Using routinely collected data to explore neurology outpatient services

by

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Abstract

In the UK a large amount of data is collected during the routine treatment of patients. This data, referred to as 'routinely collected data' within the health research community is increasingly being used in health research despite not being explicitly collected for this purpose. The fact that data collected for healthcare and administrative purposes is used for research can lead to a number of issues that need to be acknowledged and overcome.

This thesis explores the benefits and limitations of using routinely collected data to research outpatient neurology services in the North-West of England. Neurology services in the UK are under pressure, with large variations in the level of service provided in different geographical areas. We analyse data from an outpatient neurology clinic in the northwest of England covering a diverse population which is dispersed over a large area.

First the current research into neurology services using routinely collected data is explored using a systematic mapping review, identifying gaps and areas for further research. We then use data from the outpatient neurology clinic to explore the issues identified in three separate papers.

Chapter four explores the number of patients using outpatient neurology services, what resources they require and the waiting times they experience. We show that there are a small number of diagnostic categories which account for 60% of new referrals to the clinic, and that waiting times vary by diagnostic category. Chapter five examines referrals for headache patients. Using standardised residuals from a Poisson regression we identify GP practices which have referred an unexpected number of headache patients. Chapter six uses State Sequence Analysis to observe patterns in the types of appointments patients attend over time. We show that there a number of common patterns of appointments and that these patterns are somewhat related to diagnosis.

Taken together these papers show that routinely collected data can be successfully used to conduct useful and insightful research into outpatient neurology services. Our

research also identifies key areas of limitation of using this type of data - such as missing data, the difficulty of accessing data, and the difficulties presented by the lack of diagnostic coding – for which solutions are proposed in the discussion.

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List of abbreviations

AIC	Akaike Information Criterion
BI	Business Intelligence
CAG	Confidentiality Advisory Group
CCG	Clinical Commissioning Group
CNS	Central Nervous System
CONSORT	Consolidated Standards of Reporting Trials
DALY	Disability Adjusted Life Years
DMT	Disease Modifying Therapy
ECDF	Empirical Cumulative Distribution Function
EHR	Electronic Health Record
GIRFT	Getting it Right First Time
GLM	Generalised Linear Model
GP	General Practitioner
GPDPR	General Practice Data for Planning and Research
HRA	Health Research Authority
IG	Information Governance
IMD	Index of Multiple Deprivation
IRAS	Integrated Research Application System
K-S	Kolmogorov-Smirnov
LSOA	Lower Super Output Area
LTHTR	Lancashire Teaching Hospitals NHS Foundation Trust
ML	Machine Learning
MS	Multiple Sclerosis
NAO	National Audit Office
NICE	National Institute for Health and Care Excellence
NLP	Natural Language Processing
OM	Optimal Matching
PD	Parkinson’s Disease
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RCD	Routinely Collected Data
RCT	Randomised Controlled Trial

REC	Research Ethics Committee
RPH	Royal Preston Hospital
RTT	Referral to Treatment
SD	Standard Deviation
SSA	State Sequence Analysis

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My supervisors Prof Jo Knight and Prof Hedley Emsley without whom none of this would have been possible. I will be forever grateful for all of their encouragement, help and support.

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My family and friends who have kept me sane, provided welcome distraction, and given me pep talks when I needed them.

And finally Meg, the very best four legged companion there ever was.

Declaration

I declare that this thesis is my own work and has not been submitted for another degree at this or any other university.

The following chapters have been published in peer reviewed journals:

Chapter 3 - Biggin F, Emsley HCA, Knight J. Routinely collected patient data in neurology research: a systematic mapping review. BMC Neurol. 2020 Nov 27;20(1):431. doi: 10.1186/s12883-020-01993-w.

Chapter 4 - Biggin F, Howcroft T, Davies Q, Knight J, Emsley HCA. Variation in waiting times by diagnostic category: an observational study of 1,951 referrals to a neurology outpatient clinic. BMJ Neurol Open. 2021 Jun 3;3(1):e000133. doi: 10.1136/bmjno-2021-000133.

The following chapters have been submitted to peer reviewed journals and have been made available as preprints online:

Chapter 5 - Fran Biggin, Quinta Davies, Timothy Howcroft, Hedley Emsley, Jo Knight. Identifying variation in GP referral rates: an observational study of outpatient headache referrals. medRxiv 2022.02.07.22270572; doi: 10.1101/2022.02.07.22270572

Chapter 6 - Fran Biggin, Quinta Ashcroft, Timothy Howcroft, Jo Knight, Hedley Emsley. Discovering patterns in outpatient neurology appointments using state sequence analysis. PREPRINT (Version 1) available at Research Square. doi: 10.21203/rs.3.rs-2519660/v1

As this thesis was written as a series of publications, I underline here the areas I took responsibility for:
I wrote and managed the ethics application.
I linked, validated and cleaned the data.
I designed the concept of the thesis with my supervisors.
I designed the individual pieces of research.
I performed all data analyses.
I created all visualisations, graphs, charts and tables.
I wrote all the main chapters of this thesis and contributed to the writing of the appendices.

1 Introduction

During a patient's visit to any health service, including neurology services, a large amount of data is collected. This data is used for many purposes including diagnosis and treatment, finance and commissioning, auditing, and administration. Increasingly this type of 'routinely collected' data is also being recognised for its value as a resource for research. This thesis explores the ways in which routinely collected data can be used to understand the current situation in neurology services, and how it could also help to highlight areas for future improvement.

This introduction is focused on defining both routinely collected data and neurology services, identifying their relevance in the current research environment, and describing how they relate to this thesis. First routinely collected data is defined, its uses described, and its benefits and limitations explored. Next the current climate regarding routinely collected data within the NHS is presented, before the relevance of this type of data to this thesis is presented. Then neurology services are defined, and concerns regarding those services within the UK are examined, before finishing with a description of the specific neurology clinic investigated in this thesis. Taken together this information forms the background to the research undertaken in the rest of the thesis and directly leads to the aims of the research which are presented at the end of the chapter.

1.1 Routinely Collected Data

1.1.1 Definition of routinely collected data (RCD)

The phrase 'routinely collected data' has seen increasing use over the past 20 years, and in particular the last 5-10 years. A PubMed search for the phrase "Routinely collected data" and the MESH term "routinely collected health data" reveals that the first paper using this nomenclature was published in 1976. Figure 1.1 shows that the number of published papers using these phrases did not increase much between 1976 and 1990, increased steadily between 1990 and 2010, and has increased dramatically in the last 10 years.

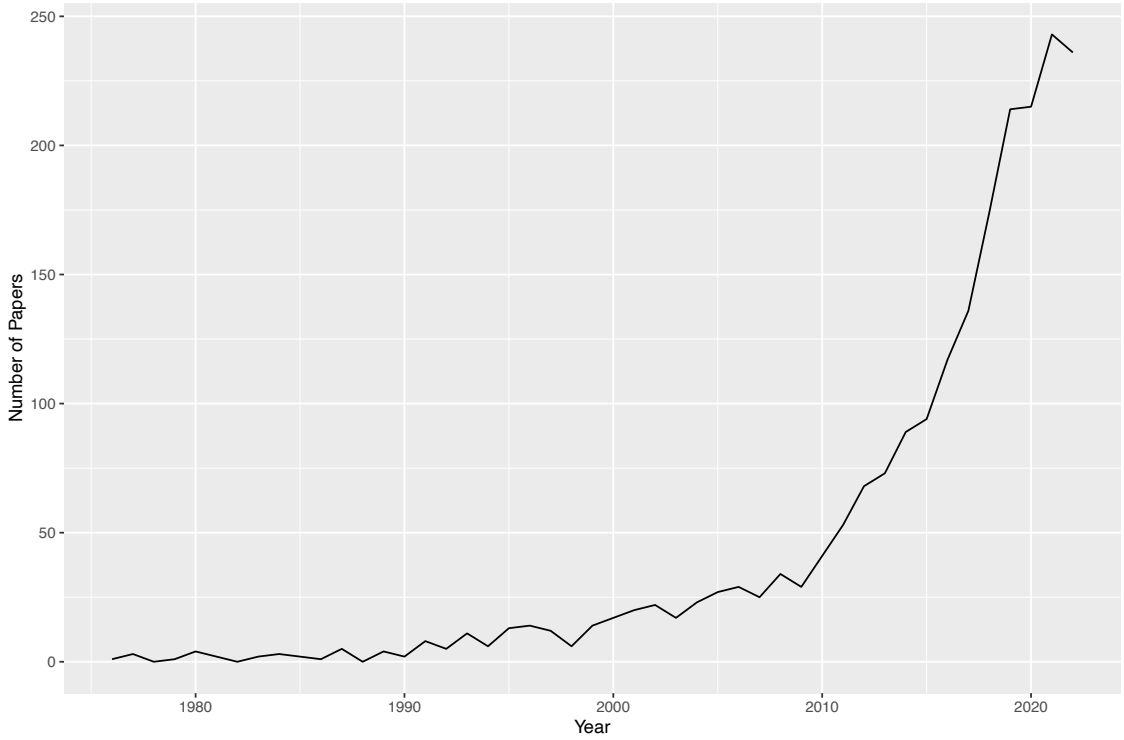


Figure 1.1 The number of papers retrieved from a PubMed search using the phrase “Routinely Collected Data” and the MeSH term “Routinely Collected Health Data”.

As the number of scientific papers published has also increased over the last 20 years, it is also necessary to compare the rise in the number of instances of the phrase ‘routinely collected data’ to something else in order to determine if this increase is simply due to the increase in the overall number of papers published. Figure 1.2 shows the results of a comparison of the number of papers using the phrase “routinely collected data” with papers containing just the word “data”. Although the proportions are very small, the proportion of papers using “routinely collected data” compared to the word “data” have increased, and this increase is most notable over the last 10 years.

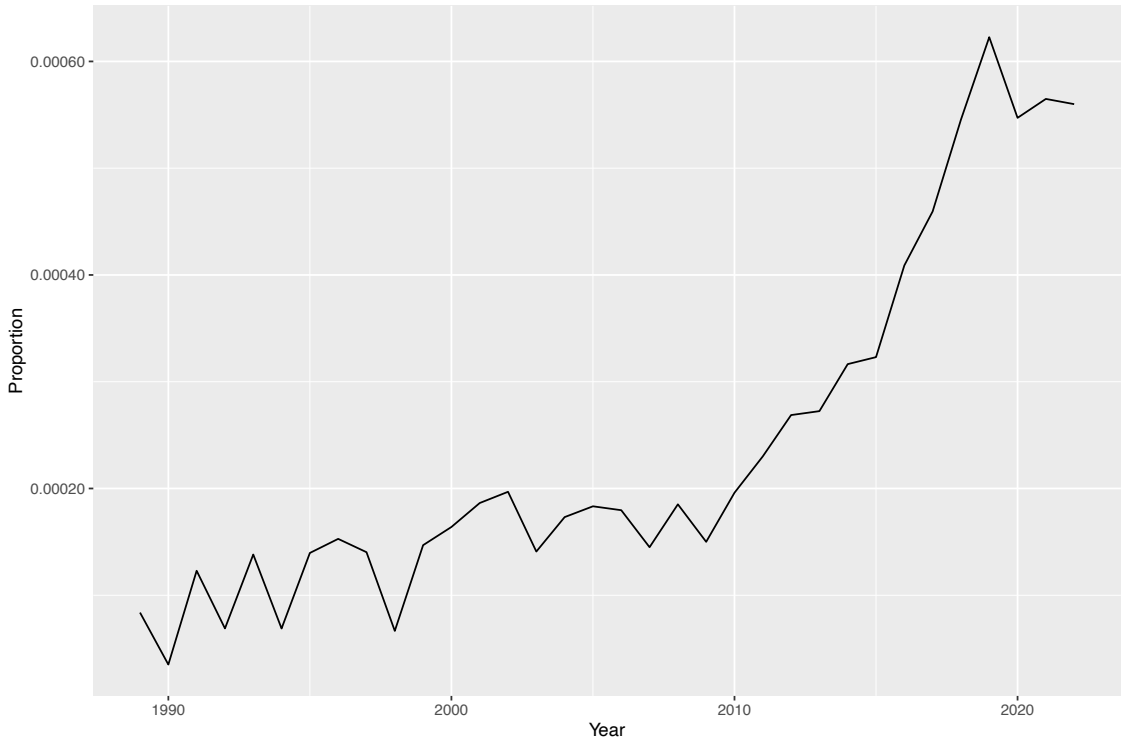


Figure 1.2 The proportion of papers using the phrase “Routinely Collected Data” compared to papers containing just the word “data”.

There are a number of common features of routinely collected data described within the papers that use this phrase, including the nature of how it is collected, where it is collected from, and definitions of what it is not.

At its core, routinely collected data is defined as data which is generated during a patient’s visits to the health services. Jorm et al. describe it as data which is “collected by governments, healthcare providers and insurers as a by-product of operating services” (1). Deeny and Steventon have a similar viewpoint and define it as being “generated as part of the routine operation of the modern healthcare service” (2). From these definitions we can see that routinely collected health data is considered as a by product, rather than as a primary goal, of the routine operation of a health service. It can also encompass data generated by services other than direct healthcare, such as health insurance companies.

In the UK this type of data is generated mainly by the NHS and includes administrative as well as clinical data. Keith et al. describe RCD in the NHS as "the data generated and stored by the NHS as part of the delivery of services. This includes data from every contact between patients and the NHS, and wider administrative and clinical data such as diagnostic test results" (3). The fact that this type of data is generated every time someone access healthcare means that it is often large, and RCD could also be considered as a type of 'big data' (1,4).

When discussing RCD it is also important to define what it is not. RCD is specifically not collected for the purposes of research and as such, research represents a secondary use of these datasets (2,4).

1.1.2 Previous uses of RCD

The way in which RCD has been used in research varies across different areas of healthcare, but there are a number of common categories of study that have used this type of data. It is often used in conjunction with other types of research, for example to guide the design of clinical trials. Using RCD can help to reduce the cost of trials by identifying potential participants and reducing the amount of data collection required from participants in a trial (5). It can also be used to identify areas of research in which clinical trials are most needed (4).

RCD can also be used for research on its own, without being a supplement to other types of research such as clinical trials. It is most commonly used in exploratory analyses, for example in the identification of inequalities, to assess the impact of policy changes, in comparative effectiveness trials, and to estimate disease prevalence. For example Morisod et al. conducted a systematic review in 2021 which examined the use of RCD to measure health inequalities in emergency care, they found that RCD could be used to improve the measurement of health equity (6). RCD is also used to examine the effects of policy changes. Daniels et al. conducted a systematic review to explore the uses of RCD in evaluating home assessment and modification interventions in the prevention of falls (7). They found that RCD can be used to evaluate the impact of such interventions, but that improvements need to be made in allowing access to RCD for such research. Many studies have also used RCD to estimate the incidence and

prevalence of diseases, for example Fatoye et al. who used it to estimate the prevalence of low-back pain (8).

As well as for the types of exploratory studies mentioned above RCD has also been used in more complex analyses such as population risk prediction and predictive modelling. In 2019 Li et al. published a paper examining the use of RCD to create population predictions of the cardiovascular QRISK3 score (9). They found that these types of predictions created from RCD performed well for populations, but not for individuals. Other types of predictive modelling have also used RCD, for example Bachmann et al. predicted the likelihood of admission to a nursing home using hospital and census data (10). Using RCD they were able to identify several factors influencing the potential admission of an individual to a nursing home.

These examples demonstrate the wide usage and great potential of RCD as a resource. It has been used in many different types of research including supporting clinical trials, identifying the effects of policy changes, estimating disease prevalence, and predictive modelling.

1.1.3 Benefits of RCD

The research undertaken over the last 20 years using routinely collected data has uncovered a number of benefits and limitations to its use. Among the most frequently cited benefits are the reduced cost of research, large sample sizes and wide coverage. As RCD is already collected for other purposes it can be a very cost-effective way of conducting research, without requiring the expensive set up of a clinical trial. RCD can be very large and cover a sizeable population which can be seen as a benefit in its own right, but also leads to other benefits such as being able to study rare outcomes (1,2,4). In addition to the amount of data collected and the size of the population covered, RCD is continuously collected and longitudinal in nature allowing for long observation periods and negating the need to wait for outcomes as you would need to in a clinical trial. The nature of continuous collection also means that research can be repeated at a later date allowing researchers to learn “from every patient interaction to continually improve services” (3).

Another area where RCD has great benefits is in the ability to conduct research where clinical trials would be either impossible or unethical, or where particular populations are underrepresented in clinical trial research. Jorm et al. note that "routine data often represent the only way to evaluate the outcomes of care in population groups for which there is no evidence from clinical trials" (1).

1.1.4 Limitations of RCD

In addition to the above benefits, there are also a number of recognised limitations to the use of RCD.

As RCD is collected for uses other than research it can be found to be incomplete. For example, when exploring the challenges of using RCD McGuckin et al. found that "not all information collected at a patient encounter has a corresponding field in an administrative database" (11) and that in addition they were unable to complete some research due to missing data. The same researchers also discovered that there was variability in recording information between databases, even within the same healthcare provider, and that fields such as diagnostic coding were completed using different taxonomies. They note that imprecise use of diagnostic codes meant that it was difficult to discern the purpose of visits. Diagnostic codes such as those defined by ICD-10 or SNOMED-CT can be useful for researchers because it allows data on diagnoses to be compared in a standardised way. Other researchers also noted that one of the limitations of RCD is the uncertain validity of the data, both in terms of its collection and its entry into the database (1,4).

Although one of the benefits of RCD is that it is large and can cover a wide population, it is limited in that it cannot tell you anything about what happens outside of a clinical encounter. RCD is generated as the result of an event – a visit to a healthcare provider or the receipt of test results for example – and as such can't reveal anything about people who haven't experienced that event (1). Deeny and Steventon importantly note that some populations are described in much more detail than others, depending on who seeks, and is offered, healthcare (2).

In addition to issues of data collection and administration, there can also be limitations for researchers in accessing RCD. As this type of data is not collected for research purposes, researchers often need to go through lengthy application process and the necessary ethical approvals in order to use RCD for research. In their 2018 paper Lugg-Widger et al. discuss in depth the difficulties of accessing RCD in the UK. They found that “delays in applying for and accessing routinely-collected data from multiple data providers poses a significant risk to project delivery" (5). They also highlight the fact that accessing different datasets requires different application procedures and that they found difficulties with changes to procedures part-way through the application process.

1.1.5 RCD in the NHS

There have been many efforts in the past decade to streamline data collection and data sharing within the NHS, not all of which have been successful, but which never-the-less reflect the growing understanding of the importance of the data generated by healthcare in the UK.

In 2013 the care.data project was announced which, among other things, sought to enable to use of anonymised data by healthcare managers and researchers. However this project met with a large amount of resistance, including a lack of confidence in the way data would be handled, and was eventually abandoned in 2016 (12). In 2021 the roll out of a new data project - General Practice Data for Planning and Research (GPDPR) – was delayed due in part to concerns about opt-out requests not being met. What both of these projects and their difficulties demonstrate is the desire of the government to enable to use of RCD for research and management, and also the corresponding need to ensure that such data are secure and used appropriately.

In the last few years a number of reports and policies regarding data in the healthcare sector have been published. An independent report published in 2021 by Wade-Gery entitled ‘Putting data, digital and tech at the heart of transforming the NHS’ made nine recommendations which aim “to put data, digital and technology at the heart of how we transform health services” (13). The 2022 Goldacre review focused more specifically on using health data for research, making several recommendations for, among other

things, the implementation of more efficient data platforms, better data security, more open working methods, better data curation, and more training for data analysts (14). The report concluded that "73 years of complete NHS patient records …. represent deeply buried treasure, that can help prevent suffering and death". Following on from the Goldacre review the Department of Health and Social Care published the Data Saves Lives policy paper in June 2022 which sets out the government's strategy for how data will be used to improve healthcare in England (15). Although not all of these reports concern the use of RCD directly, they demonstrate the importance placed on health data in the current political climate.

1.1.6 The use of RCD in this thesis

The fact that so much data is potentially available to data analysts brings us to the question of how best we can use it. In this thesis I aim to understand how we can use this important resource to provide useful insights to clinicians, healthcare managers and patients. I aim to explore the potential uses, benefits and limitations of RCD within the specific specialty area of neurology.

1.2 Neurology Services

1.2.1 Definition of neurology

A neurological condition is one which affects any part of the nervous system, including the brain, spine, nerves and muscles. These conditions can have a number of different genetic and environmental causes, including degenerative disease, traumatic injury and infections. There are over 600 different neurological diseases including conditions as diverse as traumatic brain injury, epilepsy, and Parkinson's Disease (16). The 2016 Global Burden of Disease study showed that the neurological conditions with the most impact were stroke, Alzheimer's (and other dementias), migraine and meningitis (17). Thus we can see that neurology is a complex area of medicine with practitioners requiring knowledge of many different conditions with widely varying symptoms.

1.2.2 The structure of neurology services in England

In the UK neurology services are delivered by the NHS, which is split into separate services according to the four countries which constitute the UK. In this thesis I focus on services provided in England. In England neurology services have evolved over the years according to local need, individual expertise, and geography, which has resulted in variation in the services provided between different areas (16). Neurological care is mainly provided at a hospital site in both inpatient and outpatient settings, and a patient can be admitted to specialist neurological services via different avenues such as a referral from a GP, an admission from A&E, or referral from another specialist. The GIRFT (Getting it right first time) Neurology report describes hospital sites as having different levels of neurology services, ranging from N1 a "neuroscience centre with both neurology in patients and neurosurgery" through N2 and so on to N5 a "site without access to visiting neurologists" (16). The N1 sites are distributed across England as shown in Figure 1.3.

