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Should I Stay or Should I Go Home? A Latent Class Analysis of a Discrete Choice Experiment on Hospital-At-Home

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ABSTRACT

Objectives: This study aimed 1) to quantify the strength of patient preferences for different aspects of early assisted discharge in The Netherlands for patients who were admitted with a chronic obstructive pulmonary disease exacerbation and 2) to illustrate the benefits of latent class modeling of discrete choice data. This technique is rarely used in health economics. **Methods:** Respondents made multiple choices between hospital treatment as usual (7 days) and two combinations of hospital admission (3 days) followed by treatment at home. The latter was described by a set of attributes. Hospital treatment was constant across choice sets. Respondents were patients with chronic obstructive pulmonary disease in a randomized controlled trial investigating the cost-effectiveness of early assisted discharge and their informal caregivers. The data were analyzed using mixed logit, generalized multinomial logit, and latent-class conditional logit regression. These methods allow for heterogeneous preferences across groups, but in different ways. **Results:** Twenty-five percent of the respondents opted for hospital treatment regardless of the description of the early assisted discharge program, and 46% never opted for the hospital. The best model contained four latent classes of respondents, defined by different preferences for the hospital and caregiver burden. Preferences for other attributes were constant across classes. Attributes with the strongest effect on choices were the burden on informal caregivers and co-payments. Except for the number of visits, all attributes had a significant effect on choices in the expected direction. **Conclusions:** Considerable segments of respondents had fixed preferences for either treatment option. Applying latent class analysis was essential in quantifying preferences for attributes of early assisted discharge.

Keywords: COPD, discrete choice experiment, hospital-at-home, latent-class conditional logit.

Introduction

Many patients with chronic obstructive pulmonary disease (COPD) are more or less frequently admitted to the hospital for an exacerbation of their disease. The average annual frequencies have been estimated to vary from 0.11 for patients with mild COPD (Global Initiative for Chronic Obstructive Lung Disease [GOLD] grade I, as defined by lung function [1]) and 0.16 for moderate disease (GOLD II) to 0.22 and 0.28 for severe and very severe COPD (GOLD III and IV), respectively [2]. Nevertheless, the extent to which patients are prone to exacerbations varies substantially within GOLD grades [3].

Hospitalizations for exacerbations are the main cost drivers of COPD treatment [4–9]. They put pressure on scarce hospital beds of respiratory wards, especially during winter months [10]. Patients with COPD, however, are vulnerable to infections in a hospital environment. They may prefer to be in the hospital for as short a period as possible for reasons of privacy and comfort. It may therefore be attractive to treat suitable patients at home instead of in the hospital, if this is medically possible. This approach is often called early assisted discharge. It can either substitute the entire hospital admission for home treatment (admission avoidance) or the last days of the admission (early assisted discharge) [11,12].

The GO AHEAD trial, which compared early assisted discharge with a conventional hospital admission did not lead to the conclusion that either treatment was clearly preferable from a medical or economic point of view [13,14]. No clear and significant differences were found in health outcomes or costs, although early assisted discharge was more likely to be the less costly alternative from the health care perspective. This lack of clear superiority of either treatment increases the importance of preferences of patients and their informal caregivers. Adapting a treatment program to their preferences may enhance its acceptability.

The research objective of this article was to quantify the strength of patients' and informal caregivers' preferences for different characteristics of an early assisted discharge scheme in The Netherlands and to determine when these characteristics make the new scheme more attractive than usual hospital care.

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A commonly used technique for eliciting preferences is the discrete choice experiment (DCE), in which respondents are asked to choose between alternatives, which are described by a number of attributes [15]. Statistical analysis is then used to quantify the weight of each attribute in the choices of the respondents. In health economics, one of the most widely applied methods to analyze data from such experiments is McFadden's conditional logit, otherwise known as multinomial logit (MNL) [16–18]. One of the assumptions of this technique, however, is the absence of unobserved preference heterogeneity across respondents [19]. When this assumption is violated—in other words, when some respondents have consistently different preferences than do others, which cannot be adjusted for in the analysis—the model may lead to biased results.

