CONNECTED HEALTH CITIES
A nhsa project

Greater Manchester Connected Health City (GM CHC)

Building Rapid Interventions to reduce antimicrobial resisTance and overprescribing of antibiotics (BRIT)

BRIT Dashboard Manual

Users: General Practitioners (GPs), GP Research Leads, General Practice Managers, Quality and Safety Pharmacists, Medicines Optimisation Pharmacists, Nurse Practitioners, Public Health Consultants

Content

1.Introduction

1.1 Purpose of the manual

The purpose of this manual is to enable users to obtain information on the utility of data driven approaches that are used to formulate an understanding of antibiotic prescribing behaviour across General Practice in the region.

The manual provides brief explanation about how data analytics on smart dashboards examine prescribing in the UK, using data obtained from General Practices. The manual functions as a transparent guide to explain how the analytics on the dashboards are derived including the associated statistical rationale.

1.2 Antibiotic prescribing in General Practice

The challenges of antibiotic prescribing are well documented, and include: perceived patient demand for an antibiotic for each bacterial infection; the use of policy guidelines often based on out-dated analysis and symptom scores; and health targets based on overall prescribing levels in General Practices rather than on establishing the most optimal use of antibiotics for particular patients.

A platform (BRIT dashboard) has been created in order to enable the rapid assessment of progress to targets, comparisons of antibiotics prescribing performance against local data, and the sharing of best practice in antimicrobial stewardship to improve antibiotic prescribing.

1.3 The BRIT dashboard: Feedback on prescribing

Connected Health Cities (CHC) is a three-year Department of Health funded programme, which aims to improve the health and wealth of the North of England through better use of healthcare data and citizen information. The Greater Manchester Connected Health City (GM CHC) integrates innovations in data science, clinical applications and patient care within a single co-creation entity – in a region with notable health inequality, providing a real opportunity to have a significant and positive impact on people's lives.

The Building Rapid Interventions to reduce antimicrobial resisTance and overprescribing of antibiotics (BRIT) project is part of GM CHC and aims to develop and implement at scale the infrastructure for collecting and analysing data on antibiotic prescribing, clinical interventions and patient demographics in order to better understand the drivers for antibiotic prescribing and how best to optimise their use. The BRIT dashboards provide detailed analytics on:

- How antibiotic prescribing varies greatly between General Practices by indication and patient characteristics
- Comparison of antibiotic prescription rates with rates of clinical complications (e.g. hospital admissions)
- How the current prescribing is ineffective in targeting of antibiotics to patients at high risk of clinical complications
- Tailored feedback to General Practices on their prescribing and suggestion of what to do
- The provision of detailed insight in regional prescribing patterns to policy makers to enable a better understanding of challenges and opportunities (beyond counting prescriptions in General Practices)
- The need to support evaluation of improvement interventions

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2. Comparing General Practices

Antibiotic prescribing was measured in terms of monthly prescribing volume for each General Practice from electronic health records. Comparisons between General Practices within the same Clinical Commissioning Group (CCG) are performed. This can explain differences between practices in terms of their differing characteristics. The questions chosen are based on a prior analysis of electronic health records that showed difference in antibiotic prescribing between practices that could not be explained by patient characteristics.

2.1 Questions

a. What are the predictors of antibiotic prescribing in General Practices?
b. What is each General Practices' antibiotic prescribing volume compared to other General Practices within the same CCG?

2.2 Why is this important

- To show the prescribing volume of a General Practice compared with other General Practices within the same CCG.
- To highlight characteristics and risk factors that explain prescribing volume difference across General Practices
- To show the relative contribution of risk factors such as prescribing variation for General Practices in the UK
- To reduce the overall prescribing volume by acting on the predictors of antibiotic prescribing under the General Practices' control

2.3 Methods

Study population: patients of any age who were registered with a General Practice.

Follow-up: one year

Outcome: average prescription counts in each General Practice

a. **General Practice Prescribing Performance:** Rates and Percentages

b. **Model for Predictors of Prescribing:** Negative binomial regression

Predictors: General Practice location, total number of registered patients in each calendar year, age, sex, ethnicity, socio-economic deprivation, body mass index (BMI), smoking status, Charlson co-morbidity index, average appointment duration, number of GPs per thousand consultations, proportion of patients administered flu vaccination in the year before, the number of consultations and prescriptions in the year before, consultation rates in each General Practice for common infections including lower respiratory tract infections (LRTI), upper respiratory tract infection (URTI), urinary tract infection (UTI), lung and skin infections.

