 doi:10.20944/preprints202302.0315.v1

Article

Characterising Hospital Admission Patterns and Length of Stay in the Emergency Department at Mater Dei Hospital Malta.

Lalit Garg[1,*], Natasha Attard[1], Roberta Caruana[1], Bhushan Dinkar Pawar[1], Sally I. McClean[2], Sandra C. Buttigieg[3], Neville Calleja[4]

1 Department of Computer Information Systems, Faculty of Information and Communication Technology, University of Malta, Msida, MSD 2080, Malta; lalit.garg@um.edu.mt.
2 School of Computing, University of Ulster, Co. Londonderry, Coleraine BT52 1SA, UK; si.mcclean@ulster.ac.uk
3 Department Health Systems Management and Leadership, Faculty of Health Science, University of Malta, Msida, MSD 2080, Malta; sandra.buttigieg@um.edu.mt
4 Department of Public Health, Faculty of Medicine & Surgery, University of Malta, Msida, MSD 2080, Malta; neville.calleja@um.edu.mt
* Department of Computer Information Systems, Faculty of Information and Communication Technology, University of Malta, Msida, MSD 2080, Malta; lalit.garg@um.edu.mt.

Abstract: Healthcare professionals and resource planners can use healthcare delivery process mining to ensure the optimal utilisation of scarce healthcare resources when developing policies. Within hospitals, patients' Length of Stay (LOS) and volume of admitted patients, in terms of number and characteristics (age, gender, and social determinants), are significant factors determining daily resource requirements. In this study, we used Coxian phase-type Distribution (C-PHD) based Phase-Type Survival (PTS) trees for analysing how covariates such as admission date, gender, age, district, and admissions source influence the admission rate and LOS distribution. PTS trees. This study used a two-year data set (2011-2012) of patients admitted to the Emergency Department at Mater Dei Hospital to generate models and an independent one-year data set (2013) of patients admitted to the Emergency Department at Mater Dei Hospital to evaluate. The PTS tree effectively clusters patients based on their LOS, considering the prognostic significance of different covariates related to patients' characteristics. Characterising these covariates provided meaningful results about LOS. Similarly, the PTS tree was used to effectively cluster patients based on the admission rate, considering the prognostic significance of these covariates.

Keywords: Length of stay estimation; Admission rate characterization; Resource requirement forecasting; Patientcare modelling; Hospital capacity planning; Phase type survival trees; Machine Learning; Health ML Extended Health Intelligence

1. Introduction

By forecasting daily resource requirements for admissions, healthcare planners can develop a plan to ensure the efficient and effective quality of service at a minimal cost [8] to ensure the ideal use of resources [11]. Complex strategies are often required to solve problems of admission scheduling and resource requirements to efficiently and effectively manage the healthcare system. Healthcare planners frequently experience dilemmas of ensuring equitable allocation of hospital resources when faced with long waiting lists and overcrowded emergency departments having patients waiting for admission. Thus, by finding an efficient solution to this problem, it is possible to help healthcare resource managers, hospital staff, and policymakers make the hospital more efficient. The aim of this project included developing a mathematical model, which may be used to model LOS and admissions patterns through PTS trees [8, 10-12, 28-30]. Developing this model will help healthcare professionals create policies that ensure the optimal allocation of the limited

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

resources available. This model would then predict patients' LOS and the number of admissions for independent data.

1.1. Background and Previous Research:

There has been tremendous interest in estimating the hospital length of stay from a long time [31-32] and the factors affecting it [17-18] and recent studies [33-85]. There are some recent reviews of machine learning and statistical methods for the hospital length of stay estimation. [43, 48, 51, 62, 68]. Keegan [18] argued in favour of evidence showing that bed occupancy rate is a reliable key performance indicator for hospitals' capability to provide good quality care to patients. Cooke et al. [3] suggested that if a border is set and the bed occupancy rate is below it, then the waiting times in the Emergency Department will be reduced exceptionally. Jones [17] discussed several factors which affect hospital occupancy demand, including temperature (admissions may increase or decrease the possibility of certain conditions), injuries and infections (these do not happen during certain periods and have no significant patterns), clinical practice changes, weather and environmental factors such as viruses and the rising need of end-of-life care.

Many models have been developed in the past, some of which include queuing models (Worthington D. J. [24], Gorunescu et al. [9]). In contrast, others use computer simulation or population ratio-based models (Kuzdrall et al. [19]). Fackrell [4] suggested that a realistic approach to modelling a care system uses compartmental models mainly implemented using phase-type Distribution (PHD). However, these models are unsuitable for admission scheduling and capacity planning since they mostly model patient flow within the hospital and do not consider re-admissions or community care. Garg et al. [20] proposed an alternative model developed using Markov chain modelling where the resource necessities could be forecasted using patient pathways in the future. In this study, Markov Chains were used to construct a policy that satisfies any future resource availability for the care system. However, this study is limited since it assumes a fixed number of daily admissions, which is unrealistic and cannot be used for many practical situations. In a further study by Garg et al. [11], a model was introduced where scheduling admissions, allocating resources and forecasting requirements could be achieved. This model improves the previously mentioned model [20] since it may be used for fixed and variable daily admissions. The model presented in the study [11] considers two time-dependent covariates: the current calendar year and the patient's current age. The covariates for each patient are updated daily to have a more realistic model. This model is mainly based on predictable values and can therefore forecast the number of expected patients in each phase and the daily cost of care. The authors of a further study (Garg et al. [8]) propose using covariates, such as age, gender, time of admission and diagnosis, to carry out better hospital capacity planning since these characteristics affect a patient's LOS. In this study, a PTS tree is used for smaller patient groups with respect to the LOS distribution using the characteristics as a base. In this paper, Garg et al. [8] propose an adaptable and flexible approach to intelligent healthcare planning and patient organisation, considering patient heterogeneity, essential variability and system complexity.

1.1.1. The seasonal effect on patient admissions:

Moreover, patients' admission could also be affected by several seasonal effects. Fullerton & Crawford [6] states that patient admission increases substantially during winter, mainly in general medicine and orthopaedics. This study also found fewer admissions during Christmas than the rest of the year. Green, Fullerton and Crawford ([6], [13]) agree that fewer procedures are booked for the weekend, and no elective patients are admitted to keeping bed space for weekend demand. Fullerton & Crawford [6] believe that the seasonal effect is predictable. Therefore, chaos within hospitals could be avoided if healthcare planners had to plot the admission rates better and better utilise the resources of primary care institutions.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

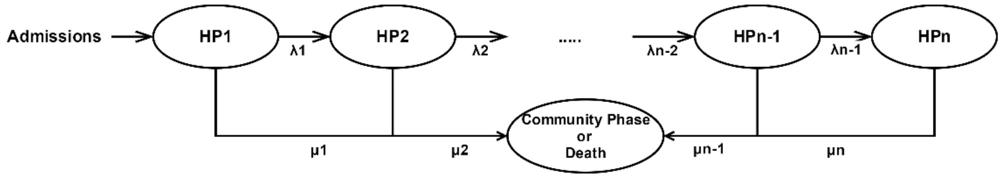


Figure 1: Patient flow in the healthcare system.

1.1.2. Models used to estimate the patient's length of stay:

Estimating the LOS of patients helps resource planners analyse and estimate the hospital's bed occupancy and thus forecast the required resources. The two most popular methods that provided almost accurate approximations in previous studies when estimating patient LOS include the Gaussian Mixture Model and the C-PHD. Using phase-type distributions in various stochastic models allows algorithmically tractable solutions to be found. General PHDs are said to be over-parametrised (Fackrell [4], Marshall A, McClean S. [21]). C-PHD are a subclass of general PHDs which requires less complex parameter estimation (Fackrell [4]). The literature provides different methods to approximate the parameters [4]. These methods included:

Maximum likelihood estimation (Asmussen et al. [2], Olsson [23], Faddy & McClean [7], Faddy [5] and Hampel [14]).

Moment matching (Johnson [16])

Least squares

Splitting the main part and the tail part of the distribution (defined on positive numbers with a PHD) and approximating them separately (Horvath and Telek [1]).

2. Materials and Methods

In this study, the patient flow within the hospital system is to be modelled. In several studies ([20], Garg et al. [11]), patient flow is categorised through the rate of transition of a patient between states. It is assumed that there are n hospital phases (acute, treatment, rehabilitation, long stay) and m community phases (dependent, convalescent, recovered). Patients move sequentially from one hospital phase to the next and similarly from one community phase to the next. A patient may be re-admitted into the first hospital phase from any community phase and may be discharged from any hospital phase to the first phase or die at any point in the process. Furthermore, the set-up consists of n hospital phases and one absorbing state within this study. This may be represented as a discrete-time Markov chain having n+1 states. In this model, patients are admitted in the first state. They could leave the system at any other state (through death or by being discharged). Figure 1 describes the possible patient flow through the system, where: HP_i represents being in hospital phase i, λ_i represents the transmission rate between HP_i to HPi+1, and μ_i represents the transmission rate between HP_i and the absorbing state, death or community phase. Therefore, as mentioned above, this study models patient flow within the healthcare system using C-PHD and PTS. These two distributions are further described below.

2.1. Coxian Phase-Type Distribution:

C-PHD is a special type of PHD. It is defined as an n-state continuous Markov process with a single absorbing state which may be reached from any phase instead of only being reached from state n. Admission into the system may only be from the first state, allowing sequential movement through the states [10]. This study uses C-PHDs to model patient flow, as shown in figure 1. The initial state distribution, p, is defined as [10]:

$$p = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \end{bmatrix} \qquad (1)$$

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

the vector q denotes the absorption probabilities and is defined as:

$$q = [\mu_1 \quad \mu_2 \quad \cdots \quad \mu_{n-1} \quad \mu_n]^T \tag{2}$$

and the transition matrix Q is defined as [10]:

$$Q = \begin{pmatrix} -(\lambda_1+\mu_1) & \lambda_1 & 0 & \cdots & 0 & 0 \\ 0 & -(\lambda_2+\mu_2) & \lambda_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 & 0 \\ 0 & 0 & 0 & -(\lambda_{n-1}+\mu_{n-1}) & \lambda_{n-1} & 0 \\ 0 & 0 & 0 & \cdots & 0 & -\mu_n \end{pmatrix} \tag{3}$$

From these definitions, the log-likelihood function is obtained [10], where N is the total number of patients in the healthcare system and t_i is the LOS of patient i.

$$L = \sum_{i=1}^{N} (log(\boldsymbol{p}\, exp(\boldsymbol{Q}t_i)\boldsymbol{q})) \tag{4}$$

Within our study, the above function is used to create PTS trees.

2.2. Phase-Type Survival Tree:

Survival trees are a regression tool used to perform survival analysis [10]. It is an effective and efficient method of collecting survival data and understanding its connection with covariates, results from treatments and LOS data. A PHD distinctly models each node in a PTS tree. PTS trees have been used to model many applications in medical research, including forecasting bed requirements. In Garg et al. [10] study, PTS trees are implemented to cluster patients' lengths of stay.

PTS trees are created by repetitively partitioning the data into subsections depending on covariates through splitting and selection conditions aiming to maximise within-node similarity or between-node splits [12]. Splitting maximises node similarity based on improving log-likelihood functions [12].

The weighted-Average information criterion (WIC) is a weighted average of Akaike's information criteria (AIC) and the Bayesian information criteria (BIC) with a small sample size correction [8]. As the splitting criteria based on the WIC combines the strengths of both the AIC and the BIC, it works well with small and large sample sizes and also in the case when the sample size is not known [25]. The following formula is used to calculate the WIC [8]:

$$WIC(d) = -2(\,Loglikelihood\,) + d + \left(\frac{d((log\,(N)-1)log\,(N))(N-(d-1))^2 + 2N(N+(d+1)))}{(2N+(log\,(N)(N-(d+1))))(N-(d+1))}\right) \tag{5}$$

Since C-PHD is being used, each node is modelled separately. If a covariate X has k values and the node splits into k partitions, then the WIC for the split can be calculated using equation 5. After splitting the node by the covariate, the WIC gain can be calculated in equation 6, where WIC_0 is the WIC before splitting [8].

$$WIC_{tot}\,(d_{tot}\,) = \sum_{i-1}^{k} \left(WIC_{K_i}(d_{X_i}\right) \tag{6}$$

$$G_X = \left(WIC_0(d_0)\right)\left(WIC_{tot}(d_0)\right) = \left(WIC_0(d_0)\right) - \left(\sum_{i-1}^{k} \left(WIC_{K_i}(d_{X_i})\right)\right. \tag{7}$$

This study uses split and selection criteria to maximise node homogeneity as recommended as the most suitable criterion by [30]. The node that minimises the WIC is selected to recursively divide the node into child nodes by starting at the root node. If a node with a negative gain occurs, then the node is set as a terminal node, and no more splitting occurs. This is the stopping criteria.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

3. Implementation:

The EMphy package is used in which all algorithms and models are implemented in MATLAB using a PHD fitting program [22]. This package, developed by Asmussen et al. [2], uses the expectation minimisation algorithm to calculate the maximum likelihood parameter estimations.

3.1. The dataset and some data analysis:

The results obtained from this study are based on datasets provided by Mater Dei Hospital, Malta and Free Metro, Online. Mater Dei Hospital provided data for patients discharged during 2011 and 2012. The patient data provided by Mater Dei was confidential and did not include any personal information. The covariates present in the data provided by Mater Dei Hospital included gender, age, locality of residence, source admission and discharge location, admissions and discharge wards and admission and discharge dates. Admission type is a crucial distribution of admission data represented in Table 1. We divided admission into three groups and included fields as No. of admissions, total Days spent during LOS and Average days spent during LOS.

Table 1. Admission Types.

Admission Type	Grp No	No of Admissions	Total LOS (Days)	Average LOS (Days)
Elective/Planned procedure	1	43 589	108 714	2.49
Day Case	2	25 748	2 856	0.11
Emergency	3	66 167	389 277	5.88

3.1.1. Admissions data:

Between 2011 and 2012, 66601 and 68903 patients were admitted to Mater Dei Hospital. Table 2 depicts the number of admissions occurring each day of the week for each month throughout both years. From table 2, the maximum number of admissions (2423 patients) occurred on Mondays during January, whilst the least number of admissions (849 patients) occurred on Sundays in August. From Table 2 and Figure 2, it could also be seen that the maximum number of admissions occurred during October when 12208 patients were admitted to the hospital. The minimum number of admissions occurred in December when 10001 patients were admitted to the hospital. From this data, it was observed that January, October and November are the months most patients were admitted to the hospital. Additionally, it may be seen from Figure 3 that the number of admissions is reduced substantially during the weekend. Figure 4 confirms that fewer elective and day cases are admitted during the weekend, mainly Saturday and Sunday, compared to the rest of the week. It may then be seen that the number of admissions on a Monday is much higher than the rest of the week in all three types of admissions. This agrees with previously mentioned studies by Fullerton and Crawford [6] and Green [13]. These authors agree that fewer procedures are booked during weekends to keep bed space for weekend demand.