The most popular method to take unobserved preference heterogeneity into account is the mixed logit (MXL) model [16]. The generalized multinomial logit (GMNL) model was developed rather recently by Fiebig et al. [20]. It handles preference heterogeneity by combining continuous normals with individual scaling.

In the context of segmented samples of respondents, latent class (LC) analysis is particularly suited. It groups respondents into a prespecified number of LCs with distinct preferences. This allows for the estimation of class-specific preference parameters and of the probability of class membership [21]. One of the developers of the DCE methodology, Louviere [22], has argued for a more frequent use of LC models because they would often fit the data at least as well as random parameter models while estimation and interpretation are easier.

In a review of DCE methods in this field, de Bekker-Grob et al. found that it was applied only once in the period from 1990 to 2008 [16], in a study on appointments with general practitioners [23]. To our knowledge, the only more recent example of LC analysis in health economics is a study on preventive treatment of tuberculosis [24].

In this article, we investigated to what extent these three models were able to accommodate the preference heterogeneity for early assisted discharge.

Methods

Selection of Attributes

A literature search led to a selection of characteristics of early assisted discharge treatments for COPD. These were considered potential attributes for the DCE. The attributes had to describe the process, not the outcomes of treatment. The provisional attributes were discussed with physicians connected to the trial and with patients with COPD who were admitted to the hospital. They were invited to mention additional attributes and levels. Attribute levels were chosen to reflect a wide range of possibilities and being able to have an effect on choices, without becoming unrealistic or unimaginable to respondents.

The final questionnaires contained the following attributes for early assisted discharge treatment: 1) specialization of the community nurse; 2) number of home visits; 3) number of different nurses involved in the treatment; 4) co-payment; 5) whom to contact in case of worsening disease; 6) burden on informal caregivers; and 7) risk of readmission to the hospital before the scheduled end of home treatment. Table 1 presents the levels of each attribute.

Design of the DCE Questionnaire

Choice sets consisted of three labeled alternatives: two early assisted discharge treatments and the usual hospital treatment (see Fig. 1 for an example). Because many characteristics of early assisted discharge are not applicable to usual hospital treatment and vice versa, only the early assisted discharge treatments were described by attributes. Because all respondents were hospitalized, they were assumed to be familiar with hospital treatment, which was constant over all choice sets.

Table 1 – Attributes and levels for early assisted discharge options in questionnaire.

Treatment attribute	Levels
Specialization of community nurse	Generic
	Pulmonary
Number of home visits per day	1
	2
	3
Number of nurses involved in treatment at home	1 or 2
	More than 2
Co-payment (€)	0
	50
	100
Contact in case of emergency	General practitioner
	Pulmonary ward, hospital
Burden on informal caregivers (h/d)	1
	3
	5
Risk of readmission (%)	1
	5
	10

No co-payment was assumed for hospital admissions. In The Netherlands, patients do not have to pay for a hospital admission once the relatively low deductible (the amount of expenses that must be paid out of pocket before an insurer will pay any expenses) has been paid. This contrasts with home care services for which a co-payment does exist.

To extract as much choice information as possible, respondents who preferred the hospital option in a certain choice set were subsequently asked which of the early assisted discharge options they preferred.

No opt-out was presented because all patients with COPD who are admitted to the hospital for an exacerbation cannot be left untreated. Respondents were asked to assume that all treatments were equally effective in medical terms; that is, after 7 days, a patient's health state would be the same under all treatment options.

SAS 9.1 software was used to generate a d-efficient design for the questionnaire, which consisted of 36 choice sets divided into three versions. Each questionnaire contained 12 choice sets, to which we added 2 fixed choice sets with a dominant alternative, that is, an alternative that is better on all attributes, to test the respondents' comprehension of the task. Choice sets were presented in random order.

Respondents

The questionnaires were presented to all patients with COPD and their informal caregivers who participated in the GO AHEAD trial, which was carried out in five hospitals in The Netherlands from November 2007 to March 2011. In the early assisted discharge arm of this randomized trial, patients spent 3 days in the hospital, after which they were treated in their own homes by community nurses for 4 more days. Patients in the control group remained in the hospital for 7 days. Participants had diagnosed COPD, were 40 years or older, had no major uncontrolled comorbidities, and had no indication for admission to an intensive care unit or for noninvasive ventilation. After 3 days in the hospital, they had to be clinically stable in order to be randomized.