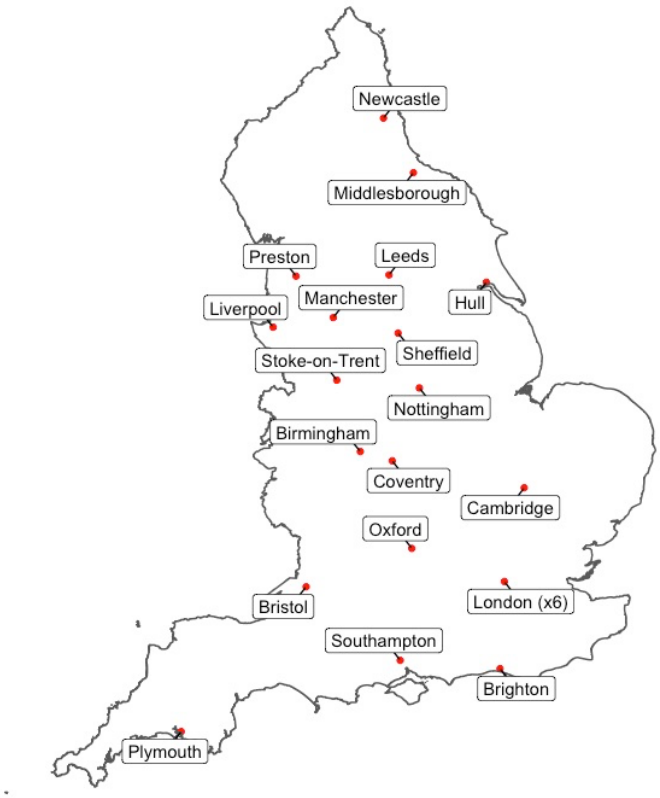


Figure 1.3 The location of N1 neuroscience centres in England.

Alongside neurological care provided at a hospital as either an inpatient or outpatient, there are other specialist clinics such as those for stroke and dementia patients. Patients with these particular conditions are often not seen by neurology services but at separate specialty clinics, for example Alzheimer's patients may be seen at a memory clinic (18). In addition to specialty services there are other parties interested in neurology services in the UK. There are a number of large charities such as the MS Trust, Parkinson's UK and Brain Research UK. Many of these charities are part of the Neurological Alliance who bring people together to campaign for change in the way people living with neurological conditions are treated.

1.2.3 Concerns regarding neurology services in the UK and England

Over the past two decades concern has been expressed by neurologists, charities and policy makers over the current state, and the future, of neurology services in the UK and England. Many of these reports include concerns over variation in the services offered in different regions of the UK and the resulting inequality this raises. Health inequality is an important and large area of research not limited to neurology. Health inequality implies that there are differences in health outcomes between populations, and this can lead to health inequities, which are unjust differences between groups (19). Many of the concerns raised about neurology services in the UK focus on issues brought about by the inequality of access to neurological care.

In 2011 Bateman wrote in an editorial to Practical Neurology that there was a 'lack of neurologists in the UK compared with some other countries' (18). He also asserted that many patients with neurological emergencies were not seen immediately by a neurologist which was due in part to the shortage of neurologists, but also to the outdated hub and spoke model providing intermittent services to outlying hospitals from a central hub. In the same year the National Audit Office produced a report entitled 'Services for people with neurological conditions'. The aim of this report was to examine changes that had been made to neurology services following the 2005 National Service Framework for Long-Term Conditions which had identified problems such as "lengthy diagnosis; poor information for patients on their condition and services; and variable access to … health and social services" (20). The report found that, although spending on neurology services had increased between 2005 and 2011,

progress in implementing the framework had been ‘poor’ and ‘significant problems with services’ remained (20). The report made a number of recommendations which were reviewed in 2015 by a House of Commons committee of public accounts who found that there had been “some progress in implementing the recommendations that the previous Committee made in 2012 ... However, these changes have not yet led to demonstrable improvements in services and outcomes for patients. It is clear that neurological conditions are not a priority for the Department of Health.” (21)

In 2015 Morrish wrote an editorial for the BMJ in which he stated that neurology services were both under-resourced and unequally distributed across the UK, leading to long waiting times, and that difficulty in accessing neurology services was undermining patient care (22). In addition, the 2018 ABN workforce survey, published in 2020, found that in the UK there is only 1 neurology consultant per 91,175 population (in contrast to France and Germany who both have a ratio of 1 per 25000) and that there is significant variation in the number of consultants throughout the UK (23).

The most recent large report on neurology services in England is the Getting It Right First Time (GIRFT) neurology report (16). The GIRFT programme is a national NHS initiative which is designed to improve patient care across all disciplines through completing in-depth reviews of current services across the country. The neurology report was published in September 2021 and presents a number of findings and recommendations based on three different types of patient: an inpatient admitted as an emergency; a patient referred to outpatients; and a patient with a chronic disorder. The report found that there is large variation in neurology services across England, including in the number of consultants which ranges from 1 per 50,000 non-elective population to 1 per 200,000. For inpatients the GIRFT report found that many of those with neurological disorders are admitted to hospitals without neurology inpatient beds, and that there is marked variation in acute inpatient neurology services across the country. These findings are corroborated in a recently published paper by Jackson et al, which found that there was significant variation in neurological hospital admissions by Index of Multiple Deprivation decile (24). The GIRFT report also found large variation in access to neurology outpatient appointments, including variations in waiting times between different regions, and variation in access to specialist investigations such as lumbar puncture (16). The report makes a number of recommendations for outpatient

services including triaging referrals, analysing outpatient activity to support service planning, reviewing follow-up strategies, and establishing a list of core neurological diagnoses that should be routinely coded.

Through these reports and articles we see that neurology services have been in the spotlight for a number of years and that efforts are being made by practitioners, researchers and policy makers to improve these services for the benefit of patients. However, it is also evident that there remains much to be done and that progress is still being made towards fulfilling the recommendations of the various reports. In this thesis I aim to use routinely collected data to try to address some of the recommendations of the GIRFT report on a local scale.

1.2.4 Neurology in this thesis

In this thesis I focus on a single outpatient neurology clinic based in the Royal Preston Hospital. This hospital is defined in the GIRFT report as an N1 site with a unified hub and spoke model, which means that neurologists are based at the regional hub in Preston and visit other sites in the region (16). The area served by this hospital is large, encompassing parts of Lancashire and Cumbria. This area of the UK is geographically and socioeconomically diverse, with both remote rural communities and larger urban areas. In the north of the area Cumbria has a sparse population and remote industrial communities on the coast. In Lancashire there are more urban centres, including Blackpool, Blackburn, Lancaster, Preston and Burnley. There is great diversity in socioeconomic status across this area from wealthy Lancashire villages to the more deprived areas in Blackpool and the Cumbria coast. Figure 1.4 shows a map of the region covered by the Trust. It shows Clinical Commissioning Groups (CCGs) as that was the administrative unit at the time that the data was collected and the analysis undertaken for this thesis. Most of this region has now been amalgamated into the Lancashire and South Cumbria Integrated Care Board.

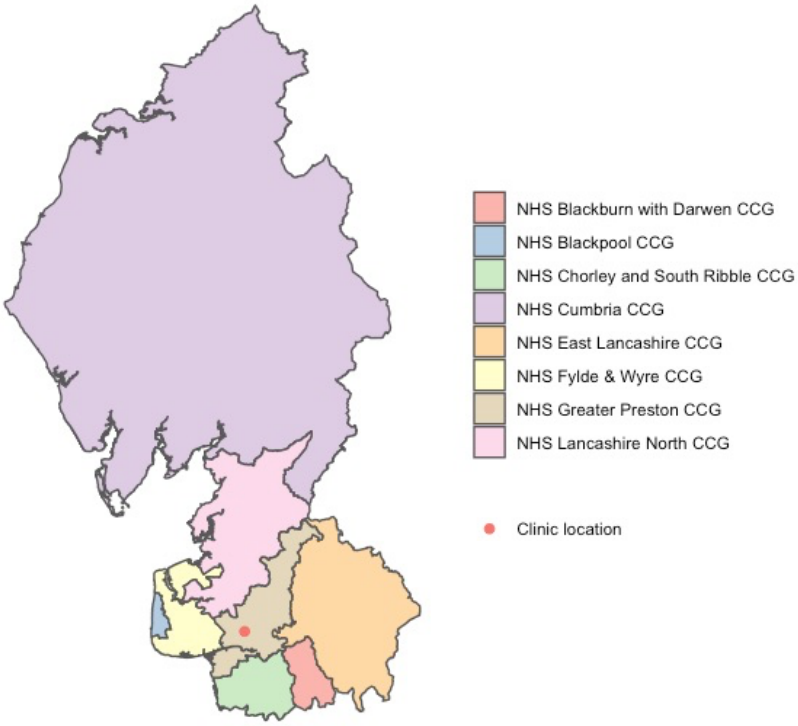


Figure 1.4 The region served by the neurology outpatient clinic at Royal Preston Hospital.

The Lancashire Teaching Hospitals NHS Foundation Trust, whose main site is the Royal Preston Hospital, were interested in using the data collected at their neurology outpatient clinic to better understand the services they are delivering. The data used in this PhD came from appointments from a single clinic at the Trust, encompassing information about clinical items such as diagnoses, which tests were ordered, and whether follow-up was required. This clinical data was then linked with administrative information from the Business Intelligence department which included administrative data such as when referrals were made and where from, and patient demographics.

The GIRFT report specifically mentions analysing outpatient activity and reviewing follow-up strategies as recommendations for ways to help improve the current state of neurology services in the UK (16). Although this PhD was conceived and designed before the report was published, the aims of this thesis are consistent with those of the GIRFT recommendations: to use routinely collected data from a neurology outpatient clinic to understand the current situation and inform future service planning.

1.3 Thesis Aims and Structure

The overarching aim of this thesis is two-fold: to use routinely collected data to understand neurology services; and to use the case study of neurology services to understand the benefits and limitations of using routinely collected data. Within these broader aims are four research objectives:

1. To understand how routinely collected data has been used in neurology research.
2. To explore who is visiting the neurology clinic in Preston, how long patients wait for a new appointment, and what resources are currently being used.
3. To identify unusual numbers of referrals, using headache patients as a specific example.
4. To explore if there are discernible patterns in the timing and types of appointments patients attended.

This thesis is broken into a number of chapters following on from this introduction. Chapters 3 to 6 are comprised of papers that have been published in, or submitted to, a journal:

Chapter 2: Methods. A brief discussion of the methods used in each subsequent chapter. As each of the following chapters comprises of a paper that has been either published or submitted to a journal, this methods chapter has been included to permit discussion which would be out of place in a published paper.

Chapter 3: Routinely collected patient data in neurology research: A systematic mapping review. A systematic overview of previous research in neurology which has used routinely collected data.

Chapter 4: Variation in waiting times by diagnostic category: an observational study of 1,951 referrals to a neurology outpatient clinic. A study of how many patients visit the clinic, what diagnoses are seen most frequently, how waiting times for appointments vary by diagnosis, and what tests and follow-up are ordered.

Chapter 5: Identifying variation in GP referral rates: an observational study of outpatient headache referrals. An investigation into how simple models can be used to identify GP surgeries which have referred an unexpected number of patients.

Chapter 6: Discovering patterns in outpatient neurology appointment using state sequence analysis. An exploratory study using a relatively novel approach for health services which attempts to uncover common patterns in outpatient visits.

Chapter 7: Discussion, future work and conclusions. A general summary of the overall aims of the thesis, and a discussion of possible future research directions.

2 Methods

This chapter explores the data and methods that are used in the papers which make up the subsequent chapters of this thesis. There is an initial description of the data and the ethical review process, and then each chapter has its own methods section. In each of these sections there is discussion as to why particular methods were chosen and, if necessary, there is further exploration of what the methodology entailed. In particular, the steps of State Sequence Analysis methodology are explained as this is a less well known technique within health research. There is necessarily some overlap with the methods section in the subsequent analysis chapters, however this chapter does expand somewhat on the information given in the published papers. Explanations and derivations of the statistical tests described have not been included but can be found in many statistical texts, for example Freund's Mathematical Statistics (25).

2.1 The data

In each paper there is a detailed description of how we used the data for that particular analysis, in some cases using a subset of the data, linking the data to other sources, or transforming it in some way. This section describes the data that we started with, which formed the basis for all subsequent analyses.

The data were drawn from a single consultant-led outpatient clinic at the Royal Preston Hospital and were collected by the consultant between the 18th September 2015 and 9th January 2019. The data included information from a total of 5902 appointments from 3098 patients. The variables collected from the clinician data included patient ID, primary and secondary diagnoses, sex, age at the time of appointment, the date of the appointment, type of appointment (new or follow-up), if the appointment was attended, investigations ordered, and any follow-up offered. These data were then linked with information from the hospital business intelligence team using unique patient IDs. The business intelligence data included the following variables: sex, ethnicity, date of appointment, type of appointment (new or follow-up), if the appointment was attended, date of referral, referral source (GP, A&E, other consultant or other source), and the LSOA of the patient's home address.

The data fields which were drawn from both the clinician data and the business intelligence data were used to cross-check entries. Where entries differed (for example sex recorded as male in one data set and female in the other) other records of that patient were sought to verify the correct data. These differences occurred in less than 1% of the data. Once the data had been linked and verified, they were anonymised before extraction and analysis.

2.2 The ethical review process

Most health research involves applying to an ethical review board and research using routinely collected NHS data is no exception, requiring approval from the Health Research Authority (HRA). As research using RCD relies on data collected for reasons other than research it was also necessary to also apply for ethical approval from the Confidentiality Advisory Group (CAG) for consent to use confidential patient data for reasons other than direct patient care. The application process for ethical approval for this PhD required liaison with the NHS Trust, the HRA, the CAG and the university, and is outlined here:

- Start an Integrated Research Application System (IRAS) form (October 2018).
- Contact the Research and Innovation team at the Trust for assistance with the application.
- Liaise with the Information Governance (IG) team to complete the relevant Trust forms.
- Apply to the Trust 'Change Committee' for access to relevant statistical software.
- Finalise the IRAS form with input from Information Governance and Research and Innovation teams.
- Attend an in-person Research Ethics Committee (REC) review.
- Respond to queries from an external CAG meeting.
- Liaise with NHS Digital regarding the Trust IG toolkit.
- Liaise with Research and Innovation to produce the relevant materials to satisfy the CAG.

- Make final application and receive approval (May 2019).
- Inform the university of the HRA approval and apply for departmental ethics.

2.3 Methods for chapter 3

Routinely collected data in neurology research: A systematic mapping review

In this chapter we explore how routinely collected data has been used in previous neurology research. As the title of this chapter suggests, the specific review methodology used is that of the systematic mapping review, which differs slightly in its approach and methods from a more standard systematic review. There are many different types of review all with slightly different aims and methodologies (26), the most commonly known type of review in medicine is the 'systematic review' and this methodology has been developed over the years by initiatives such as Cochrane (27) and the PRISMA statements (28). The systematic mapping review holds much in common with other types of review as it involves a systematic search of databases to retrieve potentially relevant papers which are then screened for inclusion in the review and synthesised to provide the results to the question the review has posed. The way in which this type of review differs from others is in its scope. The systematic mapping review aims to provide an overview of an area of research rather than answer a narrowly defined research question. Therefore it does not include any assessment of the quality of the papers synthesised (26) and often includes a large number of papers in a broad overview rather than an in depth analysis. In this way it is similar to a scoping review, however the purpose of a scoping review is the assessment of the potential of the available research literature, whereas a mapping review aims to take that a step further and identify gaps in the literature and avenues for future research.

This type of review was chosen in order to gain an overview of a large body of research rather than answer a specific question. Using a systematic mapping review allows the summary of a large number of studies to be combined with identifying trends and gaps in the current literature.

2.4 Methods for chapter 4

Variation in waiting times by diagnostic category: an observational study of 1,951 referrals to a neurology outpatient clinic

In this paper simple statistics were used to explore who visited the neurology clinic in Preston, how long patients waited between referral and appointment and what resources were being used. Some very well-known basic methods were used, including tables of means and proportions and chi square tests of independence. These types of descriptive statistics gave some clear insights into the basic properties of the data and also allowed us to determine useful information such as the number of patients with different diagnoses, the number of tests ordered, and the number of patients offered follow-up appointments. All of these factors are useful to know from both a managerial and clinical perspective.

To examine and compare waiting time distributions we used empirical cumulative distributions (ecdf) and Kolmogorov-Smirnov (K-S) tests. The ecdf is an estimate of the underlying cumulative distribution function of a variable using empirical data. In this paper the ecdf of waiting times for patients with particular diagnoses were plotted. This gave a clear picture of the distribution of waiting times, and in particular allowed easy visualisation of the proportions of patients meeting key targets such as the NHS 18 week referral to treatment benchmark (see Figure 4.2 in chapter 4). These distributions were then compared using the Kolmogorov-Smirnov (K-S) test. The K-S test quantifies the distance between two cumulative distribution functions, in this case those functions that were estimated using the ecdf. The K-S test operates under the null hypothesis that the two distributions under comparison are drawn from the same underlying distribution function but does not assume anything about the type of distribution. In this way it can be determined if the ecdf of the waiting times for particular diagnoses differ significantly. For example, it is possible to test if the distribution for headache patients is statistically significantly different from that of epilepsy patients.

2.5 Methods for chapter 5

Identifying variation in GP referral rates: an observational study of outpatient headache referrals

This paper explores variation in referrals for headache from 202 GP surgeries across the geographical area covered by the clinic in Preston, and aims to identify surgeries which refer unexpected numbers of headache patients. The first type of model considered for this paper was a geostatisitical model as described by Diggle and Giorgi (29). However, after some exploration it was discovered that there was no evidence of residual spatial variation using the empirical variogram. We also tested the data using Moran's I and found no evidence of spatial autocorrelation, so the idea of a spatial model was set aside.

The possibility of using a multi-level, or hierarchical, generalised linear model (GLM) was explored next as GP surgeries were nested within CCGs (Clinical Commissioning Groups) at the time of the study. Fixed variables at the GP level were included (list size, proportion of the patient list that were male, mean age of the patient, number of other neurology referrals made, distance of the practice from the clinic, weighted IMD, and the standard deviation of the weighted IMD (Index of Multiple Deprivation)) and random intercepts were included for the CCGs. Unfortunately, although the structure of the data suggested that a multi-level GLM would be a good fit it was not possible to satisfy the assumption of normality as there were not enough observations at each level of the model.

The final type of model that was considered for this analysis was a generalised linear model (GLM) including the CCGs as a factor variable. A number of different models were tested including negative binomial, zero-inflated Poisson, and Poisson, using the Akaike Information Criterion (AIC) (30) to compare models and find the best fit. The best fitting model was found to be a Poisson log-linear model with an offset for GP surgery list size. We used the list size as an offset instead of including it in the main body of the model as it correlated very strongly with the number of other neurology referrals. The final model used for this analysis was:

$$\log\left(\frac{\mu}{A}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_7 x_7$$

Where:

A = GP list size

x_1 = other neurology referrals

x_2 = mean age

x_3 = weighted IMD

x_4 = SD of weighted IMD

x_5 = distance from clinic

x_6 = proportion male

x_7 = CCG

Standardised residuals from this model were used to examine the difference between the number of expected and observed referrals, and therefore to identify GP surgeries with unusual numbers of referrals, as described in chapter 5.

2.6 Methods for chapter 6

Discovering patterns in outpatient neurology appointments using state sequence analysis

The paper presented in chapter 6 aims to explore and identify patterns in outpatient appointment sequences using State Sequence Analysis (SSA). SSA is a methodology that was developed primarily in the social sciences and has started to become more popular in health research over the past few years. The methodology was developed to answer questions about life course trajectories and transitions from one state of being to another, for example from education, to employment, or unemployment (31). It involves building sequences from events, comparing sequences to determine their similarity to or difference from others, and then grouping the sequences into clusters with similar attributes. We used this methodology to explore the patterns observed in the types of appointments that patients are offered and attend.

The SSA methodology consists of a number of sequential stages: choosing the timeframe and the number of states in order to build the sequences, measuring the

dissimilarity between sequences, clustering the sequences based on their (dis)similarity, choosing the optimal number of clusters, and visualising and analysing the resulting clusters. At each stage of the process there are decisions to be made regarding the precise methodologies to be used, for example choosing the type of clustering algorithm. Each of the choices made could affect the final results and so the decisions that were made are outlined here.

1. Timeframes and states

Outpatients generally attend appointments with a gap of months, rather than days or weeks, in between, and so a time unit of months was decided upon. The types of appointment found in the data were used to identify five distinct states: a straightforward appointment (A), an appointment where a test was ordered (AwT), an appointment at which a patient was discharged (AD), an appointment where a test was ordered and the patient was discharged (AWD), and an appointment that was unattended (ANA). See Figure 6.1 in chapter 6 for a visualisation of these sequences.

2. Dissimilarity

There are several different metrics that can be used to calculate the distance from one sequence to another, including Hamming distance, longest common subsequence, Jaccard coefficient and Optimal Matching (32). All of these measures rely on the principle of assigning values (or 'costs') to the number of operations (such as substitution, insertion and deletion) required to turn one sequence into the other. The different types of measure allow different types of operations to be made and different costs to be assigned to such operations. For example, to turn the sequence A-A-A into A-B-A using Hamming distance we would substitute the middle A with a B. Optimal matching on the other hand allows insertion and deletion and so we could delete an A from the first sequence and insert a B. If we assign a cost of 1 to a substitution, then turning A-A-A into A-B-A 'costs' 1. Thus, we can compare the costs of turning different sequences into each other and this cost defines the distance between two sequences.

Both Hamming distance and Optimal Matching are used in our study. Hamming distance relies solely on substitutions, and when a constant cost of 1 is used for each

substitution, it can be thought of as simply the number of positions in which the sequences differ.

Optimal Matching (OM) uses three different operations: substitution, insertion, and deletion. As deletion is an option, OM can be used to compare sequences of differing lengths. Also, different costs can be assigned to each of these operations allowing for more flexibility in the algorithm. The distance between two sequences is defined as the minimum cost of turning one sequence into the other via any or all of the three operations. Thus, if the cost of one insertion plus one deletion is less than the cost of a substitution then this is the cost the algorithm will return.

Regardless of the algorithm used the result of comparing each sequence to every other sequence is a dissimilarity matrix, and it is this matrix which is used in the next step – clustering the sequences.

3. Clustering

There are a number of different clustering techniques, but in our study we use a hierarchical clustering model known as agglomerative clustering (33). This type of clustering assumes that every individual data point initially belongs in its own cluster, these clusters are compared and the most similar are joined into a new cluster. The clustering algorithm then compares these new clusters and joins the most similar together, and so on until there is only one large cluster with all of the data points contained within it. This type of clustering was chosen because it does not make assumptions about the number of clusters, cluster shape or cluster size before clustering.

There are a number of ways in which the clustering algorithm can decide which clusters are ‘most similar’ (known as cluster linkage) including single-linkage clustering, complete-linkage, minimum increase in variance (MIVAR), and Ward’s linkage (33). A number of different linkage methods were tested, and Ward’s linkage produced the best results as defined by the agglomerative coefficient.