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3. Antibiotic Prescribing Patterns

To understand at what extent antibiotic prescribing varies in the UK there is a need to observe the proportion of consultations that result in antibiotics prescribing per practice. The antibiotic prescribing pattern of each General Practice for each infectious disease and what proportion of this deviates from the guidelines is explained. Thus, dashboard users will be able to identify which infectious conditions are being managed differently between practices.

3.1 Questions

a. What is the variability in antibiotic prescribing for each common infection between General Practices? What percent of consultations are being prescribed an antibiotic for each infectious condition and which antibiotics are prescribed?

b. When the decision to prescribe an antibiotic has been made, what proportion of these antibiotics are appropriate and what percentage deviates from the recommended guidelines?

3.2 Why is this important

a. To compare the prescribing rates between each General Practice for the infectious conditions and identify where a General Practice lies compared to other General Practices and possible areas that may need improving.

b. To understand the proportion of antibiotics being prescribed inappropriately for each infectious condition and identify which antibiotics are prescribed that deviate from the recommended guidelines. Thus, identify areas tailored to each General Practice to further optimise the prescribing of antibiotics.

3.3 Methods

Study population:

a. patients of any age registered with a General Practice

b. patients within General Practice that were prescribed antibiotics during the consultation, but were not prescribed any antibiotics in the last three months.

Follow-up: a year

Outcome: percentage of episodes that would prescribe an antibiotic prescription in each General Practice

Method:

a. Boxplots, Rates and Percentages
b. Rates and Percentages

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4. Patient Risk Profile

Prior analysis using electronic health data records showed that there is no correlation between a patient being prescribed antibiotics and the patient's risk of hospitalisation. Thus, the profile of the patient in risk of hospitalisation after visiting the GP is explored. This helps identify which patients are more likely to be hospitalised when they are not given antibiotics.

4.1 Question

What is a patient's risk of being hospitalised 30 days after they visit a GP with a common infection?

4.2 Why is this important

Based on clinical practice, antibiotics are predominantly prescribed using a symptom based approach. Thus, considering a patient's risk level and the symptoms could potentially result in a more optimal use of antibiotic (and potentially reduce overprescribing).

4.3 Methods

Study population: patients of any age registered with a General Practice

Follow-up: 30 days after the GP consultation for LRTI, Otitis Externa, Otitis Media, Sinusitis, UTI, Asthma/COPD, Skin Infection, URTI + Coughs and Colds.

Event: Hospitalisation

Predictors: Patient's age, BMI, smoking status, gender, ethnicity, number of prescriptions in the previous year, socio-economic status, Charlson score, consultation season, previous year hospitalisation, previous year outpatient referral, flu vaccine in the last year, consultation year and General Practice region.

Type of Model: Cox Proportional Hazards

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5. Infrastructure to enable continuous flow of anonymous primary care data for research purposes

The summary below provides a description of how raw General Practice data is transformed into informative visualisations on the BRIT dashboards.

Every two weeks, an anonymised data feed containing information from consultations that relate to infectious conditions and consultations that result in antibiotic prescription (excluding sensitive consultations) is transferred to our trustworthy research environment by a data provider. Data is then verified and validated to ensure an expected computable format and structure, and processed following the steps outlined below:

Import

The data is loaded from its raw form into the structured database to enable fast and standardised operations.

Translate

Data is then converted into the BRIT data model, so that new data processing applications can be built and tested without the need for actual patient data.

Pre-process

There is a large library of bespoke pre-processing software that analyses the data. Data is translated while maintaining integrity, and inference is derived to get a detailed understanding of how antibiotic prescribing in each General Practice compares to nationally recognised guidelines

Analyse

All relevant data is produced and needs to be prepared for the graphing libraries. The data analysts have written software to enable the conversion of processed data into a visual ready form. This is loaded into the final BRIT database.