Table 2. Daily and Monthly Admissions.

	Sun.	Mon.	Tue.	Wed.	Thur.	Fri.	Sat.	Total
Jan.	1135	2423	1897	1837	1630	1650	1250	11822
Feb.	989	1942	1663	2013	1585	1518	1202	10912
Mar.	917	1855	1799	2010	1941	1851	1258	11631
Apr.	999	2179	1634	1783	1580	1555	1305	11035
May	999	2064	1941	1994	1780	1621	1128	11527
Jun.	867	1835	1528	1888	1629	1731	1252	10730
Jul.	1113	2174	1873	1745	1528	1793	1222	11448

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

Aug.	849	2042	1779	2097	1802	1815	1112	11496
Sept.	934	1874	1623	1668	1756	1666	1189	10710
Oct.	973	2402	1947	2026	1683	1783	1394	12208
Nov.	946	1942	1971	2091	1891	1865	1278	11984
Dec.	894	1671	1404	1572	1469	1729	1262	10001
Total	11615	24403	21059	22724	20274	20577	14852	135504

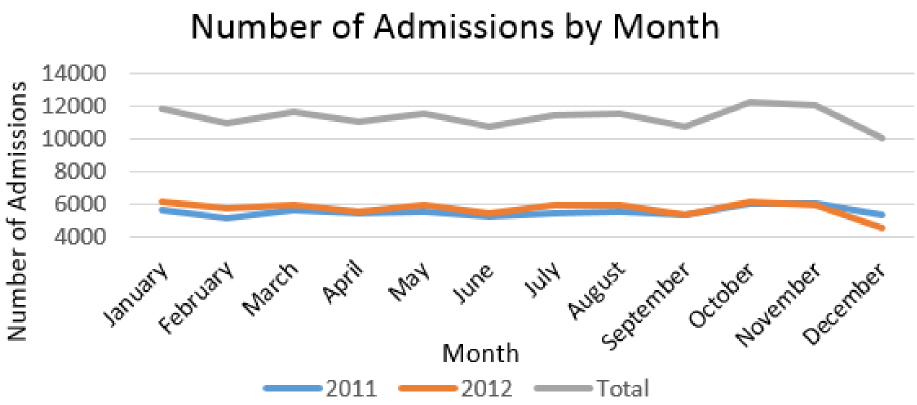


Figure 2: Patient flow in the healthcare system.

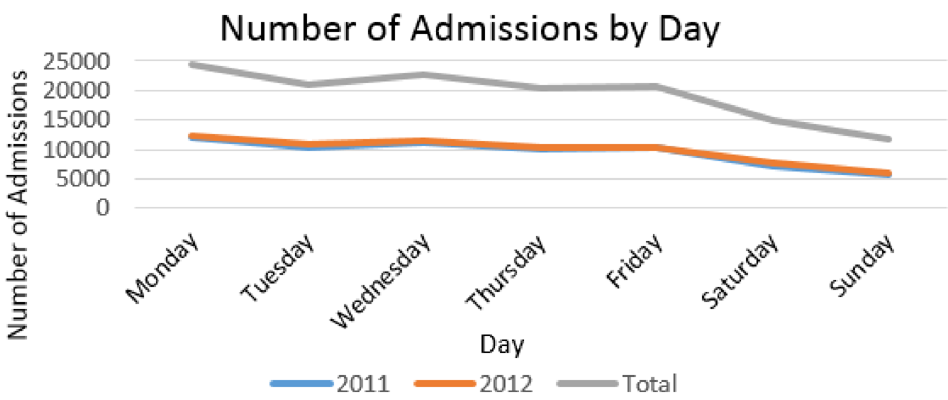


Figure 3: Admissions by Day.

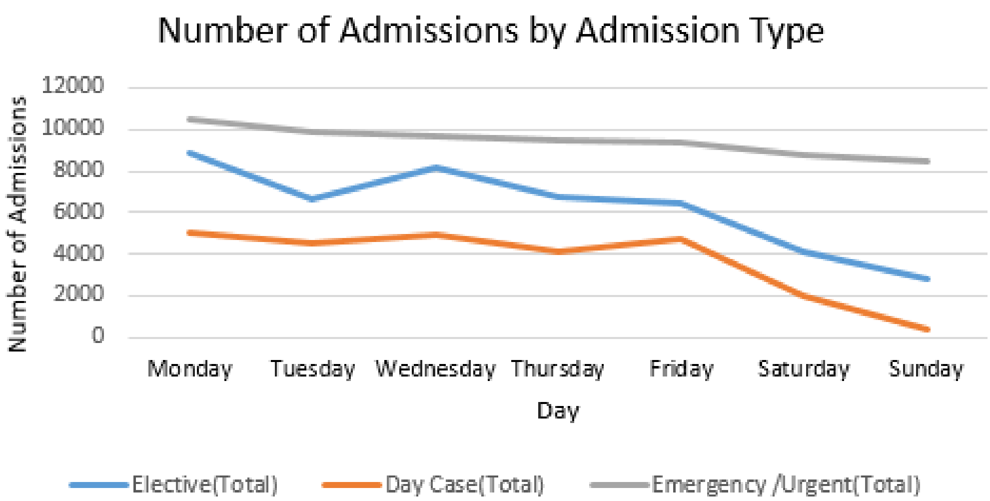


Figure 4: Type of Admission by Day.

 doi:10.20944/preprints202302.0315.v1

3.1.2. Covariants:

The covariates Gender, Age, District and SourceAdm were grouped into three groups, four groups, seven districts and five groups, respectively. The Gender covariate groups are; Male, Female and Unclassified and the Age covariate groups are; Age 0 (New-Born), Ages 1 to 30 (Under30), Ages 31 to 70 (Under70) and Ages 70 to 105 (Over71). Admissions of patients over 70 have an average LOS of approximately 5.91, longer than younger patients (excluding newborns) average LOS 6.8.

Table 3. Admissions by Covariate.

	Group	Group Number	Number of Admissions	Total LOS (Days)	Average LOS (Days)
Gender	**Male (M)**	1	64347	237774	3.7
	Female (F)	2	71154	263066	3.7
	Unclassified (U)	3	3	7	2.33
Age	**New Born (NB)**	1	2001	13602	6.8
	Under 30 (U30)	2	26675	61710	2.31
	Under 70 (U70)	3	70972	213759	3.01
	Over70 (70+)	4	35856	2117733	5.91
District	**South (S)**	1	30141	116659	3.87
	Northern Harbour (NH)	2	43544	163957	3.77
	South Eastern (SE)	3	20140	70867	3.52
	Western (W)	4	20231	68680	3.39
	North (N)	5	18320	71210	3.89
	Gozo & Comino (G&C)	2	2877	8402	2.92
	Unknown (Unkn.)	7	251	1072	4.27
Source Adm	**Private Residence (PR)**	1	131486	467002	3.55
	Elderly Home (EH)	2	2153	17741	8.24
	Other (Oth.)	3	1719	15565	9.05
	Police Custody (PC)	7	121	432	3.57
	Unknown (Unkn.)	8	25	107	4.28

The Locality of Residence covariate groups may be seen in table 3. These groupings were carried out to have better performance when running. Residents of Gozo and Comino had the minimum average LOS of 2.92 days, while the North of Malta had the longest average of 3.89 days. The SourceAdm covariate (the source of admission) groups are; Private Residence Home/ Usual Residence, Home for the Elderly (including St Vincent de Paule Residence and Zammit Clapp Hospital), Other (including Gozo Hospital, Labour Ward, Nursery, Public Hospitals (Government Institutes including Boffa Hospital & Mount Carmel Hospital) and Private and Foreign Hospitals), Police Custody and Unknown. Table 3 gives the number of admissions, total, and average LOS for each covariate group.

3.2. Phase-Type Survival Trees:

The following PTS trees were generated using the WIC-based spitting criteria for the emergency data provided by Mater Dei Hospital. This approach was used to analyse the length of stay and admission patterns.

3.2.1. Length of Stay Analysis:

Table 4. Step 1: Splitting the root node

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

	Group No (LEFT)	Group No (Right)	Phase (x)	Min WIC	Gain in WIC	Mean	Number of Patients
-1	1		5	**361646.800352**		6.883336	66166
(Gender)	Male (1)		4	177934.678409		6.863662	32534
	Female (2)		5	183735.661181		6.902368	33632
	Total			**361670.339590**	**-23.539238**		**66166**
(Age)	New Born(1)		3	10012.778853		8.477089	1723
	Under 30 (2)		3	61903.720090		3.986651	14448
	Under 70 (3)		5	151714.199007		6.254608	28783
	Over 70 (4)		3	131504.220027		9.580005	21212
	Total			**355134.917977**	**6511.882375**		**66166**
(District)	South(1)		5	85076.475744		7.039428	15425
	Northern Harbour (2)		8	117008.277057		6.920293	21655
	North(3)		8	51220.975515		6.632738	9560
	South Eastern (4)		6	47328.364778		7.100195	8673
	Western (5)		6	53183.522445		6.547929	10067
	Gozo & Comino (6)		4	3414.709925		8.647070	561
	Unknown (7)		3	1158.463349		5.520011	225
	Total			**358390.788813**	**3256.011539**		**66166**
(SourceAd)	Home/Private Residence (1)		6	342853.702690		6.877848	**62768**
	Home for the Elderly (2)		6	10848.804271		7.470127	**1925**
	Other (3)		6	7224.355637		6.384784	**1354**
	Police Custody (4)		4	527.989474		5.979381	**97**
	Unknown (5)		2	123.147744		5.863639	**22**
	Total			**361577.999816**	**68.800536**		**66166**

Tables 4-26 represents the steps used to generate the LOS PTS tree shown in Figure 5, representing the WIC-based splitting criteria from the LOS data against the covariates related to the patient's characteristics.

First, we fit the complete data (represented as a root node (1) in Figure 5 and Table 4) to Coxian Phase Type Distribution (C-PTD) and calculate its WIC. Then, for each covariate, we split the LOS data and fit each group individually to C-PTD, total the C-PTD and compare it WIC of the root node (i.e., before the split) to calculate the gain in C-PTD. We select the covariate providing the maximum positive gain in C-PTD to split the data. Table 4 shows that covariate "Age" offers the maximum positive gain in C-PTD. Therefore, we select this split to grow the tree. New nodes are shown in Figure 5 as 2 (newborn), 7 (under 30), 10 (under 70) and 20 (over 70).

Step 2: we split the LOS data for each remaining covariate (Gender, District and SourceAd), fit each group individually to C-PTD and total the C-PTD and compare the WIC of the node before the split to calculate the gain in C-PTD. We select the covariate providing the maximum positive gain in C-PTD to split the data. Here, in Tables 5-8, for nodes 2 (newborn) and 7 (under 30), covariate "Gender", while for nodes 10 (under 70) and 20 (over 70) covariate "District" offer the maximum positive gain in C-PTD. Therefore, we select this split to grow the tree, and new nodes are shown in Figure 5 as 3, 6, 8, 9, 11, 12, 13, 14, 15, 16, 19, 21, 24, 27, 28, 29, 30, and 33.

Table 5. Splitting of node 2 (newborn)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
AGE							
NEWBORN				10012.778853			
(NewBorn, Gender)	New Born(1)	Male (1)	7	5671.189081		8.468910	981

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

		Female (2)	3	4328.550269		8.487877	742
		Total		**9999.739350**	**13.039503**		**1723**
(NewBorn, District)	New Born (1)	South(1)	4	1989.266679		6.852457	366
		Northern Harbour (2)	6	2930.781916		9.024242	495
		North(3)	3	1766.753425		9.600010	290
		South Eastern (4)	6	1379.362716		8.834041	235
		Western (5)	3	1826.139737		8.422087	308
		Gozo & Comino (6)	1	130.293698		6.681803	22
		Unknown (7)	1	36.823822		4.285702	7
		Total		**10059.421993**	**-46.643140**		**1723**
(NewBorn, SourceAd)	New Born (1)	Home/Private Residence (1)	6	5820.815591		5.087955	1262.000000
		Home for the Elderly (2)	0	0.000000		0.000000	0.000000
		Other (3)	4	3476.917454		17.789126	460.000000
		Police Custody (4)					
		Unknown (5)	0	0.000000		0.000000	0.000000
		Total		**9297.733045**	**-**		**1722.000000**

Table 6. Splitting of node 7 (under30)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under 30				**61903.720090**			
(Under30,Gender)	Under 30 (2)	**Male (1)**	**8**	**24762.357659**		**4.157465**	**6014**
		Female (2)	**4**	**34819.058665**		**3.864831**	**8434**
		Total		**59581.416324**	**2322.303766**		**14448**
(Under30,District)	Under 30 (2)	**South(1)**	**4**	**12229.294247**		**3.908124**	**3015**
		Northern Harbour (2)	**7**	**19064.333156**		**3.920145**	**4646**
		North(3)	**8**	**10468.167480**		**4.010334**	**2516**
		South Eastern (4)	**8**	**7760.544477**		**4.123213**	**1818**
		Western (5)	**6**	**9248.253348**		**3.992421**	**2243**
		Gozo & Comino (6)	**5**	**670.160344**		**5.035972**	**139**
		Unknown (7)	**2**	**367.065126**		**5.098594**	**71**
		Total		**59807.818178**	**2095.901912**		**14448**
(Under30 SourceAd)	Under30 (2)	**Home/Private Residence (1)**	**5**	**59322.168631**		**3.993065**	**14280**
		Home for the Elderly (2)	**1**	**17.814737**		**2.249994**	**4**
		Other (3)	**5**	**454.471483**		**3.509091**	**110**
		Police Custody (4)	**2**	**203.869298**		**3.404259**	**47**
		Unknown (5)	**1**	**33.103980**		**3.285708**	**7**
		Total		**60031.428129**	**1872.291961**		**14448**

