Temporal Comorbidity-Adjusted Risk of Emergency Readmission (T-CARER): A Tool for Comorbidity Risk Assessment

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Abstract

Comorbidity in patients, along with attendant operations and complications, is associated with reduced long-term survival probability and an increased need for healthcare facilities. This study proposes a user-friendly toolkit to design an adjusted case-mix model of the risk of comorbidity for use by the public for its incremental development. The proposed model, Temporal Comorbidity-Adjusted Risk of Emergency Readmission (T-CARER), introduces a generic method for generating a pool of features from re-categorised and temporal features to create a customised comorbidity risk index.

Research on emergency admission has shown that demographics, temporal dimensions, length of stay, and time between admissions can noticeably improve statistical measures related to comorbidities. The model proposed in this study, T-CARER, incorporates temporal aspects, medical procedures, demographics, admission details,

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and diagnoses. And, it tries to address four weakness areas in popular comorbidity risk indices: robustness, temporal adjustment, population stratification, and inclusion of major associated factors.

Three approaches to modelling, a logistic regression, a random forest, and a wide and deep neural network, are designed to predict the comorbidity risk index associated with 30- and 365-day emergency readmissions. The models were trained and tested using England's Hospital Episode Statistics inpatient database for two time-frames: 1999–2004 and 2004–2009, and various risk cut-offs. Also, models are compared against implementations of Charlson and Elixhauser's comorbidity indices from multiple aspects. Tests using $k - fold$ cross-validation yielded stable and consistent results, with negative mean-squared error variance of -0.7 to -2.9. In terms of c-statistics, the wide and deep neural network and the random forest models outperformed Charlson's and Elixhauser's comorbidity indices. For the 30- and 365-day emergency readmission models, the c-statistics ranged from 0.772 to 0.804 across the timeframes.

The wide and deep neural network model generated predictions with high precision, and the random forest model performed better than the regression model, in terms of the micro-average of the F1-score. Our best models yielded precision values in the range of 0.582–0.639, and an average F1-score of 0.730–0.790.

The proposed temporal case-mix risk model T-CARER outperforms prevalent models, including Charlson's and Elixhauser's comorbidity indices, with superior precision, F1-score, and c-statistics. The proposed risk index can help monitor the temporal comorbidities of patients and reduce the cost of emergency admissions.
Keywords: Comorbidity Risk Index, Temporal Model, Hospital Episode Statistics, Emergency Admission, Deep Neural Network

1. Introduction

There is increasing evidence that the quantification of high-risk diagnoses, operations and procedures, and monitoring changes over time can significantly improve the quality of readmission models with adequate adjustment.

Many countries are developing strategies to reduce avoidable hospital care [1, 2]. Over the last decade, the National Health Service (NHS) of England has been transformed through efficiency-inducing measures, such as payment reform, and quality improvement measures, such as marginal rate tariffs [3]. Another approach, that has been adopted, is the use of ambulatory care sensitive conditions (ACSC)[1] as a general indicator for the optimality assessment of primary care, community services, and outpatient care [4, 5, 6, 7]. At present, 27 ACSC have been specified in the NHS Outcomes' Framework [8, 9] as markers of improved health outcomes.

Two streams of work have generally been pursued on risk-scoring comorbidities to predict resource utilisation, emergency admission, and mortality. One stream of research in the area examines the odds ratio of major diagnoses groups and is thus highly reliant on statistics concerning the entire given population. These models crudely sum up the derived weights for comorbidities based on the most recent admission data of patients without regard for temporal patterns. A popular example is the Charlson Comorbidity Index (CCI) [10], which relies on 22 comorbidity groups. A recent implementation of the CCI is the NHS England's version of the CCI (NHS-

[1]The ambulatory care sensitive conditions are also known as the primary care sensitive conditions.

CCI) that is continually being updated [11, 12, 13, 14, 15].

The second stream of models uses a diagnosis classification approach based on the similarities, type, likelihood, and duration of care. However, these measures are usually complex and are specialised to particular settings and populations. These models have also used a period of care records in the past, but have ignored temporal patterns.

One prominent method in this vein is the Elixhauser Comorbidity Index (ECI) [16, 17], which relies on 30 comorbidity groups and a one-year lookback period. Unlike the CCI, the ECI uses diagnosis-related groups (DRG) that were first developed by Fetter et al. [18, 19]. The DRG is based on data concerning diagnoses, procedures, age, sex, discharge status, complications, and comorbidities collected by the ICD (International Statistical Classification of Diseases and Related Health Problems). A recent adaptation of the ECI is the Agency for Healthcare Research and Quality (AHRQ) version of ECI, which is actively maintained by the US Public Health Service [17]. In England, the ECI has not been adapted, but the defined diagnoses groups are adopted in variety of researches that use England administrative data [20].

Another well-known method is John Hopkins' [21] adjusted clinical groups (ACGs), which is a commercial tool. The model uses a minimum of six-month and a maximum of one-year prior care records to encapsulate 32 diagnoses groups, known as aggregated diagnosis groups (ADGs), where their aggregations are called expanded diagnosis clusters (EDCs).

An alternative approach to comorbidity scoring is to use a cost function, like the UK's Healthcare Resource Groups (HRG) [22], the US's Centers for Medicare and Medicaid Services Hierarchical Condition Categories (CMS-HCC) [23, 24], or Verisk

Health's diagnostic cost group (DxCG) Medicare models [25]. It has been demonstrated [26, 27] that use of cost functions, like HRG, can improve comorbidity models performance.

In summary, these indices are initially developed to adjust for particular risks, such as the risk of mortality and care utilisation, but are commonly used in a variety of risk adjustment problems in critical care research.

In the machine learning pipeline developed in our previous study [28], the comorbidity index is a significant factor with high potential for further improvement. Moreover, little research has been conducted on temporal comorbidity risk scores [29], and the majority of temporal models [30] in the literature have focused on survival analysis in comorbidity indices. Moreover, the majority of popular comorbidity scores are either based on very old research [31, 32, 33, 34], or their performance indicators have been controversial [35]. For example, Moore et al. [36] compared the CCI across several models and concluded that it has high prediction power, but is highly dependent on the accuracy of records, comorbidity group, population, and healthcare settings. Furthermore, the majority of comorbidity risk models consider only the most recent admission and the first few diagnoses of a given patient to rank his or her risk of comorbidity. However, very sick and comorbid patients usually have multiple medical conditions and operations, or procedures involving complex conditions.

However, comorbidity risk models are constrained by population and sample characteristics, data quality (e.g. missing diagnoses, or delayed death registration), and modelling approach. Therefore, a wide range of literature [37, 33, 38, 39, 40, 41, 42] has focused on modifying and benchmarking comorbidity indices, using different datasets, cohorts, complexity, length of stay, and claims. Also, many attempts have been made to score the surgical outcomes and complications stemming from co-

morbidity [39, 43]. However, they are mainly based on non-administrative clinical variables, or are specialised to specific outcomes and populations.

There are four major areas that comorbidity index models can improve. First, to make the risk score relevant to different environments, an approach is needed to model complex correlations between variables and states. Second, to better distinguish between short- and long-term conditions, temporal dimensions may be included in the form of a *life table* [44] or a polynomial weight function [45]. Third, population stratification is a major factor in the prevalence of medical conditions that must be adjusted. Fourth, major factors correlated to diagnoses must be included directly (observable) or indirectly (latent) to improve the risk estimates, including secondary diagnoses, operations, procedures, and complications [46, 47].

The main outcome of this research is to develop a comorbidity model that can be adjusted by demographics, as well as the temporal patterns of comorbidity and major associated factors. And, the aim is to include only a set of generic features not specific to England's healthcare population and settings.

The second outcome of this research is a generic, open-source, and easy-to-use environment to model the risk of comorbidity. The proposed Temporal Comorbidity-Adjusted Risk of Emergency Readmission (T-CARER) model allows us to address the four above-mentioned issues. The toolkit consists of a user-friendly IPython Notebook that calls procedures in MySQL, Python, and third-party libraries [2]. The T-CARER toolkit and documentations are available online under Apache License (Version 2.0) [48]: https://github.com/mesgarpour/T-CARER.

[2]The main libraries are: Python (3.4), TensorFlow with GPU support (1.0), Cuda (8.0), SciKit-Learn (0.18), Numpy (1.7.1), and SciPy (0.18).

T-CARER was developed using two five-year samples across a 10-year period from England's Hospital Episode Statistics' (HES) inpatient database. In England, administrative data collected by the NHS for secondary care are recorded to the Secondary Uses Service (SUS) database by hospitals. This database contains details of admissions, clinical demographics, and finances for all three sectors: inpatient, outpatient, and accident and emergency (A&E). The NHS also publishes a cleaned, less clinical, and thoroughly validated version of the SUS on a monthly basis, known as the HES database.

Several stages of analyses were carried out to test and benchmark T-CARER. First, two data-frames across a 10-year period were selected. Then, three modelling approaches were developed: a logistic regression, a random forest, and a wide and deep neural network (WDNN). These models were benchmarked against our implementation of the NHS-CCI [49, 11], as well as the reported performance of CCIs and ECIs.

2. Methods

2.1. Data

In this study, a bespoke extract of the HES inpatient data was used that contained records from April 1999 to March 2009. Two samples were randomly selected from this database, including 20% of total unique patients from 1999–2004 and 2004–2009. Each main sample was then divided into two equal halves to be used for training and testing. The specifications of the selected data sets are presented in Table 1.

Each time frame was divided into one year of *trigger-event*, a year of *prediction-period*, and three years of *prior-history*. The population included all living patients older

Table 1
Selected samples from the HES inpatient database.

Samples	Time frame	Population size		Sample size		Selected population		
		Episodes	Patients	Episodes	Patients	Patients	No prior spell	No post spell
Sample-1	1999/04 - 2004/03	18,885,777	7,206,133	6,347,067	1,441,227	1,157,873	492,458	148,950
Sample-2	2004/04 - 2009/03	31,731,488	8,104,748	11,394,152	1,615,347	1,410,923	395,522	110,961

than one year that had been admitted within the *trigger* year. The prediction targets were 30- and 365-day emergency hospital admission to inpatient ward. The statistical analysis of the data sets, including population characteristics, was performed in previous stage of our study [30].

2.2. Features

Following data extraction, several stages of data pre-processing and feature selection were carried out using the framework introduced by Mesgarpour et al. [50]. Before carrying out feature selection, the features were aggregated and split into temporal events, to be captured through time. Definitions of main features are presented in Table 2.

2.2.1. Pre-processing

The pre-processing steps implement data selection, removal of invalid records, and the imputations of observations (Fig. A.1). Feature re-categorisation is also applied in this stage to reduce sparsity and better capture non-linear relationships (Fig. A.2).

In the re-categorisation step, a clinical grouper known as the Clinical Classifications Software (CCS) is used to categorise the diagnoses, to better capture the patterns and cross-correlations of the comorbidities (Table 3). The CCS clusters the the ICD-

Table 2
Definition of the main features considered initially.

Main feature	Definition
gender	Gender of patient (Female, Male, Other)
ethnos	Ethnicity of patient (Bangladeshi, Black African, Black Caribbean, Black Other, Chinese, Indian, Pakistani, White, Other).
imd04rk	The Index of Multiple Deprivation (IMD): overall ranking of income (22.5%), employment (22.5%), health deprivation and disability (13.5%), education & skills (13.5%), barriers to housing & services (9.3%), crime (9.3%), & living environment (9.3%).
ageTrigger	Age of patient at the trigger event. Categorisation bins: {10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90+}.
gapDays (temporal)	Delta-times from discharge to the trigger admission.
epidur (temporal)	Spell durations.
preopdur (temporal)	Pre-operative durations.
posopdur (temporal)	Post-operative durations.
operOPCSL1 (temporal)	The level-1 categories (25 groups) of operating procedure codes (OPCS), the national standard [51] version 4.0 (∼4,000 codes).
diagCCS (temporal)	The level-1 categories (302 groups) of Clinical Classifications Software (CCS) for ICD-10 [17] diagnoses (∼69,800 codes).
admimeth (temporal)	The level-1 categories (3 groups) of admission method (20 codes): {Elective, Emergency, Other}.
mainspef (temporal)	The level-1 categories (33 groups) of the main specialities of the consultants (86 codes), based on the exploratory analysis.

10 (10th revision of the ICD) diagnoses and operations into a number of categories that are clinically meaningful [52, 53].

Furthermore, operations and procedures are categorised (Table 3) using the major categories of the OPCS-4 (OPCS Classification of Interventions and Procedures, Version 4)[3], but alternative coding categorisation may be used, like the ICD-10 Procedure Coding System (PCS). The OPCS-4 is an alphanumeric nomenclature used by the NHS in England. It contains an implicit categorisation for operations based on clinical categories rather than cost or risk.

2.2.2. Life table and aggregation

Administrative healthcare data are severely imbalanced in terms of the amount of longitudinal (panel) data per patient and their distributions over the years. Statistical methods are not equipped to handle these types of imbalances directly. Therefore, the *life table* approach from survival analysis is used to keep track of temporal events

[3]It is based on the earlier Office of Population Censuses and Surveys Classification of Surgical (OPCS) Operations and Procedures.

Table 3
Groups of diagnoses, operations, and consultant specialities that are considered initially.

CCS Diagnoses Conditions:	Other complications of pregnancy	Nervous system
Abdominal pain	Other connective tissue disease	Other abdominal organs
Administrative or social admission	Other female genital disorders	Other bones & joints
Alcohol-related disorders	Other gastrointestinal disorders	Others
Allergic reactions	Other injuries & conditions due to external causes	Respiratory tract
Asthma	Other lower respiratory disease	Skin
Cardiac dysrhythmias	Other nervous system disorders	Soft tissue
Cataract	Other suspected screening (excl. mental & infectious)	Upper digestive tract
Chronic obstructive pulmonary & bronchiectasis	Other skin disorders	Upper female Genital tract
Complication of device; implant or graft	Other upper respiratory disease	Urinary
Congestive heart failure; nonhypertensive	Others	**Speciality of Consultant:**
Coronary atherosclerosis & other heart disease	Phlebitis; thrombophlebitis & thromboembolism	A&E
Deficiency & other anemia	Residual codes; unclassified	Cardiothoracic
Delirium dementia & amnestic & other cognitives	Skin & subcutaneous tissue infections	Ear, nose & throat
Diabetes mellitus without complication	Spondylosis; disc disorders; other back problems	Gastroenterology
Disorders of lipid metabolism	Thyroid disorders	General
Esophageal disorders	Urinary tract infections	General surgery
Essential hypertension	**Operations Categories:**	Geriatric
External cause codes	Arteries & veins	Gynaecology
Fetal distress & abnormal forces of labor	Bones & joints of skull & spine	Haemotology
Fracture of upper limb	Diagnostics & tests	Maternity
Genitourinary symptoms & ill-defined conditions	Female genital tract	Ophthalmology
Normal pregnancy & delivery	Heart	Others
OB-related trauma to perineum & vulva	Lower digestive tract	Paediatrics
Osteoarthritis	Lower female genital tract	Plastic
Other & unspecified benign neoplasm	Male genital organs	Psychiatry
Other aftercare	Mental health	Urology
Other birth complications; mother's puerperium	Miscellaneous operations	

[44]. Based on previous studies and initial statistical analyses, four levels of temporal features were generated: 0–30, 30–90, 90–365, and 365–730 days.

These four levels captured part of the temporal aspect of the comorbidities, in addition to the delta time between admissions (*gapDays*) and features related to the length of stay (*epidur*) including temporal metadata. Furthermore, in the modelling stage of WDNN, we applied several techniques to capture the complex temporal patterns of patients' comorbidities.

The temporal features were summarised at each temporal level based on several aggregation functions, including prevalence, count, and average. This stage increased the number of features by more than 50-fold.

