Towards an evidence based decision making healthcare system management: modelling patient pathways to improve clinical outcomes

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Abstract

The concept of patient flow modelling has attracted managers, commissioners and clinicians to better understand the operational and clinical functions of the healthcare system. Understanding major drivers could reduce inefficiencies, improve patient experience, and most importantly lead to a better outcome for patients, carers and taxpayers. In this context, we study individual clinical pathways of chronic obstructive pulmonary disease (COPD) patients, a source of concern for major stakeholders. In this study, a random effects continuation-ratio logit model is applied to capture the individual clinical pathways of patients leading to multiple readmissions. Data on COPD patients were extracted from the national English Hospital Episodes Statistics dataset. Individual patient pathways from initial admission through to more than four readmissions are captured. We notice that as patients are frequently readmitted, males are more likely to be in the higher risk group than females. Furthermore, the number of previous readmissions has a direct impact on the propensity of experiencing a further readmission. This method could easily be implemented as a decision support tool to determine disease specific (e.g. stroke, congestive heart failure) probabilities of multiple readmissions. Therefore, this could be a valuable tool for clinicians (health care managers, policy makers, etc.) for informed decision making in the management of diseases, which ultimately contributes to improved measures for hospital performance management.

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1. Introduction

Advances in medicine, a well-informed patient population, and demographic changes (e.g. an ageing population) mean that the demand on health and social care services will continue to rise. This makes it more important for us to find the most efficient and effective ways of delivering the best outcomes for people who need care and support. Furthermore, given the increasing demand and capacity constraints, most countries including the United Kingdom (UK) have forced their health organisations to work under intense pressure. This means that without affecting the quality of the existing service deliveries, providers (i.e. hospitals) and purchasers will have to find ways of providing '*better health at lower cost*'. Therefore, it is important to strike a good balance between the need for new capacity and ways of making better use of existing capacity. In many cases this may mean service re-design to ensure that patients receive the right care at the right time and in the right place.

Current UK Government policy, as set out in the 2011 Health and Social Care Bill, establishes outcomes as the measure by which the National Health Service (NHS) will be judged [1, 2]. As well as adapting to the shift in focus from process to outcomes, the NHS also faces an unprecedented resource challenge: net savings of £20 billion must be achieved over the coming 4-5 years, representing a productivity challenge of around 4% a year [3]. Since 2000, productivity in the NHS (useful outputs divided by resources) has fallen by around 1% per year [4]. The key challenge for the NHS, with its budget constrained system, is to deliver maximum patient benefit, measured as useful outcomes per pound spent. Health expenditure is estimated to cost the UK economy £120 billion/year [5]. However, in anticipation of tough times ahead, providers and purchasers are not only interested in the effectiveness of the intervention but whether the intervention is cost effective. Achieving an understanding of how best to increase value in the delivery of health care is therefore critical.

Related to this, the concept of patient flow modelling have enabled managers, commissioners and clinicians to better understand the operational and clinical functions of the health system. Understanding major drivers could reduce inefficiencies, improve patient experience, and most importantly lead to a better outcome for patients, carers and taxpayers.

The medical condition with which the patient is confronted may require a number of different interactions between services or departments, such as x-rays, tests and investigations, surgical operations, etc. At each stage of the care process patients are associated with an activity and resource use, such as the departments visited and the amount of time required to deliver care (e.g. length of stay). These studies have been devoted to two types of modelling, namely conceptual patient pathways and physical patient pathways. Conceptual patient pathways research has been undertaken to diagnose issues related to length of

stay (LoS), i.e. the conceptual (or virtual) phases that a patient goes through before discharge. Here, the interest is in determining the probability of a patient being discharged from a particular conceptual phase, giving that he/she has been in care for x number of days. Previous research has been devoted to the use of markov models [6, 7, 8, 9] and compartmental modelling [10, 11]. For instance, Faddy and McClean [6] applied a stochastic network approach to LoS modelling. In their model, a patient's stay in a geriatric department is viewed as transitions through a set of ordered phases, where the conceptual phases could correspond to the increase in disease severity, or some loosely defined stages, for instance, "short stay", "medium stay" and "long stay". However, any phase found empirically by fitting the model to a dataset may not have such a practical interpretation. Under this model, the distribution of LoS is a Coxian phase-type distribution with the least number of phases that provides adequate fit, and the estimation of model parameters is by maximum likelihood. Using a subset of data used in [8], the authors show that a model with four phases provides a good fit to the empirical LoS distribution.

However, incorporating individual patient pathways (instead of explaining the LoS distribution with virtual phases) within a modelling framework is an emerging field and so far little research has aimed at quantitatively modelling physical patient pathways.

Patient pathways can be viewed from two perspectives; operational and clinical. Though these are the traditional perspectives, common characteristics of both include an entrance, an exit, a path connecting both entrance and exit, and the random nature of the health care elements. The randomness is embodied in two features. First, for a given health care service, not all of the elements in a patient flow network may be applicable to all patients. Second, the time patients spend at each phase and the time patients spend in the overall network also implies a degree of randomness. These are the subject specific random effects. Patient pathways, thus, summarize the individual patient clinical (disease progression) and operational (movement) experience during the process of care.

Two papers on this subject were found to be highly relevant. The first developed a stochastic model (semi-Markov processes) [12] to capture individual patient's experience during a visit to the local family practice clinic. This estimated the transition probabilities between the paths (waiting room, nurse aide station, examining room, lab/x-ray, and discharge) visited by the patient. The second developed a multinomial logit model [13] to capture the individual patient's pathway in the process of care, where patient frailties are modelled as random effects. The approach identified interesting pathways such as those that resulted in a high probability of death (survival), pathways incurring the least (highest) cost of care or pathways with the least (highest) length of stay. Patient specific discharge probabilities from the healthcare system were also predicted.

