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Predictive Risk Modelling for Integrated Care: a Structured Review

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***Abstract*—If patients at risk of admission or readmission to hospital or other forms of care could be identified and offered suitable early interventions then their lives and long-term health may be improved by reducing the chances of future admission or readmission to care, and hopefully, their cost of care reduced.**

Considerable work has been carried out in this subject area especially in the USA and the UK. This has led for instance to the development of tools such as PARR, PARR-30, and the Combined Predictive Model for prediction of emergency readmission or admission to acute care.

Here we perform a structured review the academic and grey literature on predictive risk tools for social care utilisation, as well as admission and readmission to general hospitals and psychiatric hospitals. This is the first phase of a project in partnership with Docobo Ltd and funded by Innovate UK, in which we seek to develop novel predictive risk tools and dashboards to assist commissioners in Clinical Commissioning Groups with the triangulation of the intelligence available from routinely collected data to optimise integrated care and better understand the complex needs of individuals.

***Keywords*-Admission, Readmission, Hospital, Social Care, Mental Care, Predictive Risk, Integrated Care**

I. Introduction

After the controversies of the 2012 Heath and Social Care Act [1], the focus has been on the development of new predictive models for integrated care. The strategic five-year forward view of the NHS [2] outlines multiple delivery models, which are aimed to improve care and drive productivity by aligning and integrating hospital care, social care, community care, mental health and primary care. The main focus is on two models: Primary and Acute Care Systems, which is developed for hospitals, and Multi-speciality Community Providers, which is lead by primary care. The NHS, Commissioners and other providers cooperatively design services based on a model of cohort-specific integrated care with their own exemplars, risks, benefits and transition cost. Also, service providers will become responsible for a capitated budget for local population health and community services.

This structured review was carried out by the Health and Social Care Modelling Group (HSCMG) at the University of Westminster in partnership with Docobo Ltd to review recent predictive modellings for social care utilisation and admission and readmission to general hospitals and psychiatric hospitals. The focus of this review was on generic risk factors and risk prediction approaches to identify people who are at risk of poorer health outcome and enable efficient integrated care delivery.

Based on the rapid review of both gray and peer-reviewed literature using MEDLINE, Web of Science and Google Scholar, we identified eighty-three studies after removing duplicates and irrelevant publications. The review was conducted using records until September 2015, with search terms including admission, readmission, hospital, General Practitioner (GP), inpatient, outpatient, social care, mental (psychological or psychiatric), A&E (emergency department or emergency room) and comorbidity (morbidity, multi-morbidity, Charlson or Elixhauser). The majority of these researches were carried out in the United Kingdom (UK) and North America.

The main content is divided into five sections. Firstly, the predictive modelling problem is defined. Afterwards, the predictive models in social care, mental care and hospital are reviewed. Thereafter, the correlated variables are summarised. Furthermore, main risk scoring methods are briefly reviewed. Finally, a summary of this study is presented.

II. Problem

The main goal of this project was to develop and validate a new health and social care predictive risk model for integration into the Docobo's ARTEMUS-ICS system. ARTEMUS-ICS is a health analytics and risk stratification system, which will support Integrated Care delivery by identifying complex patients with a range of health and social needs. Also, ARTEMUS-ICS allows multidisciplinary teams to analyse health and utilisation information to create a holistic view of their populations. The area covered by this research was Horsham and Mid Sussex Clinical Commissioning Group (CCG) and Crawley CCG, that has a population of about 345,000 registered patients, with significant variations in population health status and deprivations [3].

III. Models

A. Social Care Models

In England and Wales, social care services are provided to individuals who are in need of practical support as a result of illness, disability, old age or a low income. Social care services can take a variety of forms, including but not limited to having assistance at home to help an individual live more independently and access to specialist equipment. In contrast to services provided through the health care system, these services are not necessarily available free at the point of use. In fact, individuals are assessed to determine the degree of their needs together with their financial circumstances and ability to fund all or part of the care they require.