2.2.3. Feature selection

Following feature generation, a feature pool was produced. The feature selection step was then carried out (Fig. A.2). The features were filtered out based on their linear cross-correlation, frequency, and sparsity (percentage of distinctness, and the ratio of the most common value to the second most common).

Following this, the continuous features were transformed using two feature transformation methods: scale to mean, and Yeo-Johnson [54]. Both methods can be used to transform the data to improve normality. Although feature transformations do not guarantee good convergence or stable variance for any dataset, they have been applied to avoid inputting skewed features into models. A disadvantage of transformations is that they make model interpretation more challenging, and can negatively impact the relationship between correlated features in the model. Therefore, the highly correlated features were removed after transformations.

Features in the training set were then sorted using the average importance score produced by the Breiman random forest algorithm [55], using six trials and three decision tree generation settings (Table A.7).

2.3. Modelling approaches

The aim of this study is to model emergency readmissions using a minimal number of generic features that can be used for short- and long-term predictions with high correlation. In this study, the four aforementioned weakness areas of comorbidity risk indices were attempted to be addressed: robustness, temporal adjustment, population stratification, and directly or indirectly including major associated factors. Also, in this research, no condition was imposed on the admission type at the *trigger*

event, and a minimal number of raw features were used. This makes it different from general readmission models, such as the ERMER [28], that use a wide range of raw features and may enforce the emergency admission condition for both *trigger events* and *future events*.

Moreover, as Jeff Hawkins [56] puts it, "finding a good representation of massive amounts of knowledge about the world is hard enough; it is compounded by the need to efficiently extract contextually relevant knowledge depending on the situation."

Therefore, based on our literature review, three different modelling algorithms were considered for training T-CARER on a bespoke high performance workstation[4]: a logistic regression, a random forest, and a WDNN.

2.3.1. Logistic regression

The first algorithm employed was logistic regression with *L1* regularisation (1.0) using the *liblinear* optimisation algorithm [57] with a maximum of 100 iterations and a warm-up period [58].

Logistic regression is a special case of the generalised linear model (GLM) that has a binary dependent variable with a logit link function, and an error term with the standard logistic distribution. The addition of *L1* regularisation allows logistic regression to select a simpler model when a moderate number of features with high sparsity are available.

[4]CPU: Intel i7-7700K 4.2 GHz 64 bit; GPU: NVIDIA Titan X 1.5 GHz, 12 GB RAM; Memory: Samsung SM951 512 GB, PCI-E v3 on Intel Z270 chipset; RAM: $4 * 16$ GB Corsair DDR4 2666 MHz C15 XMP 2.0.

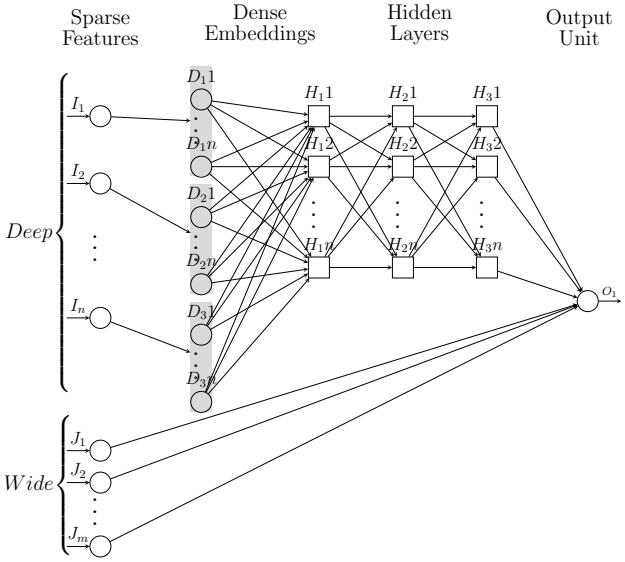

Fig. 1. Abstract graph of the implemented WDNN model.

2.3.2. Random forest

We used the random forest method using the Breiman algorithm [55, 58] with gradient-boosted regression trees and the Gini index criterion on 1,000 trees in the forest. The minimum split size was set to 100 and the minimum leaf size was configured to 50.

The random forest method is an ensemble decision tree introduced by Breiman et al. [55]. It is based on the Classification And Regression Tree (CART) algorithm [59] and the bagging ensemble method [60]. To reduce the correlation between classifiers, the Breiman algorithm implements a technique to decorrelate the base learning trees using random feature selection. However, the Breiman random forest is sensitive to highly correlated features and the scale or categories of features [61, 62].

2.3.3. Deep neural network

We implemented a deep neural network (DNN) based on the wide and deep neural network (WDNN) algorithm introduced by Cheng et al. [63]. DNNs [64, 65] are a class of artificial neural networks (ANNs) with multiple hidden layers, and allow for modelling of more complex non-linear problems. DNNs behave like ANNs but with a better ability to form complex non-linear models with a more effective representation of features in each layer. The WDNN is a DNN that combines the benefits of memorisation and generalisation. The WDNN consists of two parts: the wide model and the deep model.

The WDNN embodies two successful models, logistic regression and the deep multi-layer perceptron (MLP), to leverage the strengths of each. For administrative hospital data, logistic regression can be considered to model the linear relationship, while the MLP models the nonlinear portion. It has been shown in the literature [66] that this structure allows to effectively include prior information and easily learn the effects of individual risk factors.

The wide part of the model consists of a wide linear model for highly sparse features (random features that are rarely active), and is good at memorising specific cases. The wide part may also include groups of crossed features. Inside a group of crossed features, each level of a feature occurs in combination with each level of other features. The GLM (Eq. 1) and the cross-product transformation (Eq. 2) for the wide part are defined as follows:

$$y = w^T x + b \tag{1}$$

$$\phi_k(x) = \prod_{i=1}^{d} x_i^{c_{ki}} \quad c_{ki} \in \{0, 1\} \tag{2}$$

where y is the prediction, x is a vector of features of d features, w represents the model parameters, and b is bias. $\phi_k(x)$ is the k-th transformation for features vector x.

On the contrary, the deep part of the model consists of hidden layers of a feed-forward neural network with an embedding layer and several hidden layers for any other variable [67]. The deep part can be particularly useful for the generalisation of cross-correlations. Each hidden layer performs the following operation (Eq. 3):

$$a^{(l+1)} = f(W^{(l)}a^{(l)} + b^{(l)}) \tag{3}$$

where $W^{(l)}$, $a^{(l)}$, and $b^{(l)}$ represent the weights, actuations, and the bias for layer l, respectively. Finally, the WDNN for the logistic regression problem (Y) can be formulated as follows (Eq. 4):

$$p(Y = 1|x) = \sigma(w_{wide}^T[x, \phi(x)] + w_{deep}^T a^{(l_f)} + b) \tag{4}$$

where $\sigma(.)$ is the sigmoid function of the wide and deep features with actuations and transformations, plus bias. $\phi(x)$ represents the cross-product transformations of x feature, with $w_.$ weights. In our study, the WDNN model applied the Adadelta optimiser [68] for the gradients of the deep part and the rectified linear unit (ReLU) activation function to each layer of the ANN [69]. The ReLU was used in this study because of its effective approximation technique for the classification problem. The ReLU is defined in Eq. 5, where $f(x)$ is the rectifier for input signal x:

$$f(x) = max(0, x) \tag{5}$$

Our first objective in network tuning was to minimise the loss function in learning iterations, avoid weight decay, and ensure convergence. The second objective was to maximise the numbers of layers and neurons under limited computational resources to increase stability.

The developed WDNN was tuned after several stages of ad-hoc cross-validation to reach an optimised setting for the hyperparameters. Moreover, different regularisation parameters (i.e. neuron drop-out rates for randomly removing elements) were tested, where this value was ultimately set to zero. Finally, an implicit optimisation was set to be carried out in the background, using the Adadelta optimiser, to configure the *learning rate* dynamically.

Table 4
The outline of constructed nodes in the WDNN model.

Sub-model	Feature type	Features
Wide	Categorical	*ageTrigger* (17 states), *epidur* (6 states), *ethnos* (11 states), *gapDays* (6 states), *gender* (2 states), & *imd04rk* (11 states)
	Crossed (memorised)	*gender* $\approx$ *ethnos* (80 cross states), *imd04rk* $\approx$ *gender* (200 cross states), *imd04rk* $\approx$ *ethnos* (400 cross states), & *imd04rk* $\approx$ *ageTrigger* (400 cross states).
Deep	Embedded	*ageTrigger* (5 states), *ethnos* (3 states), *gender* (2 states), *imd04rk* (5 states), *epidur* (3 states), & *gapDays*. (3 states)
	Continuous	All the selected categories of *admimeth*, *diagCCS*, *gapDays*, *mainspef*, *operOPCSL1*, *posopdur*, & *preopdur*.

Furthermore, because of the large size of the WDNN, the designed *tensors* [70] were trained in batches of 2,000 observations per step for 40,000 iterations in total. The training of each model using our hardware and software setups took approximately 12 hours (with regular snapshots of training).

The outline of the nodes are presented in Table 4, the abstract representation of the designed model in TensorFlow is presented in Fig. 1, and the selected features are defined in Table A.7. Also, Fig. A.3, Fig. A.4, and Fig. A.5 visualise the

constructed network structure in TensorBoard Graph Visualisation, and display how nodes, edges, and operators are assembled together [70]. The wide part of the model consists of 22 categorical features (1–17 states), and four memorised crossed features (80–400 states). The deep part of the model contains 14 embedding features (3–5 states), 286 continuous features (1 state), and three hidden layers of neurons. The defined hidden layers, layers one to three, are fully interconnected, and were configured as having 24,000, 12,000, and 6,000 nodes, respectively.

Table 5
The performance statistics of T-CARER for all models across two samples.

Time horizon	**30-day**						**365-day**					
Method	**RFC**[a]		**LR**[b]		**WDNN**[c]		**RFC**		**LR**		**WDNN**	
Sample	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
Sample: Sample-1 (1999–2004)												
C-statistics	0.827	0.804	0.778	0.772	0.817	0.796	0.789	0.780	0.760	0.759	0.795	0.787
Precision	0.180	0.180	0.530	0.520	0.641	0.617	0.430	0.430	0.690	0.690	0.644	0.631
Sensitivity [d]	0.760	0.730	0.070	0.070	0.104	0.098	0.710	0.700	0.260	0.270	0.382	0.374
F1 [e]	0.300	0.280	0.130	0.130	0.178	0.170	0.540	0.530	0.380	0.380	0.480	0.470
Micro F1	0.790	0.790	0.900	0.900	0.900	0.900	0.740	0.730	0.770	0.770	0.790	0.790
Accuracy	0.728	0.724	0.926	0.925	0.928	0.928	0.718	0.713	0.802	0.802	0.808	0.805
Log-loss	9.392	9.538	2.571	2.576	2.476	2.496	9.746	9.914	6.840	6.835	6.636	6.748
Brier-score	0.168	0.171	0.061	0.061	0.059	0.060	0.186	0.188	0.144	0.144	0.137	0.139
TP & FP [f]	43,494	43,466	43,494	43,466	43,494	43,466	134,101	133,901	134,101	133,901	134,101	133,901
Total	578,936	578,937	578,936	578,937	578,936	578,937	578,936	578,937	578,936	578,937	578,936	578,937
Sample: Sample-2 (2004–2009)												
C-statistics	0.766	0.743	0.718	0.715	0.759	0.735	0.791	0.785	0.765	0.766	0.793	0.772
Precision	0.340	0.320	0.580	0.570	0.600	0.582	0.610	0.610	0.690	0.690	0.651	0.639
Sensitivity	0.590	0.550	0.110	0.120	0.207	0.198	0.690	0.690	0.460	0.460	0.585	0.573
F1	0.430	0.400	0.190	0.190	0.308	0.295	0.650	0.650	0.550	0.550	0.616	0.604
Micro F1	0.790	0.780	0.810	0.810	0.830	0.830	0.720	0.720	0.700	0.700	0.720	0.720
Accuracy	0.770	0.756	0.857	0.855	0.862	0.859	0.722	0.717	0.720	0.720	0.728	0.719
Log-loss	7.955	8.416	4.931	5.011	4.738	4.878	9.616	9.775	9.672	9.668	9.397	9.719
Brier-score	0.194	0.197	0.112	0.114	0.107	0.110	0.187	0.190	0.185	0.185	0.176	0.184
TP & FP	47,487	48,207	47,487	48,207	47,487	48,207	120,285	120,838	120,285	120,838	120,285	120,838
Total	322,300	322,301	322,300	322,301	322,300	322,301	322,300	322,301	322,300	322,301	322,300	322,301

[a] Random forest classification (RFC). [b] Logistic regression (LR). [c] Wide and deep neural network (WDNN).
[d] Recall or true positive rate. [e] F1-score (F1). [f] True and false positives.

3. Results

The three T-CARER models (the logistic regression, the random forest, and the WDNN) were first benchmarked across the two samples and the two prediction targets: 30- and 365-day emergency readmissions (Table 5). For benchmarking purpose,

several performance metrics were provided. And, the performance metrics used here are based on the compared models (CCIs and ECIs) and the commonly accepted performance measures for classification models.

Overall, the WDNN and the random forest models provided a better fit for 30- and 365-day emergency readmission problems. For the 365-day readmission, the WDNN produced a marginally better c-statistics (area under the curve) compared with the random forest, and a significantly better c-statistics than the logistic regression (Fig. 2). Moreover, the WDNN models had high precision (positive predictive value), accuracy, and micro-average F1-score (i.e. the weighted average of the precision and sensitivity). On the contrary, the random forest models had high sensitivity (true positive rate) and F1-score.

Because the classes were highly imbalanced, the precision–recall curve (Fig. 3) was used to compare the area under the curve, average precision, and average recall. The plot shows that the areas under the curves were significantly smaller for 30-day models compared with 365-day models. Further, *sample-2* (2004–2009) models had a larger area under the curve across the models.

Moreover, based on the CCIs and ECIs benchmarks in the literature, T-CARER performed considerably better for 30-day emergency admissions. However, there are no previous benchmarking study on the CCIs and ECIs for one-year emergency admissions target, due to constraints on data collection, poor predictability power, or different research priorities.

The four selected studies (Table 6) included benchmarks for various versions of CCIs and ECIs for emergency admission problems. Moore et al. [36] benchmarked the AHRQ-CCI using the AHRQ State Inpatient Databases from 18 states (2011–2012),

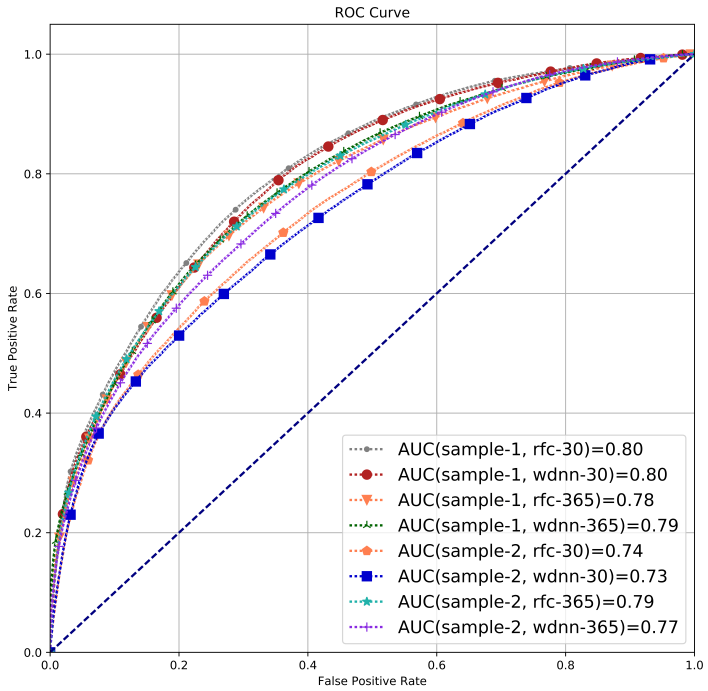

Fig. 2. Area under the curve (AUC) comparison of random forest (RFC) and WDNN models for 30- and 365-day targets, using the receiver operating characteristic (ROC) curve.

and reported c-statistics of 0.63. Moreover, Mehta et al. [39] reported c-statistics of 0.70–0.76 for CCIs and ECIs using the Texas Medicare data (2006–2011). Furthermore, Bottle et al. [71, 41] benchmarked CCIs using England's HES data (2007–2009) and reported c-statistics of 0.57–0.79. Finally, Holman et al. [33] reported c-statistics of 0.61–0.77 for CCIs, ECIs, and the Multipurpose Australian Comorbidity Scoring System (MACSS) models based on data from hospitals in Western Australia (1989–1996). Unfortunately, precision and recall were not reported in these studies, and it is thus not possible to compare them in a more granular way.