Table 7. Splitting of node 10 (under70)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under 70				**151714.199007**			
(Under70,Gender)	Under70 (3)	**Male(1)**	**8**	**83826.550005**		**6.427080**	**15908**
		Female(1)	**5**	**66625.781453**		**6.041493**	**12875**
		Total		**150452.331458**	**1261.867549**		**28783**
(Under70, District)	Under70(3)	**South(1)**	**8**	**36179.722530**		**6.491151**	**6839**
		Northern Harbour (2)	**7**	**47896.621672**		**6.245476**	**9231**
		North(3)	**5**	**21792.241004**		**6.115920**	**4227**
		South Eastern (4)	**4**	**19000.962563**		**6.234211**	**3642**
		Western (5)	**5**	**22724.694230**		**5.925784**	**4460**
		Gozo & Comino (6)	**3**	**1694.239739**		**8.551612**	**281**
		Unknown (7)	**3**	**541.203201**		**5.747590**	**103**
		Total		**149829.684939**	**1884.514068**		**28783**

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

(Under70, SourceAd)	Under70 (3)	**Home/Private Residence (1)**	**5**	**147334.046566**		**6.187096**	**28057**
		Home for the Elderly (2)	**4**	**1106.978811**		**12.406056**	**165**
		Other (3)	**3**	**2941.858154**		**8.160019**	**500**
		Police Custody (4)	**2**	**233.070968**		**4.448993**	**49**
		Unknown (5)	**1**	**74.800853**		**7.499985**	**12**
		Total		**151690.755352**	**23.443655**		**28783**

Table 8. Splitting of node 20 (over70)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Over 70				**131504.220027**			
(Over70, Gender)	Over 70 (4)	**Male(1)**	**8**	**58227.021014**		**9.111098**	**9631**
		Female(1)	**5**	**72557.524021**		**9.969958**	**11581**
		Total		**130784.545035**			**21212**
(Over70,District)	Over70 (4)	**South(1)**	**4**	**32111.561935**		**9.485891**	**5205**
		Northern Harbour (2)	**6**	**44822.046650**		**9.634491**	**7283**
		North(3)	**5**	**15668.195104**		**9.491888**	**2527**
		South Eastern (4)	**6**	**18437.143066**		**9.868703**	**2978**
		Western (5)	**5**	**18559.234106**		**9.336389**	**3056**
		Gozo & Comino (6)	**1**	**841.396961**		**12.411740**	**119**
		Unknown (7)	**2**	**252.519962**		**6.477275**	**44**
		Total		**130692.097784**			**21212**
Over70, SourceAd)	Over70(4)	**Home/Private Residence (1)**	**5**	**118526.930185**		**9.570515**	**19169**
		Home for the Elderly (2)	**5**	**10955.926971**		**9.904898**	**1756**
		Other (3)	**4**	**1686.065782**		**8.176068**	**284**
		Police Custody (4)	**0**	**0.000000**		**0.000000**	**0**
		Unknown (5)	**1**	**26.631132**		**12.999959**	**3**
		Total		**131195.554070**			**21212**

Step 3: Nodes 3, 6, 8, 9, 11, 12, 13, 14, 15, 16, 19, 21, 24, 27, 28, 29, 30, and 33 are splitted by remaining covariates, and fit each group individually to C-PTD and total the C-PTD and compare it WIC of the root node (i.e., before the split) to calculate the gain in C-PTD. We select the covariate providing the maximum positive gain in C-PTD to split the data. Here, in Tables 5-8 for node 2 (newborn) and 7 (under 30), we can see covariate "Gender" offers the maximum positive gain in C-PTD, while for node 10 (under 70) and 20 (over 70) it is covariate District. Therefore, we select this split to grow the tree and new nodes are shown in Figure 5 as 3, 6, 8, 9, 11, 12, 13, 14, 15, 16, 19, 21, 24, 27, 28, 29, 30, and 33.

Table 9. Splitting of node 3 (newborn, male)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
	(NewBorn, Gender)			9999.739350			
Male				5671.189081			
(Male, District)	Male (1)	South(1)	4	1254.339181		7.906975	215
		Northern Harbour (2)	5	1581.650098		7.764708	272
		North(3)	3	1045.542060		10.64672	167
		South Eastern (4)	4	754.318483		9.776922	130
		Western (5)	4	945.469803		6.289771	176
		Gozo & Comino (6)	1	135.295601		18.235257	17
		Unknown (7)	1	27.446517		7.499974	4
		Total		**5744.061743**	**-72.872662**		**981**
(Male, Source Adm)	Male (1)	Home/Private Residence (1)	8	3245.521267		5.026874	707

		Home for the Elderly (2)	0	0.000000		0	0
		Other (3)	3	2062.865571		17.35037	274
		Police Custody (4)	0	0.000000		0	0
		Unknown (5)	0	0.000000		0	0
		Total		**5308.386838**	**362.802243**		**981**

Table 10. Splitting of node 4 (newborn, female)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
	(NewBorn, Gender)		9999.739350				
Female				**4328.550269**			
(Female, District)	**Female (2)**	**South(1)**	**4**	**855.680118**		**7.993377**	**151**
		Northern Harbour (2)	**3**	**1260.685410**		**7.25561**	**223**
		North(3)	**3**	**784.207481**		**10.731718**	**123**
		South Eastern (4)	**3**	**635.191831**		**8.095251**	**105**
		Western (5)	**3**	**805.786816**		**9.4091**	**132**
		Gozo & Comino (6)	**1**	**35.389634**		**9.599978**	**5**
		Unknown (7)	**1**	**20.039458**		**4.333319**	**3**
		Total		**4396.980748**	**-68.430479**		**742**
(Female, Source Adm)	**Female (2)**	**Home/Private Residence (1)**	**6**	**2597.152945**		**5.165765**	**555**
		Home for the Elderly (2)	**0**	**0.000000**		**0**	**0**
		Other (3)	**3**	**1445.680286**		**18.435491**	**186**
		Police Custody (4)	**0**	**0.000000**		**0**	**0**
		Unknown (5)					**1**
		Total		**4042.833231**	**-**		**742**

Table 11. Splitting of node 8 (under30, male)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
	(Under30,Gender)			59581.416324			
Male				24762.357659			
(Male, District)	Male (1)	South(1)	4	5015.288548		3.938272	1215
		Northern Harbour (2)	7	7842.125327		3.886901	1901
		North(3)	4	4443.013215		4.152089	1052
		South Eastern (4)	4	3191.036908		4.158877	749
		Western (5)	5	4106.294365		3.878392	995
		Gozo & Comino (6)	4	301.828482		5.65574	61
		Unknown (7)	7	219.464227		5.219529	41
		Total		**25119.051072**	**-356.693413**		**6014**
(Male, Source Adm)	Male (1)	Home/Private Residence (1)	5	24609.783767		4.008127	5905
		Home for the Elderly (2)	8	25.784190		2	2
		Other (3)	3	298.838775		3.514286	70
		Police Custody (4)	2	136.570976		3.343766	32
		Unknown (5)	1	23.068196		2.800001	5
		Total		**25094.045904**	**-331.688245**		**6014**

Table 12. Splitting of node 9 (under30, female)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
	(Under30,Gender)		59581.416324				
Female				34819.058665			
(Female, District)	Female (2)	South(1)	4	7249.484970		3.887779	1800
		Northern Harbour (2)	7	11294.974230		3.94317	2745
		North(3)	8	6076.287810		3.90847	1464

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

		South Eastern (4)	4	4624.380902		4.098221	1069
		Western (5)	5	5172.844942		4.083332	1248
		Gozo & Comino (6)	4	391.544707		5.01282	78
		Unknown (7)	2	157.062802		4.933335	30
		Total		**34966.580363**	**-147.521698**		**8434**
(Female, Source Adm)	Female (2)	Home/Private Residence (1)	7	34765.233298		3.982446	8375
		Home for the Elderly (2)	8	24.488864		2.5	2
		Other (3)	2	174.300341		3.500003	40
		Police Custody (4)	1	70.391080		3.53332	15
		Unknown (5)	8	29.186046		4.500001	2
		Total		**35063.599629**	**-244.540964**		**8434**

Table 13. Splitting of node 11 (under70, South)

	Group No(LEFT)	**Group No (Right)**	**Phase(x)**	**Min WIC**	**Gain in WIC**	**Mean LoS**	**Number of Patients**
Under70, South				36179.722530			
(South,Gender)	South(1)	Male(1)	7	21259.453641		6.658919	3958
		Female (2)	4	15123.963246		6.260690	2881
		Total		36383.416887			6839
(South, SourceAd)	South(1)	Home/Private Residence (1)	7	35068.570609		6.426725	6653
		Home for the Elderly (2)	2	436.714463		11.140626	64
		Other (3)	3	511.342182		8.730343	89
		Police Custody (4)	2	146.623489		4.225823	31
		Unknown (5)	8	28.374166		7.499998	2
		Total		36191.624909			6839

Table 14. Splitting of node 12 (under70, Northern Harbour)

	Group No(LEFT)	**Group No (Right)**	**Phase(x)**	**Min WIC**	**Gain in WIC**	**Mean LoS**	**Number of Patients**
Under70, Northern Harbor				47896.621672			
(Northern Harbour, Gender)	Northern Harbour (2)	Male(1)	7	25791.494476		6.431719	4899
		Female(2)	4	22470.801040		6.034865	4332
		Total		48262.295516			9231
(Northern Harbour, Source Ad)	Northern Harbout	Home/Private Residence (1)	7	46877.911687		6.191394	9065
		Home for the Elderly (2)	3	248.362703		13.861127	36
		Other (3)	3	737.934459		7.959033	122
		Police Custody (4)	3	29.896774		8.400001	3
		Unknown (5)	1	34.054318		8.399973	5
		Total		47928.159941			9231

Table 15. Splitting of node 13 (under70, North)

	Group No(LEFT)	**Group No (Right)**	**Phase(x)**	**Min WIC**	**Gain in WIC**	**Mean LoS**	**Number of Patients**
Under70, North				21792.241004			
(North, Gender)	North	Male	5	12264.120596		6.121713	2358
		Female	7	9613.629943		6.108613	1869
		Total		21877.750539			4227

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

(North, Source Ad)	North	Home/Private Residence (1)	7	21353.617068		6.051817	4149
		Home for the Elderly (2)	2	111.206699		22.214268	14
		Other (3)	2	304.696250		7.313725	51
		Police Custody (4)	1	59.829022		4.999993	11
		Unknown (5)	8	23.024782		2.000000	2
		Total		21852.373821			4227

Table 16. Splitting of node 14 (under70, South Eastern)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under 70, South Eastern				19000.962563			
(South Eastern, Gender)	South Eastern	Male	7	10563.552355		6.486868	1980
		Female	8	8504.979825		5.933213	1662
		Total		19068.532180			3642
(South Eastern, Source Ad)	South Eastern	Home/Private Residence (1)	6	18234.008928		6.209596	3502
		Home for the Elderly (2)	1	116.581524		8.722206	18
		Other (3)	4	672.250660		6.570248	121
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	5	2.153548		7.000001	1
		Total		19024.994660			3642

Table 17. Splitting of node 15 (under70, Western)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under70, Western				22724.694230			
(Western, Gender)	Western	Male	5	12873.941204		6.140891	2470
		Female	7	9915.033235		5.658793	1990
		Total		22788.974439			4460
(Western, Source Ad)	Western	Home/Private Residence (1)	7	22142.923818		5.865305	4358
		Home for the Elderly (2)	3	223.497916		11.121216	33
		Other (3)	3	372.982708		7.333353	63
		Police Custody (4)	1	22.902645		4.249986	4
		Unknown (5)	8	32.464970		10.999995	2
		Total		22794.772057			4460

Table 18. Splitting of node 16 (under70, Gozo&Comino)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under70, Gozo&Comino				1694.239739			
(Gozo&Comino, Gender)	G&C	Male	3	1070.155036		8.477530	178
		Female	3	635.879929		8.679620	103
		Total		1706.034965			281
(Gozo&Comino, Source Ad)	G&C	Home/Private Residence (1)	3	1314.692761		7.445427	229
		Home for the Elderly (2)	0	0.000000		0.000000	0

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

		Other (3)	2	376.458138		13.423041	52
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		1691.150899			281

Table 19. Splitting of node 19 (under70, Unknown)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under70, Unknown				541.203201			
(Unknown, Gender)	Unknown	Male	3	364.431958		6.476937	65
		Female	3	187.188527		4.500013	38
		Total		551.620485			103
(Unknown, Source Ad)	Unknown	Home/Private Residence (1)	3	533.427248		5.821799	101
		Home for the Elderly (2)	0	0.000000		0.000000	0
		Other (3)	8	26.046172		2.000000	2
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		559.473420			103

Table 20. Splitting of node 21 (over70, South)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
	Over70,District			130692.097784			
Over70, South				32111.561935			
(South,Gender)	South(1)	Male(1)	7	14714.295158		9.105985	2406
		Female (2)	7	17247.234115		9.423006	2799
		Total		**31961.529273**			**5205**
(South, SourceAd)	South(1)	Home/Private Residence (1)	4	29580.700863		9.305313	4792
		Home for the Elderly (2)	4	2225.745864		9.251395	358
		Other (3)	2	320.023091		6.927273	55
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		**32126.469818**			**5205**

Table 21. Splitting of node 24 (over70, Northern Harbour)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Over70, Northern Harbor				44822.046650			
(Northern Harbour, Gender)	Northern Harbour (2)	Male(1)	7	20773.565966		9.957635	3352
		Female(2)	8	23927.621456		9.284152	3931
		Total		**44701.187422**			**7283**
(Northern Harbour, Source Ad)	Northern Harbout	Home/Private Residence (1)	4	41422.992605		9.604185	6710
		Home for the Elderly (2)	4	3049.111549		9.784550	492
		Other (3)	4	466.389961		7.604933	81
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		**44938.494115**			**7283**

Table 22. Splitting of node 27 (over70, North)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Over70, North				15668.195104			
(North, Gender)	North	Male	7	6901.967381		9.851752	1113
		Female	8	9050.657193		10.528292	1414
		Total		**15952.624574**			**2527**
(North, Source Ad)	North	Home/Private Residence (1)	4	14779.181823		10.256322	2337
		Home for the Elderly (2)	3	1031.121664		10.030494	164
		Other (3)	1	169.959218		9.153838	26
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		**15980.262705**			**2527**

Table 23. Splitting of node 28 (over70, South Eastern)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Under 70, South Eastern				18437.143066			
(South Eastern, Gender)	South Eastern	Male	6	7767.242350		9.843978	1237
		Female	8	10778.677902		9.696152	1741
		Total		**18545.920252**			**2978**
(South Eastern, Source Ad)	South Eastern	Home/Private Residence (1)	6	15927.026988		9.650990	2573
		Home for the Elderly (2)	3	2211.483030		10.540473	346
		Other (3)	2	372.784988		9.578948	57
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	8	34.289246		16.500001	2
		Total		**18545.584252**			**2978**