4. The optimal number of clusters.

There are a number of metrics by which the optimal number of clusters can be decided, for example the Dunn index, the Davies Boudin index and the silhouette width (33). Average silhouette width was chosen as it is a well understood metric and it has the added benefit of enabling the identification of outliers. The silhouette width measures how similar a sequence is to the others in the cluster to which it has been assigned and compares this to how different it is to those in other clusters. The average silhouette width of a cluster is the average of the silhouette width of all the individual sequences and thus measures how well defined (on average) the cluster is as well as whether each individual sequence has been placed in the 'correct' cluster. We chose the number of clusters which maximised the overall average silhouette width.

Once the optimal number of clusters was determined and the clusters were visualised, standard statistical tests (chi-square and t-tests) performed to determine if there were any influencing factors on which cluster a particular sequence belonged to. For example, we were able to test whether patients with a particular diagnosis were more likely to belong to certain clusters, and therefore have a particular type of appointment sequence.

3 Routinely collected patient data in neurology research: A systematic mapping review

Abstract

Background: This review focuses on neurology research which uses routinely collected data. The number of such studies is growing alongside the expansion of data collection. We aim to gain a broad picture of the scope of how routine healthcare data have been utilised.

Methods: This study follows a systematic mapping review approach which does not make a judgement on the quality of the papers included in the review, thereby enabling a complete overview of the field.

Results: Of 4481 publications retrieved, 386 met the eligibility criteria for this study. These publications covered a wide range of conditions, but the majority were based on one or only a small number of neurological conditions. In particular, publications concerned with three discrete areas of neurological practice - multiple sclerosis (MS), epilepsy/seizure and Parkinson's disease - accounted for 60% of the total. MS was the focus of the highest proportion of eligible studies (35%), yet in the recent Global Burden of Neurological Disease study it ranks only 14th out of 15 neurological disorders for DALY rates. In contrast, migraine is the neurological disorder with the highest ranking of DALYs globally (after stroke) and yet it was represented by only 4% of eligible studies.

Conclusion: This review shows that there is a disproportionately large body of literature pertaining to relatively rare disorders, and a correspondingly small body of literature describing more common conditions. Therefore, there is potential for future research to redress this balance.

3.1 Background

The global burden of neurological disorders is increasing (34). The Global Burden of Disease neurology collaborators reported that there has been a 39% increase in deaths due to neurological disorders between 1990 and 2016 (17). Alongside this increase in the burden of disease, there is a predicted future shortfall in the US neurology workforce (35), and in the UK there is considerable concern surrounding services for people with neurological disorders (20,22,36). A 2011 report by the UK National Audit Office (NAO) highlighted issues including delays in diagnosis, geographical inequalities in access to care; and a lack of good quality data (20).

Neurology is a large and diverse area of medicine with a correspondingly wide and varied body of research literature. Current neurology practice is heavily informed by the evidence provided by research, and the development of a focus on evidence based practice has been widely reported (37–39). The use of data that have not been specifically collected for research is growing but we do not currently know how these data are being used in neurology research.

Routinely collected health data are collected from many different sources. For example, data may be collected at a patient's face-to-face appointment with a healthcare professional, from administrative processes pertaining to the booking of the appointment, from laboratory results arising from tests requested at the appointment, for insurance information, or diagnostic coding for costing purposes (40). Increasingly, health data are being recorded in an electronic manner, making it easier to store and access for research purposes.

Whilst the traditional hierarchy of evidence holds the randomised controlled trial (RCT) in highest regard, the use of routinely collected data to both supplement RCTs and conduct research outside of clinical trials is growing (38). The 2018 scoping review for an extension to the Consolidated Standards of Reporting Trials (CONSORT) guidelines acknowledges the difficulties and limitations of RCTs and proposes that routinely collected data can be used to help address challenges such as cost, 'limited real-world generalisability' and recruiting representative samples to trials (41). In addition, the use of routinely collected data to conduct stand-alone research is also being advocated. For

example in their 2017 article Casey et al. explore in depth the advantages and disadvantages of using data obtained from the Electronic Health Record (EHR), a key source of routinely collected data, in population health research (42). They conclude that research using EHRs has many advantages such as low cost, large sample sizes and the ability to link to other records, enabling, for example, the incorporation of social, behavioural and environmental data.

This review aims to explore how routinely collected patient data are currently being used in neurology research outside of clinical trials. We will take a broad view of the field in order to understand themes relating to study purpose, statistical methodology, and geographical location of the research. By understanding how routinely collected data are currently being used in neurology research this study intends to identify areas in which these data can be used to enhance future research.

3.2 Methods

3.2.1 Search strategy and selection criteria

Searches were carried out in eight online databases which span the topics of health, statistics, computing and general science. No restrictions were placed on the language of the research. All eight databases were searched between the 13th and 18th December 2018. No restriction was placed on the date of the publications to be retrieved; thus, the search was designed to retrieve all available studies published before December 2018. However, it is worth noting that the searches make use of the term Electronic Health Record (EHR) and as EHRs did not come into widespread use until the 21st century, the majority of studies retrieved were published after the year 2000. Searches were not restricted to full journal articles, allowing abstracts to be retrieved. Details of the search strategy and the databases searched can be found in the Supplementary Materials.

In order to gain a large enough number of studies for analysis the searches were not limited by geographical location. However, this study concerned itself particularly with neurology research in the UK and so the search terms for the ‘neurology’ concept were developed using previous research carried out in the UK (43). Specifically, neither stroke nor dementia were used as individual search terms as neither of these conditions are

routinely seen in general neurology clinics in the UK, but rather, for the most part, in their own speciality settings (18).

3.2.2 Data collection

Once the searches had been completed, ten percent of the retrieved papers were screened against draft eligibility criteria. This subset of the papers was then examined to refine the criteria. Following this initial screen the following eligibility criteria were defined.

Papers were included in this review if:

- Neurology or a neurological condition was the main focus of the study (excluding stroke and dementia).
- The study used only routinely collected data. This includes hospital records, primary care records, health insurance databases, and dispensary data.

Papers were excluded if:

- The primary focus was stroke or dementia.
- Any extra data were collected for the study. For example, patient questionnaires, focus groups or tests ordered specifically for the research.
- They were a systematic review or qualitative study.
- The population included individuals under 16 years of age.

These eligibility criteria were then applied to the whole set of retrieved papers. To reduce the impact of human error, 20% of the papers were audited by Emsley and Knight, ensuring consistent application of the criteria.

A data extraction form was used to extract relevant data from all eligible studies. See Supplementary Table 3 for a table showing the data items extracted and used in the analysis.

The information required for the data extraction was taken from the study titles and abstracts. The full text of a paper was only retrieved if the necessary information could not be found in the abstract. Where possible, the variables were recorded verbatim as found in the paper. However, the information in the papers regarding study objective was not always explicitly clear so this was categorised whilst extracting the data. If the geographical location of the study was not explicitly mentioned in the paper then the country of the lead author's first listed institution was taken as a proxy.

3.2.3 Data analysis

Variables relating to neurological condition and statistical methodology were categorised, allowing for coherent analysis. The nine diagnosis categories used to analyse the data regarding the neurological condition(s) that formed the focus of the papers were defined using previous research and clinical expertise (43). The statistical methodologies were categorised based on descriptive information contained within the individual articles combined with formal definitions of various statistical methodologies. Definitions for both the diagnosis and statistical categories can be found in the Supplementary Materials.

3.3 Results

We retrieved 4481 papers from our database searches and five further papers by searching citations by hand. Once duplicates had been removed, 3075 papers remained for screening. The eligibility criteria were applied to these 3075 papers and 386 papers were deemed eligible for this study. Of these 386 papers, 207 were full research articles and 179 were abstracts only. This selection process can be seen in Figure 3.1.

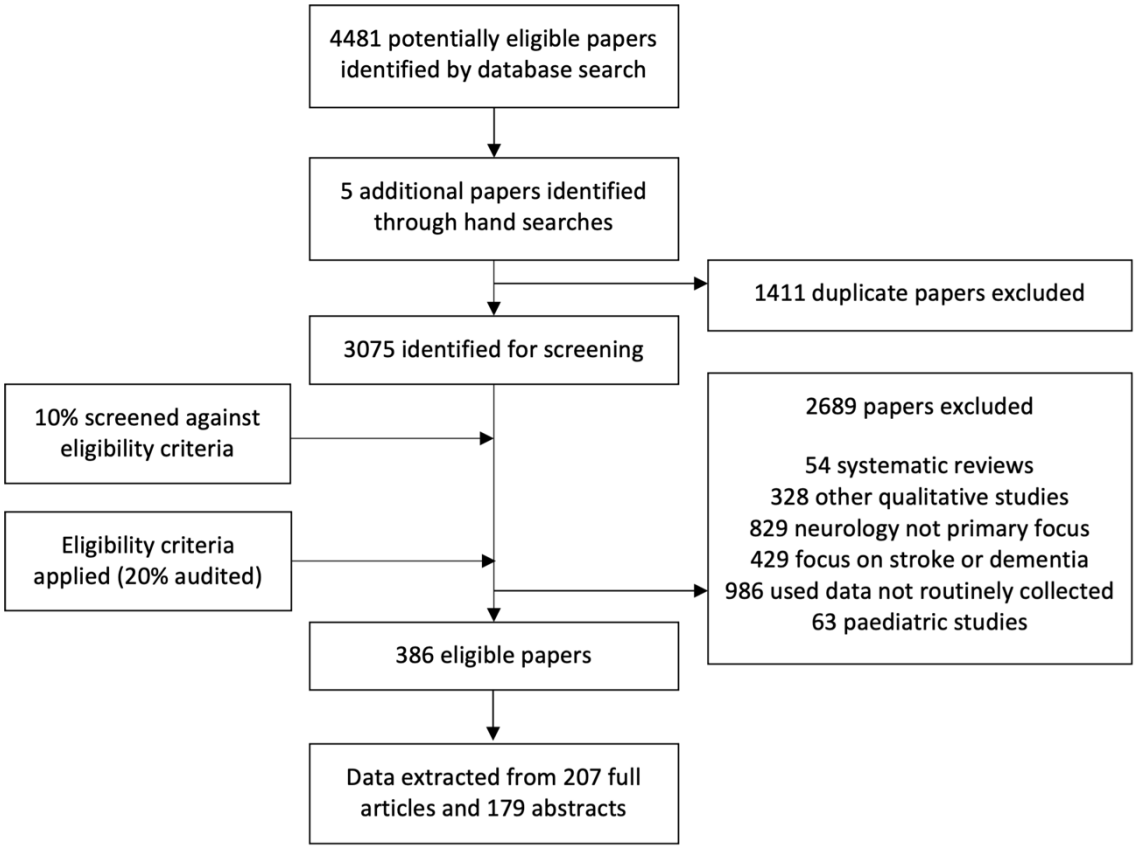


Figure 3.1 Flow chart showing study selection procedure.

We compared the number of papers retrieved by our search in PubMed to an equivalent search on all medical papers. Overall, there are relatively few papers using EHRs and routinely collected data until around the year 2000, since when the number of papers has increased steadily. The earliest neurology specific paper was published in 1991, and the numbers follow the same general upward trend (see Supplementary Table 6). Figure 3.2 shows that, as a percentage of all medical papers referencing EHRs and routine data, neurology accounted for between 0 to 3.3% until 2012, apart from in 1991 when the single neurology paper published accounts for 4.8% of all papers. Since 2012 this percentage has been steadily increasing to reach 8.1% in 2017 and 2018.

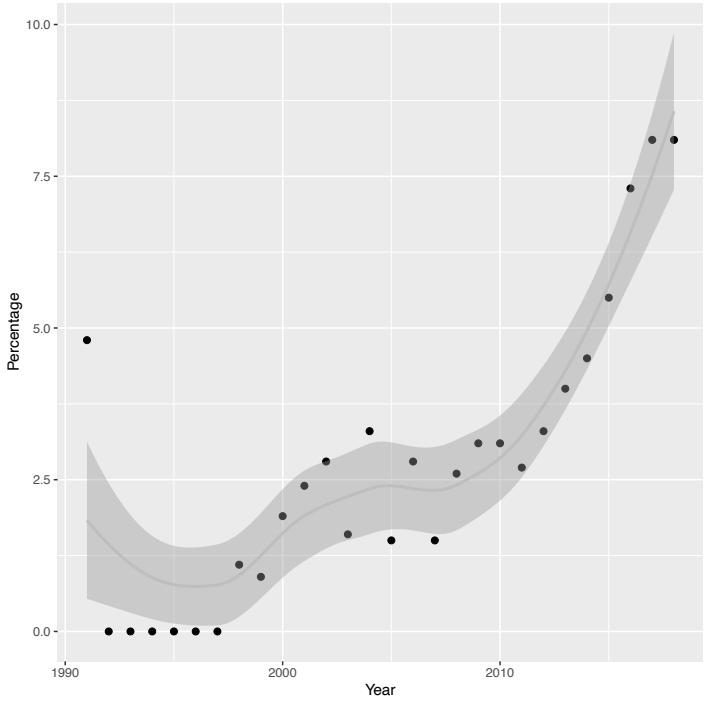


Figure 3.2 Neurology studies as a percentage of all medical studies.

An overview of the characteristics of the included papers can be seen in Table 3.1. They have been split into two separate columns – one for full articles and one abstracts only. This distinction has been made as many abstracts become, or contribute in a large part, to future full articles and it is not always possible to identify when this has occurred.

Most of the papers, both full articles and abstracts, focus on a single type of neurological condition, with only four articles and seven abstracts referring to studies analysing data from multiple conditions. The most frequently studied condition in this analysis is multiple sclerosis (MS), followed by epilepsy/seizure and Parkinson's disease (PD), which can be clearly seen in Figure 3.3A. When comparing this to the global burden of neurological disorders we see that the frequency of the conditions studied does not reflect the burden of those conditions in the population (17). Setting aside stroke and dementia (as they were specifically excluded from this study for reasons previously explained in the methods section) the top three neurological conditions ranked by age-standardised DALY (Disability-adjusted Life Years) rates in both Western Europe and North America are: migraine, spinal cord injury, and brain and central nervous system cancer. The WHO defines one DALY as "the loss of the equivalent of one year of full health. DALYs for a disease or health condition are the sum of the years of life lost to due to premature

mortality (YLLs) and the years lived with a disability (YLDs) due to prevalent cases of the disease or health condition in a population”(44).

Data Item	Category	Full Articles (n=207, %)	Abstract Only (n=179, %)
Neurological Condition	Multiple Conditions	4 (1.9)	7 (3.9)
	Single Conditions:		
	Multiple Sclerosis	61 (29.5)	78 (43.6)
	Epilepsy/Seizure	42 (20.3)	21 (11.7)
	Parkinson's Disease	15 (7.2)	14 (7.8)
	Headache (all)	18 (8.7)	12 (6.7)
	Migraine only	10 (4.8)	6 (3.4)
	Neurodegenerative Disorders	6 (2.9)	2 (1.1)
	Neuromuscular Disorders	5 (2.4)	4 (2.2)
	Other	56 (27.1)	41 (22.9)
Statistical Methodology	Descriptive	127 (61.3)	116 (64.8)
	Regression	35 (16.9)	33 (18.4)
	Survival Analysis	12 (5.8)	8 (4.5)
	Administrative Data Algorithm	9 (4.3)	6 (3.3)
	Machine Learning	5 (2.4)	2 (1.1)
	NLP	5 (2.4)	5 (2.8)
	Propensity Scoring	4 (1.9)	4 (2.2)
	ANOVA	3 (1.4)	1 (0.6)
	Other	7 (3.4)	4 (2.2)
Study Objective	Characterisation of a clinical population	46 (22.2)	44 (24.6)
	Risk Factors	42 (20.3)	31 (17.3)
	Drug Effectiveness	26 (12.6)	15 (8.3)
	Prediction	18 (8.7)	13 (7.3)
	Healthcare Utilisation	13 (6.3)	9 (5.0)
	Diagnosis Validity	13 (6.3)	5 (2.8)
	Prevalence	9 (4.3)	7 (3.9)
	Drug Safety	9 (4.3)	5 (2.8)
	Drug Adherence	8 (3.9)	8 (4.5)
	Other	24 (11.6)	42 (23.5)
Data Type	Hospital Data	91 (44.0)	66 (36.9)
	Claims Data	22 (10.6)	44 (24.6)
	Clinic Data	30 (14.5)	28 (15.6)
	Multicentre Data	23 (11.1)	21 (11.7)
	Veterans or Military Data	13 (6.3)	11 (6.2)
	Primary Care Data	16 (7.7)	2 (1.1)
	Pharmaceutical Data	3 (1.5)	6 (3.4)
	Other	9 (4.3)	1 (0.6)
Location	USA	112 (54.1)	127 (70.9)
	Europe	54 (26.1)	30 (16.8)
	Rest of World	41 (19.8)	22 (12.3)

Table 3.1 Overview of study characteristics.

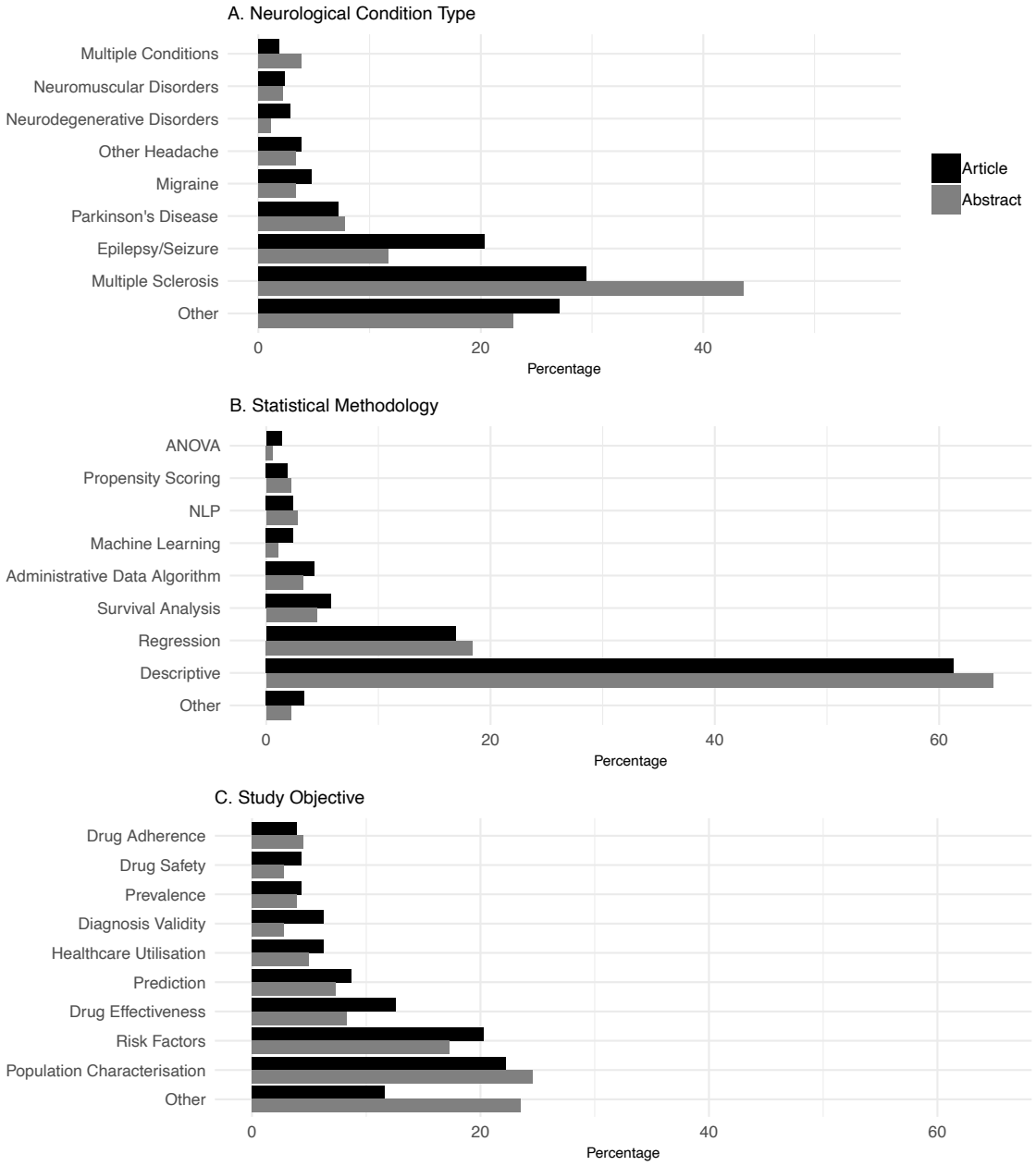


Figure 3.3 Visualisation of study characteristics.

In this review MS is the most frequently studied condition, yet globally it ranks only 14th out of 15 neurological disorders for DALY rates. In contrast, migraine is the neurological disorder with the highest ranking of DALYs globally (after stroke) and yet in this study we see only 4.8% of the full articles and 3.4% of the abstracts focus on this condition. This may reflect a number of issues such as the perception of the validity of research into a condition within the research community, the ease with which the condition can be studied, the availability of data and the availability of funding.

There are 11 papers which analyse many different neurological conditions together and are categorised as ‘multiple conditions’, four full articles and seven abstracts. Six of these papers cover a wide range of neurological conditions, however five of them focus on subsets of neurological conditions such as those treated with immunoglobulins (45,46), neurologic emergencies (47,48),and neuro-ophthalmology (49).

Figure 3.3B shows that the majority of the papers (61.3% of the full articles and 64.8% of the abstracts) exclusively used descriptive statistics in their analysis. This includes means, proportions and statistical tests such as t-tests used to test hypotheses on single variables. Of those papers that moved beyond descriptive statistics the most common type of statistical modelling used is regression modelling (16.9% of full articles and 18.4% of the abstracts). The benefit of using these forms of modelling over hypothesis testing on descriptive statistics is that the effect of many variables can be taken into account at once.

A small number of papers used methods which build on similar foundations to regression modelling including survival analysis (12 articles and eight abstracts) and propensity scoring (four articles and four abstracts). Other papers used a completely different approach to analysis using algorithmic methods. A small number of papers (nine articles and six abstracts) were dedicated to developing administrative data algorithms. Typical of these papers is Ho et al. who used a set of rules applied to data stored in a discharge database to identify patients with non-traumatic spinal cord dysfunction (50).