Furthermore, the models of T-CARER were compared against our implementation of the NHS-CCI across all categories of CCI and the ECI diagnoses (using the 2009–10

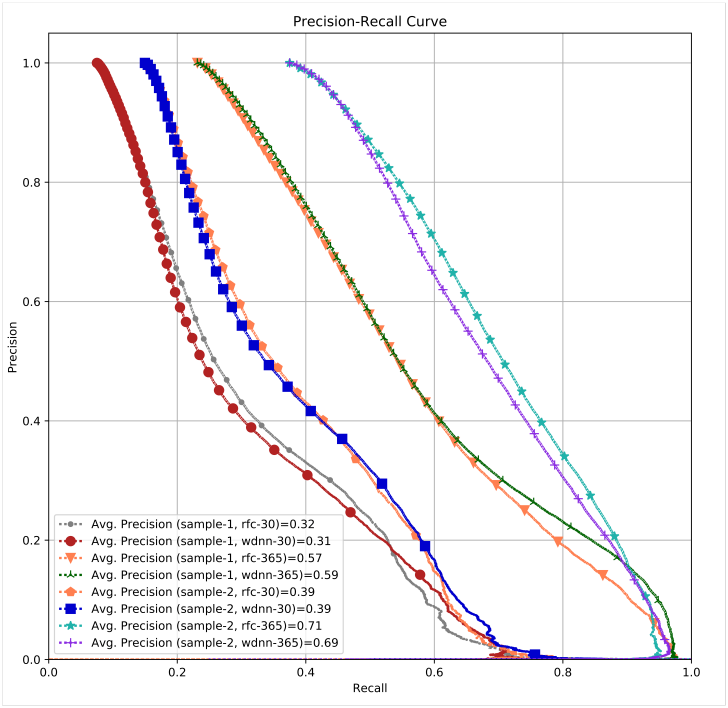

Fig. 3. Precision–recall curve of random forest (RFC) and WDNN models for 30- and 365-day targets.

diagnoses classification). The profiling tables (Table A.3, Table A.4, Table A.5, and Table A.6) indicate that T-CARER performed significantly better than the NHS-CCI for all 46 categories of diagnosis in terms of the true positive rate. WDNN models (365-day readmission) with risk cut-off of 0.70 outperformed the NHS-CCI that had risk index greater than or equal four. Moreover, the random forest model, with risk cut-off of 0.50, recorded a higher accuracy than NHS-CCI, with a score [10][5] of greater than zero for the majority of diagnoses.

[5]The CCI score has three risk groups: mild, with CCI scores of 1–2; moderate, with CCI scores of 3–4; and severe, with CCI scores $\geq$5.

Table 6
The selected CCI and ECI benchmark studies for 30-day emergency admission.

Study	Data source	Time	Records	Models	C-statistics
Moore et al. [36]	AHRQ State Inpatient (18 states)	2011–12	Community inpatients	AHRQ CCI	0.63
Mehta et al. [39]	Texas Medicare data	2006–11	39,616 patients	CCIs & ECIs	0.70–0.76
Bottle et al. [71, 41]	England's HES data	2007–09	Inpatients in England	CCIs	0.57–0.79
Holman et al. [33]	hospitals in Western Australia	1989–96	1,118,989 patients	CCIs & ECIs	0.61–0.77

Moreover, the performance of the emergency admission models using only the NHS-CCI was very poor and thus is not presented here. For instance, the constructed logistic regression and random forest for the 365-day emergency scenario by using only the NHS-CCI had c-statistics values of 0.53–0.58 across the samples.

Moreover, the two top T-CARER models (random forest and WDNN) were compared with the NHS-CCI based on eight main comorbidity groups: hypertension, depression, coronary heart disease, asthma, diabetes, cancer, chronic obstructive pulmonary disease, and congestive heart failure. The profiling of the comorbidity groups (Table A.1 and Table A.2) shows that for all the main comorbidity categories, the T-CARER models outperformed those of the NHS-CCI. This comparisons were based on 0.70 risk cut-off for T-CARER models (365-day readmission) and NHS-CCI score of four or more.

Furthermore, the results of training and tests indicate that logistic regression was more successful in parameter tuning and minimising overfitting, while some minor overfitting was observed for the WDNN and random forest models.

Finally, a *10-fold* cross-validation [72] algorithm was run for the logistic regression and the random forest, using two test sub-samples: *Sample-1* (1999–2004) and *Sample-2* (2004–2009). The cross-validation results were stable and consistent, with a negative mean squared error (MSE) variance of -0.7 to -2.9 [6]. The negative MSE

[6]MSE values close to zero indicate better stability; however, the MSE cannot be compared across

of an estimator $\hat{\tau}$ with respect to an unknown parameter τ is defined as:

$$MSE(x) = -E_{\hat{\tau}}[(\hat{\tau} - \tau)^2] \tag{6}$$

The applied $k-fold$ cross-validation algorithm split each sample into 10 equal-sized random samples. Then, $k-1$ folds were used for training and one fold for validation. Thereafter, the $k-fold$ output was generated after the cross-validation had cycled through all combinations of splits. However, $k-fold$ cross-validation was not carried out for the WDNN, because DNNs are expensive to train, and the stability of the model relies on the amount of data, number of epochs, and learning rate.

4. Discussion

We compared the performance of T-CARER models against commonly used comorbidity index models using different samples and population cohorts across a 10-year period. Overall, our comparisons of T-CARER with the NHS-CCI for different categories of diagnosis show that it delivered the best performance for the majority of comorbidity groups, and generated better results than previous surveys of CCIs and ECIs.

Furthermore, the progression of patients' comorbidities over time and patterns of care utilisation can have a significant impact on the performance of comorbidity models, and it is important that modelling algorithms are equipped to capture temporal changes and interactions among correlated factors. T-CARER's performance, in terms of predicting 30- and 365-day emergency readmissions, indicate that it can

samples.

supersede conventional risk scoring methods, owing to greater flexibility in modelling and customisation. Moreover, boosting algorithms, such as random forest, and deep learning models, such as WDNN, can adequately learn multiple levels of complexities.

In the best-case scenario, a comorbidity score can perform only as well as the included diagnostic categories and their correlated factors [73]. The deployment of a healthcare pre-processing framework [50] helped systematically perform the data pre-processing and feature engineering for comorbidity risk scoring. Furthermore, the CCS allowed to categorise ICD-10 diagnoses into a manageable number of clinically meaningful categories. And, the CCS *clinical grouper* made it simpler to understand patterns of diagnoses and easily add a wider range of comorbidity groups [74, 52, 53].

Benchmarking comorbidity risk scores can be very useful as it offers more insight into the strengths and weaknesses of models. Our benchmarking shows that the random forest modelling method can lead to a low level of positive predictive value but high sensitivity. In contrast, the proposed deep learning model (WDNN) can produce models with high precision, but with weak sensitivity.

Overall, the micro-average of F1-scores for the WDNN model was greater across samples and prediction targets, but came at a high training cost. In contrast, the implemented logistic regression models could train only estimators with weak overall performance and high bias.

However, logistic regression allows for the best interpretation of the resulting model. Although the *global* interpretability of random forest and WDNN is difficult, it is possible to understand the *local* level and manually validate local predictions (i.e.

local interpretability) [75].

In summary, the proposed temporal case-mix risk models outperformed prevalent models with superior precision, F1-score, and c-statistics. The developed risk index can help monitor temporal comorbidities of patients, and can reduce the cost of inappropriate hospital and A&E admissions. The T-CARER model can bring about a significant improvement in scoring comorbidity and assessing the health of patients.

5. Conclusions

This study proposed an approach to score commodities by the inclusion of diverse categories of diagnoses, operations, and complexities. The proposed T-CARER models perform consistently across tests and validations, and outperform Charlson and Elixhauser indices, which are widely used to predict the risk of comorbidity.

Moreover, the temporal model of comorbidities, operations and complexities was proved to notably improve the comorbidity risk model. Also, inputting a pool of features into the feature selection was lead to the discovery of important factors, including comorbidity groups, operations and complexities.

Overall, the WDNN model can better generalise unseen features using dense embedding in the deep part of the ANN. It can also memorise feature interactions using the cross-product of features in the wide part of the ANN.

Moreover, the T-CARER toolkit has been produced for use by public as a generic, user-friendly, and open-source toolkit.

Finally, to adapt the risk stratification models to different healthcare settings, fu-

ture studies on the development of admission models using transfer learning [76] approaches are desirable. Moreover, the deployment of process-mining techniques [77], which could not be derived in this research, could help with identifying more complex clusters of comorbidities and complexities.

Competing interests

None.

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Availability of data and material

The HES data were controlled by NHS Digital and governed by strict access and controls. The data supporting the findings of this study are available from NHS Digital. However, restrictions apply to the availability of these data, which were used under a license for this study, and thus are not publicly available. Data are, however, available from the authors upon reasonable request, and with the permission of NHS Digital.

Details of the variables and definitions of the derived models are available from the authors at the HSCMG (HSCMG@westminster.ac.uk).

The T-CARER software package was constructed using open-source standards, and is available online (https://github.com/mesgarpour/T-CARER).

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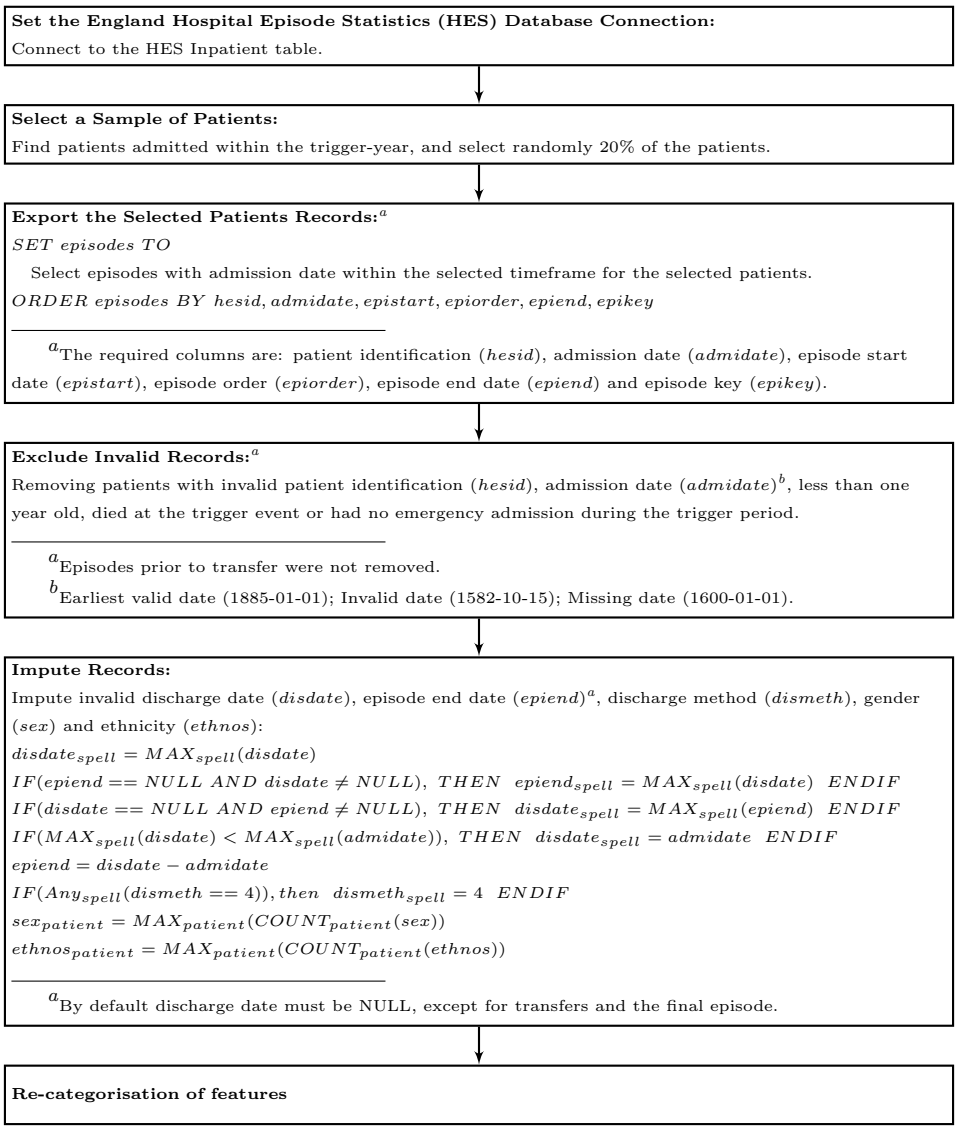

Fig. A.1. Abstract diagram of the data pre-processing step.

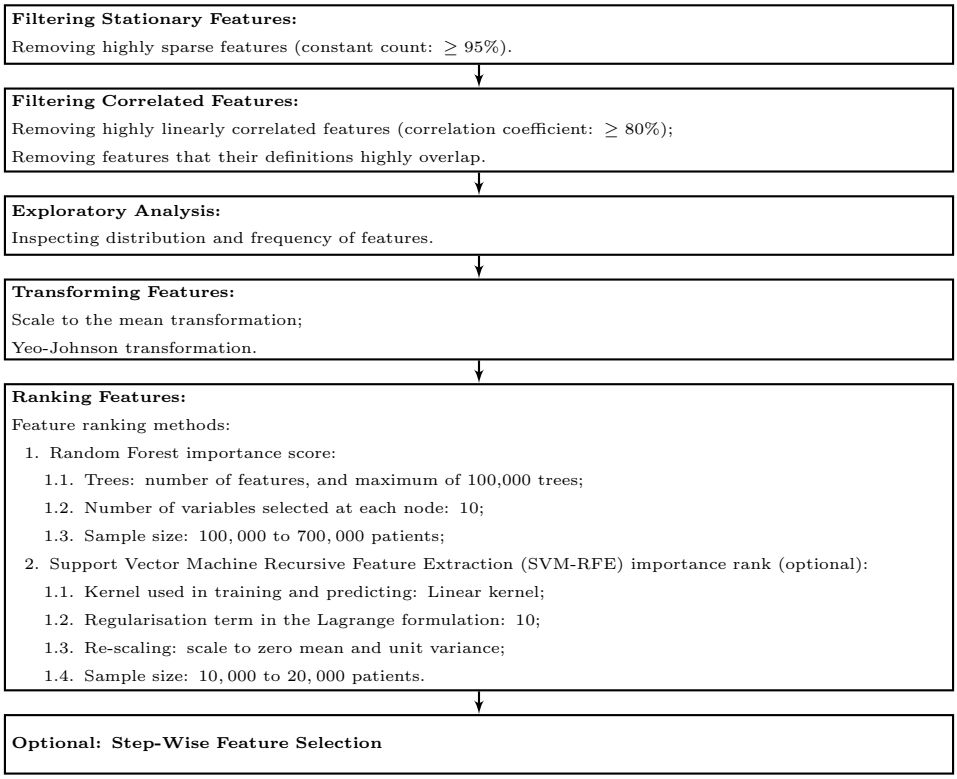

Fig. A.2. Abstract diagram of the feature selection step.