	Early assisted discharge A	Early assisted discharge B	Hospital
Nurse specialisation	Generic nurse	Pulmonary nurse	
Number of nurse visits	3 per day	1 per day	
Co-payment	50 euros	100 euros	
Re-admission risk	1 in 10	1 in 20	
Whom to contact in case of worsening disease	Hospital, pulmonary ward	General practicioner	
Informal care burden	3 hours per day	1 hour per day	
Number of different nurses	1 of 2	More than 2	
Which treatment would you choose? (Tick 1 box.)	**A** ⍰	**B** ⍰	**Hospital** ⍰
Which treatment would you choose if you can only opt for early assisted discharge? (Tick 1 box.)	**A** ⍰	**B** ⍰	

Fig. 1 – An example of a choice set in this study.

Because trial participants were more likely to have a preference for early assisted discharge than the general patient population, additional respondents were recruited among patients who were ineligible for inclusion or who did not consent.

Each respondent was asked to fill out the questionnaire during an outpatient visit to the hospital 1 month after the initial admission. If patients did not appear at the appointment, questionnaires were sent to home addresses. Ethics approval was obtained from the Ethics Board of Catharina Hospital in Eindhoven, The Netherlands.

Pilot

The three blocks of the pilot version of the questionnaire were filled out by 10 respondents each. They were asked to comment on the clarity of the questionnaire and the feasibility of choosing. This led to some clarification in the accompanying explanation. The DCE answers of these 10 respondents were analyzed in the standard MNL model. All the attribute levels had the expected sign.

None of the respondents had a fixed preference for either the hospital option or early discharge. None of the attribute levels was dominant. The design was left unchanged.

Statistical Analysis

First, we investigated how many respondents were principally willing to consider the hospital alternative as well the early assisted discharge alternative or whether they had a fixed preference, irrespective of the attribute levels of early assisted discharge alternatives. This was done by examining the initial answers of all choice sets for each respondent.

Next, several models were developed to analyze all choices simultaneously—the initial answer and the possible second answer. The formal mathematical descriptions are presented in the Appendix in Supplemental Materials found at http://dx.doi.org/10.1016/j.jval.2014.05.004.

The first model was a GMNL model [20]. This model can describe heterogeneity simultaneously in different ways, thereby incorporating both the MXL and the scaled MNL. In the MXL, individual coefficients are assumed to be random, with a certain distribution, usually a normal or lognormal distribution. This distribution is described by a mean and a variance. In the scaled MNL, the MNL is extended by an individual scaling factor. Individual coefficients are assumed to be scaled to the overall coefficient by this factor.

Individual coefficients are described by the following equation:

$$\beta_i = \theta_i\beta + \gamma k_i + (1-\gamma)\theta_i k_1$$

with β as the mean estimate of the coefficient, $\theta_i = 1 + \tau$ as the individual scaling factor, k_i as the individual deviation from the mean coefficient, and γ as a parameter that governs how θ_i varies with k_i in a model that includes both.

If θ_i equals 1, the GMNL reduces to the MXL. If the variance of k_i equals 0, the GMNL reduces to the scaled MNL. If both θ_i equals 1 and k_i equals 0, the model reduces to the MNL.

If the GMNL was no different from the MXL, the MXL was reestimated, this time allowing for correlation across coefficients. Although all distributions were normal in the GMNL, it was possible in the MXL to assume lognormal distributions for the coefficients for readmission risk and co-payments.

As an alternative to the GMNL/MXL, an LC model was used to express the potential preference heterogeneity. An LC model fits the best possible model with a predetermined number of classes. For each class, different coefficients (or discrete random effects) are estimated for one or more attributes.

Table 2 – Initially chosen treatment types.

