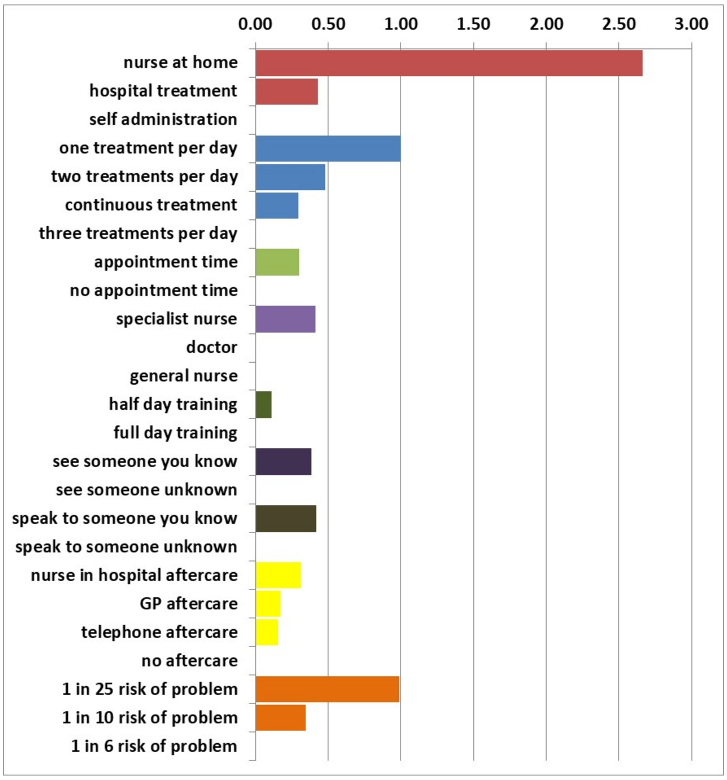
In addition to these direct socio-demographic influences on treatment type preference, there is extensive further heterogeneity. We first see a highly significant estimate for the standard deviation for hospital treatment, while, for the nurse at home option, the standard deviation has a lower level of statistical significance but remains large in size, indicating again high levels of variation across individuals in their treatment preferences. Indeed, ignoring for now the additional heterogeneity from the attitudinal construct and the socio-demographic influences, 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, as captured by the τ parameters. We see that respondents with a more positive pro-hospital attitude (i.e. more positive $\alpha_{1,n}$) have a stronger preference for in hospital treatment in the choice model (positive estimate for $\tau_{hospital,1}$) while the baseline preference for nurse treatment at home is reduced (negative estimate for $\tau_{nurse@home,1}$). Respondents who are more of the view that healthcare is a doctor's responsibility (i.e. more positive $\alpha_{2,n}$) have a stronger preference for in hospital treatment in the choice model (positive estimate for $\tau_{hospital,2}$) but the preference for nurse treatment at home is increased even further (positive estimate for $\tau_{nurse@home,2}$).

We next turn to the impact on choices of the other treatment characteristics. We see that, for treatment frequency, where continuous treatment is the base, one treatment is the preferred level ahead of two treatments, continuous treatment and three treatments per day. For appointments, not having an appointment has a negative impact on utility (with having an appointment used as the base), where the importance assigned to appointment times is however much lower for patients with long term infections. For the attribute characterising who administers the treatment in hospital, doctor is used as the base. We see that for patients not living alone, specialist nurses are preferred to general nurses which are in turn preferred to doctors. However, for patients living alone, doctors are the preferred option, ahead of specialist nurses and general nurses. For the training required for self-administration of IV, a full-day was used as the base. We see that younger patients and those with long-term infections have a strong preference for half-day training, with the opposite applying for those living alone. For other groups, the difference between half-day and full-day is not significant. For in person communication, we used communication with an unknown person as the base and found a strong preference for communication with a known person for patients aged under 50 and those with long-term infection. For communication via telephone, an unknown person was again used as the base, and here, we see a strong preference for a known person for patients with a long-term infection, but a reduced need for communication with a known person for older patients or those living alone. No socio-demographic effects were observed for aftercare, where the differences across levels are not significant, with the ordering showing appointments with a nurse being preferred to a GP or telephone appointment, where this was preferred to not having any aftercare. Turning finally to risk of adverse reactions, the 1 in 25 level was used as the base. We found that, other for patients aged over 65 and those in employment, there was no difference in sensitivity between the 1 in 6 level and the 1 in 10 level. For these two socio-demographic groups (over 65 or employed), the sensitivity to 1 in 10 was lower than to 1 in 6, especially so for the over 65.