Table A.1

The profile of T-CARER random forest model (365-day readmission) and NHS-CCI, using main comorbidity categories (all samples).

Main comorbidity groups	Population profile				T-CARER profile							NHS-CCI profile				Comparisons	
Diagnoses group [a]	Prior [b]	Male	Age [c]	LoS [d]	Total	Sens. (0.5) [e]	F1 (.5) [f]	TP (.5) [g]	TN (.5) [h]	TP (.7)	TN (.7)	CCI 1-3 [i]	CCI 1-3 (TP)	CCI 4+	CCI 4+ (TP)	Delta score (.5, 4+) [j]	Delta score (.7, 4+)
Sample: Sample-1, Test sub-sample (1999-2004)																	
Hypertension (HT)	29,207	12,311	22	9	89004	0.296	0.6	27,954	11,017	7,833	51,964	7,079	2,380	23,022	8,962	-8,962 (-10.1%)	10,926 (12.3%)
Depression	21,635	9,925	16	8	69154	0.311	0.611	22,864	7,143	5,849	41,670	6,356	2,130	18,168	7,166	-7,166 (-10.4%)	9,379 (13.6%)
CHD[k]	20,849	11,669	16	8	57550	0.222	0.504	13,540	7,616	6,146	30,555	3,871	1,547	19,360	7,776	-7,776 (-13.5%)	7,762 (13.5%)
Cancer	20,475	9,888	24	7	80579	0.479	0.768	42,240	4,699	3,921	56,183	2,054	708	14,643	5,589	-5,589 (-6.9%)	6,479 (8.0%)
Asthma	10,196	3,576	43	6	32718	0.356	0.67	12,405	4,272	2,489	20,033	559	267	18,073	5,124	-5,124 (-15.7%)	10,752 (32.9%)
Diabetes	11,249	5,799	20	8	31673	0.259	0.56	8,730	4,067	2,941	17,483	14,307	4,545	8,014	3,400	-3,400 (-10.7%)	11,435 (36.1%)
COPD[l]	9,144	4,729	14	9	19892	0.119	0.351	2,482	4,621	3,017	7,731	542	303	10,935	4,839	-4,839 (-24.3%)	3,318 (16.7%)
CHF[m]	9,248	4,466	15	10	20838	0.097	0.29	2,098	4,468	3,457	8,133	1,083	559	11,385	4,937	-4,937 (-23.7%)	3,515 (16.9%)
Prior 30-day non-emergency	781	310	43	9	2203	0.291	0.61	676	374	238	1,184	71	35	272	112	-112 (-5.1%)	-42 (-1.9%)
Prior 30-day emergency	112,570	39,530	46	6	360657	0.331	0.64	126,308	44,469	23,167	224,920	11,348	4,223	48,512	18,579	-18,579 (-5.2%)	13,891 (3.9%)
Sample: Sample-2, Test sub-sample (2004-2009)																	
Hypertension (HT)	40,163	16,555	23	7	85422	0.232	0.574	21,913	11,178	3,845	41,414	7,908	3,425	30,744	16,271	-16,271 (-19.0%)	15,111 (17.7%)
Depression	32,312	14,583	17	8	69956	0.224	0.554	17,409	7,711	3,270	34,374	7,481	3,230	27,170	14,424	-14,424 (-20.6%)	13,727 (19.6%)
CHD	21,714	11,662	18	7	42427	0.171	0.481	8,037	5,819	2,322	18,391	3,372	1,725	20,758	11,267	-11,267 (-26.6%)	8,816 (20.8%)
Cancer	15,732	6,965	25	7	33143	0.227	0.567	8,408	4,198	1,601	15,810	1,602	757	12,386	6,783	-6,783 (-20.5%)	4,847 (14.6%)
Asthma	14,124	4,562	46	6	31962	0.312	0.682	11,086	4,956	1,400	16,438	805	424	18,387	7,715	-7,715 (-24.1%)	9,653 (30.2%)
Diabetes	13,006	6,482	21	8	27138	0.221	0.56	6,649	3,489	1,357	12,775	11,730	4,834	10,368	5,794	-5,794 (-21.3%)	10,113 (37.3%)
COPD	10,717	5,439	16	7	18912	0.123	0.41	2,507	4,126	1,481	6,714	722	436	12,365	7,007	-7,007 (-37.0%)	4,163 (22.0%)
CHF	9,686	4,700	14	9	16361	0.095	0.348	1,670	3,371	1,343	5,332	1,004	598	10,722	6,470	-6,470 (-39.5%)	3,315 (20.3%)
Prior 30-day non-emergency	755	283	41	6	1394	0.201	0.567	309	311	76	563	59	35	343	200	-200 (-14.3%)	91 (6.5%)
Prior 30-day emergency	120,838	39,590	48	5	322301	0.411	0.764	147,815	39,168	9,021	192,442	12,321	5,052	55,456	26,535	-26,535 (-8.2%)	27,169 (8.4%)

[a] The Charlson Comorbidity Index (CCI) diagnoses groups. [b] Total number of patients with prior spells. [c] The Inter-Quartile Range (IQR) of patients' age. [d] The IQR of patients' length-of-stay. [e] Sensitivity, 50% cut-off point. [f] F1 score, 50% cut-off point. [g] True Positive (TP), 50% cut-off point. [h] True Negative (TN), 50% cut-off point. [i] Total number of patients scored between 1 to 3 by the NHS-CCI. [j] Subtraction of TCARER's True Positive (50% cut-off point) from the NHS-CCI of 4+. [k] Coronary heart disease (CHD). [l] Chronic obstructive pulmonary disease (COPD). [m] Congestive heart failure (CHF).

Table A.2

The profile of T-CARER WDNN model (365-day readmission) and NHS-CCI, using main comorbidity categories (all samples).

Main comorbidity groups	Population profile				T-CARER profile							NHS-CCI profile				Comparisons	
Diagnoses group [a]	Prior [b]	Male	Age [c]	LoS [d]	Total	Sens. (0.5) [e]	F1 (.5) [f]	TP (.5) [g]	TN (.5) [h]	TP (.7)	TN (.7)	CCI 1-3 [i]	CCI 1-3 (TP)	CCI 4+	CCI 4+ (TP)	Delta score (.5, 4+) [j]	Delta score (.7, 4+)
Sample: Sample-1, Test sub-sample (1999-2004)																	
Hypertension (HT)	29,207	12,311	22	9	89004	0.109	0.47	11,613	51,212	4,630	58,409	7,079	2,380	23,022	8,962	-8,962 (-10.1%)	17,371 (19.5%)
Depression	21,635	9,925	16	8	69154	0.089	0.419	7,426	41,098	2,004	46,547	6,356	2,130	18,168	7,166	-7,166 (-10.4%)	14,256 (20.6%)
CHD[k]	20,849	11,669	16	8	57550	0.117	0.455	8,238	29,601	2,454	35,477	3,871	1,547	19,360	7,776	-7,776 (-13.5%)	12,684 (22.0%)
Cancer	20,475	9,888	24	7	80579	0.051	0.332	4,949	55,706	1,564	59,401	2,054	708	14,643	5,589	-5,589 (-6.9%)	9,697 (12.0%)
Asthma	10,196	3,576	43	6	32718	0.116	0.51	4,447	19,742	2,112	21,886	559	267	18,073	5,124	-5,124 (-15.7%)	12,605 (38.5%)
Diabetes	11,249	5,799	20	8	31673	0.12	0.468	4,585	16,663	1,433	19,766	14,307	4,545	8,014	3,400	-3,400 (-10.7%)	13,718 (43.3%)
COPD[l]	9,144	4,729	14	9	19892	0.218	0.577	5,197	7,071	1,912	9,895	542	303	10,935	4,839	-4,839 (-24.3%)	5,482 (27.6%)
CHF[m]	9,248	4,466	15	10	20838	0.183	0.531	4,656	7,961	1,474	10,849	1,083	559	11,385	4,937	-4,937 (-23.7%)	6,231 (29.9%)
Prior 30-day non-emergency	781	310	43	9	2203	0.146	0.532	380	1,154	183	1,357	71	35	272	112	-112 (-5.1%)	131 (5.9%)
Prior 30-day emergency	112,570	39,530	46	6	360657	0.117	0.519	49,548	219,157	29,322	241,351	11,348	4,223	48,512	18,579	-18,579 (-5.2%)	30,322 (8.4%)
Sample: Sample-2, Test sub-sample (2004-2009)																	
Hypertension (HT)	40,163	16,555	23	7	85422	0.235	0.598	23,876	29,461	9,893	41,592	7,908	3,425	30,744	16,271	-16,271 (-19.0%)	15,289 (17.9%)
Depression	32,312	14,583	17	8	69956	0.22	0.575	18,473	24,165	6,952	34,521	7,481	3,230	27,170	14,424	-14,424 (-20.6%)	13,874 (19.8%)
CHD	21,714	11,662	18	7	42427	0.257	0.601	13,125	11,881	5,359	18,430	3,372	1,725	20,758	11,267	-11,267 (-26.6%)	8,855 (20.9%)
Cancer	15,732	6,965	25	7	33143	0.236	0.592	9,345	10,891	3,648	15,894	1,602	757	12,386	6,783	-6,783 (-20.5%)	4,931 (14.9%)
Asthma	14,124	4,562	46	6	31962	0.245	0.634	9,062	12,444	4,266	16,608	805	424	18,387	7,715	-7,715 (-24.1%)	9,823 (30.7%)
Diabetes	13,006	6,482	21	8	27138	0.24	0.598	7,772	8,931	3,181	12,846	11,730	4,834	10,368	5,794	-5,794 (-21.3%)	10,184 (37.5%)
COPD	10,717	5,439	16	7	18912	0.338	0.67	7,481	4,077	3,520	6,927	722	436	12,365	7,007	-7,007 (-37.0%)	4,376 (23.1%)
CHF	9,686	4,700	14	9	16361	0.345	0.672	6,675	3,165	3,107	5,428	1,004	598	10,722	6,470	-6,470 (-39.5%)	3,411 (20.8%)
Prior 30-day non-emergency	755	283	41	6	1394	0.336	0.688	540	365	273	564	59	35	343	200	-200 (-14.3%)	92 (6.6%)
Prior 30-day emergency	120,838	39,590	48	5	322301	0.185	0.604	69,254	162,356	34,938	193,319	12,321	5,052	55,456	26,535	-26,535 (-8.2%)	28,046 (8.7%)

[a] The Charlson Comorbidity Index (CCI) diagnoses groups. [b] Total number of patients with prior spells. [c] The Inter-Quartile Range (IQR) of patients' age. [d] The IQR of patients' length-of-stay. [e] Sensitivity, 50% cut-off point. [f] F1 score, 50% cut-off point. [g] True Positive (TP), 50% cut-off point. [h] True Negative (TN), 50% cut-off point. [i] Total number of patients scored between 1 to 3 by the NHS-CCI. [j] Subtraction of TCARER's True Positive (50% cut-off point) from the NHS-CCI of 4+. [k] Coronary heart disease (CHD). [l] Chronic obstructive pulmonary disease (COPD). [m] Congestive heart failure (CHF).

Table A.3

The profile of T-CARER random forest model and NHS-CCI (365-day), using ECI diagnoses categories (*Sample-2*, 2004–2009).

Elixhauser comorbidity index	**Population profile**				**T-CARER profile**							**NHS-CCI profile**				**Comparisons**	
Diagnoses Group [a]	**Prior** [b]	**Male**	**Age** [c]	**LoS** [d]	**Total**	**Sens. (0.5)** [e]	**F1 (.5)** [f]	**TP (.5)** [g]	**TN (.5)** [h]	**TP (.7)**	**TN (.7)**	**CCI 1-3** [i]	**CCI 1-3 (TP)**	**CCI 4+**	**CCI 4+ (TP)**	**Delta score (.5, 4+)** [j]	**Delta score (.7, 4+)**
Congestive heart failure	4,922	2,385	14	10	8,716	0.913	0.724	4,242	962	1,364	3,185	304	163	7,031	4,053	189 (2.2%)	2,510 (28.8%)
AIDS/HIV	102	67	13	6	442	0.676	0.543	69	257	20	329	219	49	89	23	46 (10.4%)	225 (50.9%)
Depression	3,029	1,114	38	8	7,196	0.647	0.585	1,961	2,454	608	3,917	327	142	1,462	733	1,228 (17.1%)	664 (9.2%)
Cardiac arrhythmias	11,194	5,377	14	8	23,006	0.812	0.66	9,089	4,546	2,565	10,603	1,550	764	10,033	5,520	3,569 (15.5%)	4,090 (17.8%)
Valvular disease	2,019	942	16	10	3,957	0.834	0.674	1,683	645	457	1,754	228	109	1,868	1,067	616 (15.6%)	736 (18.6%)
Pulmonary circulation disorder	806	377	22	10	1,745	0.797	0.649	642	408	152	868	101	41	729	397	245 (14.0%)	321 (18.4%)
Peripheral vascular disorders	1,980	1,236	14	11	3,780	0.821	0.674	1,625	583	498	1,612	108	63	3,074	1,650	-25 (-0.7%)	1,281 (33.9%)
Hypertension, uncomplicated	19,370	8,554	18	8	46,496	0.713	0.596	13,813	13,980	3,347	25,568	5,932	2,400	16,643	8,131	5,682 (12.2%)	10,486 (22.6%)
Hypertension, complicated	1,702	911	15	11	3,002	0.845	0.708	1,439	374	466	1,114	52	30	2,701	1,545	-106 (-3.5%)	992 (33.0%)
Paralysis	1,124	570	21	14	2,272	0.818	0.653	919	376	312	1,013	420	194	1,392	740	179 (7.9%)	743 (32.7%)
Other neurological disorders	5,672	2,863	35	8	11,863	0.751	0.662	4,262	3,244	1,438	5,695	604	310	3,513	1,944	2,318 (19.5%)	1,367 (11.5%)
Chronic pulmonary disease	13,510	5,865	30	6	30,516	0.754	0.656	10,184	9,672	4,018	15,589	491	269	24,090	10,669	-485 (-1.6%)	12,226 (40.1%)
Diabetes, uncomplicated	10,110	5,054	21	8	21,907	0.76	0.645	7,687	5,767	2,428	10,779	11,516	4,729	8,737	4,757	2,930 (13.4%)	9,749 (44.5%)
Diabetes, complicated	887	516	21	11	1,603	0.821	0.696	728	240	276	622	248	129	761	472	256 (16.0%)	314 (19.6%)
Hypothyroidism	3,394	685	19	9	7,859	0.767	0.632	2,602	2,233	760	4,142	695	312	2,940	1,539	1,063 (13.5%)	1,461 (18.6%)
Renal failure	3,956	2,173	16	10	6,883	0.858	0.715	3,393	780	1,222	2,492	106	61	6,161	3,556	-163 (-2.4%)	2,215 (32.2%)
Liver disease	1,527	939	22	7	2,955	0.788	0.689	1,204	663	432	1,280	189	96	1,157	668	536 (18.1%)	434 (14.7%)
Peptic ulcer disease	464	233	23	11	1,158	0.81	0.619	376	319	93	662	43	16	711	306	70 (6.0%)	400 (34.5%)
Psychoses	1,121	641	29	31	2,571	0.647	0.573	725	766	206	1,344	103	45	332	175	550 (21.4%)	109 (4.2%)
Lymphoma	462	246	18	10	743	0.764	0.709	353	100	103	222	15	9	478	289	64 (8.6%)	136 (18.3%)
Metastatic cancer	1,650	835	17	8	3,034	0.755	0.642	1,246	398	288	1,185	26	17	2,687	1,461	-215 (-7.1%)	1,036 (34.1%)
Solid tumour	3,510	2,062	18	9	6,425	0.763	0.663	2,677	1,029	684	2,542	131	74	4,750	2,621	56 (0.9%)	1,813 (28.2%)
Rheumatoid arthritis	1,603	458	19	8	3,833	0.783	0.626	1,255	1,076	342	2,045	64	28	3,176	1,369	-114 (-3.0%)	1,658 (43.3%)
Coagulopathy	416	175	40	8	1,003	0.75	0.661	312	371	120	553	42	19	265	140	172 (17.1%)	114 (11.4%)
Obesity	853	343	29	7	2,009	0.734	0.625	626	631	228	1,095	307	136	704	357	269 (13.4%)	457 (22.7%)
Weight loss	709	369	23	12	1,483	0.753	0.633	534	329	106	725	70	29	490	267	267 (18.0%)	215 (14.5%)
Fluid & electrolyte disorders	2,850	1,161	19	14	5,901	0.838	0.654	2,387	992	625	2,771	375	182	2,599	1,372	1,015 (17.2%)	1,140 (19.3%)
Blood loss anemia	69	30	28	8	204	0.638	0.494	44	70	12	127	8	2	51	26	18 (8.8%)	23 (11.3%)
Deficiency anemia	5,006	2,975	33	7	12,003	0.713	0.638	3,571	4,385	1,237	6,589	525	254	2,548	1,361	2,210 (18.4%)	1,050 (8.7%)
Alcohol abuse	2,132	1,313	23	5	5,421	0.646	0.609	1,377	2,275	461	3,148	175	81	997	547	830 (15.3%)	403 (7.4%)
Drug abuse	941	614	13	5	2,548	0.576	0.561	542	1,158	169	1,541	33	15	261	109	433 (17.0%)	104 (4.1%)