Table 24. Splitting of node 29 (over70, Western)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Over70, Western				18559.234106			
(Western, Gender)	Western	Male	7	8720.229605		9.524345	1417
		Female	4	10089.835560		9.329470	1639
		Total		**18810.065165**			**3056**
(Western, Source Ad)	Western	Home/Private Residence (1)	6	16036.719389		9.299390	2632
		Home for the Elderly (2)	5	2537.928683		10.045568	395
		Other (3)	1	198.190740		12.035684	28
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)					1
		Total		**18772.838812**			**3056**

Table 25. Splitting of node 30 (over70, Gozo&Comino)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Over70, Gozo&Comino				841.396961			
(Gozo&Comino, Gender)	G&C	Male	2	484.147245		8.088608	79
		Female	3	243.881774		8.025018	40
		Total		**728.029019**			**119**
(Gozo&Comino, Source Ad)	G&C	Home/Private Residence (1)	2	531.656682		9.120484	83
		Home for the Elderly (2)					1
		Other (3)	2	183.888567		5.600017	35

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		**715.545249**			**119**

Table 26. Splitting of node 33 (over70, Unknown)

	Group No(LEFT)	Group No (Right)	Phase(x)	Min WIC	Gain in WIC	Mean LoS	Number of Patients
Over70, Unknown				252.519962			
(Unknown, Gender)	Unknown	Male	3	173.278569		11.222235	27
		Female	1	94.360517		5.470570	17
		Total		**267.639086**			**44**
(Unknown, Source Ad)	Unknown	Home/Private Residence (1)	3	253.940100		9.238111	42
		Home for the Elderly (2)	0	0.000000		0.000000	0
		Other (3)	8	28.818760		4.000000	2
		Police Custody (4)	0	0.000000		0.000000	0
		Unknown (5)	0	0.000000		0.000000	0
		Total		**282.758860**			**44**

Tables 9-26 show that only nodes 3 and 16 provided significant WIC improvement with a split by sourceAd, and nodes 21, 24 and 30 provided significant WIC improvement with a split by gender. All remaining nodes did not provide any significant WIC improvement by any split and therefore considered terminal nodes. In Figure 5, there are 23 terminal nodes representing the data's significant clusters. The survival plots for all the terminal nodes are shown in Figure 6, which outlines the model's goodness of fit. The total gain in WIC obtained is 5782.13, where the WIC of the root node is 355134.92, and the terminal nodes' WIC sum up to 349352.79. It is possible to identify the relationship between the patient's characteristics and their LOS by analysing table 4-26 and Figure 5. From the table, the most significant split is by the covariate age, with a WIC gain of 6511.88. The mean LOS value may significantly differ between the age groups for each split. Figure 5 shows that the most significant split for newborns (node 2) and patients under 30 (node 7) occurred for the gender covariate. In contrast, the most significant split for patients under 70 (node 10) and patients over 71 further occurred for the district covariate. Figure 6 plots the survival function related to Personal Characteristics for each terminal node for the Length of Stay analysis to show the goodness of fit.

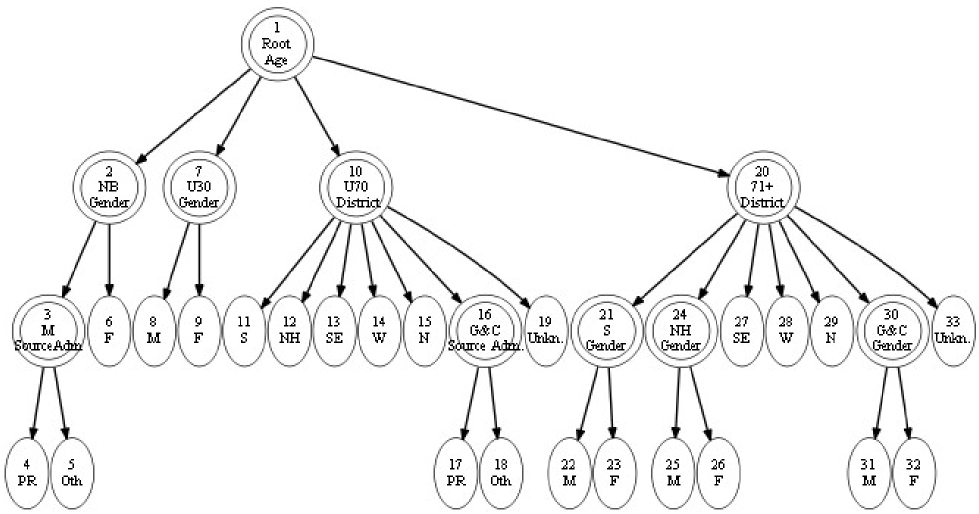
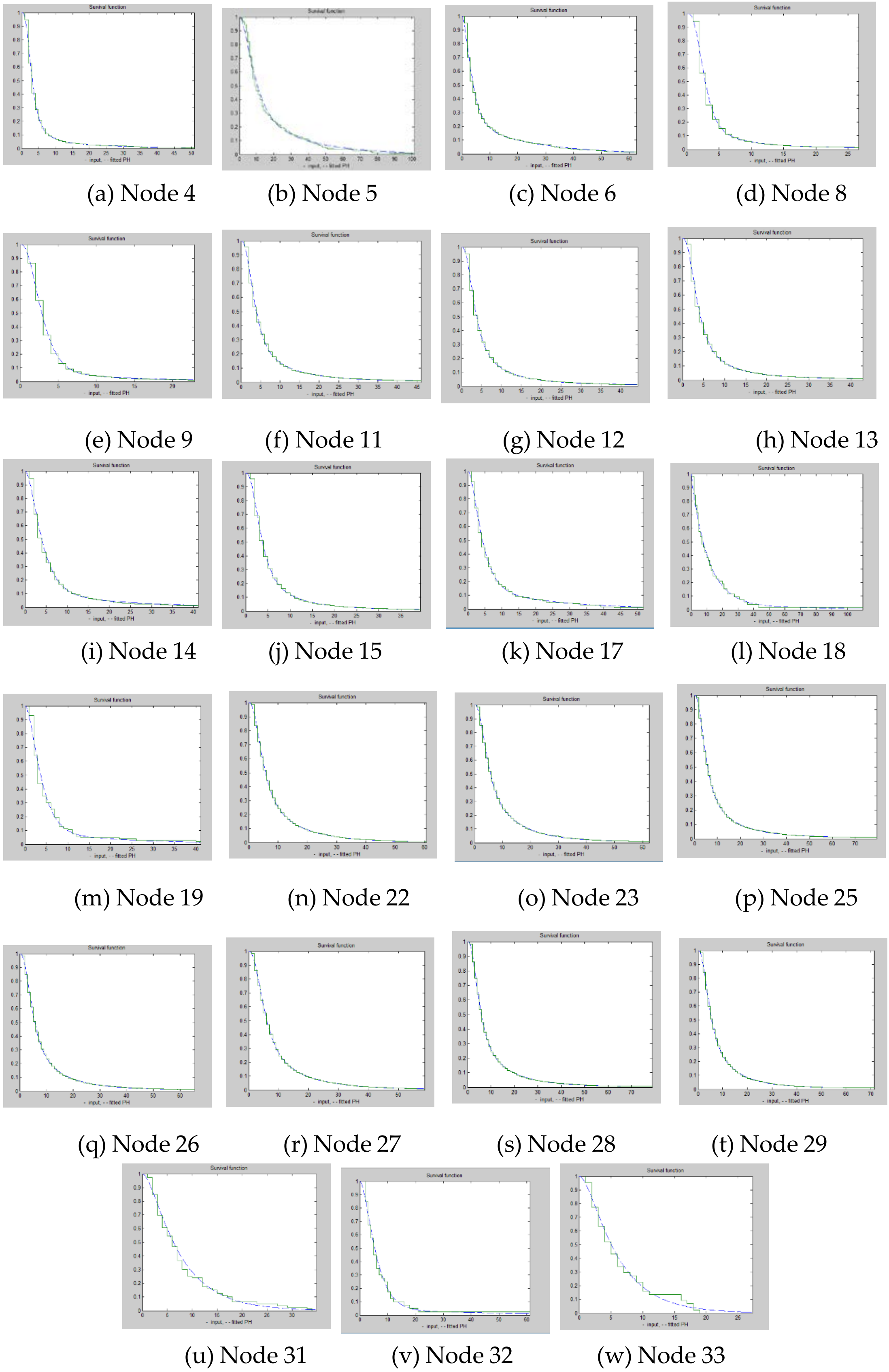


Figure 5. Length of Stay Phase-Type Survival Tree related to personal characteristics.



(a) Node 4 (b) Node 5 (c) Node 6 (d) Node 8

(e) Node 9 (f) Node 11 (g) Node 12 (h) Node 13

(i) Node 14 (j) Node 15 (k) Node 17 (l) Node 18

(m) Node 19 (n) Node 22 (o) Node 23 (p) Node 25

(q) Node 26 (r) Node 27 (s) Node 28 (t) Node 29

(u) Node 31 (v) Node 32 (w) Node 33

Figure 6. Survival Function Plots for Length of Stay analysis related to Personal Characteristics.

3.2.2. Admissions Analysis:

Tables 27-49 represent the steps used to generate the admissions PTS tree shown in Figure 7, representing the WIC-based splitting criteria from the admissions data against the covariates related to the patient's characteristics. Similar to the length of stay analysis above, here also, first, we fit the complete data (represented as a root node (1) in Figure 7 and Table 27) to Coxian Phase Type Distribution (C-PTD) and calculate its WIC. Then, for each covariate, we split the admissions data and fit each group individually to C-PTD, total the C-PTD and compare it WIC of the root node (i.e., before the split) to calculate the gain in C-PTD. We select the covariate providing the maximum positive gain in C-PTD to split the data. Table 27 shows that covariate "Source of admissions (sourceAdm)" offers the maximum positive gain in C-PTD. Therefore, we select this split to grow the tree. New nodes are shown in Figure 7 as 2 (Home/Private Residence), 3 (Home for the elderly), 4 (other), 5 (Police Custody) and 6 (Unknown).

Table 27. Step 1: Splitting the root node

(1, Number Of Admissions)	1	8	7847.1116	186.6491	721	7847.1116	
(Gender, Nr of Adm)	Male(1)	8	6797.0617	88.6602	721	3398.5308	
	Female(2)	8	6960.8298	97.9847	721	3480.4149	
	Total		**13757.8914**			6878.9457	968.1658
(Age, Nr of Adm)	New Born (1)	3	2430.8080	2.9745	667	607.7020	
	Under 30(2)	8	5529.8060	36.6685	721	1382.4515	
	Under 70 (3)	8	7111.5218	97.7795	721	1777.8805	
	Over 71 (4)	8	5922.6184	49.4494	721	1480.6546	
	Total		**20994.7541**			5248.6885	2598.4230
(District, Nr of Adm)	South(1)	8	5775.6090	41.5312	721	825.0870	
	Northern Harbour (2)	8	6256.1519	59.9944	721	893.7360	
	North(3)	8	5316.1594	27.8488	721	759.4513	
	South Eastern (4)	8	5181.7809	25.2441	721	740.2544	
	Western (5)	8	5280.4273	27.7240	721	754.3468	
	Gozo & Comino (6)	3	3044.6887	4.2870	669	434.9555	
	Unknown (7)	6	341.3544	1.5000	158	48.7649	
	Total		**31196.1717**			4456.5960	3390.5156
(SourceAd, Nr of Adm)	Home/Private Residence (1)	8	7818.1469	181.1082	721	1563.6294	
	Home for the Elderly (2)	3	2590.5717	3.1640	677	518.1143	
	Other (3)	4	2210.5691	2.6661	641	442.1138	
	Police Custody (4)	6	145.7583	1.2143	98	29.1517	
	Unknown (5)	3	42.2021	1.1905	21	8.4404	
	Total		**12807.2481**			2561.4496	5285.6619

Table 28. Step 2: Splitting node 2(Home/Private Residence)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
(SourceAd, Nr of Adm)				**12807.248112**		0	2561.449622	
Home/Private Residence (1)				**7818.146859**		721	1563.629372	
(Home, Gender)	**Home**	**Male**	**8**	**3825.276337**	**14.298197**	721	382.5276337	
		Female	**8**	**3840.042543**	**14.511790**	721	384.0042543	
		Total		**7665.318880**			766.531888	797.097484
(Home,Age)	**Home**	**New Born**	**5**	**1515.578455**	**1.945993**	574	75.77892275	

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

		Under30	**8**	**3125.114139**	**8.377254**	721	156.255707	
		Under70	**8**	**3275.132289**	**9.932039**	721	163.7566145	
		Over 70	**8**	**3164.530383**	**8.952843**	721	158.2265192	
		Total		**11080.355266**			554.0177633	1009.611609
(Home, Locality)	**Home**	**South(1)**	**8**	**2623.259152**	**6.278779**	721	74.95026149	
		Northern Harbour (2)	**8**	**2634.257255**	**6.278779**	721	75.264493	
		North(3)	**8**	**2546.221529**	**5.332871**	721	72.74918654	
		South Eastern (4)	**8**	**2517.560067**	**5.040910**	721	71.93028763	
		Western (5)	**8**	**2537.265545**	**5.391123**	721	72.49330129	
		Gozo & Comino (6)	**8**	**420.759504**	**1.256021**	332	12.02170011	
		Unknown (7)	**6**	**236.872569**	**1.345865**	133	6.767787686	
		Total		**13516.195621**			386.1770177	1177.452354

Table 29. Step 2: Splitting node 3(Home for the elderly)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Home for the Elderly (2)				2590.5717		721	518.1143	
(Home for the elderly, Gender)	Home for the elderly	Male	7	680.2011	1.4521	376	68.0201	
		Female	4	1509.5300	1.8920	602	150.9530	
		Total		**2189.7310**			218.9731	299.1412
(Home for the elderly,Age)	Home for the elderly	New Born	0	0.0000	0.0000	0	0.0000	
		Under30	1	11.3273	1.0000	4	0.5664	
		Under70	8	121.5060	1.1103	145	6.0753	
		Over 70	4	2004.0645	2.3493	647	100.2032	
		Total		**2136.8978**			106.8449	411.2695
(Home for the elderly, Locality)	Home for the elderly	South(1)	8	307.0443	1.1804	316	8.7727	
		Northern Harbour (2)	8	400.0539	1.2276	369	11.4301	
		North(3)	8	107.1798	1.0909	154	3.0623	
		South Eastern (4)	8	226.8566	1.1502	273	6.4816	
		Western (5)	8	254.9713	1.1498	327	7.2849	
		Gozo & Comino (6)				1		bad wic
		Unknown (7)	0	0.0000	0.0000	0	0.0000	