In [13] it was assumed that the movement of babies from one level of care to the other until discharge is multinomial. In reality, these movements can be considered as an improvement in their condition (or vice versa). Hence, it is plausible to assume that the outcome from previous activity (e.g. care, treatment) is likely to effect the next. In line with our previous work, we introduce

a continuation ratio random effects model to investigate readmission progression and the differential effect of gender on these progressions. In an earlier study, regional disparities were detected in multiple readmissions of COPD in the UK [14]. Note that the leading causes of emergency readmission are congestive heart failure and COPD [15]. As a result, these two disease categories are widely studied in the context of emergency readmissions. We therefore focus on COPD and extract data based on individual patient pathways from initial admission to hospital through to more than four emergency readmissions, i.e., tracking individual patient readmissions longitudinally over the full care cycle and effectively focusing on chronically ill patients. These are known to be frequent users of our services and highly costly.

In the literature, the definition of readmission varies according to the purpose of the study, generally from 30 to 90 days [16, 17], but some studies have used readmissions following certain surgeries, for shorter (14 days) [18] or longer time window (1 year) [19]. So, if a patient is readmitted within the chosen time window, then it is regarded as a quality issue otherwise it is just an unplanned admission. The chosen time windows are generally subjective. Therefore, we have used an approach [20] that objectively defined the time window for COPD patients as 36 days. In the present study, based on this time window, we classify patients into high risk and low risk readmission groups, depending on whether a patient comes back to the hospital before or after a threshold of 36 days.

The current study has two objectives. First, to introduce a random effects continuation-ratio logit model, suitable for detecting stage wise transitions, to patient pathways modelling. Second, we aim at advancing our knowledge with regard to the application of modelling techniques to patient pathways. By doing so, the aim is to widen the remit of applications of modelling techniques in health care management and assess the pertinence of the insights gained from such exercises. Therefore, given the importance of modelling patient pathways (patient readmissions in particular), our research can be of great interest to providers and commissioners of care in England and other countries. For instance, better understanding the pathways with the least and highest cost of care could enable healthcare providers to allocate resources (staff, equipment) more efficiently and effectively, which may lead to improvement in services and cost-effectiveness of care pathways. Furthermore, our results could enable senior decision makers to adopt more pro-active and evidence-based methods in the commissioning decision making process, such as re-designing care pathway to improve clinical outcomes and reduce costs, or identifying bottlenecks of services.

In the next section, we present the National Hospital Episodes Statistics (HES) data with relevant data analysis; Section 3.1 briefly summarises the generalized linear random effects models for patient pathways and the estimation of model parameters; section 3.2 and 3.2.1 describes the continuation ratio logit model and the results, respectively; section 3.3 extends our modelling approach to examine gender disparity with the results illustrated in section 3.3.1, the discussion and conclusion are in section 4 and 5, respectively.

2. The Data

The Department of Health in England releases annually HES data. The HES dataset contains personal, medical and administrative details of all patients admitted to, and treated in, NHS hospitals in England. There are approximately 12 million records for each financial year (in the UK, a financial year is from 1 April to 31 March the following year). The dataset captures all consultant episodes of a patient during their stay in hospital. A patient may encounter several successive episodes, collectively known as a spell. For each patient, readmission time is the time from discharge to admission (the difference between previous discharge and admission date). We focused our study on COPD, as it is known to be the leading cause of early readmission in the UK [21, 22]. From the HES dataset between 1997 and 2004 we extracted 962,656 episodes from patients who had the primary diagnosis codes corresponding to COPD (ICD-10 codes J40-J44). A set of 696,385 spells were derived. From these spells, the total number of live discharges from hospital constituted 638,103. From Table 1 we notice that 53% of all admissions were males; the highest admission rate was amongst the age group 81-90, and the majority of patients had a hospital length of stay between 6 to 11 days.

Table 1: Characteristics of COPD patients in England between 1997 and 2004.

Variable	**Category**	**n**	**%**
Sex	Male	368379	53
	Female	328006	47
Age group	< 40	7776	1.1
	40-50	18239	2.6
	51-60	75413	11
	61-70	181139	26
	71-80	275758	39.6
	81-90	125544	18
	> 90	12157	1.7
Length of stay (days)	< 2	86066	12.3
	2-5	199053	28.6
	6-11	228672	32.8
	> 11	178607	25.6
	NULL	4513	0.65
Admission method	Emergency	647275	92.9
	Elective	36979	5.3
	Other	12657	1.8

To examine the changes in patient admissions and readmissions we illustrate these over calender years. Between 1997 and 2004, admissions for COPD patients increased between 1998 and 2003; the percentage of readmission (patients readmitted within 36 days after discharge) has actually remained relatively stable from 2000 to 2003 (refer to Table 2).

Table 2: Levels of readmission for COPD in England for calendar years 1998 to 2003.

	Total number of admissions	High risk group patients[1]	Total number of readmissions	Percentage of readmissions [2]
1998	96,814	9866	26866	37%
1999	101,819	11338	35552	32%
2000	98,470	12363	40866	30%
2001	99,795	13309	45595	29%
2002	101,970	14012	48178	29%
2003	112,918	15209	53190	29%

3. Methodology

This section develops series of methods based around the continuation ratio random effects model to investigate readmission progression and the effect of predictors (e.g. gender) on these progressions. The objective is to capture the sequential readmission of individual patients by tracking them longitudinally from their initial admission to subsequent readmissions (see Figure 1), and determine the probability of experiencing further readmission. All patients having more than four readmissions are grouped. The justification is that we do not observe many patients having more than five readmissions. Note that each readmission is classified as high risk (within 36 days) or low risk group (greater than 36 days), hence a binary outcome at each readmission.