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Elixhauser comorbidity index	Population profile				T-CARER profile							NHS-CCI profile				Comparisons	
Diagnoses Group [a]	Prior [b]	Male	Age [c]	LoS [d]	Total	Sens. (0.5) [e]	F1 (.5) [f]	TP (.5) [g]	TN (.5) [h]	TP (.7)	TN (.7)	CCI 1-3 [i]	CCI 1-3 (TP)	CCI 4+	CCI 4+ (TP)	Delta score (.5, 4+) [j]	Delta score (.7, 4+)

[a] The Elixhauser Comorbidity Index (ECI) diagnoses groups. [b] Total number of patients with prior spells. [c] The Inter-Quartile Range (IQR) of patients' age. [d] The IQR of patients' length-of-stay. [e] Sensitivity, 50% cut-off point. [f] F1-score, 50% cut-off point. [g] True Positive (TP), 50% cut-off point. [h] True Negative (TN), 50% cut-off point. [i] Total number of patients scored between 1 to 3 by the NHS-CCI. [j] Subtraction of TCARER's True Positive (50% cut-off point) from the NHS-CCI of 4+.

Table A.4

The profile of T-CARER random forest model and NHS-CCI (365-day), using CCI diagnoses categories (*Sample-2*, 2004–2009)

Charlson comorbidity index	**Population profile**				**T-CARER profile**							**NHS-CCI profile**				**Comparisons**	
Diagnoses Group [a]	**Prior** [b]	**Male**	**Age** [c]	**LoS** [d]	**Total**	**Sens. (0.5)** [e]	**F1 (.5)** [f]	**TP (.5)** [g]	**TN (.5)** [h]	**TP (.7)**	**TN (.7)**	**CCI 1-3** [i]	**CCI 1-3 (TP)**	**CCI 4+**	**CCI 4+ (TP)**	**Delta score (.5, 4+)** [j]	**Delta score (.7, 4+)**
Myocardial infarction	4,079	2,600	21	5	7,806	0.692	0.63	2,821	1,667	602	3,509	396	221	4,493	2,373	448 (5.7%)	2,077 (26.6%)
Peripheral vascular disease	1,980	1,236	14	11	3,780	0.705	0.631	1,625	583	498	1,612	108	63	3,074	1,650	-25 (-0.7%)	1,281 (33.9%)
Cerebrovascular disease	4,651	2,206	16	14	9,911	0.911	0.671	3,640	2,044	830	4,855	598	277	5,457	2,795	845 (8.5%)	2,578 (26.0%)
Dementia	4,020	1,407	9	15	7,766	0.779	0.633	3,556	638	831	3,244	100	55	6,380	3,312	244 (3.1%)	2,611 (33.6%)
Chronic pulmonary disease	13,510	5,865	30	6	30,516	0.956	0.723	10,184	9,672	4,018	15,589	491	269	24,090	10,669	-485 (-1.6%)	12,226 (40.1%)
Rheumatic disease	1,462	394	16	9	3,438	0.261	0.349	1,174	931	318	1,801	34	15	3,110	1,342	-168 (-4.9%)	1,612 (46.9%)
Peptic ulcer disease	695	370	23	10	1,817	0.653	0.558	542	552	120	1,080	76	24	935	405	137 (7.5%)	540 (29.7%)
Mild liver disease	1,393	853	22	7	2,691	0.879	0.722	1,108	596	408	1,162	167	83	1,054	613	495 (18.4%)	389 (14.5%)
Diabetes, uncomplicated	10,162	5,087	21	8	22,027	0.964	0.709	7,730	5,796	2,449	10,842	11,560	4,747	8,780	4,780	2,950 (13.4%)	9,790 (44.4%)
Diabetes, complicated	848	496	22	11	1,501	0.223	0.327	697	213	262	564	212	115	726	456	241 (16.1%)	278 (18.5%)
Hemiplegia or paraplegia	1,124	570	21	14	2,272	0.859	0.666	919	376	312	1,013	420	194	1,392	740	179 (7.9%)	743 (32.7%)
Renal disease	3,962	2,176	16	10	6,898	0.943	0.743	3,399	784	1,222	2,500	107	62	6,168	3,558	-159 (-2.3%)	2,219 (32.2%)
Malignancy	4,216	2,435	19	9	7,589	0.85	0.702	3,199	1,217	840	2,931	155	89	5,469	3,032	167 (2.2%)	2,061 (27.2%)
Moderate or severe liver disease	359	244	20	7	607	0.227	0.334	298	75	114	211	39	23	330	196	102 (16.8%)	113 (18.6%)
Metastatic solid tumour	1,650	835	17	8	3,034	0.953	0.704	1,246	398	288	1,185	26	17	2,687	1,461	-215 (-7.1%)	1,036 (34.1%)
Congestive heart failure	4,922	2,385	14	10	8,716	0.913	0.724	4,242	962	1,364	3,185	304	163	7,031	4,053	189 (2.2%)	2,510 (28.8%)
AIDS/HIV	102	67	13	6	442	0.676	0.543	69	257	20	329	219	49	89	23	46 (10.4%)	225 (50.9%)

[a] The Charlson Comorbidity Index (CCI) diagnoses groups. [b] Total number of patients with prior spells. [c] The Inter-Quartile Range (IQR) of patients' age. [d] The IQR of patients' length-of-stay. [e] Sensitivity, 50% cut-off point. [f] F1-score, 50% cut-off point. [g] True Positive (TP), 50% cut-off point. [h] True Negative (TN), 50% cut-off point. [i] Total number of patients scored between 1 to 3 by the NHS-CCI. [j] Subtraction of TCARER's True Positive (50% cut-off point) from the NHS-CCI of 4+.

Table A.5

The profile of T-CARER WDNN model and NHS-CCI (365-day), using ECI diagnoses categories (*Sample-2*, 2004–2009).

Elixhauser comorbidity index	**Population profile**				**T-CARER profile**							**NHS-CCI profile**				**Comparisons**	
Diagnoses group [a]	**Prior** [b]	**Male**	**Age** [c]	**LoS** [d]	**Total**	**Sens. (0.5)** [e]	**F1 (.5)** [f]	**TP (.5)** [g]	**TN (.5)** [h]	**TP (.7)**	**TN (.7)**	**CCI 1-3** [i]	**CCI 1-3 (TP)**	**CCI 4+**	**CCI 4+ (TP)**	**Delta score (.5, 4+)** [j]	**Delta score (.7, 4+)**
Congestive heart failure	1,650	835	17	8	3,034	0.486	0.533	802	825	229	1,224	26	17	2,687	1,461	-659 (-21.7%)	1,075 (35.4%)
AIDS/HIV	102	67	13	6	442	0.422	0.446	43	292	15	331	219	49	89	23	20 (4.5%)	227 (51.4%)
Depression	3,029	1,114	38	8	7,196	0.487	0.522	1,474	3,018	498	3,940	327	142	1,462	733	741 (10.3%)	687 (9.5%)
Cardiac arrhythmias	11,194	5,377	14	8	23,006	0.573	0.581	6,409	7,345	2,416	10,650	1,550	764	10,033	5,520	889 (3.9%)	4,137 (18.0%)
Valvular disease	2,019	942	16	10	3,957	0.555	0.577	1,121	1,194	423	1,750	228	109	1,868	1,067	54 (1.4%)	732 (18.5%)
Pulmonary circulation disorder	806	377	22	10	1,745	0.476	0.525	384	665	128	885	101	41	729	397	-13 (-0.7%)	338 (19.4%)
Peripheral vascular disorders	1,980	1,236	14	11	3,780	0.579	0.597	1,146	1,085	465	1,621	108	63	3,074	1,650	-504 (-13.3%)	1,290 (34.1%)
Hypertension, uncomplicated	19,370	8,554	18	8	46,496	0.482	0.512	9,344	19,325	3,029	25,608	5,932	2,400	16,643	8,131	1,213 (2.6%)	10,526 (22.6%)
Hypertension, complicated	1,702	911	15	11	3,002	0.612	0.624	1,041	709	431	1,128	52	30	2,701	1,545	-504 (-16.8%)	1,006 (33.5%)
Paralysis	1,124	570	21	14	2,272	0.558	0.571	627	702	262	1,040	420	194	1,392	740	-113 (-5.0%)	770 (33.9%)
Other neurological disorders	5,672	2,863	35	8	11,863	0.567	0.594	3,214	4,257	1,161	5,762	604	310	3,513	1,944	1,270 (10.7%)	1,434 (12.1%)
Chronic pulmonary disease	13,510	5,865	30	6	30,516	0.589	0.598	7,958	11,845	3,453	15,782	491	269	24,090	10,669	-2,711 (-8.9%)	12,419 (40.7%)
Diabetes, uncomplicated	10,110	5,054	21	8	21,907	0.571	0.578	5,773	7,712	2,260	10,793	11,516	4,729	8,737	4,757	1,016 (4.6%)	9,763 (44.6%)
Diabetes, complicated	887	516	21	11	1,603	0.59	0.619	523	435	217	643	248	129	761	472	51 (3.2%)	335 (20.9%)
Hypothyroidism	3,394	685	19	9	7,859	0.534	0.551	1,812	3,089	723	4,150	695	312	2,940	1,539	273 (3.5%)	1,469 (18.7%)
Renal failure	3,956	2,173	16	10	6,883	0.634	0.643	2,510	1,580	1,081	2,516	106	61	6,161	3,556	-1,046 (-15.2%)	2,239 (32.5%)
Liver disease	1,527	939	22	7	2,955	0.599	0.623	914	937	353	1,319	189	96	1,157	668	246 (8.3%)	473 (16.0%)
Peptic ulcer disease	464	233	23	11	1,158	0.502	0.531	233	514	75	654	43	16	711	306	-73 (-6.3%)	392 (33.9%)
Psychoses	1,121	641	29	31	2,571	0.498	0.518	558	974	149	1,372	103	45	332	175	383 (14.9%)	137 (5.3%)
Lymphoma	462	246	18	10	743	0.543	0.598	251	155	91	238	15	9	478	289	-38 (-5.1%)	152 (20.5%)
Metastatic cancer	1,650	835	17	8	3,034	0.486	0.533	802	825	229	1,224	26	17	2,687	1,461	-659 (-21.7%)	1,075 (35.4%)
Solid tumour	3,510	2,062	18	9	6,425	0.512	0.557	1,796	1,775	587	2,618	131	74	4,750	2,621	-825 (-12.8%)	1,889 (29.4%)
Rheumatoid arthritis	1,603	458	19	8	3,833	0.558	0.563	895	1,548	315	2,068	64	28	3,176	1,369	-474 (-12.4%)	1,681 (43.9%)
Coagulopathy	416	175	40	8	1,003	0.55	0.586	229	451	90	547	42	19	265	140	89 (8.9%)	108 (10.8%)
Obesity	853	343	29	7	2,009	0.522	0.561	445	868	184	1,112	307	136	704	357	88 (4.4%)	474 (23.6%)
Weight loss	709	369	23	12	1,483	0.434	0.494	308	543	88	728	70	29	490	267	41 (2.8%)	218 (14.7%)
Fluid & electrolyte disorders	2,850	1,161	19	14	5,901	0.55	0.567	1,567	1,937	538	2,770	375	182	2,599	1,372	195 (3.3%)	1,139 (19.3%)
Blood loss anemia	69	30	28	8	204	0.435	0.451	30	101	12	128	8	2	51	26	4 (2.0%)	24 (11.8%)
Deficiency anemia	5,006	2,975	33	7	12,003	0.552	0.576	2,763	5,172	995	6,656	525	254	2,548	1,361	1,402 (11.7%)	1,117 (9.3%)
Alcohol abuse	2,132	1,313	23	5	5,421	0.514	0.554	1,095	2,560	366	3,179	175	81	997	547	548 (10.1%)	434 (8.0%)
Drug abuse	941	614	13	5	2,548	0.454	0.5	427	1,268	131	1,559	33	15	261	109	318 (12.5%)	122 (4.8%)

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Elixhauser comorbidity index	Population profile				T-CARER profile							NHS-CCI profile				Comparisons	
Diagnoses Group [a]	Prior [b]	Male	Age [c]	LoS [d]	Total	Sens. (0.5) [e]	F1 (.5) [f]	TP (.5) [g]	TN (.5) [h]	TP (.7)	TN (.7)	CCI 1-3 [i]	CCI 1-3 (TP)	CCI 4+	CCI 4+ (TP)	Delta score (.5, 4+) [j]	Delta score (.7, 4+)

[a] The Elixhauser Comorbidity Index (ECI) diagnoses groups. [b] Total number of patients with prior spells. [c] The Inter-Quartile Range (IQR) of patients' age.
[d] The IQR of patients' length-of-stay. [e] Sensitivity, 50% cut-off point. [f] F1-score, 50% cut-off point. [g] True Positive (TP), 50% cut-off point. [h] True Negative (TN), 50% cut-off point. [i] Total number of patients scored between 1 to 3 by the NHS-CCI. [j] Subtraction of TCARER's True Positive (50% cut-off point) from the NHS-CCI of 4+.

Table A.6

The profile of T-CARER WDNN model and NHS-CCI (365-day), using CCI diagnoses categories (*Sample-2* 2004–2009).