Table 30. Step 2: Splitting node 4(Other source of admission)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Other (3)				2210.5691			442.1138	
(Other, Gender)	**Other**	Male	7	989.2221	1.6151	465	98.9222	
		Female	8	653.6929	1.4282	376	65.3693	
		Total		1642.9149			164.2915	277.8223
(Other,Age)	**Other**	New Born	8	457.0267	1.3175	315	22.8513	
		Under30	8	81.0688	1.0792	101	4.0534	
		Under70	8	540.1501	1.3188	367	27.0075	
		Over 70	8	306.4893	1.2727	220	15.3245	
		Total		1384.7350			69.2367	372.8771
(Other, Locality)	**Other**	South(1)	8	163.8176	1.1216	222	4.6805	
		Northern Harbour (2)	8	365.7543	1.2694	271	10.4501	
		North(3)	8	126.2427	1.1154	156	3.6069	
		South Eastern (4)	8	172.8283	1.1315	213	4.9380	
		Western (5)	8	107.5059	1.0933	150	3.0716	

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

		Gozo & Comino (6)	8	90.2080	1.0900	100	2.5774	
		Unknown (7)	1	16.3980	1.1667	6	0.4685	
		Total		1042.7548			29.7930	412.3208

Table 31. Step 2: Splitting node 5(Police Custody)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Police Custody (4)				145.7583		0	29.1517	
(Police Custody, Gender)	**Police Custody**	Male	6	73.9991	1.1148	61	7.3999	
		Female	3	35.2291	1.0455	22	3.5229	
		Total		109.2281			10.9228	18.2289
(Police Custody,Age)	**Police Custody**	New Born				1	bad wic	
		Under30	5	48.9482	1.0476	42	2.4474	
		Under70	6	45.1786	1.0222	45	2.2589	
		Over 70	0	0.0000	0.0000	0	0.0000	
		Total		94.1268				
(Police Custody, Locality)	**Police Custody**	South(1)	5	52.8416	1.0714	42	1.5098	
		Northern Harbour (2)	1	16.3980	1.1667	6	0.4685	
		North(3)	5	45.3066	1.0645	31	1.2945	
		South Eastern (4)	0	0.0000	0.0000	0	0.0000	
		Western (5)	1	11.3273	1.0000	4	0.3236	
		Gozo & Comino (6)	0	0.0000	0.0000	0	0.0000	
		Unknown (7)	6	24.1800	1.0000	2	0.6909	
		Total		150.0535			4.2872	24.8644

Table 32. Step 2: Splitting node 4(Unknown source of admission)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Unknown (5)				42.2021		0	8.4404	
(Unknown, Gender)	**Unknown**	Male	2	33.3447	1.2000	15	3.3345	
		Female	1	12.9675	1.3333	3	1.2968	
		Total		46.3123			4.6312	3.8092
(Unknown,Age)	**Unknown**	New Born	0	0.0000	0.0000	0	0.0000	
		Under30	1	16.4498	1.0000	7	0.8225	
		Under70	1	26.3356	1.0909	11	1.3168	
		Over 70	1	11.2414	1.0000	3	0.5621	
		Total		54.0269			2.7013	5.7391
(Unknown, Locality)	**Unknown**	South(1)	1	11.3273	1.0000	4	0.3236	
		Northern Harbour (2)	1	14.5482	1.0000	6	0.4157	
		North(3)	1	11.2414	1.0000	3	0.3212	
		South Eastern (4)	1	11.3280	1.0000	4	0.3237	
		Western (5)	1	11.3280	1.0000	4	0.3237	
		Gozo & Comino (6)	0	0.0000	0.0000	0	0.0000	
		Unknown (7)				1	bad wic	
		Total		59.7728				

Step 2: we split the admissions data for each remaining covariate (Gender, Age and District), fit each group individually to C-PTD and total the C-PTD and compare the WIC of the node before the split to calculate the gain in C-PTD. We select the covariate providing the maximum positive gain in C-PTD to split the data. Here, in Tables 28-32 for nodes 2 (Home/Private Residence), 4 (Other admission sources) and 5 (Police Custody) covariate

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

"District" and nodes 3 (Home for the Elderly) and 6 (unknown admission source) covariate "Age" offer the maximum positive gain in C-PTD. Therefore, we select this split to grow the tree, and new nodes are shown in Figure 7 as 7, 12, 17, 22, 27, 32, 37, 42, 43, 49, 52, 57, 62, 67, 70, 75, 80, 81, 84, 87, 90, 92, 93, 94, and 95.

Table 33. Step 3: Splitting node 7(South)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
South				2623.2592			74.9503	
(South,Gender)	**South**	Male	8	1728.9181	2.9404	721	24.6988	
		Female	8	1680.8043	2.9875	721	24.0115	
		Total		3409.7224			48.7103	26.2399
(South,Age)	**South**	New Born	8	149.4513	1.1057	227	1.0675	
		Under30	8	1098.8306	1.7511	699	7.8488	
		Under70	8	963.7893	1.9653	721	6.8842	
		Over70	8	1010.9900	1.9194	720	7.2214	
		Total		3223.0612			23.0219	2600.2373

Table 34. Step 3: Splitting node 12(Northern Harbour)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Northern Harbour (2)				2634.2573			75.2645	
(Northern Harbour,Gender)	**Northern Harbour**	Male	8	1711.0654	3.1248	721	24.4438	
		Female	8	1688.6759	3.1526	721	24.1239	
		Total		3399.7413			48.5677	26.6968
(Northern Harbour,Age)	**Northern Harbour**	New Born	8	196.5910	1.1268	276	1.4042	
		Under30	8	1042.4523	1.8872	718	7.4461	
		Under70	8	931.3925	1.9931	721	6.6528	
		Over70	8	952.7085	1.9750	721	6.8051	
		Total		3123.1444			22.3082	52.9563

Table 35. Step 3: Splitting node 17(South Eastern)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
South Eastern				2517.5601			71.9303	
(South Eastern,Gender)	**South Eastern**	Male	8	1764.2662	2.4603	717	25.2038	
		Female	8	1753.4744	2.6184	718	25.0496	
		Total		3517.7405			25.7832	46.1471
(South Eastern,Age)	**South Eastern**	New Born	8	102.7033	1.0878	148	0.7336	
		Under30	8	1020.2853	1.5160	657	7.2878	
		Under70	8	1089.5342	1.8187	717	7.7824	
		Over70	8	1109.7852	1.6997	696	7.9270	
		Total		3322.3080			23.7308	48.1995

Table 36. Step 3: Splitting node 22(Western)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain

Western				2537.2655			72.4933	
(Western,Gender)	**Western**	Male	8	1754.0134	2.7060	721	25.0573	
		Female	8	1756.8674	2.6964	718	25.0981	
		Total		3510.8808			50.1554	22.3379
(Western,Age)	**Western**	New Born	8	92.8663	1.0628	191	0.6633	
		Under30	8	1099.7387	1.6385	686	7.8553	
		Under70	8	1039.6177	1.8889	720	7.4258	
		Over70	8	1116.6005	1.7094	702	7.9757	
		Total		3348.8233			23.9202	48.5731

Table 37. Step 3: Splitting node 27(North)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
North				2546.2215			72.7492	
(North,Gender)	**North**	Male	8	1751.3926	2.6147	719	25.0199	
		Female	8	1718.5607	2.7254	721	24.5509	
		Total		3469.9533			49.5708	23.1784
(North,Age)	**North**	New Born	8	101.3088	1.0798	163	0.7236	
		Under30	8	1091.1134	1.7032	684	7.7937	
		Under70	8	1034.7502	1.8898	717	7.3911	
		Over70	8	1095.0329	1.6798	684	7.8217	
		Total		3322.2052			23.7300	49.0191

Table 38. Step 3: Splitting node 32(Gozo and Comino)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
G&C				420.7595			12.0217	
(G&C,Gender)	**G&C**	Male	8	135.3123	1.0935	214	1.9330	
		Female	8	115.9542	1.0958	167	1.6565	
		Total		251.2665			3.5895	8.4322
(G&C,Age)	**G&C**	New Born	2	20.2517	1.0000	9	0.1447	
		Under30	8	80.2189	1.0714	112	0.5730	
		Under70	8	128.8773	1.1016	187	0.9206	
		Over70	8	50.0143	1.0250	80	0.3572	
		Total		279.3622			1.9954	10.0263

Table 39. Step 3: Splitting node 37(Unknown District)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Unkown				236.8726			6.7678	
(Unkown,Gender)	**Unkown**	Male	6	122.7512	1.8889	90	1.7536	
		Female	6	78.5390	1.1250	64	1.1220	
		Total		201.2902			2.8756	3.8922
(Unkown,Age)	**Unkown**	New Born	1	14.5482	1.0000	6	0.1039	
		Under30	7	41.4024	1.0370	54	0.2957	
		Under70	7	72.0095	1.0789	76	0.5144	
		Over70	4	45.3867	1.0606	33	0.3242	
		Total	.	173.3468			1.2382	5.5296

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

Table 40. Step 3: Splitting node 42(Under30)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Under30				11.3273			0.5664	
(Under30, Gender)	Under30	Male	8	20.2522	1.0000	2	0.5063	
		Female	8	20.2522	1.0000	2	0.5063	
		Total		**40.5044**			1.0126	-0.4462
(Under 30, District)	Under30	South(1)	0	0.0000	0.0000	0	0.0000	
		Northern Harbour (2)	8	20.2522	1.0000	2	0.1447	
		North(3)	0	0.0000	0.0000	0	0.0000	
		South Eastern (4)				1	0.0000	bad wic
		Western (5)				1	0.0000	bad wic
		Gozo & Comino (6)	0	0.0000	0.0000	0	0.0000	
		Unknown (7)	0	0.0000	0.0000	0	0.0000	
		Total		**20.2522**			0.1447	

Table 41. Step 3: Splitting node 43(Under70)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Under70				121.5060			6.0753	
(Under70, Gender)	Under70	Male	7	67.1647	1.0676	74	1.6791	
		Female	8	50.0143	1.0250	80	1.2504	
		Total		**117.1790**			2.9295	3.1458
(Under70, District)	Under70	South(1)	8	45.9057	1.0161	62	0.3279	
		Northern Harbour (2)	5	37.8572	1.0000	34	0.2704	
		North(3)	2	25.3496	1.0000	14	0.1811	
		South Eastern (4)	3	29.0342	1.0000	18	0.2074	
		Western (5)	5	37.2807	1.0000	32	0.2663	
		Gozo & Comino (6)		0.0000	0.0000	0	0.0000	
		Unknown (7)		0.0000	0.0000	0	0.0000	
		Total		**175.4274**			1.2531	4.8222

Table 42. Step 3: Splitting node 49(Over70)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Over70				20.2522			100.2032	
(Over70, Gender)	Over70	Male	8	549.3527	1.3798	337	13.7338	
		Female	5	1384.2249	1.7881	590	34.6056	
		Total		**1933.5776**			48.3394	51.8638
(Over70, District)	Over70	South(1)	8	177.9781	1.1111	279	1.2713	
		Northern Harbour (2)	8	322.7247	1.1880	351	2.3052	
		North(3)	8	76.7523	1.0548	146	0.5482	
		South Eastern (4)	8	193.0263	1.1303	261	1.3788	
		Western (5)	8	198.8374	1.1173	307	1.4203	
		Gozo & Comino (6)				1	0.0000	bad wic
		Unknown (7)	0	0.0000	0.0000	0	0.0000	
		Total		**969.3187**			6.9237	

Table 43. Step 3: Splitting node 52(South)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
South				163.8176			4.6805	
(South,Gender)	South	Male	8	75.5479	1.0513	156	1.0793	
		Female	8	55.6362	1.0366	82	0.7948	
		Total		131.1840			1.8741	2.8064
(South,Age)	South	New Born	7	62.1005	1.0571	70	0.4436	
		Under30	5	37.8572	1.0000	34	0.2704	
		Under70	8	43.3844	1.0116	86	0.3099	
		Over70	8	47.0520	1.0189	53	0.3361	
		Total		190.3941			1.3600	162.4576

Table 44. Step 3: Splitting node 57(Northern Harbour)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
NorthernHarbour				365.7543			10.4501	
(Northern Harbour,Gender)	Northern Harbour	Male	8	147.9584	1.1317	167	2.1137	
		Female	8	108.1670	1.0993	141	1.5452	
		Total		256.1254			3.6589	6.7912
(Northern Harbour,Age)	Northern Harbour	New Born	8	68.8909	1.0508	118	0.4921	
		Under30	3	32.9587	1.0000	32	0.2354	
		Under70	8	69.6084	1.0541	111	0.4972	
		Over70	8	56.1060	1.0390	77	0.4008	
		Total		227.5640			1.6255	8.8247

Table 45. Step 3: Splitting node 62(South Eastern)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
South Eastern				172.8283			4.9380	
(South Eastern,Gender)	South Eastern	Male	8	63.7468	1.0439	114	0.9107	
		Female	8	63.4185	1.0427	117	0.9060	
		Total		127.1653			1.3032	3.6348
(South Eastern,Age)	South Eastern	New Born	6	55.6113	1.0577	52	0.3972	
		Under30	2	26.5643	1.0000	15	0.1897	
		Under70	8	58.3950	1.0360	111	0.4171	
		Over70	7	51.4024	1.0370	54	0.3672	
		Total		191.9731			1.3712	3.5667

Table 46. Step 3: Splitting node 67(Western)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Western				107.5059			3.0716	
(Western,Gender)	Western	Male	8	59.5696	1.0400	100	0.8510	
		Female	7	46.1980	1.0169	59	0.6600	
		Total		105.7676			1.5110	1.5606

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

(Western,Age)	Western	New Born	8	51.2051	1.0294	68	0.3658	
		Under30	1	11.3273	1.0000	4	0.0809	
		Under70	5	48.4395	1.0333	60	0.3460	
		Over70	4	38.6121	1.0370	27	0.2758	
		Total		149.5840			1.0685	2.0031

Table 47. Step 3: Splitting node 70(North)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
North				126.2427			3.6069	
(North,Gender)	North	Male	8	42.6306	1.0108	93	0.6090	
		Female	8	56.1060	1.0390	77	0.8015	
		Total		98.7366			1.4105	2.1964
(North,Age)	North	New Born	8	76.4305	1.0946	74	0.5459	
		Under30	3	29.0342	1.0000	18	0.2074	
		Under70	6	45.8395	1.0204	49	0.3274	
		Over70	4	33.9331	1.0000	25	0.2424	
		Total		185.2373			1.3231	2.2838