Plot

Every time a primary healthcare provider within each General Practice loads a dashboard page on the BRIT analytics website, the relevant data for the General Practice is loaded and the plots are rendered in real time. This allows the production of accurate, dynamic plots that are interactive, so that the focus can be on the data that is important for each General Practice.

The design and implementation of the data processing has taken a considerate amount of time. However, this robust, reliable system that can process large amounts of data, produce insightful analytics could help to improve the way antibiotics are used and reduce the long term implications of antimicrobial resistance.

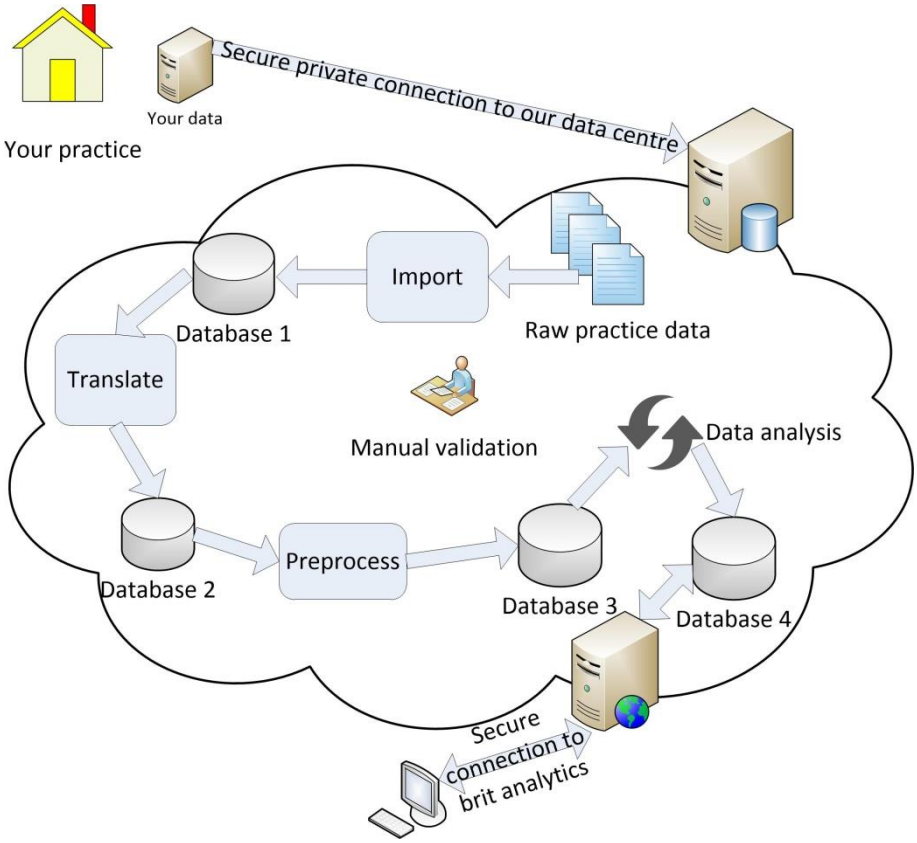

Figure 1: A visualisation of our data processing workflow

6. Appendix

a. Rate, Percentage, Boxplots

A **rate** is the ratio between two numbers. For instance the rate of penicillin prescribing to all antibiotic prescribing, it is the ratio between these two quantities *i.e.,* the number of penicillin prescribing divided by the number of total antibiotic prescribing.

Percentage is a ratio (or a number) that is expressed as a fraction with the denominator being equal to 100. When we say 5% of the total number of 100 antibiotic prescriptions in a GP practice is penicillin, we mean 5 antibiotic prescriptions are for penicillin. If the practice has 50 antibiotic prescriptions, then 5 % of 50 antibiotic prescriptions would be $\frac{5}{100} \times 60 = 3$ prescriptions for penicillin.

The age of patients that had a GP consultation today is 65, 30, 25, 75, 15, 20, 45. The **maximum** age is the highest number ie 75 and the **minimum** age is the lowest ie 15. The **mean** (average) of all ages of the patients that visited the GP today is the sum of all items divided by the number of all patients ie $\frac{65+30+25+75+15+20+45}{7} = \frac{275}{7} = 39.29$ (2 d.p).