The next section 3.1 illustrates the generalized linear random effects model for patient pathways and an estimation method based on Gaussian quadrature.

3.1. The generalized linear random effects model for patient pathways

Let $Y_p(t) = (y_{p1}, ..., y_{pT_p});\ t = 1, .., T_p$ be the random vector representing the combination of observed paths for the p^{th} patient in state T_p. In a multi-state system, the pathways represent clustered or repeated measurements for an individual patient. When repeated measurements are taken on patients, classical regression assumptions are violated. Therefore, random effects models need to be developed to model the outcome in a view to capture the correlation structure induced and the patient specific frailty. There are two distinct approaches to the analysis. First, the heterogeneity can be explicitly modelled; we will refer to this as the patient-specific approach. These patient specific effects are assumed to follow a parametric distribution across population, usually normal. Second,

[1]The high risk group patient column refers to the number of patients readmitted with a 36 day interval

[2]Percentage of readmissions within a 36 day time window is 100 × high risk group/total number of readmissions

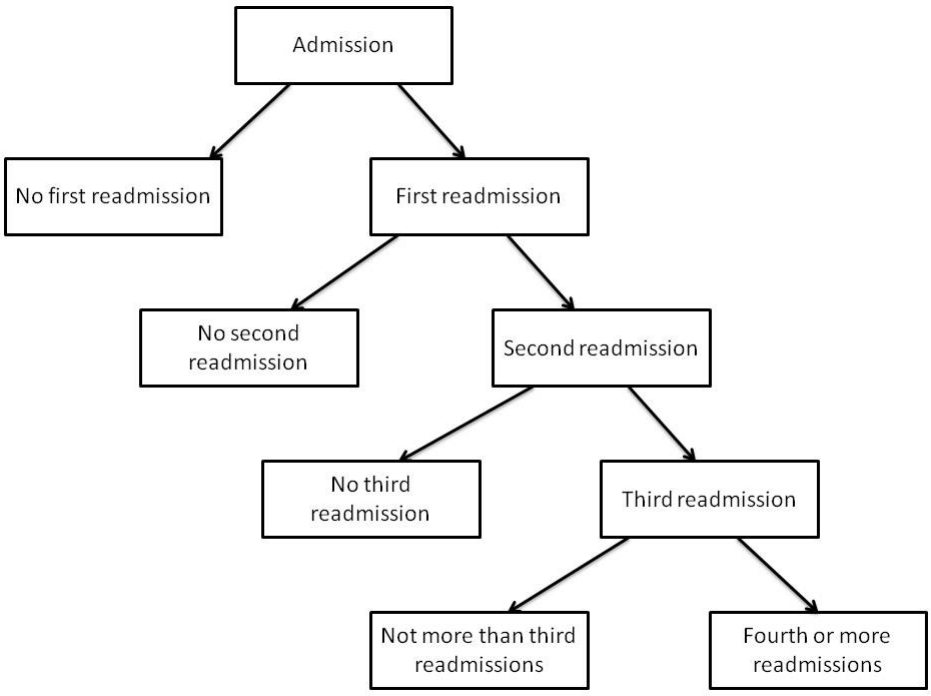

Figure 1: Multiple readmissions as disease progression

the population averaged response can be modelled as a function of covariates without explicitly accounting for patient to patient heterogeneity.

We propose a generalized linear mixed model (GLMM) for the pathways through the system with a generic random effects distribution. Generally, a function of the mean of the random vector representing the observed paths for the p^{th} patient is modelled with fixed and random parts as follows

$$\mathbf{h}(\mu_{\mathbf{p}}) = \mathbf{X}\beta_p + \mathbf{Z_p}\theta_{\mathbf{p}} \text{ and } \theta_p \sim f\left(\theta_p|\psi\right) \tag{1}$$

where $\mathbf{X}$ is the individual design matrix for the fixed effects $\beta_{\mathbf{p}}$, $\mathbf{Z_p}$ the individual design matrix for the random effects $\theta_{\mathbf{p}}$ and $\mathbf{h}\left(.\right)$ is a linear or non-linear link function. The random effects are assumed to follow some parametric distribution $f\left(\theta_p|\psi\right)$, usually a multivariate normal distribution an assumption made for appropriateness and mathematical convenience. Random effects is a generic name for the latent dimension driving some activities. For example, this may be ability in item response theory, utility in marketing research, anxiety in psychology or frailty in health related research.

3.1.1. Estimation: The likelihood

The contribution from patient p to the likelihood can be expressed with the following probability element:

$$l_p\left(\theta_p|y,\beta,\psi\right)=\prod_{t=1}^{T_p}P\left(Y_p(t)=y_p(t)|\beta,\theta_{\mathbf{p}}\right)\times f\left(\theta_p|\psi\right). \tag{2}$$

Here, T_p denotes the number of states the p^{th} patient has visited and $P\left(Y_p(t)=y_p(t)|\beta,\theta_{\mathbf{p}}\right)=\mathbf{h}^{-1}\left(\mathbf{X}\beta_p+\mathbf{Z_p}\theta_{\mathbf{p}}\right)$. We assume that the variability in paths from each patient is explained not only by the fixed effects but also by the frailties. Then the marginal likelihood for the p^{th} patient can be written as

$$l_p\left(\theta_p|y,\beta,\psi\right)=\int_{\Omega}\prod_{t=1}^{T_p}P\left(Y_p(t)=y_p(t)|\beta,\theta_{\mathbf{p}}\right)f\left(\theta_p|\psi\right)d\theta, \tag{3}$$