Table 48. Step 3: Splitting node 75(Gozo & Comino district)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
G&C				90.2080			2.5774	
(G&C,Gender)	G&C	Male	8	62.1211	1.0556	72	0.8874	
		Female	4	41.3277	1.0313	32	0.5904	
		Total		103.4488			1.4778	1.0995
(G&C,Age)	G&C	New Born	2	21.9630	1.0000	11	0.1569	
		Under30	2	21.9630	1.0000	11	0.1569	
		Under70	7	40.5254	1.0000	52	0.2895	
		Over70	5	38.1635	1.0000	35	0.2726	
		Total		122.6148			0.8758	1.7016

Table 49. Step 3: Splitting node 80(Unknown district)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Unkown				16.3980			0.4685	
(Unkown,Gender)	Unkown	Male	1	13.1124	1.2500	4	0.1873	
		Female	8	20.2522	1.0000	2	0.2893	
		Total		33.3646			0.4766	-0.0081
(Unkown,Age)	Unkown	New Born	0	0.0000	0.0000	0	0.0000	
		Under30	1	11.3273	1.0000	4	0.0809	
		Under70				1	0.0000	bad wic
		Over70	8	20.2522	1.0000	2	0.1447	
		Total	.	31.5795			0.2256	

Table 50. Step 3: Splitting node 81(South district)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
South				52.8416			1.5098	
(South,Gender)	South	Male	5	51.3721	1.0789	38	0.7339	
		Female	1	11.3273	1.0000	4	0.1618	
		Total		62.6994			0.8957	0.6141
(South,Age)	South	New Born	0	0.0000	0.0000	0	0.0000	
		Under30	3	27.7219	1.0000	23	0.1980	
		Under70	4	35.9632	1.0000	10	0.2569	
		Over70	0	0.0000	0.0000	0	0.0000	
		Total		63.6851			0.4549	52.3868

Table 51. Step 3: Splitting node 84(Northern Harbour district)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
NorthernHarbour				16.3980			0.4685	
(Northern Harbour,Gender)	Northern Harbour	Male	1	12.7720	1.0000	5	0.1825	
		Female	8	20.2522	1.0000	2	0.2893	
		Total		33.0242			0.4718	-0.0033
(Northern Harbour,Age)	Northern Harbour	New Born	0	0.0000	0.0000	0	0.0000	
		Under30	1	11.3273	1.0000	4	0.0809	
		Under70	1	11.2414	1.0000	3	0.0803	
		Over70	0	0.0000	0.0000	0	0.0000	
		Total		22.5687			0.1612	0.3073

Table 52. Step 3: Splitting node 87(Western district)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Western				11.3273			0.3236	
(Western,Gender)	Western	Male	1	11.2414	1.0000	3	0.1606	
		Female				1	0.0000	BAD WIC
		Total		11.2414			0.1606	
(Western,Age)	Western	New Born	0	0.0000	0.0000	0	0.0000	
		Under30	0	0.0000	0.0000	0	0.0000	
		Under70	1	11.3273	1.0000	4	0.0809	
		Over70	0	0.0000	0.0000	0	0.0000	
		Total		11.3273			0.0809	0.2427

Table 53. Step 3: Splitting node 90(North district)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
North				45.3066			1.2945	
(North,Gender)	North	Male	3	29.0342	1.0000	18	0.4148	
		Female	2	26.5643	1.0000	15	0.3795	
		Total		55.5985			0.7943	0.5002

(North,Age)	**North**	**New Born**	**0**	**0.0000**	**0.0000**	0	0.0000	
		Under30	**3**	**32.9587**	**1.0000**	23	0.2354	
		Under70	**2**	**21.0108**	**1.0000**	10	0.1501	
		Over70	**0**	**0.0000**	**0.0000**	0	0.0000	
		Total		**53.9695**			0.3855	0.9090

Table 54. Step 3: Splitting node 92(Unknown district)

8	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Unkown				**24.1800**			0.6909	
(Unkown,Gender)	**Unkown**	**Male**				1	0.0000	BAD WIC
		Female				1	0.0000	BAD WIC
		Total		**0.0000**			0.0000	
(Unkown,Age)	**Unkown**	**New Born**				1	0.0000	BAD WIC
		Under30				1	0.0000	BAD WIC
		Under70	**0**	**0.0000**	**0.0000**	0	0.0000	
		Over70	**0**	**0.0000**	**0.0000**	0	0.0000	
		Total	**.**	**0.0000**			0.0000	

Table 55. Step 3: Splitting node 93(Under30)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Under30				16.4498			0.8225	
(Under30, Gender)	Under30	Male	1	12.7720	1.0000	5	0.3193	
		Female	8	20.2522	1.0000	2	0.5063	
		Total		**33.0242**			0.8256	-0.0031
(Under 30, District)	Under30	South(1)	8	20.2522	1.0000	2	0.1447	
		Northern Harbour (2)				1	0.0000	BAD WIC
		North(3)	0	0.0000	0.0000	0	0.0000	
		South Eastern (4)				1	0.0000	BAD WIC
		Western (5)				1	0.0000	BAD WIC
		Gozo & Comino (6)	0	0.0000	0.0000	0	0.0000	
		Unknown (7)				1	0.0000	BAD WIC
		Total		**20.2522**			0.1447	

Table 56. Step 3: Splitting node 94(Under70)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Under70				26.3356			1.3168	
(Under70, Gender)	Under70	Male	2	21.0108	1.0000	10	0.5253	
		Female				1	0.0000	bad wic
		Total		**21.0108**			0.5253	
(Under70, District)	Under70	South(1)	8	20.2522	1.0000	2	0.1447	
		Northern Harbour (2)	1	12.7720	1.0000	5	0.0912	
		North(3)	8	20.2522	1.0000	2	0.1447	
		South Eastern (4)				1	0.0000	BAD WIC
		Western (5)	8	20.2522	1.0000	2	0.1447	
		Gozo & Comino (6)	0	0.0000	0.0000	0	0.0000	
		Unknown (7)	0	0.0000	0.0000	0	0.0000	
		Total		**73.5286**			0.5252	

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

Table 57. Step 3: Splitting node 95(Under70)

	Group Number (Left)	Group Number (Right)	Phase	WIC	Mean	Number of Records	Average WIC	WIC Gain
Over70				11.2414			0.5621	
(Over70, Gender)	Over70	Male	8	20.2522	1.0000	2	0.5063	
		Female	0	0.0000	0.0000	0	0.0000	
		Total		**20.2522**			0.5063	0.0558
(Over70, District)	Over70	South(1)	0	0.0000	0.0000	0	0.0000	
		Northern Harbour (2)	0	0.0000	0.0000	0	0.0000	
		North(3)	0	0.0000	0.0000	0	0.0000	
		South Eastern (4)	8	20.2522	1.0000	2	0.1447	
		Western (5)	0	0.0000	0.0000	0	0.0000	
		Gozo & Comino (6)	0	0.0000	0.0000	0	0.0000	
		Unknown (7)	0	0.0000	0.0000	0	0.0000	
		Total		**20.2522**			0.1447	0.4174

Tables 33-57 show that only nodes 7, 12, 17, 22, 27, 32, 37, 52, 57, 62, 67, 70, 75, 81, 84, 87 and 90 provided significant WIC improvement with a split by Age, and nodes 49, 67 and 35 provided significant WIC improvement with a split by gender and only node 43 provided significant WIC improvement with a split by District. All remaining nodes did not provide any significant WIC improvement by any split and therefore considered terminal nodes. Figure 7 shows a graphical representation of the WIC-based splitting criteria from the admissions data against the covariates, directly affecting patients' characteristics. The survival tree consists of 70 terminal nodes representing the data's significant clusters. Tables 27-57 show the results used to generate the survival tree.

Similarly to the previously generated survival tree, the average WIC is taken for the covariates Age, Gender, District and sources of Admissions. The average WIC is calculated because the root node takes the data for the whole period (721 days), while each covariate takes the whole period per subgroup. For example, considering age in each subgroup (newborn, under 30, under 70 and over 71) calculates the WIC over the same 721 days. Therefore the age would have four times the data of the root node. Therefore, for covariate Age, the average WIC is calculated by dividing the WIC per subgroup by 4. Similarly, the covariates Gender, District and Source Admissions were divided by 2, 7 and 5, respectively. This was repeated as the tree was further split. The total gain in WIC obtained is 2378.89, where the WIC of the root node is 2561.45, and the terminal nodes' WIC sum up to 182.56. It is possible to analyse the relationship between the patient's characteristics and admissions using the results from tables 27-57 and Figure 7. It may be seen that the most significant split occurs for the source of admissions covariate with a WIC gain of 4348.46. The next level shows that the most significant splits occurred for the district covariate for three groups (private residence, other and police custody) and the age covariate for two groups (elderly homes and unknown).

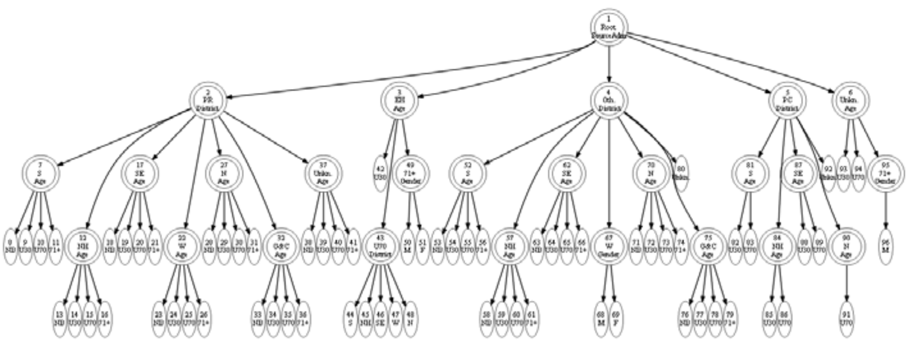


Figure 7. Admission Phase-Type Survival Tree related to personal characteristics.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

4. Result & Evaluation:

A model's Goodness-of-fit (GOF) describes how well-observed data fits into a model. By deriving the GOF, it is possible to evaluate the effect covariates have on the model fit. One of the most popular methods used as a GOF statistic is log-likelihood. Usually, the log-likelihood function is calculated by approximating the chi-square distributions and determining significance levels. The smaller result from the log-likelihood function provides a better-fit model. If the result is 0, then the model is a perfect fit [15]. A model's GOF may be assessed using GOF statistics or GOF indices. However, GOF statistics provide problems due to the small expected probabilities of obtaining accurate p-values. Due to this, most researchers prefer to make use of GOF indices. The two popular GOF indices include AIC and BIC.

Authors Wu and Sepulveda [25] showed that the WIC provides strength and stability over the models tested (including AIC and BIC etc.). The results also showed that for a small sample size, WIC performs as well as AIC. On the other hand, for a large sample size, WIC results are as well as BIC results; however, WIC exceeds the results from other criteria. This highlights the strength of WIC.

Therefore, from the literature reviewed above, it could be concluded that using WIC and log-likelihood to generate the models provides strong and stable results and, thus, models.

4.1. Predictions:

This section tests the accuracy of the predicted mean LOS values for the LOS analysis models generated. Figures 5 and 7 and their respective tables 11 and 12 (In the appendix) display the significant clusters based on patients' LOS and their relationship with temperature and patient characteristics, respectively. A total of 23 clusters are generated for the relationship with patient characteristics. The mean number of admissions for all the data with the same clusters is calculated from the 2013 data. From the respective PTS tree generation tables in Appendix A, the mean LOS of each terminal node corresponding to the group is taken and recorded. The diff between these values gives the Forecasting Error result.

4.1.1. Personal Characteristics Model

Table 58 tests the accuracy between the actual and predicted data for patient characteristics, i.e. using the covariates gender, age, district and source of admissions. The table shows that the highest percentage error of over 50% is the cluster for female patients from Gozo or Comino over the age of 71 (percentage error = 53.5%). This is followed by male patients from Gozo or Comino over the age of 71 who also have quite a high percentage error of 33.36%. In another cluster, patients under 70 from an unspecified locality have a percentage error above 20% (percentage error = 21.56%). It may also be seen that apart from these three groups, all other clusters have a low percentage error of below 16%.

Table 58. Predictions and Accuracy Tests - Length of Stay Phase-Type Survival Tree

Group	No. of Patients	Actual Mean LOS	Predicted Mean LOS	Forecast Error	Squared Error	Absolute Error	Percentage Error (%)
NewBorn, Male,Private Residence	395	5.73	5.03	-0.70	0.49	0.70	12.22
NewBorn, Male,Other	112	18.98	17.35	-1.63	2.66	1.63	8.59
NewBorn, Female	368	7.96	8.49	0.53	0.28	0.53	6.66
Under30,Male	3361	4.46	4.16	-0.30	0.09	0.30	6.73
Under30, Female	4430	4.00	3.86	-0.14	0.02	0.14	3.50
Under70, South	3403	6.35	6.49	0.14	0.02	0.14	2.20
Under 70, Northern Harbour	4830	6.22	6.25	0.03	0.00	0.03	0.48
Under70, South Eastern	2171	5.99	6.20	0.21	0.04	0.21	3.51
Under70, Western	1973	5.90	6.23	0.33	0.11	0.33	5.59
Under70, North	2294	6.38	5.93	-0.45	0.20	0.45	7.05
Under70,Gozo&Comino,	133	8.67	7.45	-1.22	1.49	1.22	14.07

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

Private Residence							
Under70, Gozo&Comino. Other	19	13.37	13.42	0.05	0.00	0.05	0.37
Under70,Unknown	173	4.73	5.75	1.02	1.04	1.02	21.56
Over71,South,Male	11145	9.02	9.11	0.09	0.01	0.09	1.00
Over71,South,Female	15101	11.18	9.42	-1.76	3.10	1.76	15.74
Over71, Northern Harbour,Male	14123	11.43	9.96	-1.47	2.16	1.47	12.86
Over71, Northern Harbour, Female	20974	10.61	9.28	-1.33	1.77	1.33	12.54
Over71, South Eastern	12593	9.80	9.49	-0.31	0.10	0.31	3.16
Over71, Western	14788	10.07	9.87	-0.20	0.04	0.20	1.99
Over71, North	14416	9.50	9.34	-0.16	0.03	0.16	1.68
Over71, Gozo&Comino, Male	352	12.14	8.09	-4.05	16.40	4.05	33.36
Over71, Gozo&Comino, Female	259	17.27	8.03	-9.24	85.38	9.24	53.50
Over71,Unknown	500	5.62	6.48	0.86	0.74	0.86	15.30

4.2. Admissions Analysis

This section tests the accuracy of the predicted mean number of admissions for the admissions analysis models generated. Figures 7 and respective tables 14 (In the appendix) display the significant clusters based on the number of patients admitted and their relationship with temperature and patient characteristics, respectively. Seventy clusters are generated for the relationship with the patient characteristics. All clusters are tested for the admissions analysis against patient characteristics 10 clusters are chosen to be tested for accuracy.