There were relatively few papers using computationally intensive methods such as Natural Language Processing (NLP) (five articles and five abstracts) and machine learning (ML) (five articles and two abstracts). However, those few papers which have taken advantage of the large body of ‘Big Data’ available in routinely collected health records have used some innovative techniques. For example Chase et al. used NLP with a naïve bayes classifier to identify patients with MS from the EHR, demonstrating how analysing large amounts of routinely collected data could lead to early diagnosis of a neurological illness (51).

The majority of the studies used hospital data in their research (44% of full papers and 37% of abstracts), with the use of claims data second most common but more prevalent

in abstracts (25%) than full papers (11%). Data from specialist clinics accounts for 14.5% of the full papers and 15.6% of abstracts. In addition, Tables 7 and 8 in the Supplementary Materials give a more detailed breakdown of the data type used for each condition (Table 7), and the types statistical analysis used for each data type (Table 8). From Table 8 we see that for studies focusing on Multiple Sclerosis claims data was most commonly used (36% of studies), however conclusions are hard to draw regarding other conditions due to sample sizes. Table 8 shows that descriptive analyses are the most common across all data types, however the distribution of statistical analyses used does vary across different data types.

The studies included in this review had a number of different study objectives, as can be seen in Figure 3.3C. The most common objectives for both full articles and abstracts are 'Characterisation of a clinical population' and 'Risk factors'. Characterising a clinical population refers to those types of study which seek to describe a group, or groups, of patients. For example in their 2016 paper Kestenbaum et al. describe the characteristics of patients with either Parkinson's disease or essential tremor who underwent deep brain stimulation (52). In contrast, the studies regarding risk factors focus more on the factors leading to a disease or outcome, for example Modi SY et.al. published a paper examining the predictors of long hospital stays in status migrainosus (53).

Other common study objectives include research on drug effectiveness, safety and adherence. Taken together these types of study account for 20.8% of the full articles and 15.6% of the abstracts. The most common condition investigated by these types of study is MS, with two thirds of all the drug studies dedicated to this condition.

The vast majority of included studies were based in the USA (54.1% of full articles and 70.9% of the abstracts), 26.1% of the full articles were from Europe and 19.8% from the rest of the world. Of all the European papers eligible for inclusion in this study 29 were UK based, 14 of which were abstracts and 15 full articles. All of the UK based research focused on single types of neurological condition with epilepsy/seizure being the most commonly researched (seven papers), followed by Parkinson's disease (four papers) and MS (four papers) showing a broadly similar trend to that seen in the whole body of eligible studies. However, we did not find a large enough number of UK based studies to do a full mapping review on this subset of research.

3.4 Discussion

This study synthesises and summarises neurological research that has been carried out using routinely collected data, that is, data which were not initially collected for research purposes, but for reasons such as diagnosis, treatment or administration.

The results show that routinely collected patient data has been used for a number of different purposes in neurology research. Primarily, the data has been used to study single neurological conditions in isolation. Within these papers we found a variety of study objectives, the most common of which relate to the characterisation of a population, risk factors for an outcome and drug safety, adherence and effectiveness outside of clinical trials. Whilst these conditions are well researched, this study highlights the fact that there are potentially areas of neurology which remain under-researched in comparison.

There is an imbalance between the numbers of papers found for particular types of conditions, and the impact of those conditions (measured in DALYs) according to the global burden of neurological disease (17). This indicates that there may be an opportunity for high impact research to take place into conditions that have a very real effect on healthcare systems, on society, and on individual patient's lives. Previous research has highlighted the fact that there is an imbalance between the amount of research conducted and the rarity of a condition, with rare neurological conditions receiving disproportionately more attention than common ones (54,55). Bishop proposes that the reason that rare conditions receive more research focus is because of their severity (54), and Al-Shahi et al. propose that the amount of research conducted should be proportional to the burden of the disease in society (55). A high rate of DALYs indicates the potential economic and social cost of common conditions such as migraine. Research into these less well-studied areas using routinely collected data could contribute to reducing the burden of disease and consequently the economic and social cost.

The statistical methodologies used in the papers included in this study range from descriptive statistics to more complex analyses based on Machine Learning techniques. Machine Learning techniques generally require large amounts of data from which to 'learn' a mathematical model which can then be applied to an unseen set of data to predict or classify future results. As the amount of routinely collected data grows, this is an area

in which future neurology research could have an impact – for example by using Machine Learning to find previously unknown associations, or for phenotyping diseases (56). However, the use of complex algorithms and computationally intensive methods relies on having the right kind of question as well as suitable data. This study shows that there are differences in statistical analyses used on different types of data (see Table 8 in Supplementary Materials). For example, the relatively high number of regression analyses undertaken on claims data may occur because claims data is often highly numerical and abundant, and therefore lends itself to this type of analysis. In addition, data from hospital records can be highly complex and include pages of written notes, and so we see that analyses using Machine Learning and NLP are used in these types of data. It is worth noting that not all types of data lend themselves to complex analyses, and statistical analyses should only be as complex as is required to answer the question at hand.

As expected, this review did not identify many studies using routinely collected data to investigate neurology services managing multiple conditions, such as outpatient clinics. Rather, this review clearly shows that the majority of research relates to single conditions or condition types such as epilepsy and MS. We found only 11 studies which included multiple conditions, and of those, only four were studies into the provision of services. Many neurology clinics provide treatment and care to patients with a wide range of conditions and as such, research relating to these services should incorporate all of those conditions (18). There is a real opportunity here for research to be conducted using routinely collected data which could be used in many different ways to support the efficient delivery of services. For example, in other disciplines, routinely collected data have been used to examine waiting times for appointment and explore patient visit patterns (57,58).

3.4.1 Limitations

Systematic mapping reviews, like all systematic reviews have some underlying limitations, which include reporting and selection biases and inaccuracies in data extraction. Particular to mapping reviews is the issue of oversimplification – because a mapping review is designed to give a broad overview of an area, it can mask underlying variations in the included studies (26). In this study we have sought to limit the impact of

reporting bias (the tendency for research with positive studies more likely to be published) by searching for and including papers that have been published as abstracts. This ensures that research in emerging areas is included, as well as studies that have perhaps not yet merited full publication.

Selection bias was limited by defining strict eligibility criteria before the papers were screened for inclusion. The application of the eligibility criteria to the list of potential papers was also quality assured in 20% of the papers to ensure that the criteria were applied consistently.

Other limitations include inaccuracy in data extraction and classification, which is inevitable when using categories to define study characteristics, however we have been consistent throughout the study and the definitions used for the categories can be found in the Supplementary Materials.

Applying the results of this review across different geographical areas should be done with caution. The majority of the studies in this review were conducted in the USA and Western Europe where neurology services and policies may differ significantly from other areas with different healthcare structures and populations. Even within Western Europe there are many differences in the way in which services are delivered and the data recorded (59). Future studies should endeavour to relate the findings of this review to their own context, and as more neurology research emerges in different countries and contexts, the gaps in research in individual areas will become clearer. In addition, applying conclusions drawn from the location of the studies should take into account the fact that study location was not always explicit. In these cases, study location was taken to be the location of the lead author's main institution.

The main strength of this review is that research on neurological conditions using routinely collected data has not been reviewed in this way before. This study allows us to see what work is already being done, and where future research could have an impact. As with all systematic reviews the methodology of this study has been well documented such that it could be repeated and the results replicated in the future.

3.5 Conclusion

There is a large body of research within neurology that exclusively uses routinely collected data, including data from electronic health records, public health records, and primary care data as well as administrative data such as medical insurance claims. This research covers a wide range of conditions, outcomes and study objectives. We have discovered an underrepresentation of studies into common conditions. It is also clear from this study that there are few studies which include multiple conditions in the same research, or which study neurology services as a whole. Future research using routinely collected data could make a large impact by considering the more common but less well-researched conditions or by considering how services could be improved by utilising data from many conditions.

3.6 Supplementary Materials

1	electronic medical record [abstract/title]
2	electronic health record [abstract/title]
3	electronic patient record [abstract/title]
4	EHR [abstract/title]
5	real world data [abstract/title]
6	real world evidence [abstract/title]
7	routinely collected data [abstract/title]
8 (PubMed only)	Electronic health records [Mesh]
9	1 or 2 or 3 or 4 or 5 or 6 or 7 or 8
10	(migraine or headache or headache disorders) [abstract/title]
11	(functional neurological disorder or functional neurological symptom disorder) [abstract/title]
12	(epilepsy or seizure) [abstract/title]
13	(multiple sclerosis or MS or demyelination) [abstract/title]
14	(degenerative spine disease or myelitis) [abstract/title]
15	(parkinson's disease or parkinsons disease or tremor or dystonia or parkinsonism) [abstract/title]
16	(syncope or transient loss of consciousness) [abstract/title]
17	(peripheral nerve disorder or polyneuropathy or mononeuropathy) [abstract/title]
18	neurol* [abstract/title]
19 (PubMed only)	Nervous Systems Disease [Mesh]
20	10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19
21	9 and 20

Supplementary Table 1. Search strategy used for the systematic mapping review.

1	PubMed
2	EMBASE: Excerpta Medica
3	CINAHL
4	Academic Search Ultimate
5	SCOPUS
6	Web of Science
7	MathSciNet
8	IEEExplore

Supplementary Table 2. Databases searched for the systematic mapping review.

Variable	**Collected As**	**Categorised to**
Neurological Condition	Free text	9 diagnostic categories
Statistical Methodology	Free text	10 methodology categories
Study Objective	Category	
Data Type	Category	
Study Location	Free text	

Supplementary Table 3. All data items extracted from the eligible papers.

Data Item	Category	Description
Statistical Methodology	Descriptive	Analysis limited to descriptive statistics such as means and proportions, and hypothesis tests on single variables.
	Regression	Statistical modelling using regression models. Includes all forms of regression including both linear and logistic regression.
	Administrative Data Algorithm	Deterministic algorithms applied to patient data. Generally used to identify patients with certain diagnoses.
	Survival Analysis	Modelling designed to analyse survival times. Include Kaplan Meier and Cox proportional hazards.
	ANOVA	Statistical modelling using Analysis of Variance.
	Natural Language Processing	Analysis of large amounts of text using computer science and computational linguistics.
	Propensity Scoring	The use of propensity score matching statistical matching technique
	Machine Learning	Analysis using algorithms where the computer learns from the data. Generally used for prediction.
	Other	Any other statistical or analytical technique not otherwise described here.

Supplementary Table 4. Definitions of the statistical methodology categories used in the analysis.

Data Item	Category	Description
Neurological Condition	Multiple conditions	Papers which analyse many different neurological conditions and diagnoses at once. For example, papers which consider all types of neurologic emergency.
	Multiple Sclerosis	Papers examining all four types of Multiple Sclerosis.
	Epilepsy/Seizure	Papers examining all types of epilepsy and seizure disorders.
	Parkinson's Disease	Papers examining Parkinson's Disease, Parkinsonism and Essential tremor.
	Headache (all)	Papers examining all types of primary headache including cluster headache, migraine and tension headache.
	Migraine only	Those papers which exclusively examine migraine.
	Neurodegenerative Disorders	Papers examining Neurodegenerative disorders other than Parkinson's disease, which has its own category, and Alzheimer's, as dementia papers were removed from the study.
	Neuromuscular Disorders	Papers examining Neuromuscular disorders other than Multiple Sclerosis, which has its own category.
	Other	Papers examining all other neurological conditions and diagnoses which do not fit into one of the above categories.

Supplementary Table 5. Definitions of the neurological condition categories used in the analysis.

Year	All papers	Neurology (%)
1991	21	1 (4.8)
1992	11	
1993	29	
1994	37	
1995	58	
1996	57	
1997	80	
1998	92	1 (1.1)
1999	107	1 (0.9)
2000	104	2 (1.9)
2001	126	3 (2.4)
2002	142	4 (2.8)
2003	193	3 (1.6)
2004	244	8 (3.3)
2005	341	5 (1.5)
2006	429	12 (2.8)
2007	462	7 (1.5)
2008	496	13 (2.6)
2009	882	27 (3.1)
2010	1703	53 (3.1)
2011	1971	53 (2.7)
2012	2355	78 (3.3)
2013	2994	121(4.0)
2014	3374	153 (4.5)
2015	3798	209 (5.5)
2016	3918	286 (7.3)
2017	4303	350 (8.1)
2018	4973	401 (8.1)

Supplementary Table 6. Numbers of papers relating to the use of EHRs and Routinely collected data retrieved each year in PubMed search.

	Multiple Sclerosis (n=139, %)	Epilepsy/ Seizure (n=63, %)	Parkinson's Disease (n=29, %)	Migraine (n=16, %)	Other Headache (n=14, %)	Multiple Conditions (n=12, %)	Neurodegenerative Disorders (n=8, %)	Neuromuscular Disorders (n=9, %)	Other (n=97, %)
Hospital	31 (22.3)	23 (36.5)	14 (48.3)	1 (6.3)	7 (50.0)	8 (66.7)	4 (50.0)	4 (44.4)	65 (67.0)
Claims	49 (35.3)	4 (6.3)	4 (13.8)	3 (18.8)		1 (8.3)	1 (12.5)	1 (11.1)	3 (3.1)
Clinic	21 (15.1)	12 (19.0)	5 (17.2)	8 (50.0)	5 (35.7)	1 (8.3)	1 (12.5)	3 (33.3)	2 (2.1)
Multicentre	21 (15.1)	10 (15.9)	1 (3.4)	3 (18.8)	1 (7.1)		1 (12.5)	1 (11.1)	6 (6.2)
Veterans	3 (2.2)	2 (3.2)	3 (10.3)	1 (6.3)	1 (7.1)				14 (14.4)
Primary Care	8 (5.8)	5 (7.9)	2 (6.9)			1 (8.3)	1 (12.5)		2 (2.1)
Pharmaceutical	3 (2.2)	3 (4.8)							2 (2.1)
Other	3 (2.2)	4 (6.3)							3 (3.1)

Supplementary Table 7. Primary condition focus split by data type used.

	Hospital (n=157, %)	Claims (n=66, %)	Clinic Data (n=58, %)	Multi-centre (n=44, %)	Veterans and military (n=24, %)	Primary Care (n=18, %)	Pharmaceutical (n=9, %)	Other (n=10, %)
Descriptive	107 (68.2)	38 (57.6)	42 (72.4)	21 (47.7)	17 (70.8)	7 (38.9)	6 (66.7)	5 (50.0)
Regression	25 (15.9)	19 (28.8)	8 (13.8)	12 (27.3)	1 (4.2)	2 (11.1)		1 (10.0)
Survival Analysis	8 (5.1)	2 (3.0)	4 (6.9)	3 (6.8)		1 (5.5)	2 (22.2)	
Administrative Algorithm	2 (1.3)	3 (4.6)		3 (6.8)	1 (4.2)	6 (33.3)		
Machine Learning	3 (1.9)		1 (1.7)	1 (2.3)				2 (20.0)
NLP	4 (2.5)	1 (1.5)	1 (1.7)		4 (16.6)			
Propensity Scoring	2 (1.3)	2 (3.0)	1 (1.7)	1 (2.3)				2 (20.0)
ANOVA	2 (1.3)	1 (1.5)				1 (5.5)		
Other	4 (2.5)		1 (1.7)	3 (6.8)	1 (4.2)	1 (5.5)	1 (11.1)	

Supplementary Table 8. Data Type split by statistical analysis used.

4 Variation in waiting times by diagnostic category: an observational study of 1,951 referrals to a neurology outpatient clinic

Abstract

Objective: To investigate the frequency of diagnoses seen among new referrals to neurology outpatient services; to understand how these services are used through exploratory analysis of diagnostic tests and follow-up appointments; and to examine the waiting times between referral and appointment.

Methods: Routine data from new NHS appointments at a single consultant-delivered clinic between Sept 2016 and January 2019 were collected. These clinical data were then linked to hospital administrative data. The combined data were assigned diagnostic categories based on working diagnoses to allow further analysis using descriptive statistics.

Results: Five diagnostic categories accounted for 62% of all patients seen within the study period, the most common of which was headache disorders. Following a first appointment, 50% of all patients were offered at least one diagnostic test, and 35% were offered a follow-up appointment, with variation in both measures by diagnostic category. Waiting times from referral to appointment also varied by diagnostic category. 65% of patients with a seizure/epilepsy disorder were seen within the 18 week referral to treatment target, compared to 38% of patients with a movement disorder.

Conclusion: A small number of diagnostic categories account for a large proportion of new patients. This information could be used in policy decision making to describe a minimum subset of categories for diagnostic coding. We found significant differences in waiting times by diagnostic category, as well as tests ordered, and follow-up offered; further investigation could address causes of variation.

4.1 Introduction

Neurology services in the UK are overwhelmed and the majority of neurologist time is spent in outpatient clinics. Demand outstrips capacity across the UK, although there is substantial geographical variation. This research has been driven by a need to better understand various aspects of neurology outpatient services, including the frequency of diagnostic categories prompting referral, how services are used, waiting times, and how these aspects vary by diagnostic category. It is perhaps surprising that research is required at all in order to investigate diagnostic categories, but unlike hospital admissions, UK neurology outpatient services have not routinely applied diagnostic coding to outpatient attendances. This undermines attempts to redesign services and optimise access for patients. The absence of outpatient diagnostic coding also prevents research on this theme, including analyses of variation between clinicians and neurological services. Even where diagnostic coding is utilised, the use of different approaches and coding systems limits comparison. We hope that, as well as offering insights into the frequency of diagnostic categories and how diagnostic categories influence investigations, follow up and waiting times, that this research should also provide a foundation from which to start the process of creating a minimum specification for outpatient neurology coding.

As a specialty neurology in the UK has been under much scrutiny over the past 10 years. In 2011 a review by the National Audit Office entitled “Services for people with neurological conditions” highlighted a number of issues within neurological care in the UK (20). These issues included, but weren’t limited to, varying quality of diagnoses, poorly coordinated care, inequalities in access to care and workforce shortages. Both an update to this review published in 2015 and a parliamentary paper published in 2016 noted that these issues were still ongoing (60,61). In order to address these issues at a grassroots level, it is necessary to know who is currently visiting neurology services, and how these services are being used.

A 2010 Kings Fund report stated that referral has direct consequences for patients’ experience of care and costs to the health system (62). Waiting times for referral can be used as an indication of how overburdened a service is. There is currently limited research on referral practices and waiting times for neurology outpatients. However, as

referrals to neurology outpatient clinics in the UK often come from patients' general practitioners (GPs), research based on all-cause referrals (rather than specialty specific research) highlights the difficulties in understanding variation and how best to respond to it. For example, in 1993 Fertig et al. found that although rates of referral varied between practices, this could not be explained by 'inappropriate referrals' and concluded that changes to referral guidelines would be unlikely to reduce referral rates (63). In contrast, a systematic review conducted by Grimshaw et al. in 2008 found that 2 strategies were successful in reducing referral rates; guidelines alongside structured referral sheets; and educational interventions by hospital consultants (64).

Previous research into neurology outpatient visits in the UK has been carried out by Stevens (1988), Hopkins et al. (1989), Wiles et al. (1996), and Stone et al. (2010) (43,65–67). These studies all examined the proportions and demographics of patients presenting with different diagnoses, however none of these papers examined waiting times, and only Wiles et al. included rates of diagnostic tests and follow-up. Stone et al. acknowledged the importance of knowing what onward treatment patients need; and we extend our investigation, conducted over a more recent time period, to these areas (43).

4.1.1 Specific Objectives of this study

This research uses routine data collected at a neurology outpatient clinic in North-West England to:

- describe the proportions of referrals of patients with different diagnostic categories in order to measure relative service use and guide future research and policy;
- analyse the number of diagnostic tests requested and follow-up appointments offered as a measure of ongoing service use;
- examine waiting times for referral in order to identify potential variation in access to services.

4.2 Methods

4.2.1 Study Design

This is a retrospective observational study using routinely collected patient data. The proposal underwent ethical review with both the NHS Research Ethics Committee (Ref: 19/NW/0178) and Confidentiality Advisory Group (Ref: 19/CAG/0056) and received approval from the Health Research Authority (HRA) on 30 May 2019 (Ref: 255676). In addition the study underwent ethical review with Lancaster University Faculty of Health and Medicine Research Ethics Committee and obtained approval on 17 June 2019 (Ref: FHMREC18092).

4.2.2 Setting and Data Collection

We used data from patients referred to, and offered an appointment in, a single consultant-delivered neurology clinic over a period of three and a half years.

Data were recorded at a neurology outpatient clinic at the Royal Preston Hospital (RPH), which is part of the Lancashire Teaching Hospitals NHS Foundation Trust (LTHTR), provider of the Lancashire and South Cumbria regional neurosciences service. The regional service covers a geographically and socio-economically diverse population of approximately 1.6 million residing in urban areas (including the cities and towns of Preston, Chorley, Lancaster, Blackpool, Blackburn and Burnley) and rural areas (the Fylde coast, rural Lancashire and south Cumbria). This clinic is principally a general neurology clinic with some vascular neurology referrals reflecting the subspecialty interest of the consultant, and is dedicated to adult care. No paediatric referrals were included.

Data were collected prospectively from all new appointments held between 18th September 2015 and 9th January 2019. This totalled 2259 appointments of which 1951 were attended and included in this study. These data were then linked to LTHTR's business intelligence (BI) database. Patients come from three different referral pathways; under the 'two-week rule' for suspected CNS cancer (68); a two-week urgent referral for first seizure (69); or on an 18 week referral to treatment (RTT) timeline

(70). Referrals are triaged by consultant neurologists on a rota, and this may lead to variation in prioritisation to urgent appointments.

The data collected during the clinic represent information which is routinely required for consultation, diagnosis and patient management. This includes information on attendance, patient age, gender, principal working diagnosis, diagnostic tests ordered, and whether a follow up appointment was offered.

The data from BI were used to verify the data collected during clinics (gender, age, and attendance) and to add information regarding the source and date of referral.

4.2.3 Variables

To undertake statistical analysis it was necessary to categorise the principal working diagnosis as the information was recorded in an uncoded free text field. Several systems exist for formally coding diagnoses (for example ICD-10 and SNOMED-CT) however, in the UK these are not routinely used to code neurology outpatient diagnoses. In the absence of a formal coding system, we used the diagnostic categories from Stone (2010), as they represent the most recent published work on neurology diagnoses and also provide a pragmatic approach (43). The categorisations were assigned manually, by a consultant neurologist, from free text notes made at the time of the patient visit. Where more than one diagnosis had been recorded the principal diagnosis was used.