where Ω is the parameter space for θ_p and $f\left(\theta_p|\psi\right)$ is as defined in (1). There are many estimation methods that have been proposed in the literature to maximize the resulting marginal maximum likelihood. We will consider direct maximization of the likelihood using adaptive gaussian quadrature as described in [23]. Numerical integration will be used to perform the integration of the resulting marginal likelihood. The integration is approximated by a summation on a number of quadrature points for each dimension of the integration. Model estimation using quadrature has been implemented in SAS PROC NLMIXED [24]. A quadrature method approximates the marginal likelihood by a weighted sum over predefined abscissas for the random effects. A good approximation is obtained with an adequate number of quadrature points as well as appropriate centering and scaling of the abscissas. Generally, adaptive Gaussian quadrature for the integral over the random effects θ_p centers the integral at the empirical Bayes estimate of θ_p, defined as a vector $\bar{\theta_p}$ that minimizes the log-likelihood resulting from

$$L_p(\theta_p|y,\beta,\psi)=-log(\int_{\Omega}\prod_{t=1}^{T_p}P(Y_p=y_p\mid\beta,\theta_{\mathbf{p}})f(\theta_p\mid\psi)d\theta_p) \tag{4}$$

with β, and ψ set to their current estimates. The final Hessian matrix from this optimization is used to scale the quadrature abscissa. The estimates of the random effects θ_p are the subject specific frailties used to construct the subsequent probabilities that are estimated by the empirical Bayes estimator $\bar{\theta}$. This estimator is given by

$$\bar{\theta}=E\left(\theta_p\mid y_p\right)=\frac{1}{P\left(.\right)}\int_{\Omega}\theta_p l_p\left(\theta_p|y_p,\beta,\psi\right)f\left(\theta_p\mid\psi\right)d\theta_p. \tag{5}$$

The variance estimator is obtained similarly as

$$V\left(\bar{\theta}\right)=\frac{1}{P\left(.\right)}\int_{\Omega}\left(\theta_p-\bar{\theta}\right)^2 l_p\left(\theta_p\mid y_p,\beta,\psi\right)f\left(\theta_p\mid\psi\right)d\theta_p, \tag{6}$$

where $P(.) = P(Y_p = y_p \mid \beta, \theta_{\mathbf{p}})$ and $l_p(\theta_p \mid y, \beta, \psi)$ is the likelihood of (2).

3.2. The generalized continuation ratio logit model

The continuation ratio model makes successive comparisons for all lower categories on a scale to the next succeeding one. Thus, the first category is compared to the second, the first two to the third and so on. Obviously, this comparison is asymmetric, and one could start from the top of the scale, instead of the bottom. This model describes the probability of moving one step on the scale, given present position. Considering the longitudinal nature of the data, the continuation ratio model is an appropriate model to adapt. For a response with K categories there will be $K-1$ comparisons. For instance, if the multinomial distribution with $K = 5$ ordinal readmissions, with probabilities $\pi_k,\ k = 1, 2, 3, 4$ with $\pi_0 = 1-\pi_1-\pi_2-\pi_3-\pi_4$, where π_k refers to the probability of the kth readmission. We can reparameterise as the series of conditional probabilities $\lambda_1 = \frac{\pi_1}{1-\pi_2-\pi_3-\pi_4}$, where λ_1 refers to the probability of a patient experiencing a second readmission after the first. Likewise, $\lambda_2 = \frac{\pi_2}{1-\pi_3-\pi_4}$, $\lambda_3 = \frac{\pi_3}{1-\pi_4}$ and $\lambda_4 = \pi_4$. Since individual patient experience can be seen as multiple readmissions, which constitutes repeated measurements, this serial dependence can also be included into the GLMM approach. Two types of dependence might be expected: those arising from heterogeneity among individual patients, often called frailties (in our case modelled as random effects) and those from serial correlation in time (not applicable in this investigation). Therefore, we propose a random effects variant of the continuation ratio model where λ_k's is now regressed not only on explanatory variables but also on random effects as

$$\lambda = logit\left(\frac{\pi_k}{1-\sum_{j\neq k}\pi_j}\right) = \mathbf{X}_p\beta + \mathbf{Z_p}\theta_{\mathbf{p}} \tag{7}$$

and the patient population based on the random effects θ_p is assumed to have a normal distribution with mean 0, variance σ_p^2. $\mathbf{X}_p$ is a matrix of patient specific covariates including previous readmissions; $\mathbf{Z}_p$ is a column of ones referring to a random intercept; β is the population effects corresponding to $\mathbf{X}_p$. This is a class of linear random effects model.

3.2.1. Results

The generalized continuation ratio logit model is applied to the HES data set summarised in section 2. Multiple readmissions play a key role in measuring disease severity [21]. The HES is a large data set, where no amount of data exploration will bring out the enormous information embedded in the data. Here, the progression to multiple readmissions as a function of initial admission and series of readmissions is modelled, hence the patient flow is clinical rather than operational.

Individual patient pathways from current readmission through to at least four previous readmissions is captured within this model. In this context, current can be defined as the patient being observed at any stage of progression. Suppose a patient is on their 2nd readmission, this could be their current and

1st can be their previous readmission. Here, the focus is to determine the probability of being readmitted for a third time. Likewise, if we observe a patient to be in their sixth readmission, this is recognized as a patient who has experienced four or more readmissions. Hence, four or more readmissions is the current readmission, and we look into the past history of readmissions to determine the probability for their next readmission. We present the model based results in the following order by group of patients according to the number of readmissions.

Model I: Group of patients having only current readmission (1st readmission)

Model II: Group of patients having a current readmission (2nd readmission) and a previous readmission (1st readmission), i.e, at most two readmissions

Model III: Group of patients having a current readmission (3rd readmission) and two previous readmissions (1st and 2nd readmission), i.e, at most three readmissions

Model IV: Group of patients having a current readmission (4th readmission) and three previous readmission (1st, 2nd and 3rd readmission), i.e, at most four readmissions

In other words, we want to determine the probability of a patient belonging to any of the lower group advancing to a higher group as a function of patients characteristics, such as gender, age, readmission history, total length of stay in hospital prior to discharge, number of previous readmissions, Charlson co-morbidity index, index of multiple deprivation(IMD), ethnicity, reasons for discharge and discharge destinations.