The mean number of admissions is calculated by counting the number of admissions and the number of records with the same clusters as those taken to be tested and dividing the number of admissions by the number of records. From the respective PTS tree generation tables in Appendix A, the respective terminal nodes are found, and the mean number of admissions of the cluster is recorded. The difference between these values gives the Forecasting Error result.

4.2.1. Personal Characteristics Model

Table 59 tests the accuracy between the actual and predicted data for patient characteristics using the covariates gender, age, district and source of admissions. Randomly ten records were selected from the 70 significant clusters, two from each level 2 subgroup in Figure 7. It may be seen (Table 59) that the highest percentage error is for the group of patients under 30 admitted from their private homes and residing in the Northern Harbour area; the percentage error value is 44.74%. The group of patients under 70 admitted from an elderly home and residing in the North had the second highest percentage error of 27.78%. Three groups had a percentage error of 0%, while three other groups had a low percentage error of under 10%. Two randomly selected clusters had no patients admitted for 2013, and thus these groups could not be tested for accuracy.

Table 59. Predictions and Accuracy Tests - Admissions Phase-Type Survival Tree

Group	No. of Records	Actual Mean Adm.	Predicted Mean Adm.	Forecast Error	Squared Error	Absolute Error	Percentage Error (%)
Private Residence, Northern Harbour Under 30	686	3.42	1.89	-1.53	2.3409	1.53	44.74
Private Residence, Gozo& Comino, Over71	34	1	1.03	0.03	0.0009	0.03	3.00
Elderly Home, Under 70, North	13	1	1.00	0.00	0.00	0.00	0.00
Elderly Home, Over 71, Males	269	1.08	1.38	0.30	0.09	0.30	27.78
Other, South, New Borns	43	1.02	1.06	0.04	0.00	0.04	3.92
Other, Western, Females	99	1.04	1.04	0.00	0.00	0.00	0.00
Police Custody, South Eastern Under 30	38	1.11	1.00	-1.27	0.01	0.11	9.91
Police Custody, North, Under 70	1	1	1.00	0.00	0.00	0.00	0.00
Unknown, Under 70	0	-	1.09	-	-	-	-

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

Unknown, Over 71, Male	0	-	1.00	-	-	-	-

More ever, our models predict the mean and actual LOS and the number of admissions while comparing results to those of independent data. The independent data is for patients admitted in 2013 as emergency cases, provided by Mater Dei Hospital. It is important to note that this data for 2013 was not used to create the model specified above.

Table 60. Accuracy tests for all cases.

		MSE	RMSE	MAD	BIAS
LOS	Personal Characteristics	1.15	1.07	0.74	-0.69
Admissions	Personal Characteristics	1.38	1.17	0.96	-0.82

Table 60 calculates the Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD) and the bias for all the models. MSE takes the average squared error values, the difference between the actual and predicted values. The RMSE is the square root of the mean square error, representing the standard deviation of differences between the actual and predicted value. This error test does not show whether there was an increase or decrease. MAD calculates the average absolute value of the forecasted error; it can show which forecasts deviate most. The bias calculated the forecast error average.

The error results for all the tests are close to 0, having an average forecast error of - -0.69 for the personal characteristics model. The average forecast error obtained for the patient characteristics model was -0.82, respectively.

From these results, it could be concluded that the models created can help healthcare professionals to strategically plan future resources on accurate forecasts of demands predicted by patients' characteristics. More accurate results could be obtained by splitting the covariate groups differently or considering factors like the type of emergency diagnosis. Types of cases such as surgical or chest pain may cause a patient to be admitted to the hospital, thus making patients' LOS longer than those with minor injuries such as fractures or sprains. Analysing these factors can provide more accurate results on a patient's LOS and the number of beds and resources available.

5. Conclusion

This study used a C-PHD approach on a 2-year data set (2011/2012) provided by Mater Dei Hospital and Free Metro to generate PTS trees for admissions and LOS on patient characteristics groupings for emergent patients. The PTS trees reveal the factors which significantly affect the admission rate and LOS. The average admission rate and LOS were predicted using the models and compared to the actual average admission rate and LOS for 2013 (an independent data set). The difference between the predicted and actual results was evaluated using accuracy measures. These measurement results showed that the most accurate admission model created was related to patient characteristics, while the LOS models created both showed promising results.

Further improvement to the LOS results obtained in the predictions may be achieved by extending the model to use covariates such as diagnosis, type of admission (emergency/elective), and type of procedure (e.g. BUPA classification of complex major, major+, major, intermediate and minor). Admissions results may be improved by extending the model to use day or month of admissions to accommodate daily and monthly patterns. It is also possible that admission results will be improved by considering seasonal and weekend effects. These recommendations would be carried out by running the EMpht program and reconstructing a tree using the additional covariates. Once a model that provides accurate results is created, healthcare professionals can use the model for more accurate forecasting of demand and forward planning.

Author Contributions: Conceptualisation, L.G., N.A., S.M. and N.C.; methodology, L.G., N.A., R.C. and S.M.; software, L.G., N.A. and S.M.; validation, L.G., N.A., R.C., S.M. and S.B.; formal analysis, L.G. and S.M.; investigation, L.G., N.A., S.M. and S.B.; resources, L.G., S.B. and N.C.; data curation, L.G., N.A., S.B. and N.C.; writing—original draft preparation, L.G., N.A., R.C. and B.P.; writing—review and editing, L.G., N.A., B.P. and S.B.; visualisation, L.G., N.A. and S.M.; supervision, L.G. and S.M.; project administration, L.G., S.B. and N.C.; funding acquisition, L.G., S.B. and N.C. All authors have read and agreed to the published version of the manuscript."

Funding: This research was partially funded by the University of Malta Internal Research Grants Programme's Research Excellence Fund (Grant Reference NICE-Healthcare). Any views or opinions presented herein are those of the authors and do not necessarily represent those of funders, their associates or their sponsors.

Data Availability Statement: The authors will make the data used in this research available on request.

Acknowledgments: We acknowledge the Belfast City Hospital for providing data for this study.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References:

1. M. Telek A. Horvath. Approximating heavy tailed behaviour with phase-type distributions. 2000.
2. S. Asmussen, O. Nerman, and M. Olsson. Fitting phase-type distributions via the em algorithm. Scandinavian J. of Stat., 23(4):419–441, 1996.
3. M. W. Cooke, S. Wilson, J. Halsall, and A. Roalfe. Total time in english accident and emergency departments is related to bed occupancy. Emergency Medicine J., 21(5):575–576, 2004.
4. M. Fackrell. Modelling healthcare systems with phase-type distributions. Health Care Manage. Sci., 12(1):11–26, 2009.
5. M. J. Faddy. On inferring the number of phases in a coxian phase-type distribution. Commun. in Stat. Part C: Stochastic Models, 14(1-2):407–417, 1998.
6. V. L. Fullerton and K. J. Crawford. The winter bed crisis - quantifying seasonal effects on hospital bed usage. QJM: monthly J. of the Assoc. of Physicians, 92(4):199– 206, 1999.
7. M. J. Faddy and S. I. McClean. Analysing data on lengths of stay of hospital patients using phase-type distributions. Appl. Stochastic Models Bus. Ind., 15(4):311– 317, 1999.
8. L. Garg, S. I. McClean, M. Barton, B. J. Meenan, and K. Fullerton. Intelligent patient management and resource planning for complex, heterogeneous, and stochastic healthcare systems. IEEE Trans. Syst. Man Cybern. A., Syst. Humans, 42(6):1332–1345, 2012.
9. F. Gorunescu, S. I. McClean, and P. H. Millard. A queuing model for bed-occupancy management and planning of hospitals. The J. of the Operational Research Soc., 53(1):19–24, 2002.
10. L. Garg, S. McClean, B. Meenan, and P. Millard. A phase type survival tree model for clustering patients' length of stay. In Edmundas K. Zavadskas Leonidas Sakalauskas, Christos Skiadas, editor, Proceedings of the XIII Interna tional Conference on Applied Stochastic Models and Data Analysis (ASMDA 2009), pages 497–502. Vilnius Gediminas Technical University Press, 2009.
11. L. Garg, S. McClean, B. Meenan, and P. Millard. A non-homogeneous discrete time markov model for admission scheduling and resource planning in a cost or capacity constrained healthcare system. Health Care Manag Sci, 13(2):155–169, 2010.
12. L. Garg, S. McClean, B. Meenan, and P. Millard. Phase-type survival trees and mixed distribution survival trees for clustering patients' hospital length of stay. Informatica, 22(1):57–72, 2011.
13. L. V. Green. How many hospital beds? Inquiry, 39(4):400–412, 2002. 14
14. K. Hampel. Modelling phase-type distributions. University of Adelaide, South Australia, 1997.
15. G. D. Hutcheson and N. Sofroniou. The Multivariate Social Scientist. SAGE, 1999.
16. M. A. Johnson. Selecting parameters of phase distributions: combining non-linear programming heuristics and erlang distributions. ORSA J. on Comput., 5(1):69–83, 1993.
17. R. Jones. Myths of ideal hospital size. Medical J. of Australia, 193(5):298–300, 2010.
18. A. D. Keegan. Hospital bed occupancy: more than queuing for a bed. Medical J. of Australia, 193(5):291–293, 2010.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 20 February 2023 doi:10.20944/preprints202302.0315.v1

19. P. J. Kuzdrall, N. K. Kwak, and H. Schmitz. Simulating space requirements and scheduling policies in a hospital surgical suite. Simulation, 36(5):163–171, 1891.
20. S. I. McClean, L. Garg, B. Meenan, and P. H. Millard. Optimal control of patient admissions to satisfy resource restrictions. 21st IEEE Int. Symp. on Comput. Based Medical Syst., pages 512–517, 2008.
21. S. I. McClean and A. H. Marshall. Using coxian phase-type distributions to identify patient characteristics for duration of stay in hospital. Healthcare Manage. Sci., 7(4):285–289, 2004.
22. O. Nerman, S. Asmussen, and M. Olsson. Papers and programs for downloading, empht.
23. M. Olsson. Estimation of phase-type distributions from censored data. Scand. J. of Stat., 23(4):443–460, 1996.
24. D. Worthington. Hospital waiting list management models. The J. of the Operational Research Soc., 42(10):833–843, 1991.
25. T. J. Wu and A. Sepulveda. The weighted average information criterion for order selection in time series and regression models. Stat. and Probability Letters, 39(1):1– 10, 1998.
26. TOMASELLI, G., GARG, L., GUPTA, V., XUEREB, P.A., BUTTIGIEG, S.C. and VASSALLO, P., 2020. Communicating Corporate Social Responsibility in Healthcare Through Digital and Traditional Tools: A Two-Country Analysis. Novel Theories and Applications of Global Information Resource Management. IGI Global, pp. 184-208.
27. GAFA, M., GARG, L., MASALA, G. and MCCLEAN, S.I., 2017. Applications of phase type survival trees in HIV disease progression modelling, 2017 17th International Conference on Computational Science and Its Applications (ICCSA) 2017, IEEE, pp. 1-8.
28. GARG, L., MULVANEY, A., GUPTA, V. and CALLEJA, N., 2015. Real-Time Hospital Bed Occupancy and Requirements Forecasting, 22nd EurOMA International Annual Conference (EurOMA 2015), June 26th- July 1st., At Neuchatel, Switzerland 2015.
29. Garg, L., McClean, S.I., Barton, M., Meenan, B.J., Fullerton, K., Buttigieg, S.C., Micallef, A. (2022). Phase-Type Survival Trees to Model a Delayed Discharge and its Effect in a Stroke Care Unit. Algorithms, 15(11), 414. https://doi.org/10.3390/a15110414
30. Garg, L., McClean, S.I., Barton, M., Meenan, B.J., Fullerton, K., Kontonatsios, G., Trovati, M., Konkontzelos, I., Xu, X., Farid, M., 2021 Evaluating Different Selection Criteria for Phase Type Survival Tree Construction. Big Data Research. 15;25:100250. https://doi.org/10.1016/j.bdr.2021.100250.
31. Robinson, G.H., Davis, L.E. and Leifer, R.P., 1966. Prediction of hospital length of stay. Health services research, 1(3), p.287.
32. Gustafson, D.H., 1968. Length of stay: prediction and explanation. Health Services Research, 3(1), p.12.
33. Abd-Elrazek, M.A., Eltahawi, A.A., Abd Elaziz, M.H. & Abd-Elwhab, M.N. 2021, "Predicting length of stay in hospitals intensive care unit using general admission features", Ain Shams Engineering Journal, vol. 12, no. 4, pp. 3691-3702.
34. Achilonu, O.J., Fabian, J., Bebington, B., Singh, E., Nimako, G., Eijkemans, R.M.J.C. & Musenge, E. 2021, "Use of Machine Learning and Statistical Algorithms to Predict Hospital Length of Stay Following Colorectal Cancer Resection: A South African Pilot Study", Frontiers in Oncology, vol. 11.
35. Alsinglawi, B., Alshari, O., Alorjani, M., Mubin, O., Alnajjar, F., Novoa, M. & Darwish, O. 2022, "An explainable machine learning framework for lung cancer hospital length of stay prediction", Scientific Reports, vol. 12, no. 1.
36. An, J., Jung, M., Ryu, S., Choi, Y. & Kim, J. 2023, "Analysis of length of stay for patients admitted to Korean hospitals based on the Korean National Health Insurance Service Database", Informatics in Medicine Unlocked, vol. 37.
37. Andiani, M.S., Gustina, M., Camilla, D.R., Yulianti, F., Putri, E., Cahyani, S.D. & Rahayu, S. 2022, "Factors Influencing the Patients' Length of Stay in a Tertiary Hospital Emergency Department", HIV Nursing, vol. 22, no. 2, pp. 2179-2185.
38. Aßfalg, V., Hassiotis, S., Radonjic, M., Göcmez, S., Friess, H., Frank, E. & Königstorfer, J. 2022, "Implementation of discharge management in the surgical department of a university hospital: exploratory analysis of costs, length of stay, and patient satisfaction", Bundesgesundheitsblatt - Gesundheitsforschung - Gesundheitsschutz, vol. 65, no. 3, pp. 348-356.
39. Bann, M., Rosenthal, M.A. & Meo, N. 2022, "Optimizing hospital capacity requires a comprehensive approach to length of stay: Opportunities for integration of “medically ready for discharge” designation", Journal of Hospital Medicine, vol. 17, no. 12, pp. 1021-1024.
40. Bastakoti, M., Muhailan, M., Nassar, A., Sallam, T., Desale, S., Fouda, R., Ammar, H. & Cole, C. 2022, "Discrepancy between emergency department admission diagnosis and hospital discharge diagnosis and its impact on length of stay, up-Triage to the intensive care unit, and mortality", Diagnosis, vol. 9, no. 1, pp. 107-114.
41. Bayer-Oglesby, L., Zumbrunn, A. & Bachmann, N. 2022, "Social inequalities, length of hospital stay for chronic conditions and the mediating role of comorbidity and discharge destination: A multilevel analysis of hospital administrative data linked to the population census in Switzerland", PLoS ONE, vol. 17, no. 8 August.
42. Chrusciel, J., Girardon, F., Roquette, L., Laplanche, D., Duclos, A. & Sanchez, S. 2021, "The prediction of hospital length of stay using unstructured data", BMC Medical Informatics and Decision Making, vol. 21, no. 1.
43. Colella, Y., De Lauri, C., Ponsiglione, A.M., Giglio, C., Lombardi, A., Borrelli, A., Amato, F. & Romano, M. 2021, "A comparison of different machine learning algorithms for predicting the length of hospital stay for pediatric patients", ACM International Conference Proceeding Series.
44. Davis, M.P., Van Enkevort, E.A., Elder, A., Young, A., Correa Ordonez, I.D., Wojtowicz, M.J., Ellison, H., Fernandez, C. & Mehta, Z. 2022, "The Influence of Palliative Care in Hospital Length of Stay and the Timing of Consultation", American Journal of Hospice and Palliative Medicine, vol. 39, no. 12, pp. 1403-1409.