For the financial year 2014-15, it was reported that there were over 1.8 million requests for social support from individuals not already in receipt of support. Of these requests, 72% were from individuals aged 65 years and above [4]. Overall 41% of these new requests resulted in the individual being offered some form of social care services leading to approximately 304,000 new ongoing low-level support packages, 218,000 short term but intensive packages and 144,000 long-term support packages. Individuals aged 65 and over accounted for 68% of all individuals accessing long-term support in various settings, like nursing and residential homes.

In light of the increased preventative social care strategy in England and Wales, together with a broader international challenge to offer care and support to older people, there has been a shift towards a more proactive approach towards identifying the care needs of the elderly [5]. One such strand of research examines the factors that drive social care usage at the individual level across a range of different services. Such studies are often linked with the assumption that an earlier social care intervention strategy, based on well-defined patient characteristics, can help individuals to live independently for longer and ultimately at a lower cost to society as a whole.

B. Hospital Models

The main driving force behind emergency readmission [6] is inappropriate care support for high-risk patients [7]. It was estimated that the cost of emergency admissions to the NHS in England is about £11 billion per year [8]. According to a retrospective study by Clarke et al. [7], about half of the 30-day emergency readmissions were potentially preventable between 2004 and 2010.

Emergency rates of admission for ambulatory or primary care sensitive (ACS) and non-ACS conditions are rising at a comparable rate, and there is no explanation for the causes. According to a recent study by the Nuffield Trust [9], ACS conditions make up for about 20% of all emergency admissions (2001 to 2013).

In 2005, the Patients at Risk of Re-hospitalisation (PARR) [10] algorithm and PARR++ software for Primary Care Trusts were commissioned by the UK Department of health (DoH) [8]. The objective of PARR was to classify individuals based on the risk of emergency readmission to a hospital within a year using the inpatient data from the Hospital Episode Statistics (HES) database. The produced PARR model was very similar to PRISM for the NHS Wales and SPARRA for the NHS Scotland. Then, in 2006 to address the need for identifying patients at risk of admission to hospital, the Combined Predictive Model (CPM) was released by the DoH [11].

Thereafter, an upgrade from the PARR and CPM models was commissioned by the DoH in 2011 [12], and the Patients at Risk of Readmission within 30 days (PARR-30) model was developed. The PARR-30 was based on a broad range of measures used in the PARR and was aimed to predict the risk of 30-day readmission to acute hospitals.

C. Mental Health Models

Mental health services in England have to provide care services for children and adults with various mental health needs, like psychosis conditions, drugs and alcohol services and dementia. These services may be organised differently from one local area to another and be age and/or mental health condition specific [13].

At the end of July 2015, 922,001 people were in contact with mental health services including 22,608 people in psychiatric units [14]. These patients may be:

- Voluntary patients who agree to be admitted;
- Compulsory patients were admitted under the Mental Health Act (i.e. against their wishes if it is in the interests of their health and safety, or to protect others).

Within this context, a review report commissioned by the DoH [15] acknowledged that the relationship between readmission rate and quality of care can be complex, as for severely ill patients multiple re-admissions may help them to engage in treatment which might not be possible otherwise. However, several studies stated that high readmission rates, more particularly within 30 days of discharge, can be quite disruptive to patients and their families and costly [16] [17].

To our knowledge, few UK studies attempted to identify predictors of (re-)admissions to psychiatric units (or hospitals) as the major challenge is the availability and accessibility of relevant data. In 2008, the Information Services Division Scotland developed a risk predictive tool similar to SPARRA to identify individuals at risk of readmission to psychiatric units, namely SPARRA Mental Disorder (Scottish Patients at Risk of Readmission and Admission (to psychiatric hospitals or units) [18].

IV. Correlated Variables

Table I presents correlated variables to admission risk based on selected studies.