The **median** (or second quartile) is the number that splits the array that contains the ages into two equal parts ie the number that is in the middle. To do that, we first re-arrange the ages from the lowest to the highest ie 15, 20, 25, 30, 45, 65, 75. We have 7 patients and thus the 4th patient in the row is the median (it had 3 patients before and 3 patients after) and so, the median=30. The **first** and **third quartiles** can be estimated using the following: a) Use the median to split the data into two halves. If there is an odd number of patients, do not include median in either half. If even number of items, split this in half. b) The first quartile is the median of the lower half and the third quartile is the median of the upper half. The first quartile is the median of 15, 20, 25, Q_1 = 20 and the third quartile is the median of 45, 65, 75 and thus, Q_3 = 65. (There are two other methods to find the quartiles). The difference between $Q_3 - Q_1$ is called **interquartile range** (IQR). In this case IQR= 65-20 = 45.

In case that there is an even number of patients, say 6, their ages are: 15, 20, 25, 30, 45, 65, then the median is in $\frac{n+1}{2}\ place = \frac{6+1}{2}\ place = 3.5\ place$, where n is the number of patients. Thus, we take the patients that are in 3rd and 4th place and find their mean ie median = $\frac{25+30}{2} = \frac{55}{2}$ = 27.5. Now, Q_1 is the median of 15, 20, 25 and Q_3 is the median of 30, 45, 65 and thus, Q_1 = 20, Q_3 = 45 and IQR=45-20=25

Suppose that there are 30 consultation visits in a practice in a weekday. We want to examine how many times these 30 patients (15 women and 15 men) had come to the practice the last 5 years. We found the following numbers for men 5, 1, 30, 20, 0, 9, 11, 23, 50, 41, 29, 40, 20, 17, 99 and the following for women 10, 50, 15, 49, 99, 21, 40, 60, 65, 11, 21, 31, 33, 49, 30. For men, Q1, Q2 and Q3 are 10, 20 and 35 respectively. For women, Q1, Q2 and Q3 are 21, 33 and 49.50 respectively. See Figure 2 below for the boxplots.