The Charlson index of comorbidity [25] is a measure of patient severity, which is based on ICD-10 diagnosis codes, where various weights are attached to the presence of conditions, such as congestive heart failure and cancer. The IMD [26] is a weighted index based on seven factors of deprivation, which can be recognized and measured separately, and are related to: income; employment; health and disability; education, skills and training; barriers to housing and services; living environment and crime. The English Indices of Multiple Deprivation identifies the most deprived areas across the country. They combine the seven indicators into a single deprivation score for each small area in England. Charlson comorbidity index and IMD are not available in the HES dataset and a number of steps had to be taken to incorporate this information.

The Charlson co-morbidity index is only statistically significant (see Table 3) for patients having more than four readmissions (Model IV). Patients belonging to this group are suffering more from other opportunistic infections as a result of COPD (and or related diseases contributing to multiple readmissions for COPD).

Methods of discharge are as follows: discharged on clinical advice or with clinical consent (clinical); self discharged or discharged by a relative or advocate

Table 3: Parameter estimates for progression to multiple readmission as a function of previous readmissions and covariates. $^{\wedge}p < 0.10,^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$. Daydiff is the number of days spent in the community before readmission and CC index is Charlson Comorbididy index. The values in square brackets are 95% confidence intervals on parameter estimates.

Variable	Model I	Model II	Model III	Model IV
Patient Characteristics				
Intercept	8.1017*** [6.4000, 9.8029]	11.6600 *** [9.8742, 13.4457]	3.1418** [1.2484, 5.0352]	4.8973*** [2.6164, 7.1781]
Age	0.0001 [0, 0.0003]	0.0002* [0, 0.0004]	0.0004*** [0.0002, 0.0007]	0.0004** [0.0001, 0.0006]
Daydiff	0.0007*** [0.0006, 0.0008]	0.0008*** [0.0007, 0.0009]	0.0012*** [0.0010, 0.0013]	0.0009*** [0.0008, 0.0011]
IMD	0.0040*** [0.0018, 0.0006]	0.0045*** [0.0023, 0.0066]	-0.0020* [-0.0038, -0.0001]	0.0007 [-0.0012, 0.0026]
No. of admissions	-6.1643* [-6.2134, -6.1152]	-4.8665*** [-4.9169, -4.8160]	-1.0388*** [-1.0634, -1.0142]	-1.8196*** [-1.8443, -1.7948]
CC index	0.0053 [-0.0231, 0.0337]	0.0226 [-0.0054, 0.0506]	-0.0384** [-0.0646, -0.0121]	-0.0164 [-0.0425, 0.0098]
Gender	-0.02904 [-0.0755, 0.0175]	-0.0357 [-0.0804, 0.0090]	0.0180 [-0.0214, 0.0575]	-0.0122 [-0.0521, 0.0277]
Readmission history				
First readmission	-0.1021*** [-0.1622, -0.0419]	-0.1468*** [-0.2011, -0.0925]	-0.0492* [-0.0955, 0.0028]	-0.0983*** [-0.1455, -0.0511]
Second readmission	NA	-0.5867*** [-0.6379, -0.5354]	-0.3222*** [-0.364, -0.2803]	-0.2679*** [-0.3106, -0.2251]
Third readmission	NA	NA	-0.3571*** [-0.3995, -0.3147]	-0.4058*** [-0.4497, -0.3618]
Fourth readmission	NA	NA	NA	-0.6681*** [-0.7148, -0.6213]
Discharge Destinations				
Home	-0.7236 [-2.3612, 0.9139]	-2.0296* [-3.7969, -0.2623]	-1.2257 [-2.8203, 0.3689]	-0.3052 [-2.3283, 1.7179]
Penal	0.7758 [-2.5603, 4.1119]	-2.0970 [-5.6426, 1.4486]	-11.4136 [-292.96, 270.14]	0.7514 [-2.0208, 3.5224]
NHS	-0.6813 [-2.3239, 0.9614]	-1.9668* [-3.7386, -0.1949]	-1.2481 [-2.8480, 0.3518]	-0.3256 [-2.3526, 1.7014]
Local	-0.7985 [-2.4837, 0.8867]	-1.8222* [-3.6323, -0.0121]	-0.9911 [-2.6200, 0.6378]	-0.3480 [-2.4018, 1.7058]
NoNHS	-0.6120 [-2.2615, 1.0375]	-1.8683* [-3.6464, -0.0901]	-1.0230 [-2.6288, 0.5828]	-0.1949 [-2.2262, 1.8364]
Ethnic origin				
White	-0.2178*** [-0.2712, -0.1643]	-0.2451*** [-0.2980, -0.1921]	-0.1940*** [-0.2415, -0.1464]	-0.1842*** [-0.2322, -0.1362]
Mixed white	-0.0736 [-0.5732, 0.4259]	0.0562 [-0.4428, 0.5552]	-0.2978 [-0.7527, 0.1571]	-0.0121 [-0.4448, 0.4207]
Asian	-0.2836* [-0.5019, -0.0652]	-0.4725*** [-0.6744, -0.2706]	-0.3474*** [-0.5211, -0.1737]	-0.3774*** [-0.5567, -0.1981]
Black	-0.2723 [-0.8550, 0.3104]	-0.5084^[−1.0454, 0.0286]	-0.1953 [-0.5718, 0.1812]	-0.2815 [-0.6880, 0.1250]
Other	0	0	0	0
Discharge methods				
Clinical	1.7324*** [1.0436, 2.4211]	2.2645*** [1.5449, 2.9840]	3.3451*** [2.2928, 4.3974]	3.5310*** [2.4759, 4.5861]
Selfadv	1.7356*** [1.0014, 2.4698]	2.2107*** [1.4519, 2.9694]	3.1408*** [2.0691, 4.2125]	3.4192*** [2.3433, 4.4950]
Tribunal	0.5964 [-1.0651, 2.2578]	2.5558 [-0.1874, 5.2990]	4.7151** [1.7467, 7.6835]	4.0344* [0.3678, 7.7010]