45. Del Giorno, R., Quarenghi, M., Stefanelli, K., Rigamonti, A., Stanglini, C., De Vecchi, V. & Gabutti, L. 2021, "Phase angle is associated with length of hospital stay, readmissions, mortality, and falls in patients hospitalized in internal-medicine wards: A retrospective cohort study", Nutrition, vol. 85.
46. Dogu, E., Albayrak, Y.E. & Tuncay, E. 2021, "Length of hospital stay prediction with an integrated approach of statistical-based fuzzy cognitive maps and artificial neural networks", Medical and Biological Engineering and Computing, vol. 59, no. 3, pp. 483-496.
47. Dykes, P.C., Lowenthal, G., Lipsitz, S., Salvucci, S.M., Yoon, C., Bates, D.W. & An, P.G. 2022, "Reducing ICU Utilization, Length of Stay, and Cost by Optimizing the Clinical Use of Continuous Monitoring System Technology in the Hospital", American Journal of Medicine, vol. 135, no. 3, pp. 337-341.e1.
48. Eskandari, M., Alizadeh Bahmani, A.H., Mardani-Fard, H.A., Karimzadeh, I., Omidifar, N. & Peymani, P. 2022, "Evaluation of factors that influenced the length of hospital stay using data mining techniques", BMC Medical Informatics and Decision Making, vol. 22, no. 1.
49. Fang, C., Pan, Y., Zhao, L., Niu, Z., Guo, Q. & Zhao, B. 2022, "A Machine Learning-Based Approach to Predict Prognosis and Length of Hospital Stay in Adults and Children With Traumatic Brain Injury: Retrospective Cohort Study", Journal of Medical Internet Research, vol. 24, no. 12.
50. Fekadu, G., Lamessa, A., Mussa, I., Beyene Bayissa, B. & Dessie, Y. 2022, "Length of stay and its associated factors among adult patients who visit Emergency Department of University Hospital, Eastern Ethiopia", SAGE Open Medicine, vol. 10.
51. Fernandez, G.A. & Vatcheva, K.P. 2022, "A comparison of statistical methods for modeling count data with an application to hospital length of stay", BMC Medical Research Methodology, vol. 22, no. 1.
52. Fiorillo, A., Picone, I., Latessa, I. & Cuocolo, A. 2021, "Modelling the length of hospital stay in medicine and surgical departments", ACM International Conference Proceeding Series.
53. Ghosh, A.K., Unruh, M.A., Ibrahim, S. & Shapiro, M.F. 2022, "Association Between Patient Diversity in Hospitals and Racial/Ethnic Differences in Patient Length of Stay", Journal of General Internal Medicine, vol. 37, no. 4, pp. 723-729.
54. Hajj, A.E., Labban, M., Ploussard, G., Zarka, J., Abou Heidar, N., Mailhac, A. & Tamim, H. 2022, "Patient characteristics predicting prolonged length of hospital stay following robotic-assisted radical prostatectomy", Therapeutic Advances in Urology, vol. 14.
55. Han, T.S., Murray, P., Robin, J., Wilkinson, P., Fluck, D. & Fry, C.H. 2022, "Evaluation of the association of length of stay in hospital and outcomes", International Journal for Quality in Health Care, vol. 34, no. 2.
56. Hughes, A.H., Horrocks, D., Leung, C., Richardson, M.B., Sheehy, A.M. & Locke, C.F.S. 2021, "The increasing impact of length of stay “outliers” on length of stay at an urban academic hospital", BMC Health Services Research, vol. 21, no. 1.
57. Jain, R., Singh, M., Rao, A.R. & Garg, R. 2022, "Machine Learning Models To Predict Length Of Stay In Hospitals", Proceedings - 2022 IEEE 10th International Conference on Healthcare Informatics, ICHI 2022, pp. 545.
58. Keene, S.E. & Cameron-Comasco, L. 2022, "Implementation of a geriatric emergency medicine assessment team decreases hospital length of stay", American Journal of Emergency Medicine, vol. 55, pp. 45-50.
59. Kolcun, J.P.G., Covello, B., Gernsback, J.E., Cajigas, I. & Jagid, J.R. 2022, "Machine learning to predict passenger mortality and hospital length of stay following motor vehicle collision", Neurosurgical Focus, vol. 52, no. 4.
60. Kurihara, M., Kamata, K. & Tokuda, Y. 2022, "Impact of the hospitalist system on inpatient mortality and length of hospital stay in a teaching hospital in Japan: a retrospective observational study", BMJ open, vol. 12, no. 4, pp. e054246.
61. Lauque, D., Khalemsky, A., Boudi, Z., Östlundh, L., Xu, C., Alsabri, M., Onyeji, C., Cellini, J., Intas, G., Soni, K.D., Junhasavasdikul, D., Cabello, J.J.T., Rathlev, N.K., Liu, S.W., Camargo, C.A., Slagman, A., Christ, M., Singer, A.J., Houze-Cerfon, C.-., Aburawi, E.H., Tazarourte, K., Kurland, L., Levy, P.D., Paxton, J.H., Tsilimingras, D., Kumar, V.A., Schwartz, D.G., Lang, E., Bates, D.W., Savioli, G., Grossman, S.A. & Bellou, A. 2023, "Length-of-Stay in the Emergency Department and In-Hospital Mortality: A Systematic Review and Meta-Analysis", Journal of Clinical Medicine, vol. 12, no. 1.
62. Lequertier, V., Wang, T., Fondrevelle, J., Augusto, V. & Duclos, A. 2021, "Hospital Length of Stay Prediction Methods: A Systematic Review", Medical care, vol. 59, no. 10, pp. 929-938.
63. Li, H.-., Chen, C.C.-., Yeh, T.Y.-., Liao, S.-., Hsu, A.-., Wei, Y.-., Shun, S.-., Ku, S.-. & Inouye, S.K. 2022, "Predicting hospital mortality and length of stay: A prospective cohort study comparing the Intensive Care Delirium Screening Checklist versus Confusion Assessment Method for the Intensive Care Unit", Australian Critical Care, .
64. Li, Y., Liu, H., Wang, X. & Tu, W. 2022, "Semi-parametric time-to-event modelling of lengths of hospital stays", Journal of the Royal Statistical Society.Series C: Applied Statistics, vol. 71, no. 5, pp. 1623-1647.
65. Likka, M.H. & Kurihara, Y. 2022, "Analysis of the Effects of Electronic Medical Records and a Payment Scheme on the Length of Hospital Stay", Healthcare Informatics Research, vol. 28, no. 1, pp. 35-45.
66. Liu, Y. & Qin, S. 2022, An Interpretable Machine Learning Approach for Predicting Hospital Length of Stay and Readmission.
67. Mashao, K., Heyns, T. & White, Z. 2021, "Areas of delay related to prolonged length of stay in an emergency department of an academic hospital in South Africa", African Journal of Emergency Medicine, vol. 11, no. 2, pp. 237-241.
68. MEKHALDI, R.N., CAULIER, P., CHAABANE, S., CHRAIBI, A. & PIECHOWIAK, S. 2021, "A comparative study of machine learning models for predicting length of stay in hospitals", Journal of Information Science and Engineering, vol. 37, no. 5, pp. 1025-1038.

69. Negasi, K.B., Tefera Gonete, A., Getachew, M., Assimamaw, N.T. & Terefe, B. 2022, "Length of stay in the emergency department and its associated factors among pediatric patients attending Wolaita Sodo University Teaching and Referral Hospital, Southern, Ethiopia", BMC Emergency Medicine, vol. 22, no. 1.
70. Profeta, M., Cesarelli, G., Giglio, C., Ferrucci, G., Borrelli, A. & Amato, F. 2021, "Influence of demographic and organizational factors on the length of hospital stay in a general medicine department: Factors influencing length of stay in general medicine", ACM International Conference Proceeding Series.
71. Quirós-González, V., Bueno, I., Goñi-Echeverría, C., García-Barrio, N., del Oro, M., Ortega-Torres, C., Martín-Jurado, C., Pavón-Muñoz, A.L., Hernández, M., Ruiz-Burgos, S., Ruiz-Morandy, M., Pedrera, M., Serrano, P. & Bernal, J.L. 2022, "What about the weekend effect? Impact of the day of admission on in-hospital mortality, length of stay and cost of hospitalization", Journal of Healthcare Quality Research, vol. 37, no. 6, pp. 366-373.
72. Rahman, M.M., Kundu, D., Suha, S.A., Siddiqi, U.R. & Dey, S.K. 2022, "Hospital patients' length of stay prediction: A federated learning approach", Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 10, pp. 7874-7884.
73. Renwick, K.A., Sanmartin, C., Dasgupta, K., Berrang-Ford, L. & Ross, N. 2022, "The Influence of Psychosocial Factors on Hospital Length of Stay Among Aging Canadians", Gerontology and Geriatric Medicine, vol. 8.
74. Rothman, R.D., Peter, D.J. & Harte, B.J. 2021, "Improving Healthcare Value: Managing Length of Stay and Improving the Hospital Medicine Value Proposition", Journal of hospital medicine, vol. 16, no. 10, pp. 620-622.
75. Sharma, R., Singh, B.K., Rautaray, S. & Pandey, M. 2022, Length of Stay Prediction of Patients Suffering from Different Kind of Disease to Manage Resource and Manpower of Hospitals.
76. Shevchenko, E.V., Danilov, G.V., Usachev, D.Y., Lukshin, V.A., Kotik, K.V. & Ishankulov, T.A. 2022, "Artificial intelligence guided predicting the length of hospital-stay in a neurosurgical hospital based on the text data of electronic medical records", Zhurnal Voprosy Nejrokhirurgii Imeni N.N.Burdenko, vol. 86, no. 6, pp. 43-51.
77. Shin, J., San Gabriel, M.C.P., Ho-Periola, A., Ramer, S., Kwon, Y. & Bang, H. 2022, "The Impact of Legal Procedures on Hospital Length of Stay: Balancing Legal and Clinical Concerns", Journal of Korean Academy of Psychiatric and Mental Health Nursing, vol. 31, no. 2, pp. 181-191.
78. Sridhar, S., Whitaker, B., Mouat-Hunter, A. & McCrory, B. 2022, "Predicting Length of Stay using machine learning for total joint replacements performed at a rural community hospital", PLoS ONE, vol. 17, no. 11 November.
79. Suha, S.A. & Sanam, T.F. 2022, "A Machine Learning Approach for Predicting Patient's Length of Hospital Stay with Random Forest Regression", 2022 IEEE Region 10 Symposium, TENSYMP 2022.
80. Wang, T., Zhang, H., Duclos, A., Payet, C. & Li, D. 2022, "Prediction of hospital length of stay to achieve flexible healthcare in the field of Internet of Vehicles", Transactions on Emerging Telecommunications Technologies, vol. 33, no. 5.
81. Wondmagegn, B.Y., Xiang, J., Dear, K., Williams, S., Hansen, A., Pisaniello, D., Nitschke, M., Nairn, J., Scalley, B., Xiao, A., Jian, L., Tong, M., Bambrick, H., Karnon, J. & Bi, P. 2021, "Increasing impacts of temperature on hospital admissions, length of stay, and related healthcare costs in the context of climate change in Adelaide, South Australia", Science of the Total Environment, vol. 773.
82. Xu, Z., Zhao, C., Scales, C.D., Henao, R. & Goldstein, B.A. 2022, "Predicting in-hospital length of stay: a two-stage modeling approach to account for highly skewed data", BMC Medical Informatics and Decision Making, vol. 22, no. 1.
83. Yokokawa, D., Shikino, K., Kishi, Y., Ban, T., Miyahara, S., Ohira, Y., Yanagita, Y., Yamauchi, Y., Hayashi, Y., Ishizuka, K., Hirose, Y., Tsukamoto, T., Noda, K., Uehara, T. & Ikusaka, M. 2022, "Does scoring patient complexity using COMPRI predict the length of hospital stay? A multicentre case-control study in Japan", BMJ open, vol. 12, no. 4, pp. e051891.
84. Zheng, J., Tisdale, R.L., Heidenreich, P.A. & Sandhu, A.T. 2022, "Disparities in Hospital Length of Stay Across Race and Ethnicity Among Patients With Heart Failure", Circulation: Heart Failure, vol. 15, no. 11, pp. E009362.
85. Zolbanin, H.M., Davazdahemami, B., Delen, D. & Zadeh, A.H. 2022, "Data analytics for the sustainable use of resources in hospitals: Predicting the length of stay for patients with chronic diseases", Information and Management, vol. 59, no. 5.