Choice pattern	Patients (n = 114)	Informal caregivers (n = 89)
Always usual hospital care	29 (25)	23 (26)
Both	33 (29)	26 (29)
Always early assisted discharge	52 (46)	40 (45)

Note: Values are n (%).

The optimal number of classes was determined in an iterative procedure, by making comparisons of models with different numbers of classes, on the basis of Akaike Information Criterion 3 (AIC3) and supported by the AIC. The AIC3 is more critical toward models with more parameters than is the AIC. It imposes a penalty of 3 instead of 2 points per model parameter. According to Andrews and Currim [25], the AIC3 is the best performing criterion in determining the optimal number of classes in logit models.

A preliminary number of classes were determined by comparing models with the early assisted discharge dummy as the sole random coefficient. In the second step, the resulting number of classes was used in models with additional random effects. This was done by allowing other attributes to have latent class-specific coefficients and comparing the resulting model with the previous model using a likelihood ratio test.

In the third step, the attributes selected to have a random coefficient were applied in models with different numbers of classes. Again, the model with the lowest AIC was considered superior to the other models, unless it predicted one or more classes with a very small membership.

The associations of class membership with treatment group and COPD severity grade defined by GOLD [1] were explored in the final LC models by adding them as covariates for predicting class membership. In all models, likelihood ratio tests were applied to decide whether quantitative attributes could be used as linear covariates instead of dummies for each level.

Initially, a dummy was added to the hospital alternative to detect a general preference for or aversion to this treatment relative to early assisted discharge, and for one of the early assisted discharge options, to test a possible ordering effect (i.e., whether respondents were more likely to choose the option that was presented as first or second). If the coefficient for this dummy for one of the assisted discharge options was not significantly different from zero, it would be removed from the model. The dummy for the hospital option would be removed

Table 3 – Results of mixed logit analyses.

Variable	Patients		Informal caregivers	
	Coefficient/SD	*P*	Coefficient/SD	*P*
Dummy early assisted discharge				
Mean	3.736	<0.0005	3.991	<0.0005
SD	9.793	<0.0005	8.271	<0.0005
Generic nurse	Reference category		Reference category	
Pulmonary nurse				
Mean	0.900	<0.0005	0.566	<0.0005
SD	0.972	<0.0005	0.986	<0.0005
1 or 2 nurses	Reference category		Reference category	
More nurses				
Mean	−0.674	<0.0005	−0.834	<0.0005
SD	0.799	<0.0005	0.833	<0.0005
Nurse visits per day				
Mean	−0.110	0.090	−0.192	0.267
SD	0.257	0.380	0.577	<0.0005
Co-payment (per €)				
Mean*	−0.110	<0.0005	−4.985	<0.0005
SD*	1.254	<0.0005	1.385	<0.0005
Readmission risk (%)				
Mean*	−6.554	<0.0005	−4.486	0.002
SD*	3.020	<0.0005	2.245	<0.0005
Contact: pulmonary ward	Reference category		Reference category	
Contact: general practitioner				
Mean	−0.816	<0.0005	−0.337	<0.0005
SD	1.312	<0.0005	1.164	<0.0005
Informal carer burden per day (h)				
Mean*	−2.033	<0.0005	−0.240	<0.0005
SD*	3.197	<0.0005	2.773	<0.0005
AIC	2336.173		1858.328	
AIC3	2580.173		1902.328	
Number of respondents	114		89	
Number of choice sets	2036		1577	

AIC, Akaike information criterion; SD, standard deviation

* Coefficients for these attributes were assumed to be lognormally distributed. For other attributes, normal distributions were assumed.

and replaced by a dummy for both early assisted discharge options.

The final models were compared by assessing the AIC and by the respondents' predicted willingness to change the location of treatment on the basis of changes in the specification of the early assisted discharge treatment. This was done by comparing the predicted choice shares if patients and their caregivers were allowed to choose between 1) hospital treatment and the most desirable early assisted discharge specification and 2) hospital treatment and the least desirable early assisted discharge specification. We used 2500 Halton draws when simulating predicted probabilities for the MXL model.

Furthermore, the fit of the MXL element of the GMNL was evaluated by inspecting whether the predicted individual coefficients had the assumed posterior distribution.