4.3. Analysis of preferences and heterogeneity

To get a first sample level overview of sensitivities, we calculated the value for each parameter in the model for every individual in the sample, incorporating the socio-demographic and random heterogeneity, both directly and through the latent attitudes. We then compute the mean value across respondents for each parameter, as well as the standard deviation. The results from this process are summarised in Figure 2, where we have for each category renormalized the levels by fixing the least attractive to zero (noting that comparisons across attributes can only be performed by looking at differences between levels anyway). 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. 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 by 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 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

So far, our discussion of Figure 2 has focussed on the sample level means. However, with the different socio-demographic interactions used in the model, heterogeneity in sensitivities arises for many of the levels. Only the frequency of treatment and the aftercare attributes have no variation across socio-demographic groups, where, in the specification search (cf. section 3.5), no significant socio-demographics effects were found, as reflected in the absence of γ parameters for these effects in Table 6. In addition, for the type of treatment, there is extensive random heterogeneity, and further heterogeneity, both deterministic and random, through the latent variables.

With the various socio-demographic interactions used in the model, a total of 48 different socio-demographic groups exist in our model. 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 for each individual. 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. These orderings apply at the mean values for each respondent, i.e. after averaging across the random heterogeneity. Of course, due to this 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 that was felt by the advisory group to represent the most likely configuration of services. This had the following attributes:

- one treatment per day for each type of service;
- specialist IV nurse for in hospital and nurse at home delivery;
- 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 again calculate the utilities for the three alternatives for each individual in the sample, incorporating all deterministic and random heterogeneity. We then calculate the probabilities, which as a result have extensive heterogeneity too, as shown in Figure 3. We obtain mean probabilities of 24.2% for hospital, 61.7% for nurse at home, and 14.1% for self-administration. The extent of heterogeneity is such that for all options, the lower limit of a 95% confidence interval approaches 0, while the upper limit approaches 1 for the nurse option, 94% for the hospital option, and 88% for the self-administration option. Figure 3 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.

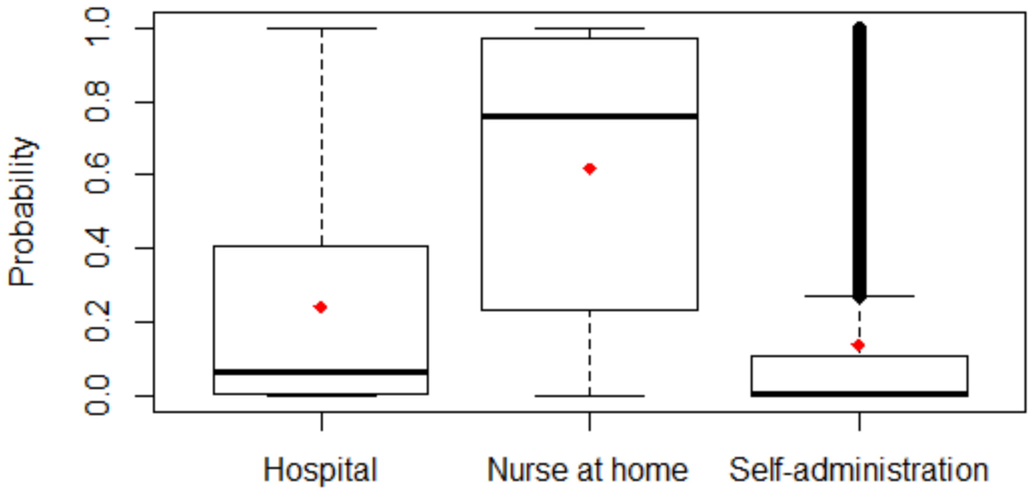


Figure 3: Heterogeneity in probabilities for base scenario

The incorporation of attitudes in the model also 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 the probability for hospital increasing from 24.2% to 25.3%, the probability for the nurse at home option decreasing from 61.7% to 56.5%, and the probability for self-administration increasing from 14.1% to 18.2%. These effects are small as they relate only to the deterministic part of the attitudes, with extensive remaining random variation of attitudes across individual patients.