(selfadv); discharged by a mental health review tribunal (tribunal); and death. Note that death records from this dataset has been removed because interest lies in modeling readmissions, as deceased patients cannot be readmitted. Destination of discharge are as follows: the usual place of residence including no fixed abode (home); Penal establishments (penal); NHS other hospital provider or nursing/residential homes (NHS); local authority residential accommodation (local); and non-NHS run hospital, nursing or residential homes (nonhs).

There are no significant age effects on having only a first readmission. However, significant age effects can be seen in other readmission groups. There is a slight increase in the number of readmissions as COPD patients become older, making older patients more prone to multiple readmissions. The same phenomenon could be observed for length of stay (LOS), where multiple readmissions is associated with prolonged hospital stay. The index of multiple deprivation (IMD) increases with multiple readmissions, making people who are highly deprived to be more likely to have multiple readmissions. IMD, however, is lower for the group of patient with three previous readmissions. There is a significant decrease in the number of new admissions as readmission progresses after adjusting for death on admission. Progress in readmissions results in increased readmission, for example patients with only one readmission before the current are less likely to progress to multiple readmissions. Across the groups it is less likely for any patient to be readmitted as low risk, that is most patients across the group are more likely to be readmitted as high risk patients as readmission progresses. This might be true since multiple readmissions are clinically related to advancement in the medical condition leading to more frequent visits to hospitals.

The majority of patients in each of the groups are White and people of Asian origin. Surprisingly, gender doesn't seem to be playing any significant role in multiple readmissions. Since smoking is the main causal agent of COPD, gender might not significantly play a role in choosing a "good" smoker. Though, female smokers may be at greater risk of developing COPD, possibly due to sex differences in the metabolism of cigarette smoke [27], nothing is known on how gender influences multiple COPD readmissions. The model presented above might not be adequate to capture the gender difference in multiple COPD readmissions. Therefore, in the next section, we investigate gender bias in COPD readmission progression, since it has been shown that gender difference in the diagnosis, treatment and management of COPD is an important research area that is still lagging behind in the epidemiological study of COPD [27].

3.3. A continuation ratio logit model for gender disparity

Gender disparities for those treated for COPD have been studied amongst many public health issues. However, for those experiencing frequent readmissions, these have have not been considered. The objective here is to determine the probability of a patient having an early readmission (or probability of being readmitted within 36 days), given patient and gender specific previous readmissions. Several studies investigated gender disparities in the outcomes and

treatment of COPD. These studies have examined mortality disparities of patients by gender. For a review of studies on gender differences in the diagnosis, management, and surveillance of COPD, refer to [27]. Following the footsteps of cardiovascular researchers, clinicians and the pulmonary scientific community on the exploration of how gender may impact the diagnosis, treatment, and surveillance of COPD, we hereby investigate gender disparities in COPD readmissions. This has not been investigated by any other researchers in the field of COPD epidemiology and public health. Investigating individual patient pathways, i.e. following patients from their initial admission to subsequent readmissions, we determine the probability of experiencing a further readmission, based on the variation between males and females.

The continuation ratio logit model of the previous section is modified to accommodate gender bias as follows:

$$\lambda = logit\left(\frac{\pi_k}{1-\sum_{j\neq k}\pi_j}\right) = \mathbf{X}_p(\beta^\star - \delta^\star gender) + \mathbf{Z_p}\theta_\mathbf{p} \tag{8}$$

where all the arguments are as presented earlier and the patient population based on the random effects θ_p is partitioned into male and female subpopulations each having a normal distribution with mean 0, variance σ^2_{male} and μ_{female}, variance σ^2_{female}, respectively. The mean of the male is fixed at 0 to ease computational complexity. δ is the gender disparity parameter imposed on β.

3.3.1. Results

As in section 3.2.1, we present the results according to the number of readmissions. Model I referred to the group of patients having only current readmission (1st readmission), Model II the group of patients having a current readmission (2nd readmission) and a previous readmission (1st readmission), i.e, at most two readmissions, and so on. In this section we further examine to see if these results will be different if the fourth group is split into two, that is, an additional group with four readmissions and at least five readmissions. Note that in section 3.2.1 we modelled individual patient pathways from current readmission through to at least four previous readmissions and if a patient had 6 previous readmissions this was considered to be at least four readmission.

Result for Group I

In this group, there are 444,495 observations, which constitutes 69% of all the records extracted from the HES dataset. These patients are seen for the first time as a readmission and no previous records of readmission are known. Approximately 24% are classified as high risk group (HRG) of which 56% are male. From the 76% of low risk group (LRG) patients, 52% were male. In Table 4 Model I, we present the modelling results for this group of patients having only a current readmission (1st readmission). We notice that it is less likely to progress beyond the current readmission for this group of patients

(log-odd $-2.2907, p < .0001$). Therefore, the probability of predicting the second readmission from this model is low, i.e., patients with only a 1st readmission are less likely to experience multiple readmissions ($e^{-2.2907} = 0.10$). In terms of gender disparity, female patients with a single readmission are about 67% more likely than males to have multiple readmissions (log-odd $0.5141, < .0001$) and they are just about 5% more likely to return as HRG (log-odd $0.0468, .0444$) .