Diagnostic tests were also categorised from a free text field and include requests for central nervous system (CNS) imaging, other imaging, neurophysiology tests and 'other' tests (eg lumbar puncture). For the purposes of this analysis CNS imaging included requests for brain, cervical spine, thoracic spine and/or lumbosacral spine.

4.2.4 Statistical Methods

For analysis we used R Studio (version 1.2.5019) (71). For the analysis of diagnostic categories and patient demographics analysis we used descriptive statistics including means and proportions. Proportions were also used in the analysis of the number of tests and follow up appointments offered. Chi-square tests of independence were used

to test the independence of diagnostic tests ordered and follow-up offered from the diagnostic category.

Raincloud plots and smoothed curves of waiting times from referral for each diagnostic category were created for visual comparison (72). Empirical cumulative distribution functions (ecdf) with kolmogorov-smirnov tests were used to compare selected distributions of waiting times.

4.2.5 Missing Data

One record was missing the age of the patient and so does not contribute to the calculations of average age. There were 25 appointments with missing information regarding referral dates. These appointments were included in the analysis of diagnostic category, testing and follow-up frequency, but were excluded from the analyses regarding waiting times. We did not consider any special treatment of missing data as the number of missing records is small (around 1%) and no particular pattern of missingness could be detected.

4.3 Results

4.3.1 Patient Demographics and Diagnostic Category Frequency

During the study period 1951 first appointments were attended. The mean (SD) age of patients overall was 50.0 (18.6) years and varied from 43.2 (18.6) years for seizure/epilepsy to 74.9 (11.7) years for dementia. The overall proportion of females in the study was 0.56 and the proportions ranged from 0.33 (muscle disorder) to 0.77 (multiple sclerosis).

We recorded 17 different diagnostic categories from approximately 1200 unique free text instances, as described in the methods section, and Table 4.1 shows an overview of these categories. The five most common diagnostic categories accounted for 62% of all diagnoses and comprised headache, seizure/epilepsy, psychological/functional disorders, movement disorders and peripheral nerve/neuromuscular disorders.

Diagnostic category	Number of appointments (proportion*)	Mean age (sd)	Proportion female	Number of appointments resulting in at least one test (proportion**)	Number of patients offered follow-up appointment (proportion**)	Average number of tests ordered per appointment
Headache (all)	378 (0.19)	44.4 (16.9)	0.69	165 (0.44)	41 (0.11)	0.49
Seizure/Epilepsy	282 (0.15)	43.2 (18.6)	0.41	146 (0.52)	205 (0.73)	0.82
Psychological/Functional	189 (0.10)	44.3 (14.9)	0.63	85 (0.45)	36 (0.19)	0.69
Movement Disorders (all)	180 (0.09)	61.5 (18.0)	0.48	55 (0.31)	94 (0.52)	0.36
Peripheral nerve/neuromuscular	166 (0.09)	59.5 (15.3)	0.49	119 (0.72)	40 (0.24)	0.84
Spinal Disorders	98 (0.05)	60.0 (15.3)	0.45	80 (0.82)	20 (0.20)	1.32
Syncope/transient loss of consciousness	97 (0.05)	45.8 (18.1)	0.54	58 (0.60)	19 (0.20)	1.03
Stroke (all)	92 (0.05)	62.1 (16.3)	0.46	42 (0.46)	38 (0.41)	0.66
No definite neurological diagnosis	66 (0.03)	48.2 (17.5)	0.58	41 (0.62)	25 (0.38)	0.97
Multiple Sclerosis/demyelination	43 (0.02)	47.4 (14.9)	0.77	21 (0.49)	34 (0.79)	1.09
General Medical	30 (0.02)	48.3 (18.3)	0.57	14 (0.47)	4 (0.13)	0.50
Dementia	20 (0.01)	74.9 (11.7)	0.30	9 (0.45)	9 (0.45)	0.45
No Diagnosis Made	12 (0.01)	49.6 (9.6)	0.83	0 (0.00)	0 (0.00)	0.00
Brain Tumour	10 (0.01)	69.8 (16.4)	0.80	6 (0.60)	2 (0.20)	0.70
Muscle	9 (0.00)	47.3 (21.5)	0.33	5 (0.56)	6 (0.67)	1.33
Motor Neurone Disease	8 (0.00)	67.4 (7.9)	0.75	4 (0.50)	7 (0.88)	0.5
Miscellaneous Neurological Disorders	271 (0.14)	50.6 (18.8)	0.62	162 (0.60)	107 (0.39)	0.83
TOTAL/SUMMARY	1951	50.0 (18.6)	0.56	1012 (0.52)	686 (0.35)	0.75

Table 4.1 Characteristics of dataset by diagnostic category.

Chi square test of independence of Number of appointments resulting in at least one test and Diagnostic category: $p < 0.5 \times 10^{-10}$. Chi square test of independence of Number of patients offered follow-up appointment and Diagnostic category: $p < 0.5 \times 10^{-10}$. *proportion of column total. **proportion of diagnostic category.

4.3.2 Tests ordered and follow up offered

Table 4.1 shows the proportion of appointments that resulted in at least one diagnostic test being ordered; the proportion that resulted in a follow-up appointment being offered; and the average number of tests offered per appointment. Overall 52% of patients were offered at least one test, and 35% of patients were offered a follow-up appointment. In most of the diagnostic categories it was more likely that at least one test was ordered, than a follow-up appointment being offered. This indicates that some patients were offered a test and simultaneously discharged from the outpatient clinic.

Of the five most common diagnostic categories, seizure/epilepsy patients were offered the highest proportion of follow-up appointments (73%). The smallest proportion of

follow-up appointments were offered to headache patients (11%), indicating that 89% of patients falling into the diagnostic category of headache disorders were discharged after only one appointment. The proportion of patients for whom a test was requested is more similar; 52% of seizure/epilepsy patients were offered at least one test compared to 44% of headache patients. Of those tests requested, the majority were for CNS imaging: 98% for headache patients and 82% for seizure/epilepsy. This highlights the heterogeneity of patient pathways which depends largely on diagnostic category. Tests of independence were performed to examine the relationship between test request and diagnostic category, and between follow-up appointment and diagnostic category (p-values shown in the legend of Table 4.1). The results confirm that there is a significant association between both of these variables and diagnostic category.

4.3.3 Waiting time from referral to appointment

Both raw data and smoothed distributions of waiting times for 11 of the 17 diagnostic categories can be seen in Figure 4.1. The six diagnostic categories with 30 or fewer appointments over the study period, plus individual appointments with waiting times over 40 weeks (n=2) have been excluded from this figure to optimise visualisation. The full results can be seen in Supplementary Figure 1. The two vertical dotted lines on Figure 4.1 show the targets for a two-week urgent referral pathway for first seizure and suspected CNS cancer, and the standard 18 week referral to treatment (RTT) target for non-urgent consultant led appointments. This clearly shows that many patients were not seen within the 18 week timeline.

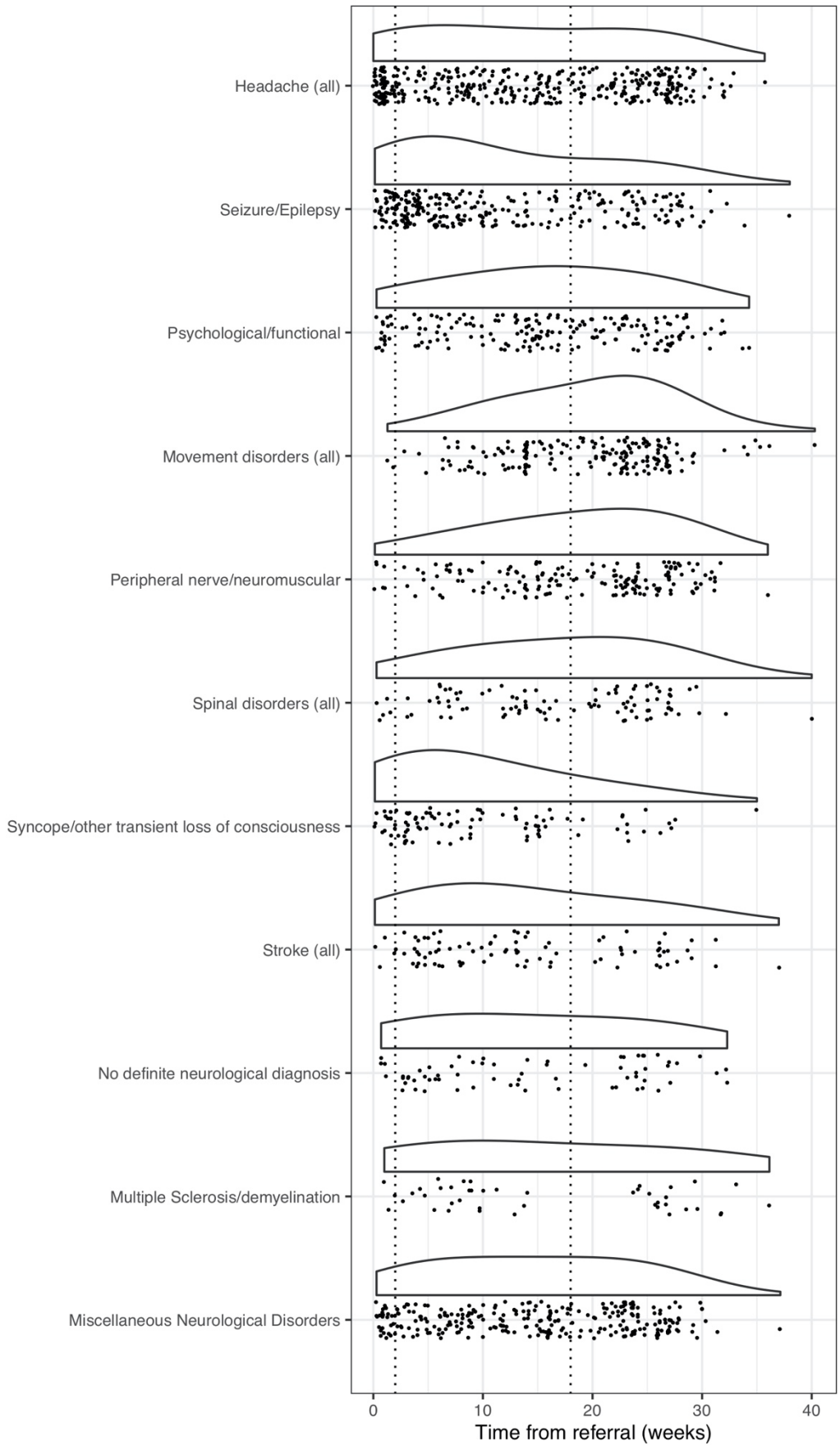


Figure 4.1 Distribution of waiting time from referral to new appointment.

Diagnostic Category	Number of referrals	Number referred on two-week pathways (proportion)	Number referred on standard pathway (proportion)	Unknown (proportion)
Headache (all)	378	62 (0.16)	306 (0.81)	10 (0.03)
Seizure/Epilepsy	282	41 (0.15)	226 (0.80)	15 (0.05)
Psychological/functional	189	13 (0.07)	170 (0.90)	6 (0.03)
Movement Disorders (all)	180	2 (0.01)	173 (0.96)	5 (0.03)
Peripheral nerve/neuromuscular	166	5 (0.03)	158 (0.95)	3 (0.02)

Table 4.2 Number and proportion of patients from the 5 most common diagnostic categories referred on a two-week pathway (suspected CNS cancer or first seizure), compared to the standard 18 week referral to treatment.

The proportion of patients referred under two-week pathways or the 18 week RTT pathway varied by diagnostic category. Table 4.2 shows the number and proportion of patients referred on a two-week urgent pathway for the five most common diagnostic categories, 100% of two-week headache referrals were on the suspected CNS cancer pathways and 88% of two-week seizure referrals were on the first seizure pathway. In order to compare waiting times between diagnostic categories, we identified and removed all referrals made on the two-week CNS cancer rule or first seizure pathway, allowing us to compare routine 18 week referral to treatment only.

Figure 4.2 shows the empirical cumulative distribution functions (ecdfs) of waiting times for the 5 most common diagnostic categories. The x-axis shows waiting time in weeks and the y-axis represents the proportion of patients who have attended their appointment. Reading along the horizontal dashed line at 0.5 shows the time at which 50% of patients have been seen. Following the vertical line at 18 weeks shows that 65% of seizure/epilepsy patients are seen within target waiting times, compared to only 38% of those diagnosed with a movement disorder.

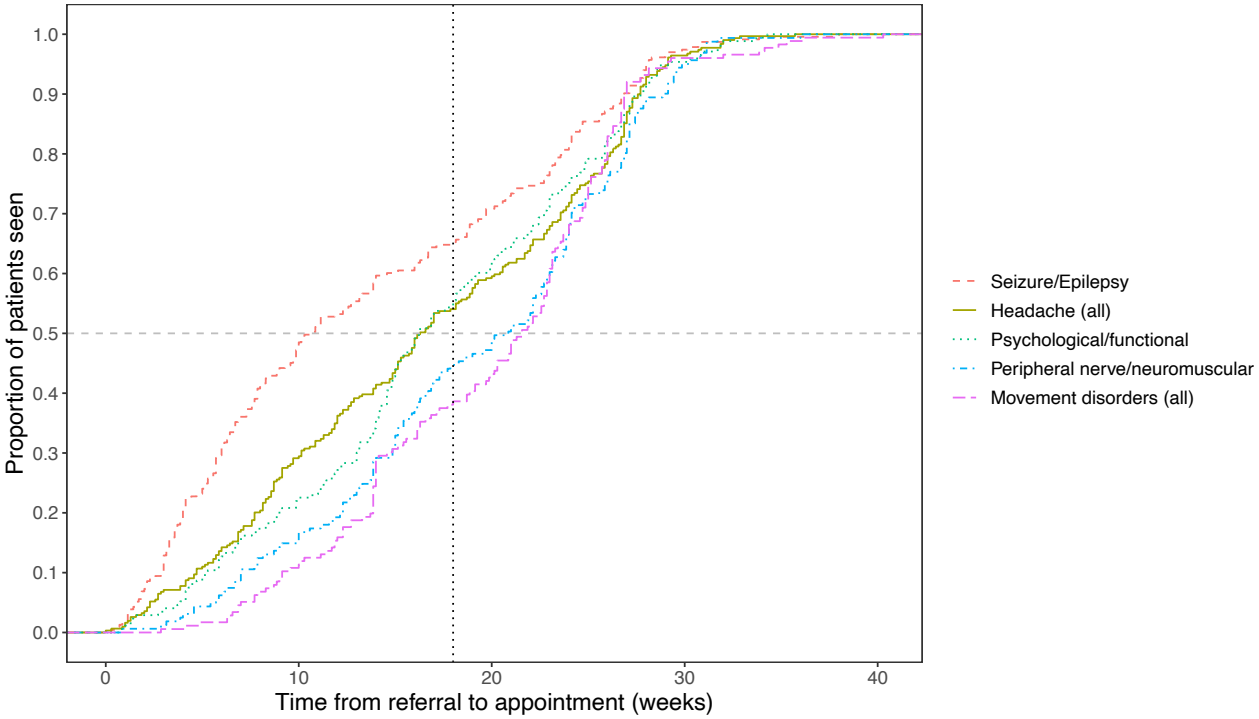


Figure 4.2 Empirical cumulative distribution of waiting time for the 5 most common diagnostic categories.

A table showing p-values from pairwise comparisons of these distributions using kolmogorov-smirnov tests with Bonferroni corrections can be found in Supplementary Table 1. These comparisons show that patients diagnosed with seizures have a significantly different distribution of waiting times than all other diagnostic groups, and are typically seen much sooner. Those with movement disorders wait longest, and these waiting time distributions are significantly different to those from patients with headache or seizure.

4.4 Discussion

This study adds to the current body of research by replicating previous studies examining frequency of principal working diagnoses and diagnostic categories, and extending this to look at numbers of diagnostic tests and follow-up appointments offered. We also compare waiting times from referral to appointment, identifying variations in access to care. Our work is more contemporary by comparison with earlier published work, and has been undertaken during a period impacted by numerous changes in NHS structure and guidance.

4.4.1 Patient demographics and diagnostic category frequency

The most common diagnostic categories identified in this study were headache, seizure/epilepsy and psychological/functional disorders. This simple but important analysis sheds light on the proportions of patients visiting neurology outpatient clinics falling into headline diagnostic categories. This helps to inform future research and provides valuable information to facilitate service planning and development.

Comparing our results to Stone et al. we see that their four most common diagnostic categories align with four of the five most common diagnostic categories identified by this study; headache, psychological/functional disorders, epilepsy, and peripheral nerve disorders (43). Despite the fact that the studies were conducted 10 years apart, in different regions of the UK, and using different approaches to data collection - a single consultant in a single centre versus multiple consultants in multiple centres - it is striking that the most common diagnostic categories were similar in both proportion and rank. This points towards a relatively unchanging and predictable list of the most frequent diagnostic categories presenting to UK neurology clinics. This provides an important basis for defining a minimum subset of categories which could be used in the coding of outpatient neurology episodes within electronic health records.

4.4.2 Diagnostic tests ordered and follow up offered

We identify that a large proportion of first appointments result in a diagnostic test being ordered. These tests may be for imaging such as CT or MRI, or neurophysiological tests such as EEG and EMG. They may be requested to provide supportive evidence for a clinical diagnosis or to exclude particular conditions, however many complex factors underpin these requests. Brain imaging requests in particular are surprisingly complex and further discussion is beyond the scope of this work, but it is important to recognise that there are multiple influences beyond direct clinical factors, for example patient reassurance and patient expectations. The need to reassure a patient must be counterbalanced by the potential for incidental findings to provoke anxiety, and it must be acknowledged that patient expectations may be shaped by many influences such as other clinicians, the media, and friends or relatives.

Examining the number of tests ordered and follow-up appointments offered gives a picture of service utilisation which is not shared equally between diagnostic categories. Some diagnostic categories, such as headache, result in a high number of tests, and others such as seizure/epilepsy in a higher proportion of follow-up appointments. This highlights the need for future work into patient pathways in order to examine the way different patients use neurology services.

4.4.3 Waiting time from referral to appointment

This study shows that waiting times for referral differ by diagnostic category, and that many patients are not seen within the 18 week referral to treatment target. In particular, patients who receive a principal working diagnosis of a movement disorder or a peripheral nerve disorder wait longer on average for their appointment than those with conditions such as headache and seizure/epilepsy. This may be a reflection of the perceived severity and speed of progression of these disorders, and so referrals are made with less urgency. In addition, some variation in prioritisation of referrals as urgent may occur at the point of consultant triage. Referral to a neurology clinic is of often needed in order to assess a patient's condition, provide a working or definitive diagnosis, and create a plan of care to manage these chronic conditions (73). Ensuring that the right patients are seen by the right healthcare professional within the most appropriate time frame are key functions of a good referral system (62), and this study indicates that this may not be happening for those with some disorders.

Waiting times for referral can affect patient satisfaction, interim quality of life, the progression of symptoms, and clinical course (74). However, more research needs to be conducted into the impact of waiting times on patients referred to neurology services. Although studies have been conducted into ways of streamlining referrals and reducing waiting times, it is currently unknown how or in what way longer waiting times may affect clinical outcomes for patients with neurological conditions.

4.4.4 Limitations

This study exclusively uses routinely collected data for which there are well established benefits and limitations of its use in research (1). In the context of this study, the benefit

of using routinely collected data lies in its cost-effectiveness, population reach and its reflection of the 'real world'. Using routinely collected data allows us to see what happens in real time in a clinical population. However, this data is limited in scope, and can suffer from uncertain validity, incompleteness, inaccuracy and inconsistency (75). For example, because diagnostic coding is not routinely used in neurology outpatient clinics in England the diagnosis information in this study is less reliable than if a standardised system had been used.

In order to ensure the data was as accurate as possible, administrative data from the Business Intelligence team was used to verify fields in the data collected from the clinic. This involved linking the data using both NHS and hospital numbers and cross-checking information such as dates of birth, sex and visit dates. Where inconsistencies were found individual records were checked. However, this study is also limited by the unavailability of data that is not collected routinely such as individual socioeconomic status, education level, and comorbidities, which would help to form a more rounded picture.

Changes in policy and referral practices during the study period may also affect the results, however, we don't have enough data in this study to determine the possible impact of these changes. Future research could be undertaken to examine key policy changes and their impact on referral times.

Due to the lack of standardised diagnostic coding at neurology outpatient clinics in the UK, this study is limited to a single consultant and geographical area. This leads to limitations in generalisation as referrals are made under local constraints, and decisions regarding diagnosis and management of patients are made by a single consultant who may not be representative of neurologists as a whole. A national neurology outpatient coding programme would go a long way to addressing these particular limitations, allowing for the creation of larger studies with greater generalisability and enabling comparison between geographical regions.

4.4.5 Future Research

This study has opened up many potential avenues for future research. Initially larger studies using data from multiple clinics should be conducted. This would allow for greater generalisability of results and also allow comparison across geographical areas to be made. However, this would be reliant on the introduction of standardised diagnostic coding across the UK.

The identification of the most common diagnostic categories, although unsurprising, may give us the evidence needed to target research to areas which will potentially benefit large groups of patients. This could be directly through innovative approaches to managing common conditions, or indirectly by releasing capacity where possible for other conditions, for instance through the use of alternative headache management pathways.

This study gives insight into how many follow-up appointments and tests are offered. Examining what happens at these follow-up appointments and analysing findings from test results would give us deeper insight into how these resources are bring used, and ultimately whether they are the most appropriate option. This research should be coupled with a health economic approach to examine whether different pathways through referral and diagnosis present different costs and benefits.