Finally, willingness to pay for each attribute was calculated using results from the most appropriate regression model.

All analyses were performed in Stata 12.1 (Statacorp, College Station, TX). The gllamm procedure was used for LC models [26,27]. For the GMNL model, the recently developed gmnl command was used [28]. The mixlogit command [29] delivered estimates for the MXL model, and the mixlbeta command was used to calculate individual-level coefficients. The latter command applies the method proposed by Revelt and Train [30], in which the individual-level parameters are simulated on the basis of the prior distribution from the MXL model combined with each observed individual choice pattern [19].

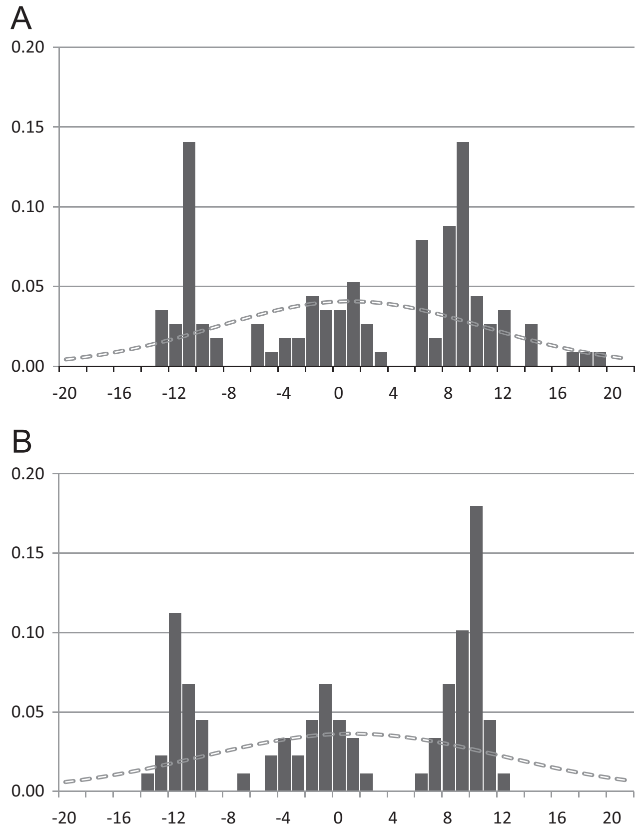

Fig. 2 – Posterity density distribution of the individual-specific dummy coefficient for early assisted discharge compared with the normal distribution assumed by the mixed logit model for (A) patients and (B) informal caregivers.

Results

From the GO AHEAD trial, 107 patients and 83 informal caregivers completed the questionnaire. Their characteristics are listed in Appendix Table 1 in Supplemental Materials found at http://dx.doi.org/10.1016/j.jval.2014.05.004. In addition, seven nontrial patients and six informal caregivers returned the questionnaire. The response rate among GO AHEAD participants was 77% for patients and 64% for informal caregivers.

Table 2 shows that a quarter of respondents chose the hospital care option in all 14 choice sets, whereas approximately 45% always chose the early assisted discharge option. The preference of the remaining 29% of the respondents depended on the description of the early assisted discharge treatment.

Generalized Multinomial Logit

The results from the full GMNL models, with scaling and random effects for all attributes, are presented in Appendix Table 2 in Supplemental Materials found at http://dx.doi.org/10.1016/j.jval.2014.05.004. For patients and caregivers, both the γ and the τ parameter were not significantly different from zero, while most of the SDs for the coefficients were statistically different from zero. This means that there appeared to be a value in treating the heterogeneity as normally distributed deviations from mean coefficients, but there is no additional value in describing it with a scaling factor.

Mixed Logit

The results from an MXL model with correlated random effects are presented in Table 3. The positive coefficient for the early assisted discharge options points to a preference for this type of treatment, given the reference levels of other attributes. All attributes had a significant impact on patients' and informal caregivers' choices in the expected direction, except for the number of home visits per day, among patients, and the readmission risk, among informal caregivers, which were not statistically significant. Furthermore, a higher number of home visits by nurses were not appreciated.