Result for Group II

This group constitutes 60,916 records, which accounts for 9% of the extracted HES dataset. These patients are observed for the second time as a readmission with one previous readmission. From this extraction, 74% are classified as LRG of readmission of which 51% are male. Here, we notice that it is 28% more likely to progress beyond the current readmission for this group of patients (log-odd $0.2458, p < .0001$), i.e. patients with a current readmission and a previous readmission are more likely to experience multiple readmissions. Females are about 68% more likely than males to experience multiple readmissions after their current and one previous readmission (log-odd $0.5181, p < .0001$), whereas they are less likely to belong to the HRG of readmission (log-odd $-0.0982, p = .0444$).

Result for Group III

This group has 37,413 records, which is about 5% of all the records extracted. These patients are observed twice before their current readmission (3rd readmission). About 69% are classified as LRG of which 51% are male. From the 31% in the HRG, approximately 55% are male. In Table 4 Model III, the result of the modelling shows that it is more likely to progress beyond the current readmission for this group of patient, taking into account that they have been readmitted twice before (log-odd $0.2958, p < .0001$), i.e. patients with a current readmission and two previous readmission are more likely to have multiple readmission. Females in this group are less likely to have multiple readmissions after their current and two previous readmissions (log-odd $-2.2279, p < .0001$) . Gender has no significant effect on LRG or HRG of readmission (log-odd $0.0702, p = .0242$) .

Result for Group IV

This group is based on those patients with a current readmission (fourth readmission) and at most three previous readmissions (24,725 records - 4% of HES), where 66% are classified as LRG of readmission (51% are male). Table 4 Model IV shows that it is more likely to progress beyond the current readmission for this group of patient's taking into account that they have already been readmitted on three occasions (log-odd $0.3455, p < .0001$). Females are less likely than males to experience multiple readmissions (log-odd $-2.0710, p < .0001$) ., and gender has no effect on LRG or HRG of readmission ($p > .05$).

Result for Group V

Table 4: Parameter Estimates for the continuation ratio logit model for gender disparity. $^{***}p < 0.001$,** $p < 0.01$,* $p < 0.05$.

Parameter	Model I	Model II	Model III	Model IV	Model V
mean of female population	0.4860***	-0.2476***	-2.2399***	-2.0677***	-1.8858***
average effect of readmission	-2.2907***	0.2458***	0.2958***	0.3455***	0.3457***
effect of first readmission	-2.4151***	0.6200***	0.3756***	0.3283***	0.2405***
effect of a previous readmission	–	0.8500***	0.5061***	0.3356***	0.3274***
effect of a second previous readmission	–	–	0.7490***	0.4856***	0.3350***
effect of a third previous readmission	–	–	–	0.7588***	0.4768***
effect of at least a fourth previous readmission	–	–	–	–	0.8228***
diff effect of average readmission	0.5141**	0.5181***	-2.2279***	-2.0710***	-1.8310***
diff effect of first readmission	0.0468*	-0.098***	0.0297	0.0602	0.0084
diff effect of a previous readmission	–	-0.0602*	0.0165	0.0483	0.0080
diff effect of a second previous readmission	–	–	0.0702*	0.0034	0.0324
diff effect of a third previous readmission	–	–	–	0.0540	0.0073
diff effect of at least a fourth previous readmission	–	–	–	–	-0.0196
variance of male population	2.3126***	0.8005***	0.4121***	0.2645***	0.1766***
variance of female population	2.4144***	0.5544***	0.3941***	0.2493***	0.0149***
-2LogLikelihood	632223	233928	153320	106405	76635
AIC	632237	233942	153342	106431	76665

This group (76,354 records, 12% of HES dataset) are those who have experienced at least four previous readmissions before their current readmission (more than four readmissions). Here, 54% are classified as LRG (52% are male). Table 4 Model V illustrates that it is more likely to progress beyond the current readmission for this group of patient's, taking into account that they have been readmitted at least four times previously (log-odd $0.3457, p < .0001$), i.e. patients with a current readmission and four previous readmissions are more likely to have multiple readmissions. Females in this group are less likely than males to have multiple readmissions (log-odd $-1.8310, p < .0001$) . Patients belonging to the HRG are more likely to have multiple readmissions ($p < .0001$.) and gender has no effect on readmission based on LRG or HRG ($p > .05$).

4. Discussion

The recession and the banking crisis forced the UK government to cut funding to public services. During 2010-11, the National Health Service will need to save £20bn over the next 4-5 years, and thus every service provider and purchaser is faced with the challenge of making the best use of their resources and showing value for money at every opportunity. One of the most effective ways of doing this is to truly understand service provision and thus make informed decision in the face of uncertainties, e.g. is our services improving patient outcomes, is it effective, and are there any unknown patterns and trends in the use of our services?

The recent Transparency in Outcomes [28] paper clearly stresses the importance of measuring the outcomes of care as well as structure and process in order to evidence and drive up quality. Providers and purchasers seek to ensure that their funds are used effectively to address the underlying determinants of patients in their local population. They need to constantly identify where developments and changes need to occur and predict the outcomes of services to improve both patient outcomes and practice in relation to the organisation and delivery of health care.

Given that healthcare outcomes (readmissions in particular) are at the heart of the UK Government's (and other countries) initiative towards improving patient satisfaction and safety, it is important that robust and effective methodologies are developed to better understand the behaviour of those patients who are frequently readmitted, that is, focusing on the main drivers associated with patients progression to multiple readmissions. From the point of view of individual patients, hospital managers and primary care trusts, the identification of these risk factors is of considerable importance.

In essence, the four models profile COPD patients based on readmission groups and relate group membership to characteristics, demographics and prior use of medical services. For example, in all the models, it can be noticed that the propensity to experience a second readmission is higher for those who had a first readmission. Therefore, this model is very useful in detecting the most

critical threshold at which multiple readmissions are more probable. Clinicians should note that a first readmission signifies a problem in the process of care and if care is not taken this may be the beginning of many subsequent readmissions.