As a final step, we now investigate what share of the overall heterogeneity in the preferences for different treatment deliveries can be attributed to the two attitudinal constructs. Going back to Equation [2], remember that the preferences for hospital and nurse at home delivery (with self-administration as the base) vary 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 7 first looks at the random components of heterogeneity. We see that the total amount of random heterogeneity is fairly similar for both services, with $\sigma^2_{hospital} + \tau^2_{hospital,1} + \tau^2_{hospital,2}$=17.97, and $\sigma^2_{nurse@home} + \tau^2_{nurse@home,1} + \tau^2_{nurse@home,2}$ = 18.46. 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 relates to unexplained differences across patients that cannot be linked to the two attitudinal constructs. For either service option, the attitude towards hospitals does not drive a large share of the overall heterogeneity, as reflected in the smaller estimates for $\tau_{hospital,1}$and $\tau_{nurse@home,1}$ in Table 6.

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 7: role of latent attitudes in shaping heterogeneity

	Utility for hospital (vs self-administration)			Utility for nurse at home (vs self-administration)		
	direct ($\sigma^2_{hospital}$)	through pro-hospital latent attitude ($\tau^2_{hospital,1}$)	through healthcare responsibility latent attitude ($\tau^2_{hospital,2}$)	direct ($\sigma^2_{nurse@home}$)	through pro-hospital latent attitude ($\tau^2_{nurse@home,1}$)	through healthcare responsibility latent attitude ($\tau^2_{nurse@home,2}$)
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%

	direct ($\gamma_{hospital}z_n$)	through pro-hospital latent attitude ($\tau_{hospital,1}\gamma_{\alpha_1}z_n$)	through healthcare responsibility latent attitude ($\tau_{hospital,2}\gamma_{\alpha_2}z_n$)	direct ($\gamma_{nurse@home}z_n$)	through pro-hospital latent attitude ($\tau_{nurse@home,1}\gamma_{\alpha_1}z_n$)	through healthcare responsibility latent attitude ($\tau_{nurse@home,2}\gamma_{\alpha_2}z_n$)
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

5. Discussion

The use of advanced discrete choice models is becoming more commonplace in health research, with a growing focus on methods that incorporate flexible treatments of heterogeneity in preferences across individual patients. A key purpose of conducting such studies should however be not just the desire to apply the latest and greatest econometric tools, but to produce insights that are of help to policy makers. This was a key aim of the present study.

Our work was undertaken against a background where 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 into the design of new services. The use of choice modelling, especially based on 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 heterogeneity in healthcare preferences.

At the sample level, the 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).

Our work recognises that preferences are likely to vary across patients. In this study, younger patients tended to prefer to come to hospital for their care, and older people tended 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 could 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. We chose a flexible specification of a hybrid choice model, incorporating the role of attitudes in preference formation but also recognising that not all heterogeneity can be linked back to these attitudinal constructs. We identified two key underlying attitudes. The first of this is a pro-hospital attitude, which is stronger for patients living alone, and weaker for female and non-white patients. A more positive pro-hospital attitude leads to an increased probability of choosing the hospital option, and a reduced probability of choosing the nurse at home option. The second attitude relates to the responsibility for healthcare lying with healthcare professionals, where we find that this is stronger for older and non-white patients, and weaker for more highly educated patients. Those patients who are more of the opinion that healthcare responsibility lies with the professionals as opposed to the patients have a far reduced probability of choosing the option to self-administer their IV antibiotics. The attitudinal constructs play a very substantial role in our model. 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 (cf. Huls et al., 2019). 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. 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.

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. 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. We did not have additional information that may have helped in this context, such as choice certainty or revealed preference data. Our survey purposefully did not include an opt-out, which, although seen by some researchers as improving external validity of predictions, is not realistic in the clinical context, where patients would not receive a ‘no treatment’ option. Finally, 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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