Figure 2A,B shows the posterior distribution of individual-specific dummy coefficient for the early assisted discharge for patients and caregivers, respectively. Both reveal a non-normal, trimodal distribution. In combination with the value of coefficients, this indicates rather fixed preferences for either treatment option.

Latent Class

For patients, the model with four classes was the most appropriate of all models with only a random coefficient for the early assisted discharge dummy, based on the AIC3. The AIC supported this conclusion. This is presented in Appendix Table 3 in Supplemental Materials found at http://dx.doi.org/10.1016/j.jval.2014.05.004. For informal caregivers, the models with three and four classes appeared to be equally appropriate.

In the four-class model, adding the burden on informal caregivers as a discrete random effect led to the largest improvement in the model fit, which was statistically significant. Adding more random coefficients did not improve the model further. When these random coefficients were included, the AIC3 pointed to models with five classes for patients as well as caregivers. This would have resulted, however, in two classes with a predicted probability of less than 10% for patients and less than 5% for caregivers. Therefore, the final models were limited to four LCs with random coefficients for hospital at home and for the burden on informal caregivers. The results from these models and the willingness-to-pay estimates are presented in Table 4.

Table 4 – Results of latent class conditional logit analyses.

Variable	Patients		Informal caregivers	
	Coefficient	P	Coefficient	P
Class 1				
Constant early assisted discharge	−5.418	<0.0005	−4.6578	<0.0005
Informal carer burden per day (h)	−0.036	0.483	−0.053	0.271
Class 2				
Constant early assisted discharge	−0.772	0.023	−0.956	0.075
Informal carer burden per day (h)	−0.510	<0.0005	0.117	0.227
Class 3				
Constant early assisted discharge	2.000	<0.0005	1.250	<0.0005
Informal carer burden per day (h)	−0.277	<0.0005	−0.407	<0.0005
Class 4				
Constant early assisted discharge	6.068	<0.0005	5.402	<0.0005
Informal carer burden per day (h)	−0.112	0.001	−0.120	<0.0005
Shared results for all classes				
Generic nurse	Reference category		Reference category	
Pulmonary nurse	0.501	<0.0005	0.454	<0.0005
One or two nurses	per % Reference category		Reference category	
More nurses	−0.393	<0.0005	−0.507	<0.0005
Nurse visits per day	−0.050	0.414	−0.072	0.267
Co-payment (€)	−0.011	<0.0005	−0.0070	<0.0005
Readmission risk (%)	−0.043	<0.0005	−0.034	0.002
Contact: pulmonary ward	Reference category		Reference category	
Contact: general practitioner	−0.589	<0.0005	−0.490	<0.0005
AIC	2523.902		1981.462	
AIC3	2540.902		2998.462	
Number of respondents	114		89	
Number of choice sets	2036		1577	
Willingness to pay (€)	**Patients**		**Informal caregivers**	
Pulmonary instead of generally trained nurse	46.67		64.43	
One/two nurses instead of more	36.64		71.99	
Additional nurse visit per day	−4.67		−10.15	
Lower readmission risk, per %-point	3.97		4.85	
Hospital instead of general practitioner as contact	54.88		69.61	
Early assisted discharge				
Class 1	−505.12		−661.18	
Class 2	−71.94		−135.76	
Class 3	185.98		17.75	
Class 4	565.62		766.80	
Burden on caregiver, per hour				
Class 1	−3.32		−7.49	
Class 2	−47.53		−23.63	
Class 3	−25.82		−57.83	
Class 4	−10.45		−17.08	

AIC, Akaike information criterion.

For patients, class 1 consisted of respondents with a very strong aversion to early assisted discharge in general and no concerns about an increasing burden on the informal caregiver. Class 2 contained respondents with a moderate aversion to early assisted discharge and serious concerns about higher levels of burden on the informal caregiver. In class 3, respondents had a moderate general preference for the hospital and moderate concerns about higher levels of burden on the informal caregiver. Class 4 was formed by patients with the strongest preference for early assisted discharge, with slight concerns about an additional burden on the informal caregiver.