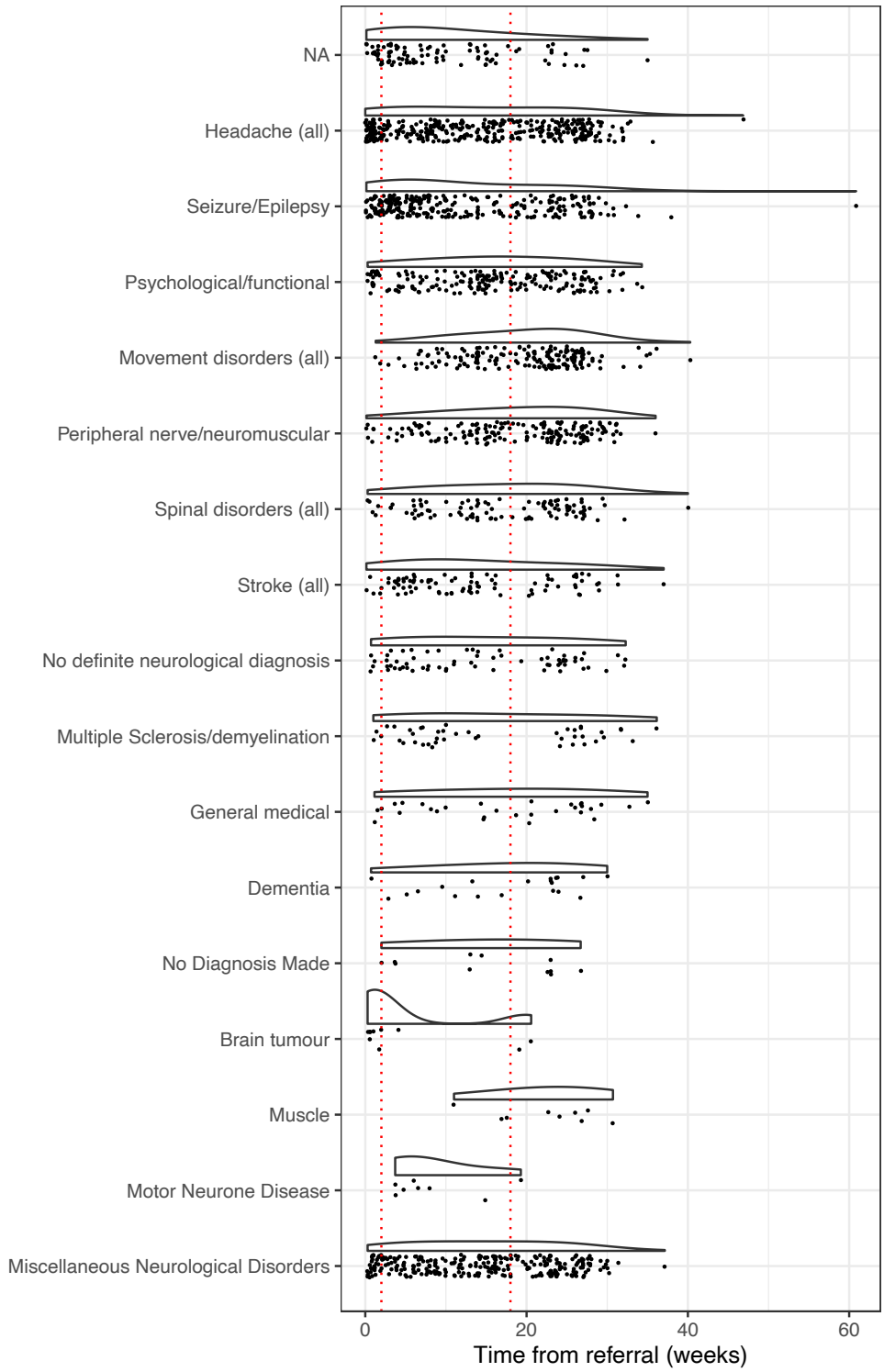
Although we identified differences in waiting times for different diagnostic categories, it is unclear how experiencing long waiting times may affect clinical outcomes. More research is needed into how different patient groups experience waiting times, and the potential impact those extended times have on prognosis and treatment.

4.5 Conclusion

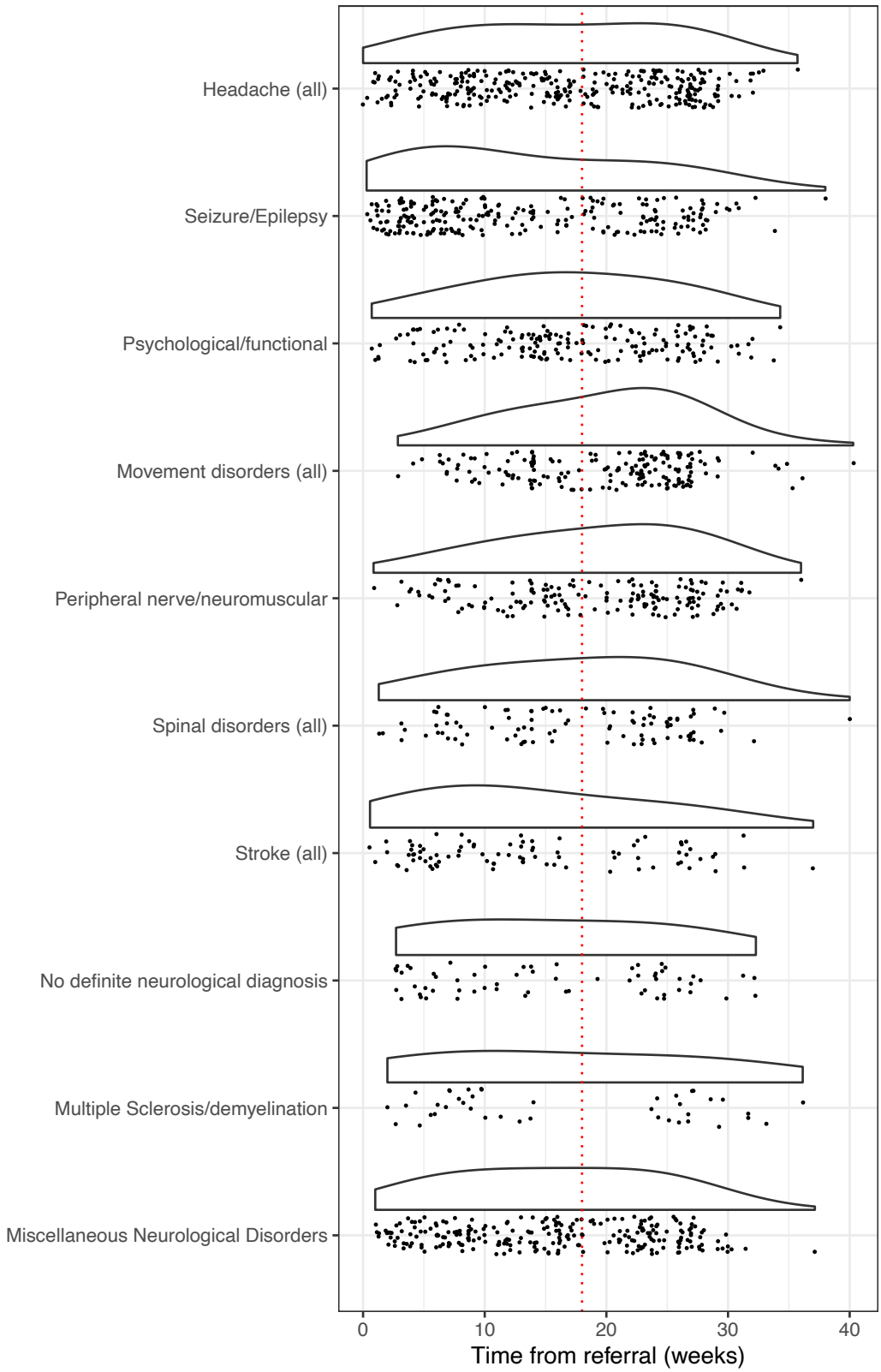
This study of routinely collected data shows that the principal working diagnoses in more than 60% of patients referred to a neurology outpatient clinic fall into one of only five diagnostic categories. Variation in the number of tests and follow up appointments highlights the numerous pathways through the service, and differences in waiting times demonstrates variable access between diagnostic categories. This study shows how

insight can be gained from routine data, however for these insights to be extended to a larger scale, coding of outpatient appointments across the UK would be required. The information provided by this study is likely to be valuable in the development of outpatient neurology coding, and highlights a need to ensure greater consistency of access to outpatient neurology care.

4.6 Supplementary Materials



Supplementary Figure 1. Distribution of waiting time from referral to new appointment including outliers and small categories.



Supplementary Figure 2. Distribution of waiting time from referral to new appointment after removing patients referred on a two-week pathway for suspected CNS cancer or a first seizure.

	Seizure/Epilepsy	Psychological/ Functional	Movement Disorders	Peripheral nerve/ neuromuscular
Headache (all)	2.0×10^{-5} *	0.15	1.3×10^{-4} *	4.4×10^{-3}
Seizure/Epilepsy		1.9×10^{-7} *	3.6×10^{-14} *	2.0×10^{-10} *
Psychological/functional			3.3×10^{-3}	0.05
Movement Disorders				0.41

Supplementary Table 1. P-values from pairwise Kolmogorov-Smirnov tests of the ECDFs of waiting time for the 5 most common diagnostic categories. *indicates statistical significance at alpha = 0.05 using Bonferroni corrections for multiple testing.

5 Identifying variation in GP referral rates: an observational study of outpatient headache referrals

Abstract

Objective: To identify GP surgeries with unexpected rates of referral to specialist services, using headache referrals to outpatient neurology as an example. Identifying surgeries with unexpectedly high or low referral rates allows for further investigation and potential support to be targeted where it is most likely to be effective.

Methods: This is a retrospective observational study using routinely collected and open-source data. Data was collected from a single consultant outpatient neurology clinic and 202 GP surgeries across seven CCGs in the Northwest of England. The number of headache referrals from each GP surgery during a study period of 3 ¼ years was used as the primary outcome in a Poisson model. The standardised residuals from this model were then used to identify GP surgeries that were likely to have referred unexpected patient numbers for headaches to an outpatient neurology clinic during the study period.

Results: We identified four GP surgeries with unexpected numbers of referrals. This model also showed that there were two main predictors of headache referral, namely other neurology referrals and the distance of the GP surgery from the outpatient clinic.

Conclusion: GP surgeries with unexpected numbers of referrals to specialist services were identified using a flexible methodology. This methodology was demonstrated using headache referrals but could be adapted to any type of referral or geographical area.

5.1 Introduction

5.1.1 Referral

General Practitioners (GPs) provide a number of key services, including referral to specialist treatment when needed. Referrals can be made for a number of reasons including for investigation, diagnosis, management or reassurance (62). In the UK referral rates from GPs vary for a number of complex reasons such as resource availability, population health needs, patient pressure, and lack of consensus on which conditions benefit most from specialist input (62,76).

Variability in referral rates from GPs to specialist services is a complex issue with interacting social, geographic, and demographic influences. Understanding variability in referral rates has been an area of interest in health research for many years. In 1989 Coulter et al. (77) found that there were many reasons given for GP referral, including to establish diagnosis, for a test or investigation, for treatment, for advice on management, and to reassure both the GP and/or the patient. These differing reasons for referral can contribute to the observed variations in referral rates (78). Other research has shown that individual GP characteristics such as the ability to tolerate risk also affects rates of referral (79,80). A literature review conducted in 2000 identified 91 relevant papers and from these summarised the amount of variation found in referral rates and identified reasons for this variation (81). It found that most variation in referral rates was unexplained, with patient and GP characteristics only accounting for half of all observed variation.

A number of different research approaches have been made to investigate referral rates, two recent studies have used Poisson regression to investigate referrals from primary care to specialist services. Jessen et al. (82) used a Poisson model to investigate the relationship between GP cancer suspicion and referral rates to standardised cancer referral pathways. They found that referral rates varied by cancer type and whether a GP had an initial suspicion of cancer. Kaur et al. (83) used Poisson regression to investigate referrals for physical therapy for osteoarthritis during the COVID-19 pandemic.

Over the years other work has focused on investigating interventions that may reduce unnecessary variations in referral and has come to contradictory conclusions. Fertig et al. (63) concluded that 'inappropriate referrals' were not the cause of variation, and that guidelines may therefore not reduce referral numbers. However, there have been further studies since, including a systematic review by Akbari et al. (64) who found effective interventions included targeted dissemination of guidelines and involvement of consultants in educational activities for GPs.

Recently the National Health Service (NHS) has tried to identify potential areas for improvement, both in terms of patient outcomes and reducing costs. Two initiatives include RightCare and Getting It Right First Time (GIRFT). GIRFT aims to 'improve medical care within the NHS by reducing unwarranted variations' (84). The GIRFT Neurology project divides England into 'neuroscience regions' for analysis and examines visits to NHS Trusts to 'deep dive' into local issues (16,85). The NHS RightCare initiative seeks to help CCGs 'Diagnose the issues and identify the opportunities with data, evidence and intelligence; develop solutions, guidance and innovation; and deliver improvements for patients, populations and systems' (86). However, the RightCare methodology has been criticised, including the manner in which similar CCGs are identified, and the way in which CCGs are compared, resulting in overestimation of differences (87). The methodology we develop in this paper to identify GP surgeries of interest is not intended as a replacement for either RightCare or GIRFT methodology, but offers an alternative approach.

5.1.2 Headache Referral

In this study we focus on the specific issue of referrals from primary care to neurology outpatient care for headaches (including migraine).

Headache is a common and disabling condition, with migraine representing the second largest contribution to global disability of all neurological conditions (17). Headache, including migraine, accounts for a large proportion of consultant neurologist appointments in the UK (43,65–67,88), and is a common presenting complaint at GP surgeries. GPs refer between 2 to 3% of the headache patients they see in primary care (89), and report experiencing pressure from patients to refer to specialist care (90),

despite evidence that headache conditions are often best managed at primary care level (91). This puts pressure on both GP and outpatient neurology services (22).

GPs are under pressure to provide quality referrals to specialist care, including neurological outpatient care. Brilla et al. (2008) found that interventions made at the neurology service level for reducing 'inappropriate referrals', such as email triage, are ineffective (92). This study concluded instead that interventions should be made at the point of referral by enhancing guidance for referral decisions for GPs. Davies et al. also emphasised the benefit of interventions at primary care level, recommending improved education for GPs to help reduce the burden of headache (93). Most recently Huang et al. found that an online headache referral guideline for GPs was successful in reducing the number of referrals to neurology services (94).

If interventions such as structured guidelines and education are best applied at the point of referral, then identifying where these interventions may be most effective would be of interest. In addition, identifying GP surgeries where referral rates are reduced may offer further insights into the spectrum of variation in referral patterns, as under-referral can also potentially signal the need for intervention to improve care.

5.1.3 Specific Objectives

In this study we identify GP surgeries with unexpected rates of referral. Although the specific case study used is headache referrals, this study aims to provide a methodology which is flexible and can be applied to any type of referral both within and outside of the neurology specialty.

5.2 Methods

5.2.1 Study Design

We used routinely collected data from outpatient appointments alongside open access data in a retrospective observational study. We recorded the number of patients referred for headache to, and offered an appointment in, a single consultant-delivered neurology clinic over a period of three years and four months (18th September 2015 to 9th January

2019). We had access to identifiable information during data collection, but data were anonymised before analysis.

The study received relevant approvals, including NHS Research Ethics (Ref: 19/NW/0178) and Confidentiality Advisory Group (Ref: 19/CAG/0056), as well as Health Research Authority (HRA) on 30 May 2019 (Ref: 255676). The study was also approved by the Lancaster University Faculty of Health and Medicine Research Ethics Committee on 17 June 2019 (Ref: FHMREC18092).

5.2.2 Data Sources

Data regarding the number of referrals from GPs within the catchment CCGs were taken from neurology outpatient clinic records at the Royal Preston Hospital (RPH), which is part of the Lancashire Teaching Hospitals NHS Foundation Trust (LTHTR). As the clinic is dedicated to adult care no paediatric referrals were included. The data covers all GPs within 7 Clinical Commissioning Groups (CCGs): Greater Preston; Chorley and South Ribble; East Lancashire; Fylde and Wyre; Blackpool; Blackburn with Darwen; and Lancashire North. A small number of referrals for headache arose outside this catchment area, but their small number made them unsuitable for inclusion in the analysis (6 from Cumbria CCG, and 1 each from West Lancashire and Wigan Borough CCGs).

Data regarding GP surgery characteristics was downloaded from NHS Digital open access repositories https://digital.nhs.uk/services/organisation-data-service/data-downloads/gp-and-gp-practice-related-data This study did not use the latest data available as, although the data is updated regularly, we felt it more appropriate to use data from the start of our study period (October 2015). This allowed us to capture information for GP surgeries that have subsequently been closed or amalgamated with other locations.

5.2.3 Variables

The outcome of interest was the number of headache referrals from each GP surgery during the study period. Explanatory variables were chosen for both their relevance and

their availability. These variables included GP surgery list size (adults over 14 years of age); proportion of males; mean age; number of other neurology referrals made; distance of the surgery from the clinic at Royal Preston Hospital (RPH); weighted Index of Multiple Deprivation (IMD); and the standard deviation of the weighted IMD. Previous studies have found that socioeconomic deprivation, young age, and female gender appear to be associated with greater headache burden and the likelihood of referral (62,95,96), hence the inclusion of IMD, age, and gender in our analysis. Ethnicity was considered as a variable for inclusion for the model, but it was poorly recorded with around 30% of the data missing, and we were unable to determine a pattern of missingness nor verify the data with other sources.

5.2.4 Weighted IMD calculation

The Index of Multiple Deprivation (IMD) is often used as an indicator of the deprivation of an area. It is collected at the census unit of the Lower Super Output Area (LSOA). As GP catchments overlap fragments of many LSOAs, to be able to explore relative deprivation levels of GP surgeries we calculated a weighted score for each surgery. We followed the methodology devised by Zheng et al. (97). We combined data on the number of patients from each LSOA on each GP's list (available online from NHS Digital https://digital.nhs.uk/data-and-information/publications/statistical/patients-registered-at-a-gp-practice/october-2015) with IMD data available from the gov.uk website (https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015), creating a weighted index for each GP surgery. We also created a variable for the standard deviation of those weighted indices as a measure of the variability of the IMDs contributing to each GP surgery.

5.2.5 Statistical Methods

Data Preparation

The data were analysed using R Studio version 1.2.5019. The separate datasets were joined using GP surgery codes. After joining, we calculated weighted IMD, standard deviation of the weighted IMD, and the straight-line distance of each surgery from the clinic at RPH using the Ordnance Survey coordinate system.

Modelling

First we identified which variables drive variation in referral numbers and then calculated expected referral rates from the GP surgeries using a Poisson log-linear model with an offset for GP surgery list size. We included the CCGs as a factor with Greater Preston CCG as the comparator. We included list size as an offset in order to include both list size and 'other neurology referrals' as potential factors influencing referral. We chose a Poisson model as it provided the best fit when compared with zero-inflated Poisson, negative binomial, and zero inflated negative binomial. Models were compared using the Akaike Information Criterion (AIC).

Our model included data from GPs in the 7 CCGs which make up the catchment area for the clinic. Towards the outer edges of this area it is likely that some patients are referred elsewhere for neurology outpatient care. GPs and patients have an element of choice of outpatient clinic to which to refer/visit, and one of the factors influencing this choice is likely to be distance from the clinic. In general, the farther the GP surgery is from the clinic at RPH, the more likely a patient is to choose an appointment elsewhere. We account for this by including both distance from the clinic at RPH and the number of other types of neurology referral made by each GP surgery.

Examining the differences

In order to identify surgeries which refer fewer or more patients that expected, we extracted predicted values from the model described above and compared them to the actual values observed during the study period. This gave us the differences between observed and expected referrals which can be visualised to determine if surgeries are referring as expected. We also examined potential spatial autocorrelation between the differences using Moran's I. This index is similar in concept to a correlation coefficient and gives a value between -1 and 1. However, -1 indicates perfect clustering of dissimilar values, and 1 perfect clustering of similar values. A Moran's I of 0 indicates perfect randomness. Investigating spatial autocorrelation allows us to determine if GP surgeries which are located close together are more likely to have similar differences between observed and expected number of referrals than those further apart, and thus if there are any potential factors related to location which affect referrals.

5.3 Results

We analysed data from 202 GP surgeries across 7 CCGs (see Figure 5.1), which provided 388 headache referrals in total over the period of the study. Over the same period these surgeries referred 1371 patients for other suspected neurological disorders, thus headache accounts for 19% of all neurology referrals over this study period. The largest number of surgeries is in East Lancashire CCG, but the largest number of both headache and other neurology referrals was from the Greater Preston CCG. This may stem from the fact that GPs can refer patients to other neurology clinics if the patient prefers, and the farther away a GP surgery is from the outpatient clinic, the more likely they are to refer elsewhere. The characteristics of the GP surgeries in each CCG can be found in Table 5.1.

				GP Surgery Characteristics				
Clinical Commissioning Group	Number of Surgeries	Number of Headache Referrals	Number of other neurology referrals	Mean Age of List (range)*	Mean List Size (range)*	Mean Weighted IMD (range)*	Mean Distance from RPH in km (range)*	Mean Percentage of Males (range)*
Blackburn with Darwen	27	26	110	43 (37-47)	5020 (1303-13273)	3.4 (1.5-5.9)	16 (14-19)	51 (47-55)
Blackpool	22	47	126	46 (39-52)	6577 (1939-12525)	2.8 (1.4-4.6)	22 (21-24)	51 (48-54)
Chorley and South Ribble	31	61	237	46 (38-51)	4695 (1190-13651)	6.4 (3.7-9.1)	13 (6-21)	50 (47-54)
East Lancashire	57	53	206	45 (36-50)	5267 (894-15839)	3.8 (1.4-8.5)	28 (20-40)	51 (47-55)
Fylde and Wyre	21	65	123	49 (45-53)	6442 (1507-10167)	5.8 (2.7-7.5)	20 (11-25)	49 (47-53)
Greater Preston	32	111	503	44 (35-49)	5214 (1427-14408)	4.5 (1.6-9.1)	4 (0.5-9)	52 (48-60)
Lancashire North	12	25	66	45 (31-50)	10768 (5824-26512)	5.5 (3.4-7.8)	28 (13-38)	50 (47-52)
Overall	202	388	1371	45 (31-53)	5729 (894-26512)	4.4 (1.4-9.1)	19 (0.5-40)	51 (47-60)

Table 5.1 Study Characteristics.