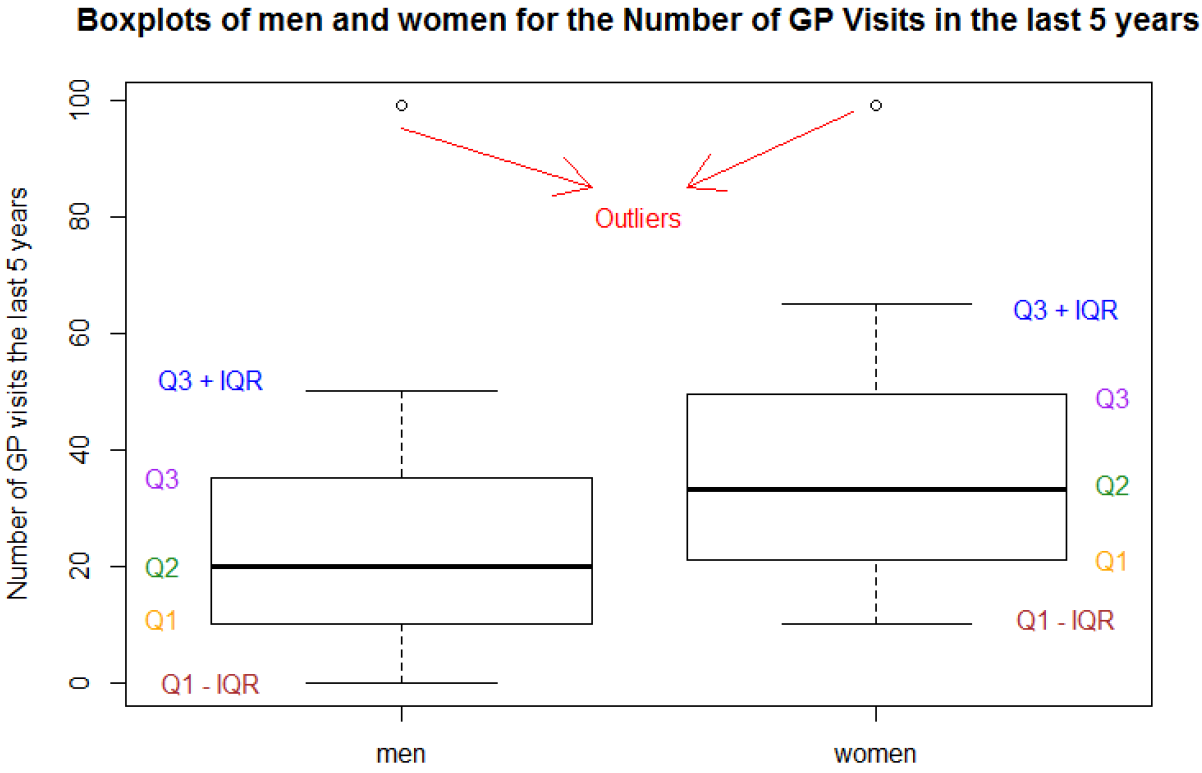

Figure 2: Boxplots

b. Negative Binomial

Note:
y= exp(x) or y = e^x is called the natural exponential function, where e =2.718… , and y=exp(0)=1 (same with all powers).
$y = e^x \Leftrightarrow \ln y = \ln e^x \Leftrightarrow \ln y = x \ln e \Leftrightarrow \ln y = x$

When we want to find the number of times (counts) an event occurs, instead of using a linear relationship, we use a **negative binomial regression** (belongs to a family called generalised linear models). To make the relationship linear, we want the log of mean of counts instead of using the counts. Suppose we are interested in the number a patient visits (counts) the GP practice last year. This is a complicated relationship. But, if we shift our interest to the log of mean yearly patient GP visits we could obtain a linear relationship. We found the following relationship:
ln of mean of GP visits last year = γ × gender of the patient + δ × disease of the patient + θ × mean number of patients with infectious disease registered with the GP practice last year + 1 × ln(mean number of patients registered with the GP last year).
If γ=2, δ=-5, θ=1, gender is 1 for a woman and 0 for a man and disease is 1 for a cardiovascular disease and 0 for chronic obstructive pulmonary disease (COPD). Suppose the mean number of patients with infectious disease in the practice was 5 and the mean number of patients registered with the GP last year was 100, then for a man that had COPD:
ln of mean of last year's GP visits of a male patient that has COPD= 2 × 0 – 5 × 0 + 1 × 5 + 1 × ln (100)= ln (100).
mean of last year's GP visits of a male patient that has COPD = exp(ln(100))= 100

c. Cox Proportional Hazards Model

Hazard function (or hazard rate) is the instantaneous probability of an event to occur within a small time interval, given that it did not happen up to beginning of that interval. See Figure 3 below. Hazard ratio is the ratio of two hazard rates.

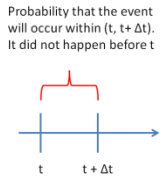

Figure 3: Hazard Function

When we want to find the hazard ratio we use a **Cox proportional hazards model.** To ease our calculations, we use a linear relationship. Suppose we want to estimate the hazard ratio between two group of patients. One with treatment A and the other with treatment B.

ln(hazard ratio)=baseline × (α × gender + β × treatment).

If α = 1, β=1, treatment is 1 if the patient takes treatment A and 0 if the patient takes treatment B, gender is 1 if the patient is a woman and 0 if not. Then for a woman who takes treatment A, ln(hazard ratio)=baseline × (1 × 1 + 1 × 1) =2 × baseline. For a woman who takes treatment B, ln(hazard ratio)=baseline × (1 × 1 + 1 × 0) = baseline. The ln(hazard ratio of a woman who takes treatment A with respect to a woman who takes treatment B) = $\frac{2 \times baseline}{baseline}$ = 2. Thus, the hazard ratio of a woman who takes treatment A with respect to a woman who takes treatment B = exp (2).

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7. Further Information about the Statistical Rationale

a. Interpreting data: boxplots and tables, The Open University, 2016
b. Negative Binomial Regression, Joseph M Hilbe, Cambridge University Press, 2012
c. Proportional Hazards Regression, John O'Quigley, Springer: Statistics for Biology and Health, 2008

Contact ACTION@manchester.ac.uk, if you wish to find out more about the BRIT project. We are able to provide further information on how our analytics are derived, the statistical techniques behind them, and what this means for your practice.