V. Risk Scoring Indices

A. Comorbidities

Adjustment for comorbidity is common in clinical outcome risk adjustment. Two most common measures [19] are Charlson Comorbidity Index (CCI) [20] and Elixhauser Comorbidity Index (ECI) [21], which are used for predicting admission and mortality. There have been revised versions of CCI and ECI, including the most recent CCI updates by

Table I
CORRELATED VARIABLES

Category	Examples
Case mix group of diagnoses	Patterns of Morbidity with Adjusted Clinical Groups, chronic condition with Expanded Diagnosis Clusters, diagnosis categorisation, ACS, frequent comorbidities & chronic conditions.
Case mix group of operations	National Clinical Coding Standards (OPCS) classification, & Agency for Healthcare Research and Quality (AHRQ) procedure categorisation.
Insurance & medical claims	Grouping clinically similar treatments with Healthcare Resource Groups (HRGs).
Demographics	Age, race, gender, & marital.
Deprivations	Index of Multiple Deprivation (IMD), which includes: income, employment, health & disability, education, skills & training, barriers to housing & services, living environment, & crime.
Times, types, consultations, sources, waiting & length-of-stays for admissions or discharges	Using clinically homogeneous units that describe complete episodes of care using Optum Episode Treatment Groups, the number of emergency admissions in different timeframes, & types and the number of specialities.
Geographical location of patient & care provider	Type & location of hospital & population estimates of local authorities.
Physical condition	Functional physical activities, & general health.
Social care status	Skilled nursing facility, rehab, hospice & palliative care.
Psychological health, emotional state & social functioning	Social isolation, loneliness, physical activities, life satisfaction, anxiety & depression, quality of life, & general mental health.
Clinical indicators, treatments, medications & compliance	Lab test results, & prescribed medications.
Risk indices	A version of Charlson comorbidity index & Elixhauser comorbidity index.

Dr. Foster [22] and bottle et al. [23], and AHRQ adaptation of ECI [24].

Moreover, ACS conditions [9] are seen as potentially avoidable, and are highly correlated to multiple admissions over time and quality of care [25]. Also, there have been other attempts to cluster conditions based on factors, like length-of-stay and severity, such as John Hopkin's Aggregated Diagnosis Groups and Selection of Multipurpose Australian Comorbidity Scoring System [26]. Moreover, another approach to comorbidity scoring is using a cost function, like UK's HRG [27], and the Centre for Medicare and Medicaid Services Hierarchical Condition Category (CMS-HCC) [28].

However, use of comorbidity scoring in predictive models is sometimes criticised. Criticisms stem from using unrepresentative timeframes and population, coding inaccuracy of diagnoses, the inconsistency of cost functions, implementing additive risk model and not adjusting for important factors, such as age, gender, deprivations and length-of-stay.

B. Operations and Procedures

Moreover, there is an increasing evidence that quantification of high-risk operations and procedures with adequate adjustment can greatly improve mortality and readmission models [29]–[31]. But, unlike comorbidity, there is no generic risk model for operations and procedures, and the categorisations are mainly done based on clinical groups. In the UK, NHS uses OPCS [32], and AHRQ's procedure categorisation scheme is used in the USA [33].

Nonetheless, there have been attempts to define a scoring mechanism for patients with specific conditions, such as the Royal College of Surgeons Charlson Score [34], EuroSCORE [35] and the model developed by Aktuerk et al. [36] using HES.

In addition, there are a number of cost grouping models besides HRG and CMS-HCC, which are more detailed, like Bupa Operative Severity Score [37] and Surgical Outcome Risk Tool [38].

C. Frailty

Frailty is one of the main problematic expression of elderly and it develops as a consequence of ageing. The time that is spent in poor general health, a limiting chronic health or disability, can be attributed to frailty in some cases. Frailty can be defined as a state of high vulnerability and the decreased ability to sustain homeostasis, which is correlated with high risk of adverse outcome including falls, delirium, immobility and disability, incontinence and susceptibility to medications side effect [39].