*Indicates the range of values from the individual GP Surgeries within the CCGs

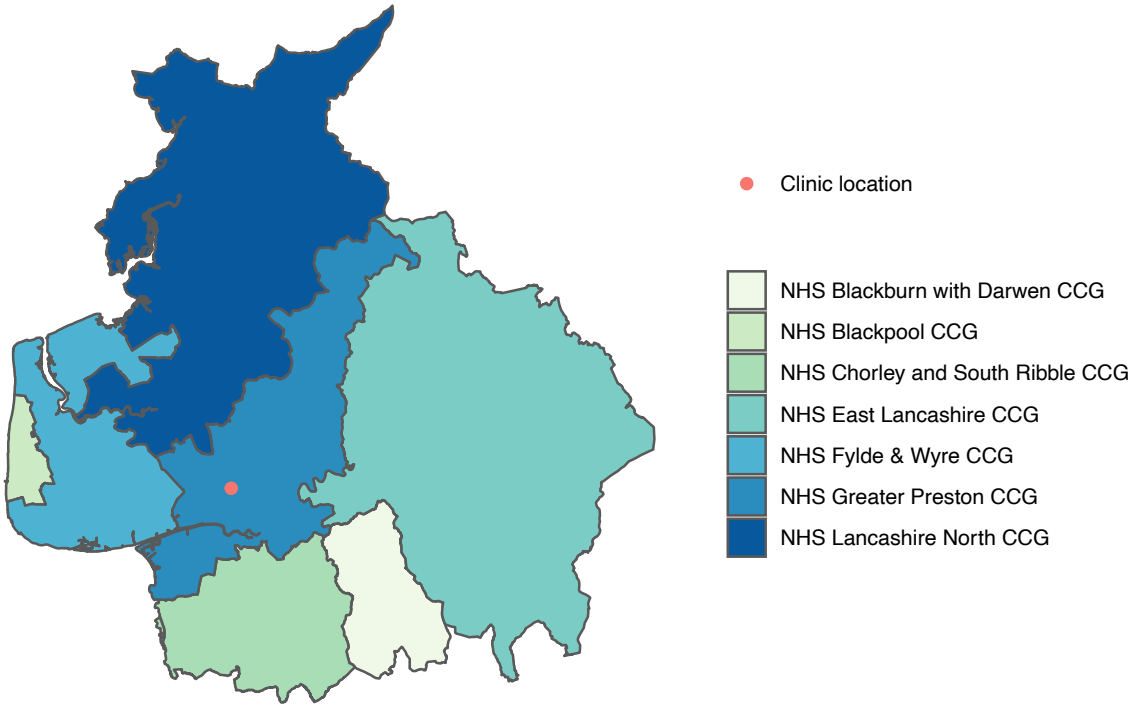


Figure 5.1 A map of the contiguous CCGs included in the study.

GP surgery size varies greatly across the catchment area, from the smallest surgery of 894 patients in East Lancashire CCG to the largest surgery with 26,512 patients in Lancashire North. The distance of the surgeries from the clinic at RPH varies from 550m to 39.5km, with an average distance of 18.9km. The calculated weighted IMD for each surgery varies greatly from a low of 1.4 in Blackpool and East Lancashire CCGs to 9.1 in Greater Preston and Chorley and South Ribble CCGs, indicating marked diversity in the socioeconomic characteristics across the CCGs.

Within the CCGs GP surgeries referred differing numbers of patients for both headaches and other types of neurological conditions. Figure 5.2 shows the relationship between the number of headache patients a GP surgery referred and the number of other neurology referrals. This relationship is shown separately for each CCG and demonstrates that there is a consistently positive relationship between headache and other neurology referrals, although this relationship appears to differ between CCGs.

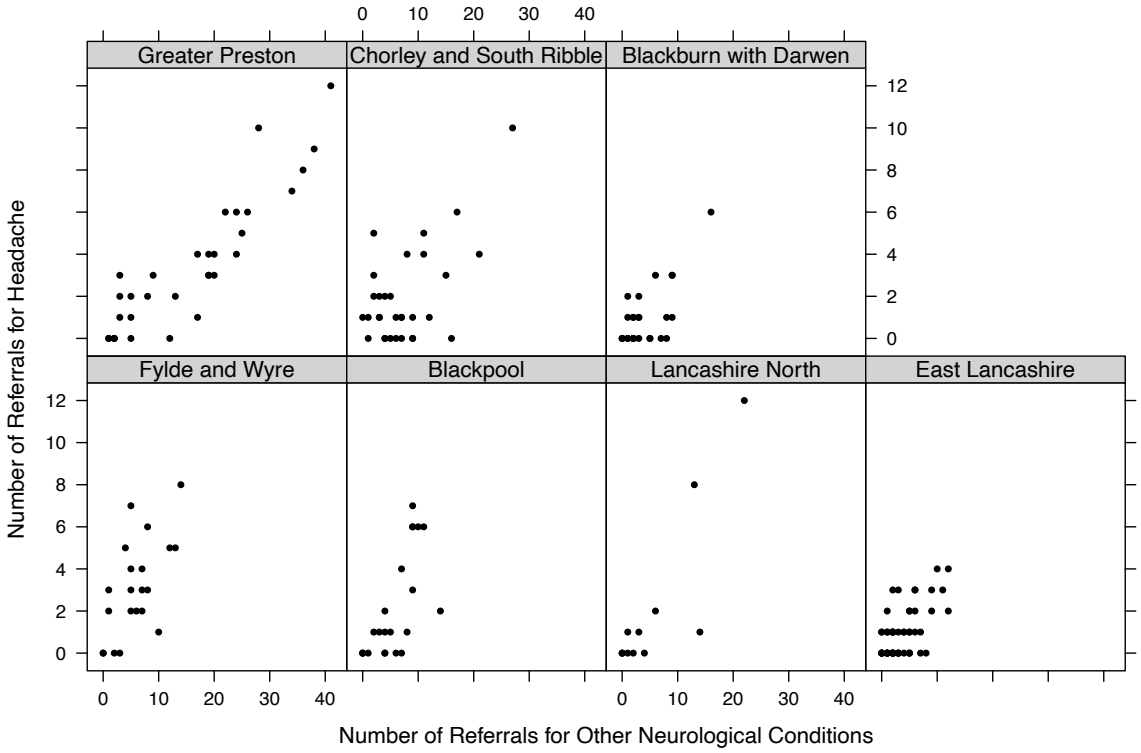


Figure 5.2 Correlation of the number of headache referrals and other neurology referrals from all GP surgeries split by CCG.

5.3.1 Model Results

Results from the model can be seen in Table 5.2. We see variation in referral is influenced by the number of other neurology referrals, and by the distance of a GP surgery from the clinic. These results suggest that the further a surgery is from the clinic the fewer headache referrals are made.

	Estimate	Std Error	IRR* (95%CI)	P value
Intercept	-8.06	2.72		0.003
Other Neurology Referrals	0.04	0.008	1.04 (1.02-1.06)	< 0.001
Mean Age	0.03	0.02	1.03 (0.99-1.06)	0.21
Weighted IMD	-0.03	0.04	0.96 (0.88-1.05)	0.46
SD of weighted IMD	-0.25	0.12	0.78 (0.61-0.98)	0.03
Distance from clinic	-4.2×10^{-5}	1.3×10^{-5}	0.99 (0.99-0.99)	< 0.001
Proportion male	-0.78	4.3	0.46 (7.2×10^{-5}-213)	0.85
Blackburn with Darwen	0.04	0.29	1.05 (0.59-1.82)	0.87
Blackpool CCG	0.46	0.32	1.59 (0.85-2.95)	0.14
Chorley and South Ribble CCG	0.37	0.21	1.45 (0.95-2.18)	0.08
East Lancashire CCG	0.37	0.34	1.45 (0.74-2.82)	0.27
Fylde and Wyre CCG	0.81	0.27	2.25 (1.30-3.89)	0.004
Lancashire North CCG	0.27	0.34	1.31 (0.65-2.55)	0.43

Table 5.2 Results from the Poisson model.

*IRR: Incident Rate Ratio. As the list size of each practice was included as an offset in the model, the output of the model is a rate which depends on the list size of the GP.

5.3.2 Examining the differences

The standardised difference between the number of expected and observed referrals for each surgery within the seven CCGs is shown graphically in Figure 5.4. This figure shows a boxplot of the distribution of the overall differences, and a dot for each GP surgery colour coded by CCG. Values below -3 or above +3 can be considered statistically significant.

There were no surgeries which referred fewer headache patients than expected, and 4 surgeries that referred statistically significantly more than expected, given the variables that were accounted for in the model. A plot comparing the raw (non-standardised) values of observed and predicted referrals can be found in Supplementary Figure 1.

Testing for spatial correlation in the differences between expected and observed referrals using Moran's I, we found there to be no spatial autocorrelation for the GPs across the 7 included CCGs (Moran's I = -0.013, p = 0.605).

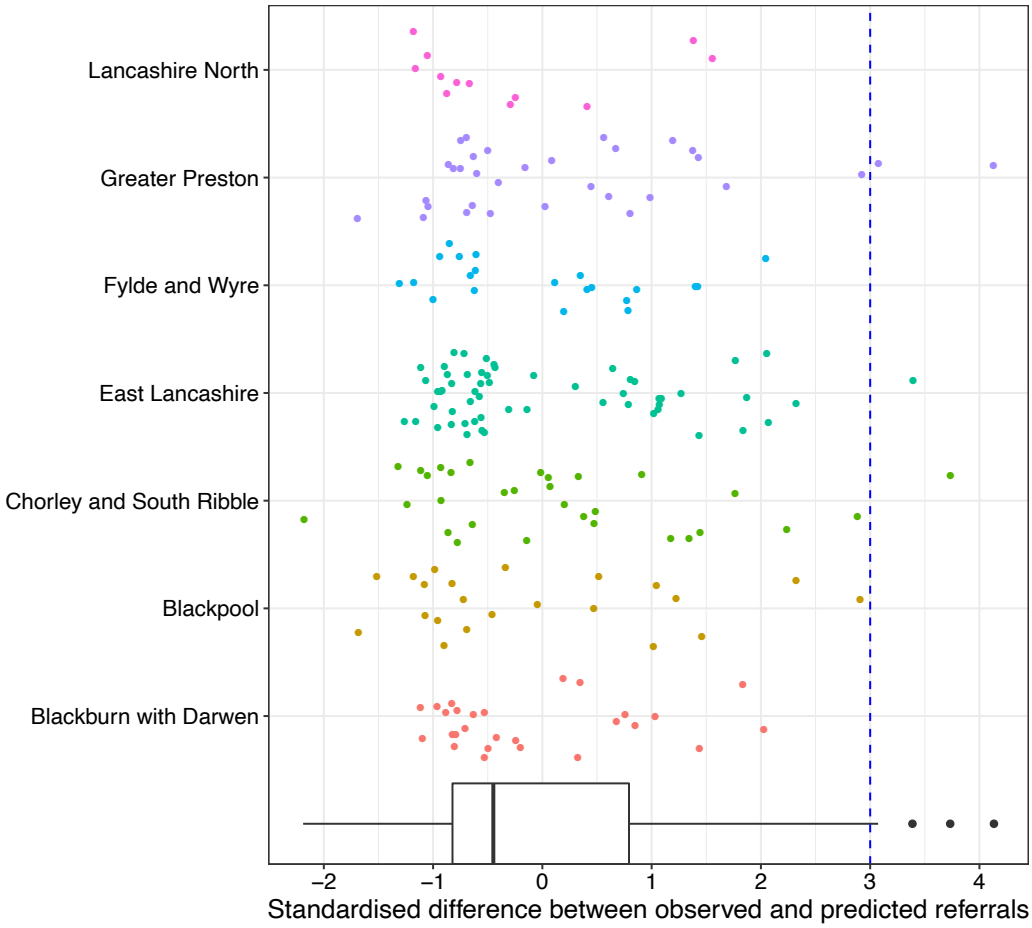


Figure 5.3 Boxplot and point clouds of the standardised difference between expected and observed numbers of headache in all 7 CCGs.

Points lying below -3 or above +3 (blue lines) are considered statistically significant outliers.

5.4 Discussion

5.4.1 Principal findings

This study shows that it is possible to identify GP surgeries which refer unexpected numbers of patients to an outpatient clinic. This is achieved by identifying a set of explanatory variables to be included in a Poisson model, the results of which are then used to give predicted values for comparison against observed referral numbers. Once surgeries with unusual numbers of referrals are identified, further investigation can then be carried out to understand the circumstances leading to the unexpected referral

numbers. This would allow support to be targeted to the places that need it, and lessons to be learnt, which could be shared across the CCGs.

5.4.2 Strengths and limitations

The basic methodology outlined in this paper could be modified and extended to other specialties. Although other specialties have their own drivers for referral patterns, they could be examined using the same methodology by adjusting the explanatory variables included in the initial model. The methodology could also be extended to cover larger geographical areas.

As with all studies which include statistical modelling, if an informative variable has been excluded, either through unavailability of data or through not understanding the drivers of referral, then the results of the second stage of the process - identification of the unexpected referral rates – would be less accurate. Researchers need to understand the drivers behind the type of referral under investigation, and to be able to access valid data on which to build models. If understanding is limited, or if data is unavailable (or inconsistent) any assumptions drawn from modelling will be flawed.

The way that data is collected from GP surgeries can change over time. Surgeries can be closed, and new surgeries can be created from both amalgamation and splitting of previous surgeries. In this study we extracted data from the NHS Digital open access repositories for the dates at the start of the study as this allowed us to capture information for GP surgeries that have subsequently been closed or amalgamated. In addition, some GP surgeries are small single locations, whereas others comprise of a large hub surgery and several smaller affiliated branch surgeries. In this study we did not split branch surgeries from their parent location, as branches which come under a single surgery grouping are likely to have much in common. For example, they are likely to share the same educational training and use the same referral guidelines.

This study only includes data on the referring practice and not the individual referrer. Ideally the study would include information on the individual who made the referral as this may have an impact on the number of referrals. For example, Advanced Nurse Practitioners (ANPs) are able to refer patients to Secondary care. Due to their different

training pathways, roles and responsibilities within primary care, and scope of practice, it is feasible that ANPs may have different referral thresholds to GPs (98).

This study has a relatively small sample size, in particular there are few surgeries which refer large numbers of headache patients. Therefore it should be replicated with a larger dataset, in order to corroborate the results seen in this study. Expanding the study to a larger geographical area, including other clinics, or including a longer study period would also help to alleviate the limitation of a small dataset, as well as expanding the generalisability to other areas. However, this expansion would be reliant on the availability of coded outpatient neurology diagnoses.

The methodology used in this study can be adapted to any type of referral, geographical location, and timescale by adjusting the explanatory variables used in the initial model. Although the results of the model used as a case study in this paper are not generalisable to other geographical locations or timescales, the methodology is generalisable. It would be possible to expand this analysis of headache referrals to a national level, but this would rely on the availability of consistent coding of neurology outpatient appointments.

5.4.3 Relation to previous studies

Previous studies have used statistical modelling to investigate the impact of different variables on referral rates from GPs to specialist services (82,83). We have based the first stage of our study on this modelling process, and then extended the analysis to include the identification of GP surgeries which are referring unexpected numbers of patients for headache.

The NHS RightCare methodology identifies areas of opportunity for improvement for CCGs, and although our study does not seek to replicate or replace the RightCare methodology, the intention behind it is similar – to allow CCGs to identify GP surgeries where interventions may be of use. However our methodology differs in a number of ways from RightCare which allows it to avoid the difficulties highlighted by Dropkin (87). RightCare compares CCGs across large dislocated geographical distances, whereas we limit the study to a single contiguous geographical area, meaning that the

CCGs are more likely to be similar in unmeasured ways. In addition the RightCare methodology has a fixed set of demographic variables against which the CCGs are measured regardless of the outcome of interest, whereas we recommend that the explanatory variables used in the initial model are changed depending upon the outcome under investigation. It cannot be assumed that the explanatory variables used for headache referral would be relevant for orthopaedic referral, for example.

5.4.4 Meaning of the study

In a previous study we found that the majority of patients with headache who were referred to a neurology outpatient clinic had only one appointment (88). Many of these patients were discharged after only one appointment without investigation. Whilst a single consultation with a neurologist can make an important contribution to the patient's management, much of the advice given, particularly in relation to lifestyle factors and avoidance of medication overuse headache, could be delivered in primary care (91). Demand is rising and capacity, including in general practice, is limited. Identifying which surgeries could potentially support patients through alternative routes to treatment would be both more convenient for the patient and free up resources for other patients needing to access care.

This study provides an indication of GP surgeries from which there may be unexpected numbers of referrals, but it does not explain why those unexpected referrals may have occurred. However, identifying variation is the first step towards understanding it, and this methodology could be used by CCGs or outpatient clinics to understand where their patients are coming from, and to plan further targeted investigations.

5.4.5 Unanswered questions and future research

More research needs to be done to validate this methodology with a larger dataset, and to extend it into other areas of referral. It could also be extended and refined to apply to larger geographies, or to other outpatient specialties. Expanding this research to larger geographical areas would require consistent coding of diagnoses resulting from outpatient neurology appointments, which is unfortunately not yet available. Further research is also needed to confirm the utility of conducting these types of analysis, in

particular whether identifying unexpected referral rates leads to implementation of policies that improve patient care.

It would also be of interest to analyse what happens to patients following referral in order to determine if the referral was 'appropriate' or useful to the patient. This would necessitate collecting qualitative data on the patient experience and would provide a more holistic view of referrals. Another area that we were unable to explore in this paper is any alternative treatment that a patient may seek if denied the opportunity for a referral to specialist consultant care. Future research could address this by examining whether patients who attend the GP with symptoms of headache and are not referred to specialist care are more likely to attend more appointments with the GP, or seek treatment elsewhere such as at the emergency department.

5.5 Conclusion

Identifying GP surgeries with unexpected numbers of referrals is a useful first step towards understanding the larger issue of variability in referral rates. Once identified, those GP surgeries with unexpected numbers of referral can be investigated further to help understand why their referral rates differ from those expected, and if necessary, interventions can be targeted to where they are most needed. Using GLMs is an efficient way of including explanatory variables that are relevant to the type of referrals under investigation and variables can be changed to directly relate to any type of referral requiring investigation. This ensures that the methodology presented here is flexible enough to be applied to different types of referral or geographical area.

5.6 Supplementary Materials

Identification of multicollinearity

During the model selection process analysis was undertaken to identify correlations between variables. All variables were tested for correlation using Pearson's correlation coefficient. Any pair of variables found to have a Pearson's coefficient of over 0.7 were further tested by comparing two simple models of each variable with the outcome of interest (number of referrals for headache) and compared using the Akaike Information Criterion (AIC) to determine which one provided the best fit. The variable providing the best fit was retained for inclusion in the main model and the less well-fitting variable discarded.

List size and 'other neurology referrals' were found to be highly correlated. When comparing the two models, the model using 'other neurology referrals' was found to be a better fit and so this variable was retained for inclusion in the model. List size was not included in the main body of the model, but was used as an offset.

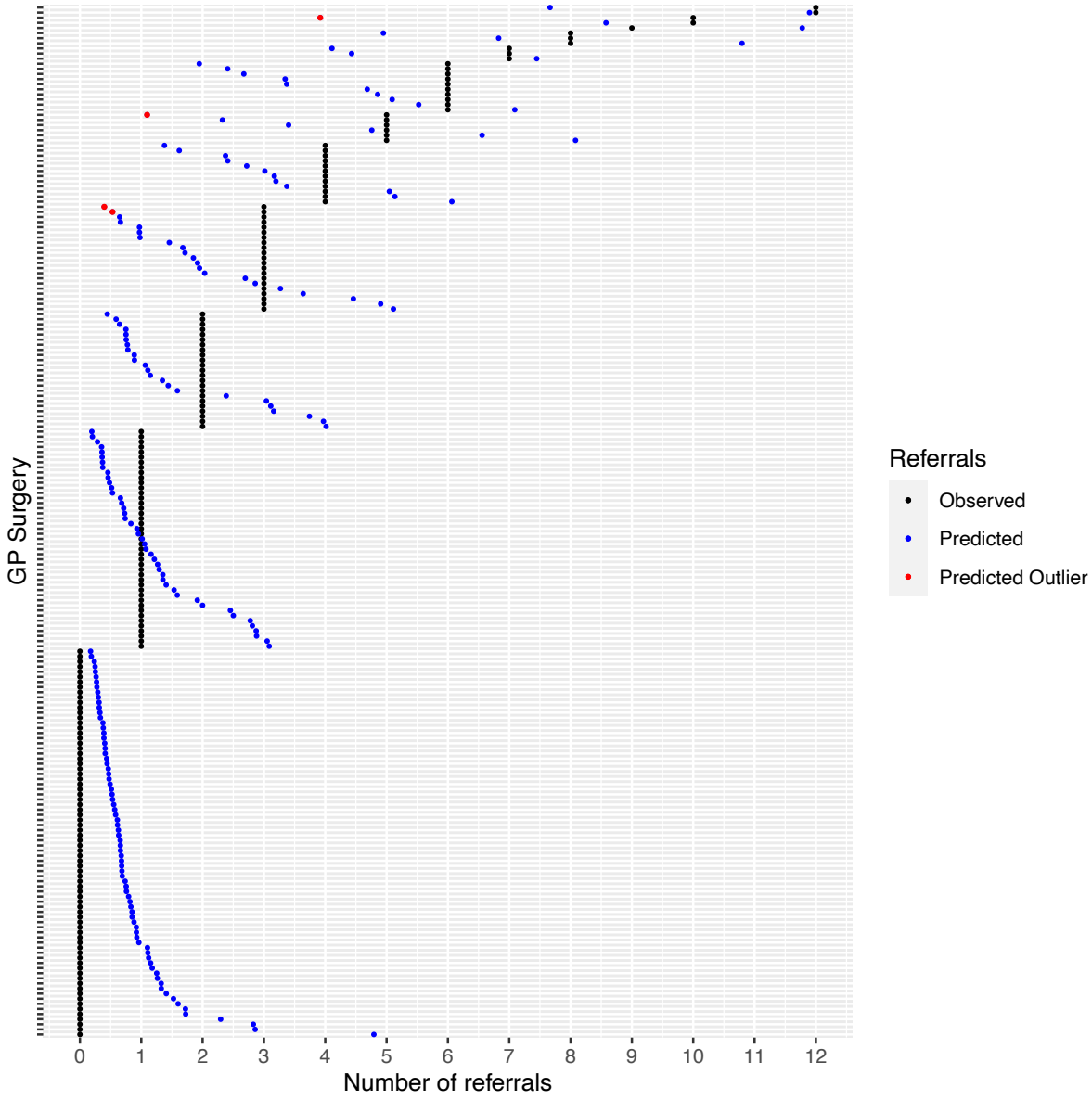
Variable selection

Once the variables had been tested for multicollinearity and the best type of regression model had been selected, backwards selection was used to test models including different explanatory variables. This initially resulted in a model including only the number of other neurology referrals as an explanatory variable. However, when testing this one-variable model against the full model, the model including only other neurology referrals was found not to provide a statistically significantly better fit that the full model. Therefore, the full model was chosen in order to retain as much information about the variables as possible.