Exploring how gender may impact the diagnosis, treatment and surveillance of COPD is beginning to be popular [27]. This is made possible by the complex questions surrounding how differences in male/female biology may interact with gender differences in environmental, societal, cultural and behavioural determinants of health to influence outcomes. Our results suggest a critical point in readmission progression to be those patients with a second readmission. However, the result of gender disparity means that female patients are worse off at this critical point. Therefore, clinicians should especially note female patients on a second readmission as they are more prone to more readmissions beyond the second readmission.

Note that pathways capture both the operational and clinical experience of patients within the health system. By representing these in a model, patients experience can be studied to detect points at which clinical decisions were taken and the outcome of such decisions. It also offers an opportunity to make adjustments when necessary to improve the clinical outcome.

Rapid patient discharge to free beds for incoming patients is a controversial debate in the UK. Some argue that patients may have been discharged too soon, raising the issue that patients are being discharged 'sicker and quicker' [29]. As a result, early discharges may generate high levels of readmissions, which could possibly be seen as patients being discharged inappropriately. However, results suggest that the LOS effect on readmission progression is minimal in this study population. In this respect, other measures different from keeping patients unnecessarily longer in hospital and which may result in the reduction of emergency readmissions, increase patient and staff satisfaction, reduce waiting lists, increase the performance of the hospital, and given the economic conditions in the UK, cost savings need to be developed.

Almost all public organisations including the NHS in England are data rich, but starving for information. This suggests a potential to bring together data sources to routinely evaluate outcomes. Given this vast amount of data, the current study has led to some important insights concerning COPD patient readmissions progression and their behaviour in the health care system. However, it has only added to our thirst to learn more about this important element of the management of specific disease categories. The results of this research have already paved the way to the investigation of more issues regarding the management of healthcare services. For example, it would be very interesting to know the effects of management policies, changes to admission policies, integration of services, and restructuring of delivery structures on the performance of these systems.

Our research has the potential to have numerous benefits for providers and purchasers of health and social care, such as: 1) the availability of techniques to support strategic and business planning through effective evaluation of patient readmissions; 2) the transferable skills in advanced data analytics using large and complex datasets; 3) the health outcomes for the local population through

more timely and effective interventions (reduction in waiting lists, mitigating financial risks and hence cost savings); 4) developing a holistic understanding of how the local population accesses and uses health service; 5) identification of patterns and pathways of service usage previously unrecognized; 6) understanding how information is applied in making strategic decisions, particularly in the health sector based around emergency readmissions; and 7) practical involvement in how information informs commissioning decisions.

5. Conclusion

Under new government plans NHS hospitals will face financial penalties if patients are readmitted as an emergency within 30 days of being discharged. Hospitals in England will be paid for initial treatment but not paid again if a patient is brought back in with a related problem.

There is an acknowledgment of a lack of robust analysis of routine data to inform models that measures outcomes (i.e. readmissions), cost and effectiveness. Substantial and often unwarranted variations exist across the NHS and other health systems both in terms of inputs to care and the useful outputs (quality, or outcomes) of care. In this context, it is important that clinicians, hospital managers and commissioners have a better understanding of "individual" patient pathways from initial admission to subsequent readmissions (longitudinal cycle of care).

To truly understand the operational and clinical functions of the healthcare system, patient centred outcomes (e.g. readmissions) must be aggregated around the patient rather than discrete services. It is the longitudinal aspect of providing care that matters and so far very little research has aimed at tracking individual patient pathways that are modelled within an advanced statistical framework.

The majority of published papers can be grouped into two categories: 1) risk factors and prediction models [30, 31]; and 2) whether readmission is an indicator of poor process of care (quality of care) [32, 33, 34, 35, 36, 37, 38]. Our research aims at advancing our knowledge in this newly emerging field of modelling care pathways, hence does not belong to either categories. Our primary objective is to showcase this new approach as an additional decision making tool that can be complementary to other techniques.

It is accepted that clinical factors explain variations better than using administrative data. However, in the absence of such data, we have developed a framework that incorporates patient history of readmissions with frailty modelled as random effects, an important concept often neglected in this area of research. Using the national HES dataset, we demonstrate the use of clinical pathway to model probability of progression to multiple readmissions. The models show differences in case-mix. Individual profiles (pathways) of multiple readmissions is a novel approach that has been modelled to capture patient to patient heterogeneity, ensuring that individual patients progression to multiple readmission is incorporated into the model. In the majority of studies, this heterogeneity is not accounted for due to its complexity and the lack of availability

of data. Though we have only considered COPD patients, this model could easily be adapted to other disease categories. This method could easily be implemented as a software toolkit to determine disease specific (e.g. COPD, stroke, congestive heart failure, etc) probabilities of multiple readmissions. Therefore, this could be a valuable tool for clinicians (health care managers, policy makers, etc.) for informed decision making in the management of diseases, which ultimately contributes to improved measures for hospital performance management.

We have presented models that capture patients pathways, but an elegant way will be to jointly model length of stay (for each readmission patients stay in hospital for a period of time) and clinical flow paths for improvement in the process of care and better planning. Therefore, future work will be devoted to the joint analysis of patients pathways and length of stay. We will develop a method for the joint modelling of mixtures of ordinal (multiple readmissions) and continuous (i.e. LOS) outcomes, since models for this type of problem are new to health services research in general and LOS modelling in particular.

In conclusion, we demonstrated that the random effects continuation ratio logit model can be used to capture COPD patients progression to multiple readmissions as a function of initial admission, previous readmissions and predictors (e.g. IMD, age, gender). This model is very useful in detecting the most critical threshold at which multiple readmissions are more probable, thereby informing decision making in the management of COPD.

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