Caregivers were distributed across similar classes. The only difference is that people in class 2 did not have a significant aversion to a heavier burden on informal caregivers.

For the other attributes, strengths of preferences, as shown by the size of the coefficients, were estimated to be equal across classes. For both groups of respondents, all attributes had a significant effect on choices, in the expected direction, except for the number of visits by homecare nurses per day. High co-payments would lead to the highest amount of disutility for patients as well as informal caregivers, given that the level of co-payments ranged from €0 to €100.

Apart from the general preference for or aversion to early assisted discharge, attributes with the highest willingness to pay were the pulmonary specialization of the homecare nurses, being able to contact the hospital in case of an emergency, and, for some classes, (a reduction in) the burden on informal caregivers.

Table 5 – Predicted membership of latent classes, per GOLD severity grade and per treatment received.

Class	Attitude toward early assisted discharge/burden on caregiver	Total	Severity of COPD (%)				Treatment received	
			GOLD 1	GOLD 2	GOLD 3	GOLD 4	Hospital	Early assisted discharge
	Patients							
1	Strong aversion/ neutral	28 (24.6%)	12.5%	33.3%	11.9%	36.8%	34.0%	15.5%
2	Moderate aversion/ serious concerns	10 (8.8%)	0.0%	5.6%	11.9%	5.3%	6.44%	8.6%
3	Moderate preference/ moderate concerns	22 (19.3%)	12.5%	11.1%	23.8%	21.1%	14.9%	20.7%
4	Strong preference/ moderate concerns	54 (47.4%)	75.0%	50.0%	52.4%	36.8%	44.7%	55.2%
	Total		100%	100%	100%	100%	100%	100%
	Informal caregivers							
1	Strong aversion/ neutral	26 (29.2%)	16.7%	39.4%	16.1%	26.7%	31.6%	23.4%
2	Moderate aversion/ neutral	5 (5.6%)	0.0%	3.0%	9.7%	6.7%	5.3%	6.4%
3	Moderate preference/ moderate concerns	14 (15.7%)	0.0%	9.1%	29.0%	6.7%	18.4%	12.8%
4	Strong preference/ moderate concerns	44 (49.4%)	83.3%	48.5%	45.2%	60.0%	44.7%	57.5%
	Total		100%	100%	100%	100%	100%	100%

GOLD, Global Initiative for Chronic Obstructive Lung Disease.

Latent Class Membership

The median predicted probabilities of the designated classes were all around 99%, which means that there was little uncertainty with regard to the classes that respondents belonged to. The great majority of patients as well as informal caregivers were in extreme classes, that is, with the strongest aversion to or preference for the early assisted discharge (see Table 5).

No clear and statistically significant patterns arose with regard to the association of predicted class membership and treatment or COPD severity, indicating that the preference was not associated with the severity of the airflow limitation.

Comparison of Models

Table 6 presents the predicted choice shares for early assisted discharge when patients and their caregivers are allowed to choose between 1) hospital treatment and the most desirable early assisted discharge specification and 2) hospital treatment and the least desirable early assisted discharge specification. From this table it is clear that MXL predicts that many people would change the location of their treatment on the basis of a change in the characteristics of the early assisted discharge option. In contrast, the LC models predict that the majority of people— respondents in classes 1 and 4—are not willing to switch away from their preferred treatment option,

Table 6 – Predicted choices between early assisted discharge and hospital for mixed logit and latent class multinomial logit models.

Model/class	Most attractive specification of EAD preferred over hospital	Least attractive specification of EAD preferred over hospital	Share of sample in class
Patients			
Mixed logit	58.6%	33.9%	
Latent class 1	0.6%	0.1%	24.6%
Latent class 2	29.5%	5.5%	8.8%
Latent class 3	86.7%	53.7%	19.3%
Latent class 4	99.9%	98.8%	47.4%
Caregivers			
Mixed logit	58.5%	33.7%	
Latent class 1	1.3%	0.2%	29.2%
Latent class 2	31.5%	6.4%	5.6%
Latent class 3	45.5%	13.7%	15.7%
Latent class 4	99.8%	97.6%	49.4%

EAD, early assisted discharge.

at least not within the range of attributes that we consider (Table 6).