Charlson comorbidity index	**Population profile**				**T-CARER profile**							**NHS-CCI profile**				**Comparisons**	
Diagnoses Group [a]	**Prior** [b]	**Male**	**Age** [c]	**LoS** [d]	**Total**	**Sens. (0.5)** [e]	**F1 (.5)** [f]	**TP (.5)** [g]	**TN (.5)** [h]	**TP (.7)**	**TN (.7)**	**CCI 1-3** [i]	**CCI 1-3 (TP)**	**CCI 4+**	**CCI 4+ (TP)**	**Delta score (.5, 4+)** [j]	**Delta score (.7, 4+)**
Myocardial infarction	4,079	2,600	21	5	7,806	0.41	0.491	1,671	2,670	536	3,504	396	221	4,493	2,373	-702 (-9.0%)	2,072 (26.5%)
Peripheral vascular disease	4,922	2,385	14	10	8,716	0.611	0.623	3,009	2,065	1,271	3,231	304	163	7,031	4,053	-1,044 (-12.0%)	2,556 (29.3%)
Cerebrovascular disease	1,980	1,236	14	11	3,780	0.579	0.597	1,146	1,085	465	1,621	108	63	3,074	1,650	-504 (-13.3%)	1,290 (34.1%)
Dementia	4,651	2,206	16	14	9,911	0.488	0.525	2,269	3,529	768	4,896	598	277	5,457	2,795	-526 (-5.3%)	2,619 (26.4%)
Chronic pulmonary disease	4,020	1,407	9	15	7,766	0.621	0.591	2,496	1,819	795	3,235	100	55	6,380	3,312	-816 (-10.5%)	2,602 (33.5%)
Rheumatic disease	13,510	5,865	30	6	30,516	0.589	0.598	7,958	11,845	3,453	15,782	491	269	24,090	10,669	-2,711 (-8.9%)	12,419 (40.7%)
Peptic ulcer disease	1,462	394	16	9	3,438	0.573	0.572	837	1,349	296	1,823	34	15	3,110	1,342	-505 (-14.7%)	1,634 (47.5%)
Mild liver disease	695	370	23	10	1,817	0.453	0.498	315	867	98	1,069	76	24	935	405	-90 (-5.0%)	529 (29.1%)
Diabetes, uncomplicated	1,393	853	22	7	2,691	0.614	0.633	855	843	337	1,195	167	83	1,054	613	242 (9.0%)	422 (15.7%)
Diabetes, complicated	10,162	5,087	21	8	22,027	0.571	0.578	5,807	7,756	2,273	10,856	11,560	4,747	8,780	4,780	1,027 (4.7%)	9,804 (44.5%)
Hemiplegia or paraplegia	848	496	22	11	1,501	0.586	0.62	497	394	208	585	212	115	726	456	41 (2.7%)	299 (19.9%)
Renal disease	1,124	570	21	14	2,272	0.558	0.571	627	702	262	1,040	420	194	1,392	740	-113 (-5.0%)	770 (33.9%)
Malignancy	3,962	2,176	16	10	6,898	0.634	0.642	2,512	1,586	1,081	2,524	107	62	6,168	3,558	-1,046 (-15.2%)	2,243 (32.5%)
Moderate or severe liver disease	4,216	2,435	19	9	7,589	0.511	0.561	2,156	2,062	722	3,020	155	89	5,469	3,032	-876 (-11.5%)	2,150 (28.3%)
Metastatic solid tumour	359	244	20	7	607	0.577	0.617	207	143	91	224	39	23	330	196	11 (1.8%)	126 (20.8%)
Congestive heart failure	1,650	835	17	8	3,034	0.486	0.533	802	825	229	1,224	26	17	2,687	1,461	-659 (-21.7%)	1,075 (35.4%)
AIDS/HIV	102	67	13	6	442	0.422	0.446	43	292	15	331	219	49	89	23	20 (4.5%)	227 (51.4%)

[a] The Charlson Comorbidity Index (CCI) diagnoses groups. [b] Total number of patients with prior spells. [c] The Inter-Quartile Range (IQR) of patients' age. [d] The IQR of patients' length-of-stay. [e] Sensitivity, 50% cut-off point. [f] F1-score, 50% cut-off point. [g] True Positive (TP), 50% cut-off point. [h] True Negative (TN), 50% cut-off point. [i] Total number of patients scored between 1 to 3 by the NHS-CCI. [j] Subtraction of TCARER's True Positive (50% cut-off point) from the NHS-CCI of 4+.

Table A.7

The weights of features using the Random Forest method for *Sample-2* (2004-2009).

#	Name	Weight	Temporal	Definition
1	mainspef_0t30d_prevalence_2_cnt	9.33E-02	0-30	Main Speciality: Maternity
2	diagCCS_0t30d_prevalence_10_cnt	6.60E-02	0-30	CCS group: Other complications of pregnancy
3	epidur_0t30d_avg	5.93E-02	0-30	Average episode duration
4	posopdur_0t30d_avg	5.79E-02	0-30	Average Post-operation duration
5	gender_1	5.09E-02	Trigger	Gender: Male
6	diagCCS_0t30d_prevalence_3_cnt	4.77E-02	0-30	CCS group: Normal pregnancy and delivery
7	diagCCS_0t30d_prevalence_13_cnt	4.23E-02	0-30	CCS group: OB-related trauma to perineum & vulva
8	diagCCS_0t30d_others_cnt	3.50E-02	0-30	CCS group: others
9	ethnos_0	3.11E-02	Trigger	ethnicity: Not known
10	mainspef_0t30d_prevalence_5_cnt	2.80E-02	0-30	Main Speciality: Gynaecology
11	operOPCSL1_0t30d_prevalence_1_cnt	2.05E-02	0-30	Operation group: Female Genital Tract
12	posopdur_365t730d_others_cnt	2.04E-02	365-730	Post-operation duration
13	diagCCS_0t30d_prevalence_22_cnt	1.93E-02	0-30	CCS group: Fetal distress & abnormal forces of labor
14	mainspef_0t30d_prevalence_6_cnt	1.90E-02	0-30	Main Speciality: Plastic
15	preopdur_180t365d_others_cnt	1.80E-02	180-365	Pre-operation duration
16	epidur_365t730d_avg	1.80E-02	365-730	Average episode duration
17	gapDays_365t730d_avg	1.74E-02	365-730	Average Gap-Days
18	preopdur_365t730d_others_cnt	1.71E-02	365-730	Pre-operation duration
19	mainspef_0t30d_prevalence_1_cnt	1.71E-02	0-30	Main Speciality: General
20	gapDays_365t730d_others_cnt	1.54E-02	365-730	Gap-Days
21	preopdur_0t30d_avg	1.47E-02	0-30	Average Pre-operation duration
22	admimeth_180t365d_prevalence_1_cnt	1.33E-02	180-365	Admission method: Unknown
23	epidur_365t730d_others_cnt	1.30E-02	365-730	Episode duration
24	epidur_0t30d_others_cnt	1.10E-02	0-30	Episode duration
25	mainspef_0t30d_prevalence_9_cnt	1.06E-02	0-30	Main Speciality: Paediatrics
26	mainspef_0t30d_prevalence_4_cnt	1.06E-02	0-30	Main Speciality: A&E
27	diagCCS_365t730d_others_cnt	9.36E-03	365-730	CCS group: others
28	admimeth_365t730d_prevalence_1_cnt	7.48E-03	365-730	Admission method: Unknown
29	mainspef_0t30d_prevalence_3_cnt	7.40E-03	0-30	Main Speciality: General Surgery
30	diagCCS_90t180d_others_cnt	7.32E-03	90-180	CCS group: others
31	diagCCS_180t365d_others_cnt	7.27E-03	180-365	CCS group: others
32	diagCCS_0t30d_prevalence_7_cnt	7.18E-03	0-30	CCS group: Abdominal pain
33	mainspef_180t365d_others_cnt	6.95E-03	180-365	Main Speciality: Others
34	diagCCS_0t30d_prevalence_24_cnt	6.77E-03	0-30	CCS group: Other birth complications; mother's puerperium
35	epidur_90t180d_others_cnt	6.22E-03	90-180	Episode duration
36	ethnos_1	5.97E-03	Trigger	ethnicity: White
37	epidur_180t365d_avg	5.79E-03	180-365	Average episode duration
38	mainspef_0t30d_prevalence_7_cnt	5.76E-03	0-30	Main Speciality: Geriatric
39	posopdur_180t365d_others_cnt	5.35E-03	180-365	Post-operation duration
40	diagCCS_0t30d_prevalence_16_cnt	5.25E-03	0-30	CCS group: Chronic obstructive pulmonary & bronchiectasis
41	admimeth_90t180d_prevalence_1_cnt	5.13E-03	90-180	Admission method: Unknown
42	epidur_180t365d_others_cnt	4.97E-03	180-365	Episode duration
43	diagCCS_0t30d_prevalence_11_cnt	4.85E-03	0-30	CCS group: Other upper respiratory disease
44	operOPCSL1_0t30d_others_cnt	4.50E-03	0-30	Operation group: Others
45	gapDays_180t365d_avg	4.34E-03	180-365	Average Gap-Days
46	diagCCS_0t30d_prevalence_2_cnt	3.80E-03	0-30	CCS group: Essential hypertension

Table A.7

(Continued)

#	Name	Weight	Temporal	Definition
47	posopdur_0t30d_others_cnt	3.74E-03	0-30	Post-operation duration
48	diagCCS_0t30d_prevalence_21_cnt	3.68E-03	0-30	CCS group: Delirium dementia & amnestic & other cognitives
49	mainspef_180t365d_prevalence_1_cnt	3.49E-03	180-365	Main Speciality: General
50	diagCCS_0t30d_prevalence_1_cnt	3.37E-03	0-30	CCS group: Others
51	diagCCS_0t30d_prevalence_5_cnt	3.14E-03	0-30	CCS group: Coronary atherosclerosis & other heart disease
52	mainspef_90t180d_others_cnt	3.09E-03	90-180	Main Speciality: Others
53	mainspef_0t30d_others_cnt	2.88E-03	0-30	Main Speciality: Others
54	diagCCS_30t90d_others_cnt	2.86E-03	30-90	CCS group: others
55	gapDays_90t180d_avg	2.73E-03	90-180	Average Gap-Days
56	gapDays_90t180d_others_cnt	2.69E-03	90-180	Gap-Days
57	admimeth_90t180d_others_cnt	2.47E-03	90-180	Admission method: Others
58	admimeth_30t90d_prevalence_1_cnt	2.46E-03	30-90	Admission method: Unknown
59	gapDays_30t90d_avg	2.23E-03	30-90	Average Gap-Days
60	posopdur_30t90d_others_cnt	2.09E-03	30-90	Post-operation duration
61	diagCCS_0t30d_prevalence_29_cnt	2.03E-03	0-30	CCS group: Other injuries & conditions due to external causes
62	gapDays_180t365d_others_cnt	1.99E-03	180-365	Gap-Days
63	preopdur_0t30d_others_cnt	1.88E-03	0-30	Pre-operation duration
64	diagCCS_0t30d_prevalence_6_cnt	1.83E-03	0-30	CCS group: Cardiac dysrhythmias
65	admimeth_180t365d_others_cnt	1.82E-03	180-365	Admission method: Others
66	posopdur_90t180d_others_cnt	1.75E-03	90-180	Post-operation duration
67	epidur_30t90d_others_cnt	1.67E-03	30-90	Episode duration
68	diagCCS_365t730d_prevalence_4_cnt	1.62E-03	365-730	CCS group: Normal pregnancy and/or delivery
69	admimeth_365t730d_others_cnt	1.60E-03	365-730	Admission method: Others
70	mainspef_30t90d_others_cnt	1.58E-03	30-90	Main Speciality: Others
71	diagCCS_0t30d_prevalence_4_cnt	1.54E-03	0-30	CCS group: Residual codes; unclassified
72	diagCCS_0t30d_prevalence_9_cnt	1.45E-03	0-30	CCS group: Diabetes mellitus without complication
73	epidur_90t180d_avg	1.44E-03	90-180	Average episode duration
74	mainspef_0t30d_prevalence_8_cnt	1.40E-03	0-30	Main Speciality: Cardiothoracic
75	admimeth_365t730d_prevalence_2_cnt	1.31E-03	365-730	Admission method: Elective
76	diagCCS_0t30d_prevalence_17_cnt	1.29E-03	0-30	CCS group: Urinary tract infections
77	diagCCS_365t730d_prevalence_12_cnt	1.19E-03	365-730	CCS group: Other complications of pregnancy
78	diagCCS_365t730d_prevalence_1_cnt	1.15E-03	365-730	CCS group: Others
79	diagCCS_0t30d_prevalence_12_cnt	9.98E-04	0-30	CCS group: Asthma
80	mainspef_180t365d_prevalence_3_cnt	9.82E-04	180-365	Main Speciality: Gynaecology
81	preopdur_30t90d_others_cnt	9.59E-04	30-90	Pre-operation duration
82	posopdur_365t730d_avg	9.39E-04	365-730	Average Post-operation duration
83	mainspef_90t180d_prevalence_1_cnt	9.33E-04	90-180	Main Speciality: General
84	diagCCS_0t30d_prevalence_8_cnt	8.77E-04	0-30	CCS group: External cause codes: Fall
85	mainspef_0t30d_prevalence_10_cnt	8.66E-04	0-30	Main Speciality: Gastroenterology
86	diagCCS_0t30d_prevalence_20_cnt	8.31E-04	0-30	CCS group: Other connective tissue disease
87	diagCCS_180t365d_prevalence_1_cnt	8.23E-04	180-365	CCS group: Others
88	imd04rk_2	8.15E-04	Trigger	imd04rk: 3248 to 6496
89	admimeth_180t365d_prevalence_2_cnt	7.73E-04	180-365	Admission method: Elective
90	diagCCS_0t30d_prevalence_14_cnt	7.62E-04	0-30	CCS group: Other lower respiratory disease
91	diagCCS_0t30d_prevalence_28_cnt	7.05E-04	0-30	CCS group: Deficiency & other anemia
92	diagCCS_0t30d_prevalence_26_cnt	6.92E-04	0-30	CCS group: Alcohol-related disorders

Table A.7

(Continued)

#	Name	Weight	Temporal	Definition
93	imd04rk_3	6.76E-04	Trigger	imd04rk: 6496 to 9745
94	diagCCS_0t30d_prevalence_19_cnt	6.69E-04	0-30	CCS group: Phlebitis; thrombophlebitis & thromboembolism
95	imd04rk_1	6.60E-04	Trigger	imd04rk: 0 to 3248
96	epidur_30t90d_avg	6.27E-04	30-90	Average episode duration
97	ageTrigger_25	6.14E-04	Trigger	Age: 25-30
98	diagCCS_0t30d_prevalence_23_cnt	6.11E-04	0-30	CCS group: Allergic reactions
99	operOPCSL1_0t30d_prevalence_3_cnt	5.94E-04	0-30	Operation group: Lower Digestive Tract
100	ageTrigger_85	5.85E-04	Trigger	Age: 85+
101	admimeth_30t90d_others_cnt	5.73E-04	30-90	Admission method: Others
102	diagCCS_365t730d_prevalence_7_cnt	5.61E-04	365-730	CCS group: Cardiac dysrhythmias
103	diagCCS_0t30d_prevalence_25_cnt	5.57E-04	0-30	CCS group: Complication of device; implant or graft
104	diagCCS_0t30d_prevalence_18_cnt	5.49E-04	0-30	CCS group: Other gastrointestinal disorders
105	diagCCS_90t180d_prevalence_9_cnt	5.45E-04	90-180	CCS group: Other complications of pregnancy
106	preopdur_90t180d_others_cnt	5.44E-04	90-180	Pre-operation duration
107	posopdur_180t365d_avg	5.17E-04	180-365	Average Post-operation duration
108	diagCCS_365t730d_prevalence_13_cnt	4.91E-04	365-730	CCS group: Chronic obstructive pulmonary & bronchiectasis
109	imd04rk_6	4.84E-04	Trigger	imd04rk: 16241 to 19489
110	gapDays_30t90d_others_cnt	4.40E-04	30-90	Gap-Days
111	imd04rk_5	4.30E-04	Trigger	imd04rk: 12993 to 16241
112	ageTrigger_35	4.22E-04	Trigger	Age: 35-40
113	preopdur_90t180d_avg	4.11E-04	90-180	Average Pre-operation duration
114	operOPCSL1_0t30d_prevalence_8_cnt	4.04E-04	0-30	Operation group: Upper Female Genital Tract
115	ageTrigger_15	4.03E-04	Trigger	Age: 15-20
116	imd04rk_4	4.02E-04	Trigger	imd04rk: 9745 to 12993
117	imd04rk_8	3.96E-04	Trigger	imd04rk: 22737 to 25986
118	diagCCS_180t365d_prevalence_2_cnt	3.93E-04	180-365	CCS group: Essential hypertension
119	imd04rk_7	3.88E-04	Trigger	imd04rk: 19489 to 22737
120	diagCCS_0t30d_prevalence_15_cnt	3.85E-04	0-30	CCS group: Disorders of lipid metabolism
121	mainspef_180t365d_prevalence_6_cnt	3.83E-04	180-365	Main Speciality: Plastic
122	ageTrigger_80	3.75E-04	Trigger	Age: 80-85
123	diagCCS_365t730d_prevalence_5_cnt	3.68E-04	365-730	CCS group: Coronary atherosclerosis & other heart disease
124	ageTrigger_60	3.55E-04	Trigger	Age: 60-65
125	diagCCS_180t365d_prevalence_9_cnt	3.44E-04	180-365	CCS group: Chronic obstructive pulmonary & bronchiectasis
126	imd04rk_9	3.42E-04	Trigger	imd04rk: 25986 to 29234
127	preopdur_365t730d_avg	3.27E-04	365-730	Average Pre-operation duration
128	admimeth_30t90d_prevalence_2_cnt	3.23E-04	30-90	Admission method: Elective
129	diagCCS_365t730d_prevalence_3_cnt	3.15E-04	365-730	CCS group: Essential hypertension
130	ageTrigger_30	3.12E-04	Trigger	Age: 30-35
131	operOPCSL1_0t30d_prevalence_4_cnt	3.11E-04	0-30	Operation group: Diagnostics & Tests
132	diagCCS_0t30d_prevalence_30_cnt	3.05E-04	0-30	CCS group: Thyroid disorders
133	ethnos_3	3.02E-04	Trigger	ethnicity: Pakistani
134	operOPCSL1_0t30d_prevalence_2_cnt	2.99E-04	0-30	Operation group: Miscellaneous Operations
135	diagCCS_365t730d_prevalence_2_cnt	2.96E-04	365-730	CCS group: Residual codes; unclassified
136	mainspef_180t365d_prevalence_4_cnt	2.87E-04	180-365	Main Speciality: Geriatric
137	diagCCS_0t30d_prevalence_27_cnt	2.79E-04	0-30	CCS group: Other nervous system disorders