Frailty considerably changes care utilisation pattern due to a significant increase in risks of comorbidity [40]–[42] and adverse outcomes, such as fall, post-operative complications, disability, mortality, prolonged length-of-stay, readmission and institutionalisation. Therefore, there is a considerable benefit in identifying these patients and proactively planning their care to enable rapid control of symptoms and prioritisation of anticipated needs.

There are three major instruments in modelling frailty: frailty phenotype model introduced by Fried et al. [40] (5 parameters), Canadian Study of Health and Ageing Frailty Index (FI) by Rockwood et al. [43] (92 parameters) and the Yorkshire and Humber Academic Health Science Network's electronic Frailty Index (eFI) [44] (36 parameters). The eFI was developed in the UK using GP data, and currently available via SystemOne primary care software in some areas.

Also, it has been shown that more manageable 30 parameters of FI model [45], simpler models with minimal overlap in identification [46] or existing electronic health record data can have competitive predictive validity [44].

D. Social Isolation

Socially isolated individuals are typically two to five times more likely to die prematurely. Social isolation is an objective measure of the number of interactions a person has in social life, and it is closely related to loneliness, which is more subjective.

Social isolation and loneliness have no age boundary; but, it is more likely to appear in older age, such as bereavement, illness, physical or mental disability [47]. Also, findings from the English Longitudinal Study of Ageing [48] shows that disadvantaged socioeconomic groups are less likely to participate in social activities and volunteering.

In the UK, the DoH has developed at set of 39 indicators [49] to address both short and long-term health inequalities. In addition, the Quality and Outcomes Framework came into place to address the health inequalities needs in primary care, and were defined based on the prevalence of disease and deprivations. Also, the introduction of Health Impact Assessments [50] process allowed local authorities to assess the health effects of all relevant council policies, decisions and investments.

Moreover, varieties of measurement tools were developed to assess social integration, social networks and social support. The assessment tools may be categorised into four main criteria: social relations, social support, negative relationships and loneliness [51].

Firstly, social relation measures, such as Social Network Index, Social Relationships and Activity and Social Contacts and Resources, mainly assess social ties and social integration.

Secondly, the social network category formally assesses aspects of social network structures and are mainly used in epidemiology, psychology and most recently in healthcare. Two examples of social network measures are Egocentric Network Name generators and Qualitative Network Measures.

Thirdly, the social support measures usually assess several types of supports including emotional, instrumental, financial and appraisal. It includes measures, such as Lubben Social Network Scale [52], Multidimensional Scale of Perceived Social Support (MSPSS) [53], Social Support Questionnaire, Norbeck Social Support Questionnaire, Medical Outcomes Study Social Support Survey and Duke Social Support Index. Lubben and MSPSS have shown to be relatively reliable and consistent.

Fourthly, there are types of social relationships that have a negative influence on health, network structure and social behaviours, such as childhood trauma stemming from abuse, marital quality and regulation of contact with an infectious disease. Examples of negative relationships measurements are Positive and Negative Social Scale Exchanges, Inventory of Negative Social Interactions and Social Undermining Scale.

Finally, the measurements in the loneliness category assess loneliness in terms of quantity and quality of social life. Most of the measurements are based on the Lubben version of the UCLA Loneliness Scale [54] and includes feeling isolated, being part of a group and having someone talk to.

E. Other Markers

Other special population markers can be used including disability conditions, pregnancy states, other complications and adverse outcome, diagnosis specific, other psychological conditions and other care specific models. An example is JBS3 [55], which is used for prevention of cardiovascular disease. More details about common clinical scoring practices can be found online from the NHS England and Hippo Education team [56].

VI. Conclusion

In this rapid review, recent predictive modellings for social care utilisation and admission and readmission to general and psychiatric hospitals were highlighted. Major risk factors and risk prediction approaches were discussed. Then, risk scoring methods were briefly summarised, including comorbidities, operations, procedures, frailty and social isolation.

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