Discussion

This study used several different estimation models to quantify the preferences of patients and informal caregivers for aspects of early assisted discharge after a hospital admission for a COPD exacerbation.

Choosing the optimal model to describe the respondents' choices was not immediately obvious. The GMNL model added needless complexity. Apart from relative differences in preferences for different attributes, it estimated differences in the strength of preferences across respondents. In other words, it took into account that some respondents might be more certain and predictable than others. This was not reflected, however, in our results, because the τ parameter was not different from zero.

The remaining two models, the LC logit model and the MXL model, both had their strengths and weaknesses. The MXL models had a better fit, as expressed by the AIC, than did the LC models. They showed heterogeneity in preferences for most of the attributes, whereas the LC models did not detect this.

Nevertheless, we feel that the MXL model was not appropriate in this case. In contrast to the LC model, the MXL model was unable to identify distinct groups in the sample, with widely different preference with regard to early assisted discharge in general. Exploring the individual-specific coefficients for early assisted discharge that were estimated by the MXL model showed that the normal distribution (or any one-modal distribution) was inappropriate in this case.

The results have shown that the average patient and the average informal caregiver do not exist.

For both patients and caregivers, four distinct classes were distinguished, which had different preferences for being treated at home or in the hospital. Large proportions of respondents had a preference for either treatment option that could not be influenced by proposing realistic changes in the characteristics of the early assisted discharge treatment.

This finding is crucial. When the existence of the separate groups is disregarded, it appears possible to construct early discharge programs with a higher or lower average utility than the hospital treatment for the average patient. In our simulations, the MXL model predicted important shifts in choices when the specifications of the early assisted discharge option were changed. Clearly, this is misleading, because large proportions of patients preferred one of the treatment options irrespective of the description of the early assisted discharge program. The predictions from the LC model reflected this.

Results from this study could be used in the design of early assisted discharge programs for this category of patients. The existence of classes with different preferences for either treatment option is an important finding. Apparently, the choice between home and hospital of many respondents cannot be influenced much by adjusting the treatment at home. If this treatment were to become the standard, it would be against the wishes of a large proportion of patients and caregivers. Vice versa, many respondents value early assisted discharge and would not like to be confined to the hospital treatment. Although patients and caregivers who experienced home treatment were more likely to prefer it, the experience did not lead to enthusiasm in everyone. The results of this study, combined with the effectiveness and cost outcomes of the GO AHEAD trial, argue for giving patients a choice between treatment options. This is practical because the full hospital treatment option must also be available to patients who are ineligible for early assisted discharge. The distinction between eligible and ineligible patients is not always clear-cut. Another recommendation would be to eliminate possible co-payment requirements for hospital-at-home if these do not apply to regular hospital treatment. This would remove the negative financial incentive for patients.

A limitation of this study is that the sample is not representative of the population of patients in similar health states and their caregivers. Almost half of the respondents always opted for early assisted discharge. The proportion of people in the overall population is likely to be smaller, because most of the respondents participated in the GO AHEAD trial, in which early assisted discharge was compared with regular hospital treatment. It is obvious that most of them did not have strong reservations against being treated at home. Patients who wanted to be treated in the hospital could achieve this by not participating in the trial.

In recent years, the MXL model has been quite popular in the field of health economics [16], whereas the LC models were hardly used. In general, both have their merits, besides the issue of model fit, as discussed in this paper. On the one hand, LC requires the prespecification of a number of classes. On the other hand, it frees the analyst from making—possibly incorrect—assumptions on the distribution of parameters across respondents [31] and the results are more readily interpretable [22]. Furthermore, it makes it easier to explore the relationship between preferences (class membership) and background characteristics [21].

In conclusion, different classes of patients and informal caregivers have different fixed preferences for the hospital or early assisted discharge treatment. These preferences are not changed by alterations in the early assisted discharge program. When choosing between two home options, respondents put the largest weight on co-payments and the burden on the informal caregiver. The number of visits per day did not play a role.

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Supplemental Materials

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