Table A.7

(Continued)

#	Name	Weight	Temporal	Definition
138	admimeth_90t180d_prevalence_2_cnt	2.73E-04	90-180	Admission method: Elective
139	diagCCS_365t730d_prevalence_28_cnt	2.71E-04	365-730	CCS group: Cataract
140	ageTrigger_45	2.57E-04	Trigger	Age: 45-50
141	ethnos_9	2.39E-04	Trigger	ethnicity: Any other
142	diagCCS_365t730d_prevalence_6_cnt	2.36E-04	365-730	CCS group: Diabetes mellitus without complication
143	operOPCSL1_365t730d_others_cnt	2.36E-04	365-730	Operation group: Others
144	mainspef_90t180d_prevalence_5_cnt	1.95E-04	90-180	Main Speciality: Maternity
145	diagCCS_180t365d_prevalence_20_cnt	1.95E-04	180-365	CCS group: Other complications of pregnancy
146	diagCCS_365t730d_prevalence_29_cnt	1.94E-04	365-730	CCS group: Other birth complications; mother's puerperium
147	mainspef_90t180d_prevalence_3_cnt	1.78E-04	90-180	Main Speciality: Gynaecology
148	diagCCS_365t730d_prevalence_9_cnt	1.74E-04	365-730	CCS group: Abdominal pain
149	mainspef_30t90d_prevalence_2_cnt	1.69E-04	30-90	Main Speciality: Maternity
150	mainspef_30t90d_prevalence_1_cnt	1.68E-04	30-90	Main Speciality: General
151	ageTrigger_50	1.68E-04	Trigger	Age: 50-55
152	operOPCSL1_365t730d_prevalence_4_cnt	1.67E-04	365-730	Operation group: Upper Female Genital Tract
153	ageTrigger_20	1.65E-04	Trigger	Age: 20-25
154	mainspef_180t365d_prevalence_5_cnt	1.64E-04	180-365	Main Speciality: A&E
155	gapDays_0t30d_avg	1.64E-04	0-30	Average Gap-Days
156	posopdur_90t180d_avg	1.64E-04	90-180	Average Post-operation duration
157	diagCCS_90t180d_prevalence_2_cnt	1.56E-04	90-180	CCS group: Essential hypertension
158	diagCCS_365t730d_prevalence_20_cnt	1.54E-04	365-730	CCS group: Administrative/social admission
159	operOPCSL1_0t30d_prevalence_16_cnt	1.51E-04	0-30	Operation group: Lower Female Genital Tract
160	diagCCS_30t90d_prevalence_5_cnt	1.50E-04	30-90	CCS group: Other complications of pregnancy
161	diagCCS_90t180d_prevalence_1_cnt	1.45E-04	90-180	CCS group: Others
162	diagCCS_180t365d_prevalence_28_cnt	1.38E-04	180-365	CCS group: Congestive heart failure; nonhypertensive
163	preopdur_180t365d_avg	1.37E-04	180-365	Average Pre-operation duration
164	diagCCS_365t730d_prevalence_14_cnt	1.34E-04	365-730	CCS group: Other lower respiratory disease
165	operOPCSL1_180t365d_others_cnt	1.34E-04	180-365	Operation group: Others
166	mainspef_90t180d_prevalence_6_cnt	1.28E-04	90-180	Main Speciality: A&E
167	diagCCS_365t730d_prevalence_30_cnt	1.24E-04	365-730	CCS group: Fetal distress & abnormal forces of labor
168	diagCCS_365t730d_prevalence_16_cnt	1.20E-04	365-730	CCS group: Complication of device; implant or graft
169	diagCCS_90t180d_prevalence_17_cnt	1.19E-04	90-180	CCS group: Normal pregnancy and/or delivery
170	ethnos_7	1.18E-04	Trigger	ethnicity: Black - Other
171	diagCCS_180t365d_prevalence_8_cnt	1.14E-04	180-365	CCS group: Abdominal pain
172	diagCCS_365t730d_prevalence_11_cnt	1.13E-04	365-730	CCS group: Other gastrointestinal disorders
173	operOPCSL1_0t30d_prevalence_5_cnt	1.08E-04	0-30	Operation group: Urinary
174	diagCCS_30t90d_prevalence_12_cnt	1.08E-04	30-90	CCS group: Normal pregnancy and/or delivery
175	ageTrigger_55	1.07E-04	Trigger	Age: 55-60
176	mainspef_180t365d_prevalence_9_cnt	1.00E-04	180-365	Main Speciality: Maternity
177	diagCCS_90t180d_prevalence_7_cnt	9.95E-05	90-180	CCS group: Chronic obstructive pulmonary & bronchiectasis
178	ageTrigger_75	9.56E-05	Trigger	Age: 75-80
179	diagCCS_180t365d_prevalence_4_cnt	9.53E-05	180-365	CCS group: Coronary atherosclerosis & other heart disease
180	diagCCS_365t730d_prevalence_10_cnt	9.40E-05	365-730	CCS group: Other upper respiratory disease
181	diagCCS_365t730d_prevalence_8_cnt	9.34E-05	365-730	CCS group: Asthma
182	ageTrigger_40	9.26E-05	Trigger	Age: 40-45
183	diagCCS_90t180d_prevalence_3_cnt	9.12E-05	90-180	CCS group: Residual codes; unclassified

Table A.7

(Continued)

#	Name	Weight	Temporal	Definition
184	diagCCS_90t180d_prevalence_15_cnt	8.65E-05	90-180	CCS group: Other upper respiratory disease
185	diagCCS_365t730d_prevalence_22_cnt	8.55E-05	365-730	CCS group: OB-related trauma to perineum & vulva
186	diagCCS_365t730d_prevalence_18_cnt	8.52E-05	365-730	CCS group: External cause codes: Fall
187	diagCCS_180t365d_prevalence_19_cnt	8.33E-05	180-365	CCS group: Normal pregnancy and/or delivery
188	ethnos_6	8.31E-05	Trigger	ethnicity: Black - African
189	diagCCS_180t365d_prevalence_5_cnt	7.85E-05	180-365	CCS group: Diabetes mellitus without complication
190	diagCCS_365t730d_prevalence_26_cnt	7.83E-05	365-730	CCS group: Genitourinary symptoms & ill-defined conditions
191	diagCCS_365t730d_prevalence_15_cnt	7.72E-05	365-730	CCS group: Phlebitis; thrombophlebitis & thromboembolism
192	diagCCS_30t90d_prevalence_1_cnt	7.68E-05	30-90	CCS group: Others
193	mainspef_180t365d_prevalence_2_cnt	7.60E-05	180-365	Main Speciality: General Surgery
194	ethnos_2	7.27E-05	Trigger	ethnicity: Indian
195	ethnos_5	6.89E-05	Trigger	ethnicity: Black - Caribbean
196	diagCCS_365t730d_prevalence_21_cnt	6.70E-05	365-730	CCS group: Disorders of lipid metabolism
197	mainspef_90t180d_prevalence_7_cnt	6.49E-05	90-180	Main Speciality: Plastic
198	operOPCSL1_180t365d_prevalence_1_cnt	6.42E-05	180-365	Operation group: Miscellaneous Operations
199	operOPCSL1_365t730d_prevalence_3_cnt	6.26E-05	365-730	Operation group: Female Genital Tract
200	diagCCS_180t365d_prevalence_7_cnt	6.23E-05	180-365	CCS group: Asthma
201	diagCCS_180t365d_prevalence_3_cnt	6.11E-05	180-365	CCS group: Residual codes; unclassified
202	diagCCS_365t730d_prevalence_24_cnt	6.08E-05	365-730	CCS group: Other screening (excl. mental & infectious)
203	diagCCS_90t180d_prevalence_24_cnt	6.04E-05	90-180	CCS group: Alcohol-related disorders
204	diagCCS_180t365d_prevalence_6_cnt	6.03E-05	180-365	CCS group: Cardiac dysrhythmias
205	ageTrigger_70	5.71E-05	Trigger	Age: 70-75
206	diagCCS_90t180d_prevalence_8_cnt	5.54E-05	90-180	CCS group: Abdominal pain
207	diagCCS_365t730d_prevalence_23_cnt	5.13E-05	365-730	CCS group: Allergic reactions
208	diagCCS_365t730d_prevalence_17_cnt	5.09E-05	365-730	CCS group: Other connective tissue disease
209	diagCCS_180t365d_prevalence_27_cnt	5.05E-05	180-365	CCS group: Delirium dementia & amnestic & other cognitives
210	operOPCSL1_0t30d_prevalence_7_cnt	4.98E-05	0-30	Operation group: Soft Tissue
211	diagCCS_180t365d_prevalence_16_cnt	4.98E-05	180-365	CCS group: Disorders of lipid metabolism
212	ageTrigger_65	4.85E-05	Trigger	Age: 65-70
213	ethnos_4	4.84E-05	Trigger	ethnicity: Bangladeshi
214	diagCCS_365t730d_prevalence_19_cnt	4.78E-05	365-730	CCS group: Urinary tract infections
215	mainspef_30t90d_prevalence_8_cnt	4.69E-05	30-90	Main Speciality: Plastic
216	operOPCSL1_365t730d_prevalence_2_cnt	4.59E-05	365-730	Operation group: Urinary
217	diagCCS_180t365d_prevalence_17_cnt	4.57E-05	180-365	CCS group: External cause codes: Fall
218	diagCCS_365t730d_prevalence_25_cnt	4.10E-05	365-730	CCS group: Other nervous system disorders
219	diagCCS_180t365d_prevalence_25_cnt	4.03E-05	180-365	CCS group: Administrative/social admission
220	diagCCS_365t730d_prevalence_27_cnt	3.87E-05	365-730	CCS group: Deficiency & other anemia
221	diagCCS_180t365d_prevalence_26_cnt	3.70E-05	180-365	CCS group: Genitourinary symptoms & ill-defined conditions
222	mainspef_90t180d_prevalence_2_cnt	3.64E-05	90-180	Main Speciality: General Surgery
223	diagCCS_180t365d_prevalence_12_cnt	3.63E-05	180-365	CCS group: Phlebitis; thrombophlebitis & thromboembolism
224	diagCCS_90t180d_prevalence_5_cnt	3.61E-05	90-180	CCS group: Diabetes mellitus without complication
225	gapDays_0t30d_others_cnt	3.42E-05	0-30	Gap-Days
226	diagCCS_180t365d_prevalence_13_cnt	3.30E-05	180-365	CCS group: Complication of device; implant or graft

Table A.7

(Continued)

#	Name	Weight	Temporal	Definition
227	diagCCS_180t365d_prevalence_30_cnt	3.30E-05	180-365	CCS group: Mood disorders
228	diagCCS_180t365d_prevalence_24_cnt	3.23E-05	180-365	CCS group: Alcohol-related disorders
229	operOPCSL1_365t730d_prevalence_1_cnt	2.98E-05	365-730	Operation group: Miscellaneous Operations
230	preopdur_30t90d_avg	2.90E-05	30-90	Average Pre-operation duration
231	diagCCS_30t90d_prevalence_3_cnt	2.76E-05	30-90	CCS group: Residual codes; unclassified
232	diagCCS_90t180d_prevalence_20_cnt	2.71E-05	90-180	CCS group: Congestive heart failure; nonhypertensive
233	diagCCS_180t365d_prevalence_11_cnt	2.68E-05	180-365	CCS group: Other upper respiratory disease
234	operOPCSL1_0t30d_prevalence_12_cnt	2.66E-05	0-30	Operation group: Mental Health
235	diagCCS_90t180d_prevalence_25_cnt	2.64E-05	90-180	CCS group: Other screening (excl. mental & infectious)
236	diagCCS_30t90d_prevalence_8_cnt	2.53E-05	30-90	CCS group: Abdominal pain
237	diagCCS_180t365d_prevalence_10_cnt	2.51E-05	180-365	CCS group: Other gastrointestinal disorders
238	operOPCSL1_365t730d_prevalence_6_cnt	2.25E-05	365-730	Operation group: Heart
239	diagCCS_180t365d_prevalence_22_cnt	2.15E-05	180-365	CCS group: Deficiency & other anemia
240	diagCCS_180t365d_prevalence_14_cnt	2.14E-05	180-365	CCS group: Other lower respiratory disease
241	admimeth_0t30d_prevalence_2_cnt	2.11E-05	0-30	Admission method: Elective
242	diagCCS_180t365d_prevalence_29_cnt	2.11E-05	180-365	CCS group: Epilepsy; convulsions
243	mainspef_180t365d_prevalence_8_cnt	2.09E-05	180-365	Main Speciality: Gastroenterology
244	diagCCS_90t180d_prevalence_18_cnt	1.99E-05	90-180	CCS group: Disorders of lipid metabolism
245	operOPCSL1_365t730d_prevalence_5_cnt	1.97E-05	365-730	Operation group: Lower Digestive Tract
246	mainspef_180t365d_prevalence_10_cnt	1.86E-05	180-365	Main Speciality: Urology
247	operOPCSL1_365t730d_prevalence_10_cnt	1.83E-05	365-730	Operation group: Diagnostics & Tests
248	operOPCSL1_365t730d_prevalence_7_cnt	1.72E-05	365-730	Operation group: Upper Digestive Tract
249	operOPCSL1_30t90d_others_cnt	1.60E-05	30-90	Operation group: Others
250	posopdur_30t90d_avg	1.38E-05	30-90	Average Post-operation duration
251	mainspef_90t180d_prevalence_10_cnt	1.36E-05	90-180	Main Speciality: Urology
252	diagCCS_180t365d_prevalence_23_cnt	1.18E-05	180-365	CCS group: Other nervous system disorders
253	operOPCSL1_180t365d_prevalence_2_cnt	1.13E-05	180-365	Operation group: Urinary
254	operOPCSL1_90t180d_others_cnt	1.06E-05	90-180	Operation group: Others
255	mainspef_90t180d_prevalence_4_cnt	9.57E-06	90-180	Main Speciality: Geriatric
256	diagCCS_180t365d_prevalence_15_cnt	9.27E-06	180-365	CCS group: Urinary tract infections
257	diagCCS_30t90d_prevalence_20_cnt	7.40E-06	30-90	CCS group: Other screening (excl. mental & infectious)
258	diagCCS_30t90d_prevalence_9_cnt	6.74E-06	30-90	CCS group: Chronic obstructive pulmonary & bronchiectasis
259	operOPCSL1_90t180d_prevalence_1_cnt	6.66E-06	90-180	Operation group: Miscellaneous Operations
260	diagCCS_180t365d_prevalence_18_cnt	5.75E-06	180-365	CCS group: Other connective tissue disease
261	diagCCS_90t180d_prevalence_4_cnt	5.75E-06	90-180	CCS group: Coronary atherosclerosis & other heart disease
262	diagCCS_90t180d_prevalence_22_cnt	5.58E-06	90-180	CCS group: Other connective tissue disease
263	diagCCS_90t180d_prevalence_11_cnt	5.30E-06	90-180	CCS group: Other gastrointestinal disorders
264	operOPCSL1_180t365d_prevalence_5_cnt	5.27E-06	180-365	Operation group: Upper Female Genital Tract
265	mainspef_180t365d_prevalence_7_cnt	4.97E-06	180-365	Main Speciality: Cardiothoracic
266	mainspef_30t90d_prevalence_3_cnt	4.60E-06	30-90	Main Speciality: General Surgery
267	diagCCS_90t180d_prevalence_12_cnt	4.38E-06	90-180	CCS group: Other lower respiratory disease
268	mainspef_30t90d_prevalence_4_cnt	4.26E-06	30-90	Main Speciality: Gynaecology
269	diagCCS_30t90d_prevalence_19_cnt	4.23E-06	30-90	CCS group: Congestive heart failure; nonhypertensive
270	diagCCS_30t90d_prevalence_14_cnt	4.16E-06	30-90	CCS group: Complication of device; implant or graft
271	mainspef_30t90d_prevalence_6_cnt	4.15E-06	30-90	Main Speciality: A&E

Table A.7

(Continued)

#	Name	Weight	Temporal	Definition
272	diagCCS_90t180d_prevalence_19_cnt	3.96E-06	90-180	CCS group: External cause codes: Fall
273	operOPCSL1_180t365d_prevalence_3_cnt	3.58E-06	180-365	Operation group: Lower Digestive Tract
274	operOPCSL1_180t365d_prevalence_12_cnt	3.58E-06	180-365	Operation group: Mental Health
275	diagCCS_30t90d_prevalence_10_cnt	3.48E-06	30-90	CCS group: Other gastrointestinal disorders
276	diagCCS_90t180d_prevalence_29_cnt	3.48E-06	90-180	CCS group: Other nervous system disorders
277	diagCCS_90t180d_prevalence_14_cnt	3.27E-06	90-180	CCS group: Complication of device; implant or graft
278	diagCCS_30t90d_prevalence_7_cnt	2.94E-06	30-90	CCS group: Cardiac dysrhythmias
279	operOPCSL1_365t730d_prevalence_8_cnt	2.88E-06	365-730	Operation group: Soft Tissue
280	diagCCS_90t180d_prevalence_13_cnt	2.58E-06	90-180	CCS group: Phlebitis; thrombophlebitis & thromboembolism
281	operOPCSL1_90t180d_prevalence_2_cnt	1.66E-06	90-180	Operation group: Urinary
282	diagCCS_180t365d_prevalence_21_cnt	1.65E-06	180-365	CCS group: Allergic reactions
283	operOPCSL1_180t365d_prevalence_8_cnt	1.24E-06	180-365	Operation group: Female Genital Tract
284	diagCCS_90t180d_prevalence_6_cnt	9.76E-07	90-180	CCS group: Cardiac dysrhythmias
285	diagCCS_90t180d_prevalence_30_cnt	9.27E-07	90-180	CCS group: Mood disorders
286	diagCCS_30t90d_prevalence_4_cnt	8.25E-07	30-90	CCS group: Coronary atherosclerosis & other heart disease
287	operOPCSL1_0t30d_prevalence_9_cnt	7.08E-07	0-30	Operation group: Upper Digestive Tract
288	diagCCS_30t90d_prevalence_6_cnt	1.63E-07	30-90	CCS group: Diabetes mellitus without complication

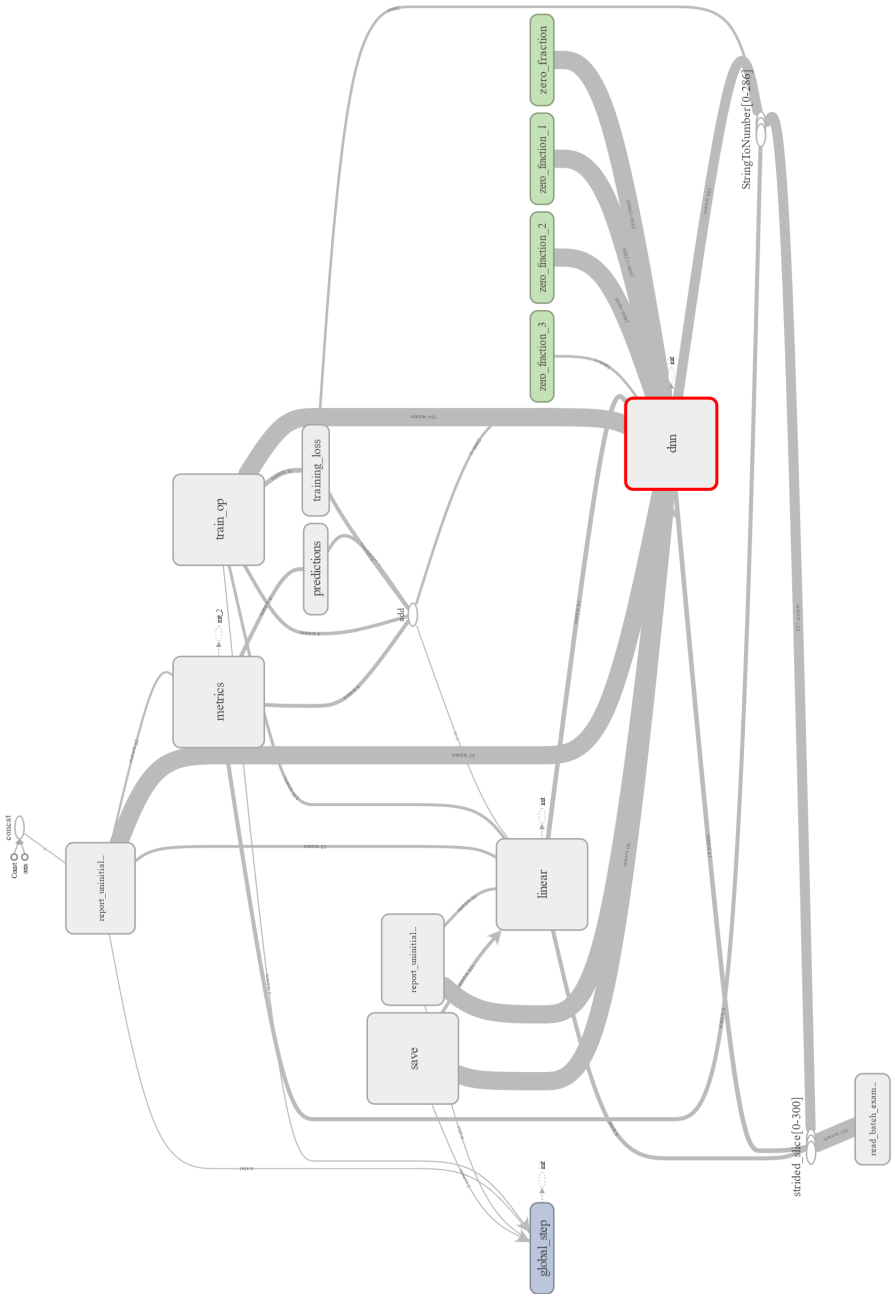

Fig. A.3. The TensorBoard Graph Visualisation of the designed WDNN.

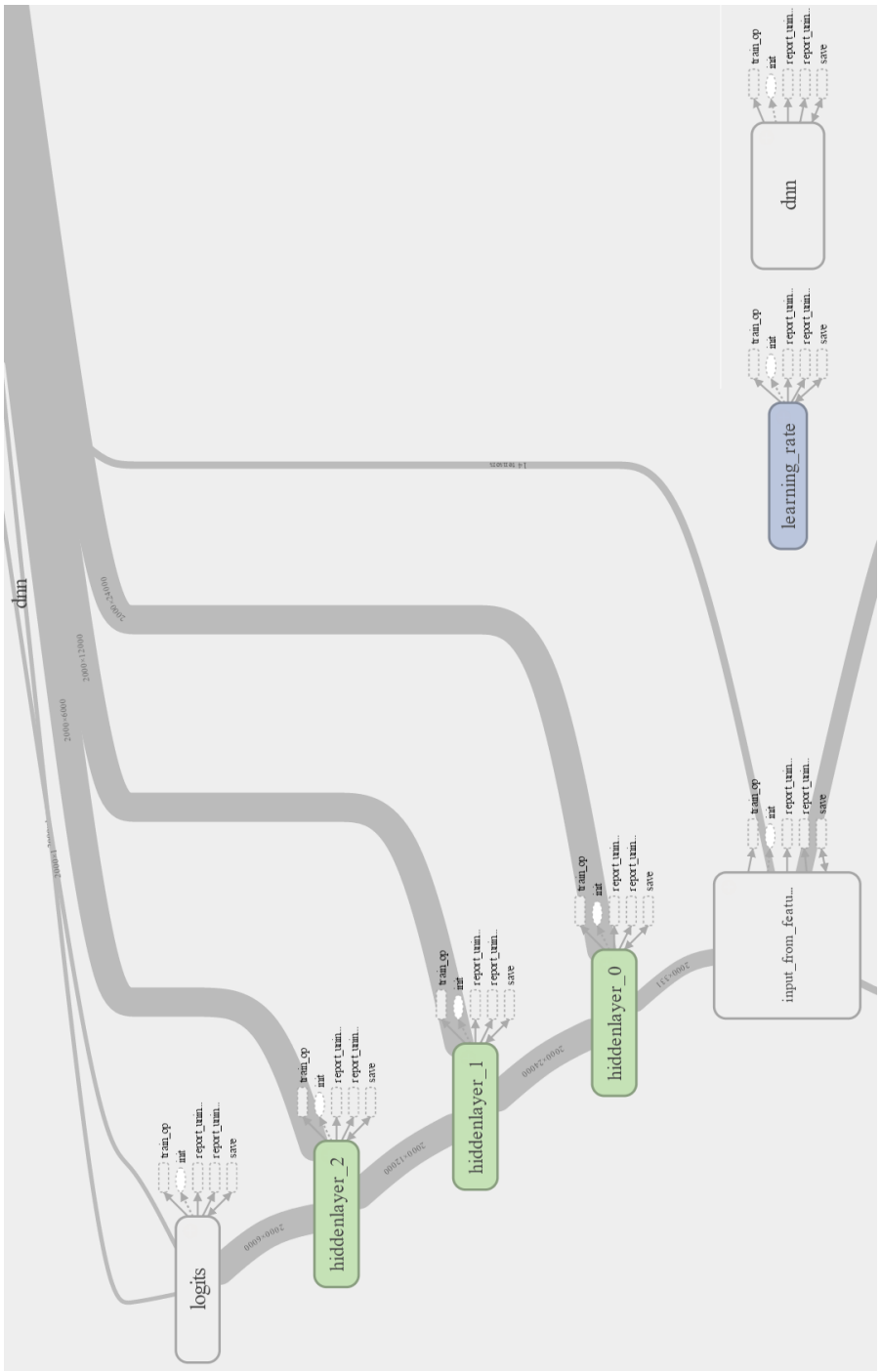

Fig. A.4. The TensorBoard Graph Visualisation of the deep part of the designed WDNN.

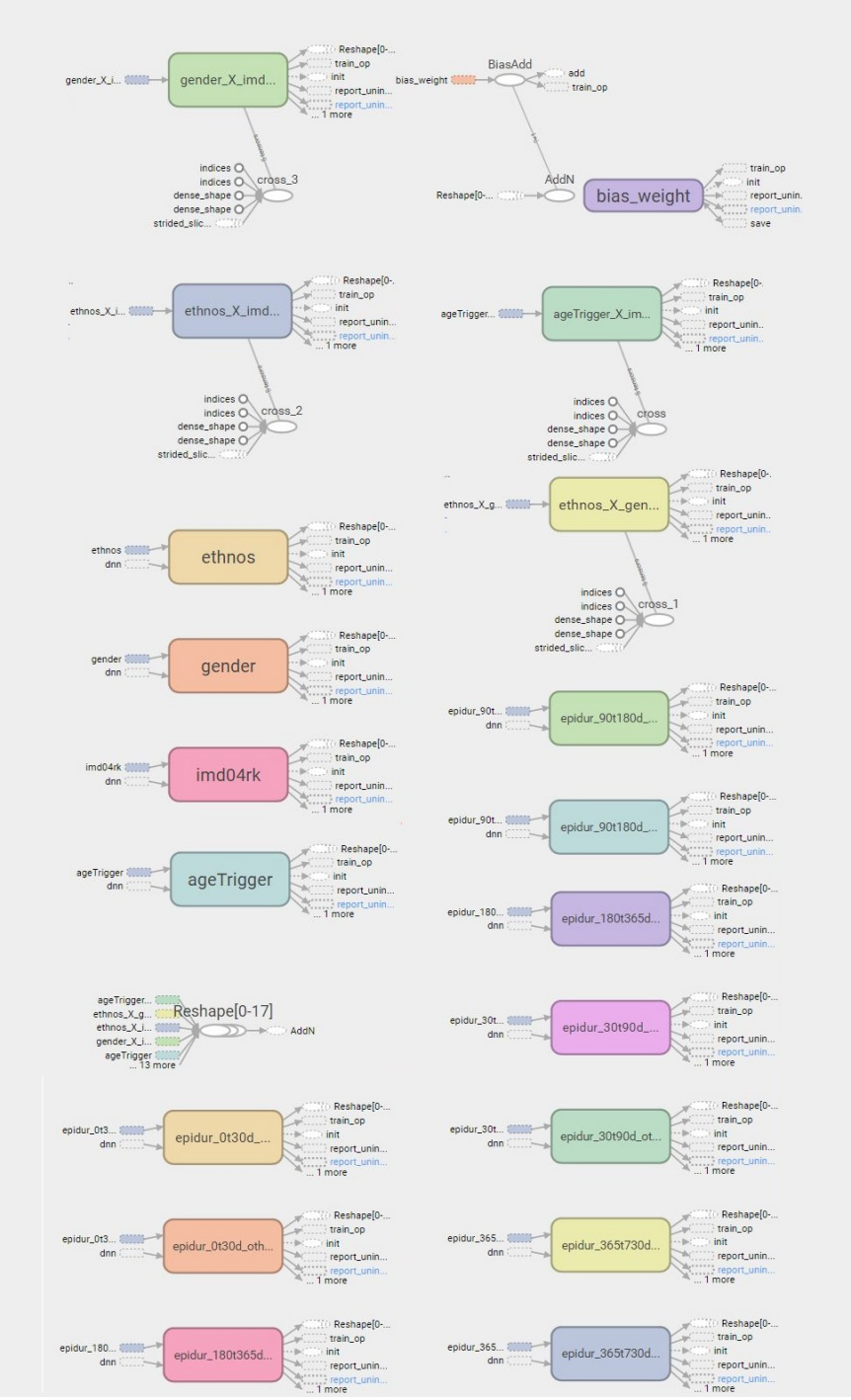

Fig. A.5. The TensorBoard Graph Visualisation of the linear part of the designed WDNN.