Observed vs predicted referrals

In Supplementary Figure 1 we can clearly see the pattern of the number of observed referrals during the study period, with the largest group of surgeries referring zero patients during the study and a general trend of decreasing numbers referring larger

numbers of patients. We can also see that as the groups get smaller the predictions become more difficult to make as the model has less information to work from.



Supplementary Figure 1. Observed and predicted numbers of headache referrals. Each black dot represents the observed number of headache referrals over the study period. Each blue dot represents the raw number of referrals as predicted by the Poisson model. The red dots show which surgeries were determined to have referred significantly unexpected numbers of referrals.

6 Discovering patterns in outpatient neurology appointments using state sequence analysis

Abstract

Background: Outpatient services in the UK, and in particular outpatient neurology services, are under considerable pressure with an ever-increasing gap between capacity and demand. To improve services, we first need to understand the current situation. This study aims to explore the patterns of appointment type seen in outpatient neurology, in order to identify potential opportunities for change.

Methods: We use State Sequence Analysis (SSA) on routinely collected data from a single neurology outpatient clinic. SSA is an exploratory methodology which allows patterns within sequences of appointments to be discovered. We analyse sequences of appointments for the 18 months following a new appointment. Using SSA we create groups of similar appointment sequence patterns, and then analyse these clusters to determine if there are particular sequences common to different diagnostic categories.

Results: Of 1315 patients 887 patients had only one appointment. Among the 428 patients who had more than one appointment a 6 monthly cycle of appointments was apparent. SSA revealed that there were 11 distinct clusters of appointment sequence patterns. Further analysis showed that there are 3 diagnosis categories which have significant influence over which cluster a patient falls into: seizure/epilepsy, movement disorders, and headache.

Conclusions: Neurology outpatient appointment sequences show great diversity, but there are some patterns which are common to specific diagnostic categories. Information about these common patterns could be used to inform the structure of future outpatient appointments.

6.1 Background

Outpatient care in the UK is under considerable pressure (99), and in response to this the NHS (National Health Service) has initiated a programme for strategic transformation. The NHS Outpatient Recovery and Transformation programme aims to 'deliver a personalised outpatient model that better meets individual patient need and improves quality of care and patient outcomes' (100). The current model of outpatient care delivery is based on a traditional standard that has not been subject to significant scrutiny or quantitative analysis. In order to determine the nature of any change required, we need to understand the current situation, including current outpatient resource utilisation. The aim of any future recommended changes is to ensure optimal use of available resources, releasing capacity where possible, and improving access to care.

Neurology services in the UK are under particular pressure (60,61), with a large gap between capacity and demand, and this is especially severe in the geographical area covered in this study (Lancashire and South Cumbria) (101). The majority of neurology care in the UK is provided in an outpatient setting, so with the current drive for improvements in outpatient care in general and the capacity gap for neurology in particular, there is a pressing need to understand the pressures and potential opportunities for change in this specialty. Although this study is focused on a neurology clinic in England, similar pressures are being experienced elsewhere, and the principles this study is based on are transferable to other geographical and clinical areas.

Understanding the nature of outpatient resource utilisation such as the type of appointments that patients attend, and the order and frequency with which they occur, is useful for both resource planning and improving patient access to appropriate care. An analytical technique called State Sequence Analysis (SSA) has been used in other fields, in particular social sciences, to study patterns in longitudinal data (31,102). SSA is used to identify groups of common patterns or sequences of 'states' that occur over time. It is a relatively new methodology to healthcare, but a number of studies in the last few years have used SSA. These studies fall into two primary types; those which examine temporal data such as patterns of drug adherence (103,104) or mortality following

illness (105); and others which study trajectories of care (for example appointment sequences and hospital stays).

Examples of studies which have investigated care trajectory or patient pathway include Le Meur et al. who used SSA to study care consumption in pre-natal care (106) and to examine the determinants of care trajectories in end-stage renal disease (107). Vanasse et al. used the technique to study healthcare use after hospitalisation with Chronic Obstructive Pulmonary Disease (108). The same team also used SSA to study care trajectories preceding a diagnosis of schizophrenia (109). Other recent studies using SSA in healthcare include an examination of social inequalities in care trajectories following a diagnosis of diabetes (110), and a study of referral trajectories in patients with vertigo (111).

Some studies have applied SSA to neurology, in 2021 LeBlanc et al. used SSA in their study of disease modifying therapy (DMT) usage in patients with multiple sclerosis (MS) (112). They used SSA to identify patterns of DMT use and were able to classify patients into groups with similar usage patterns. In addition, Roux et al. used SSA to analyse care pathways of patients with MS (113,114). In their 2019 study they analysed the amount of care that patients 'consumed', including GP (General Practitioner) consultations, consultations with a neurologist, and hospital admissions. They were able to identify five different groups of patients with distinct levels of care consumption. In their 2021 study they compared groups of patients with incident and prevalent MS and extended their methodology to include 'multiple channels'. In this study they use multi-channel SSA to identify 12 care consumption groups for patients with incident MS and 6 groups for prevalent MS.

These previous studies show that it is possible to use SSA in a healthcare setting – including within neurology – to group patients by differing levels of care consumption, drug adherence, and patterns of care observed over time. Previous studies in neurology using SSA have only analysed a single diagnosis in multiple settings, in this study we analyse the number, type and order of appointments across all diagnoses in a single neurology outpatient clinic. We aim to discover common patterns in types of appointment, the number of appointments attended, and the interval at which appointments occur. We will use SSA to create groups of similar appointment sequences

and then analyse these groups to determine if there are particular sequences common to different diagnostic categories.

6.2 Methods

6.2.1 The study population, design and variables

This is a retrospective observational study using SSA to explore patterns in patient appointments in the 18 months following a new appointment. We used routinely collected data from neurology outpatient appointments, from a single clinician, collected over a period of three years and four months (18th September 2015 to 9th January 2019). Data were drawn both from those recorded by the clinician at the time of the appointment, and from administrative information collected by the hospital business intelligence team.

The variables used to create the sequences include; the date of an appointment, whether the appointment was attended, if a test was ordered from an appointment and whether a patient was discharged following an appointment. A number of variables were used in further analysis after the sequences had been constructed and clustered, including the diagnosis given to a patient, the patient's age at the first appointment, the sex of the patient, and the time from referral to the patient's first appointment.

6.2.2 SSA methodology

Identifying timeframes, defining states and building sequences.

To analyse both the timing of appointments and the patterns found in types of appointments we created two separate sets of sequences from the same data. First, we created a set of sequences showing whether an appointment took place in a certain month; this can be seen in Figure 6.1a. In this sequence set we used two simple states of "Appointment" and "No Appointment".

The second set of sequences included only the months in which an appointment was recorded but incorporated additional information about the type of appointment that

occurred (Figure 6.1b). In this sequence set five states were defined as: an attended appointment without either a recorded test, or discharge (A); an appointment where a test was ordered (AwT); an appointment at which a patient was discharged (AD); an appointment where a test was ordered and the patient was discharged (ATD); and an appointment that was unattended (ANA). Unattended appointments included cancellations by both the clinic and the patient, and 'did not attends' i.e., where a patient did not cancel, but did not turn up at their allotted time.

Organising the data into two different types of sequence allowed for separate analysis of different aspects of patient appointment patterns.

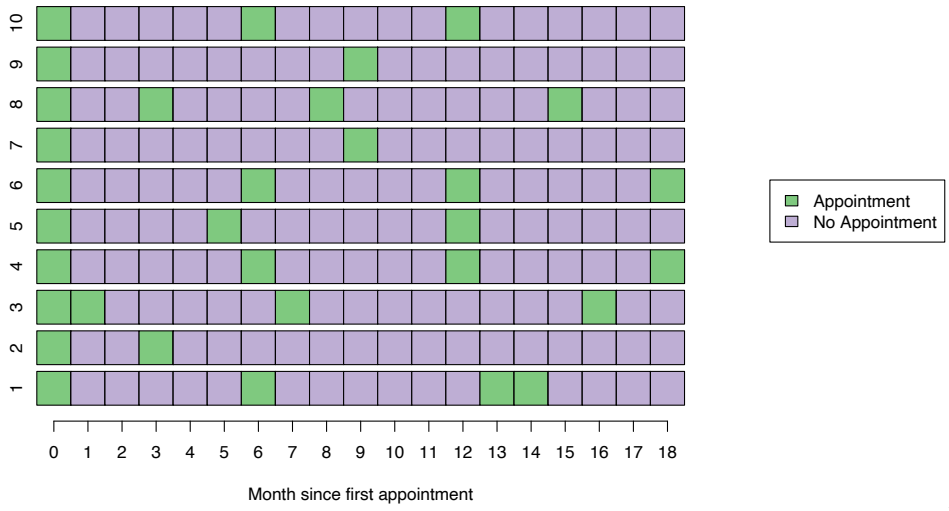


Fig 6.1 a)

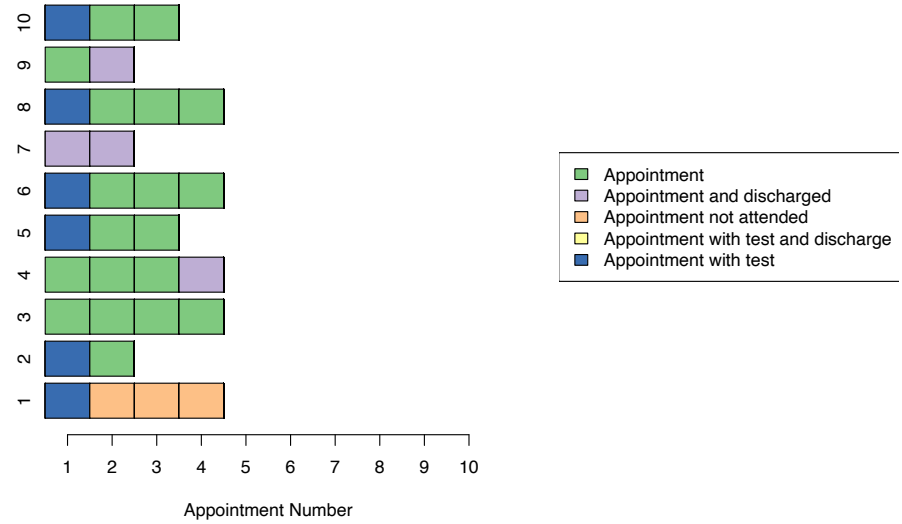


Fig 6.1 b)

Figure 6.1 Example of the two types of sequence. a) Timing of appointments within the 18-month period and b) Appointment type

Measuring dissimilarity between sequences.

We used Optimal Matching and Hamming distance algorithms to measure dissimilarity numerically between sequences and create the matrices required for clustering. For the sequences based on the timing of appointments we used Hamming distance as this is the most common method applied to sequences of the same length. In addition Hamming distance does not use insertion and deletion and so it preserves the order of the states and the timing of the appointments. Optimal Matching allows for sequences of differing lengths to be compared and was used for the sequences of appointment types.

Both algorithms rely on the principle of assigning a value to the number of operations required to turn one sequence into the other. For example, the sequence A-A-A can be transformed into sequence A-B-A by replacing the middle character with a B. We can assign a numerical 'cost' to this operation, for example a value of 1 and then compare costs of transformation between all different sequences.

Clustering.

We used hierarchical agglomerative clustering with Ward's criterion. This type of clustering assumes that every individual data point initially belongs in its own cluster, these clusters are compared, and the most similar data points are joined to form clusters. The algorithm then compares these new clusters and again joins the most similar together, and so on until there is only one large cluster with all the data points contained within it. Once the clustering is complete it is necessary to determine the optimal number of clusters.

Optimising the number of clusters.

The optimal number was chosen using average silhouette width. Silhouette width measures how similar a sequence is to the cluster to which it has been assigned and compares this to how different it is from the other clusters. Average silhouette width is the average of the silhouette width of all the individual sequences and thus measures how well defined (on average) the clusters are, as well as whether each individual

sequence has been placed in the ‘correct’ cluster. The metric ranges in value from -1 to 1 with -1 indicating that the clusters are not well defined and individual sequences are not likely to be placed in the ‘correct’ cluster. A score of 1 indicates that the clusters are perfectly separated, and each sequence is very likely to be assigned to the ‘correct’ cluster.

Hypothesis testing

After selecting the optimal number of clusters we extracted the diagnosis and demographic information for the patients falling into each cluster. Using chi squared tests and t-tests (where appropriate) we were able to determine if cluster membership was independent from these demographic factors. Analysis included diagnosis category, age at first appointment, sex, and time from referral to first appointment.

6.2.3 Ethics

The research proposal underwent ethical review with both the NHS Research Ethics Committee (Ref: 19/NW/0178) and Confidentiality Advisory Group (Ref: 19/CAG/0056) and received approval from the Health Research Authority (HRA) on 30 May 2019 (Ref: 255676). In addition, the study underwent ethical review with Lancaster University Faculty of Health and Medicine Research Ethics Committee and obtained approval on 17 June 2019 (Ref: FHMREC18092).

6.3 Results

6.3.1 Selection Criteria

During the study period data was recorded from 3908 patients who, between them, had 5902 appointments. As patients entered and left the study period at different times, only patients who had a first appointment at least 18 months before the end of the study period were included (see Figure 6.2). In addition, many patients only attended one appointment and these patients were removed for separate analysis. This left 428 patients to be included in the sequences analysis.

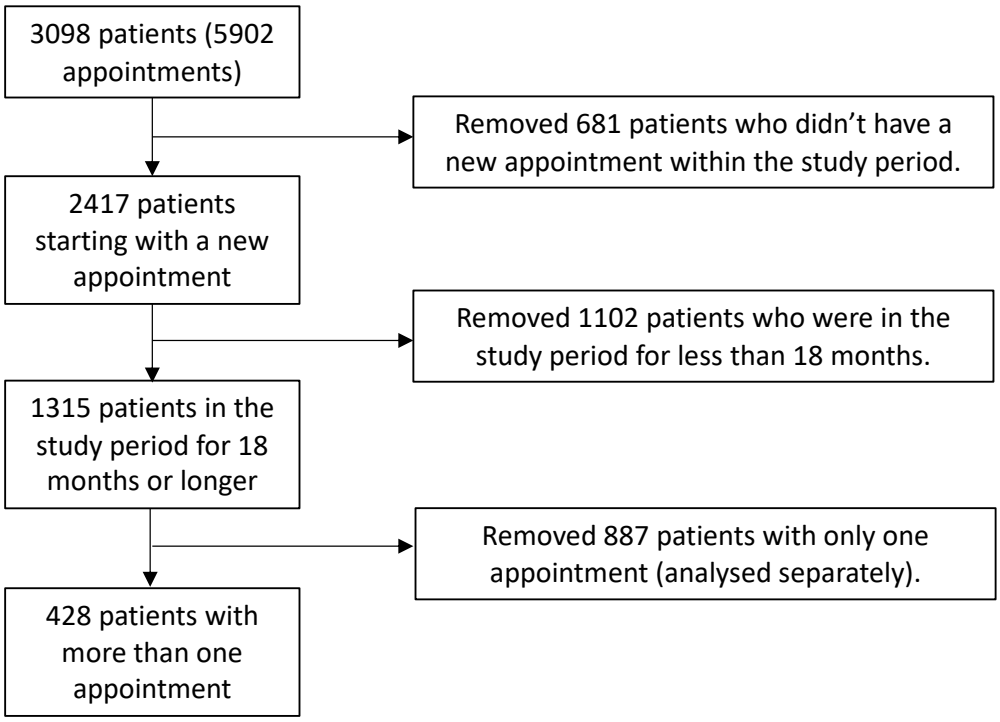


Figure 6.2 Flow chart showing selection criteria for the study.

6.3.2 Patient Characteristics

Of the 1315 patients who had new appointments followed by at least 18 months of data in the study period, 887 only had one appointment. Table 6.1 shows the baseline characteristics for these 1315 patients, split to allow comparison between those with only one appointment to those with sequences of two or more appointments. Figure 6.3 displays the numbers of patients falling into each diagnostic category, directly comparing those who return for more than one appointment with those who only have one appointment.

The mean age at first appointment is similar for both groups of patients – 49.6 for those who only have one appointment compared to 49.2 for those who attend more than one appointment. The time from referral is also similar, 14.6 vs 13 weeks.

	Number with one appointment. Total=877	Number with more than one appointment Total=428
Sex (%):		
Female	504 (57)	210 (49)
Male	373 (43)	217 (51)
Mean age at first appointment (SD)	49.6 (18.9)	49.2 (18.7)
Time from referral in weeks (SD)	14.6 (9.6)	13.0 (8.9)
Diagnosis Category (%):		
Seizure/epilepsy	37 (4.2)	109 (25.5)
Miscellaneous Neurological Disorders	87 (9.9)	51 (11.9)
Movement Disorders	51 (5.8)	49 (11.4)
Peripheral nerve/neuromuscular	67 (7.6)	37 (8.6)
Stroke	30 (3.4)	29 (6.8)
Headache	219 (25.0)	28 (6.5)
Psychological/functional	89 (10.1)	25 (5.8)
Multiple Sclerosis/demyelination	8 (0.1)	22 (5.1)
No Diagnosis Made	152 (17.3)	22 (5.1)
Spinal disorders	38 (4.3)	19 (4.4)
Syncope/transient loss of consciousness	45 (5.1)	12 (3.0)
No definite neurological diagnosis	18 (2.1)	11 (2.5)
Dementia	5 (0.1)	4 (0.9)
Muscle	1 (0.01)	3 (0.7)
Motor Neurone Disease	2 (0.02)	3 (0.7)
Brain tumour	6 (0.1)	1 (0.01)
General medical	22 (2.3)	1 (0.01)
Appointment Type (%):		
Appointment and discharge	381 (43.4)	16 (3.7)
Appointment, test request and discharge	314 (35.8)	45 (10.5)
Appointment not Attended	140 (16.0)	17 (3.9)
Appointment	22 (2.5)	134 (31.2)
Appointment with test request	20 (2.3)	216 (50.4)

Table 6.1 Patient and appointment characteristics at the first appointment.

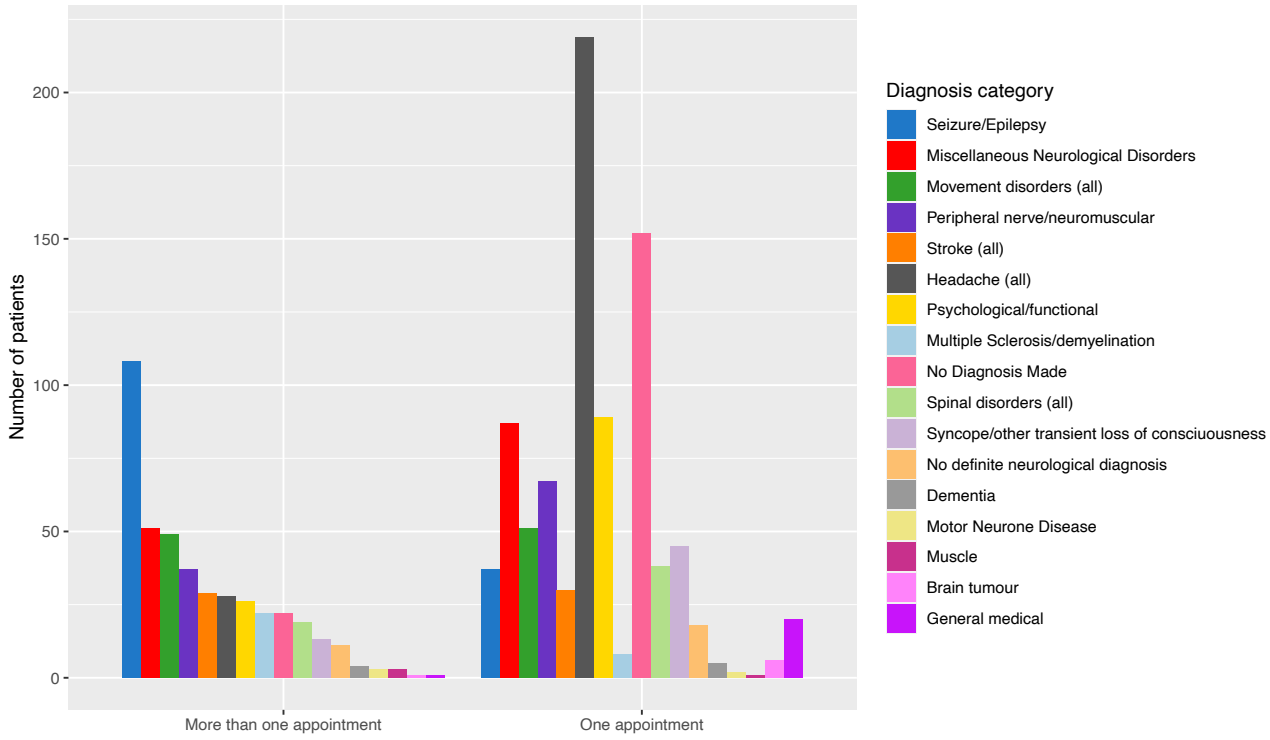


Figure 6.3 The number of patients within each diagnostic category who return for more than one appointment, compared to those who only have one appointment.

In Figure 6.3 we see that, overall, the greatest number of patients attend only one appointment. We also see marked differences in the numbers of patients in each diagnostic category. Headache (25.0%) and psychological/functional (10.1%) were the most frequent diagnostic categories seen in patients with only one appointment. In addition, patients with only one appointment have a large proportion of unattended appointments (16%) which leads to a high rate of patients where no diagnosis was made (17.3%). Within the group of patients who go on to have more than one appointment, the most common diagnosis is seizure/epilepsy (25.5%), followed by movement disorders (11.4%). The rate of unattended first appointments is much lower in this group (3.9%).

Within the group of patients with only one appointment there are a number of diagnostic categories where it is likely that a patient has been referred on to a different service after their first and only appointment; for example, patients with brain tumour referred to neuro-oncology; those with psychological and functional disorders referred

on to relevant services including neuropsychology or neuropsychiatry; and those with 'general medical' diagnoses referred to different services.

6.3.3 Timing of appointments

Within the group of patients with more than one appointment there is a predominant underlying 6 monthly cycle of appointments, as seen in Figure 6.4. After a first appointment (at month zero) most patients return at, or around, the 6 month mark. There is then another peak around 12 months, and a smaller peak at 18 months. Very few patients return in the first or second month following their first appointment, and there is a general decline in the number of appointments after 6 months.

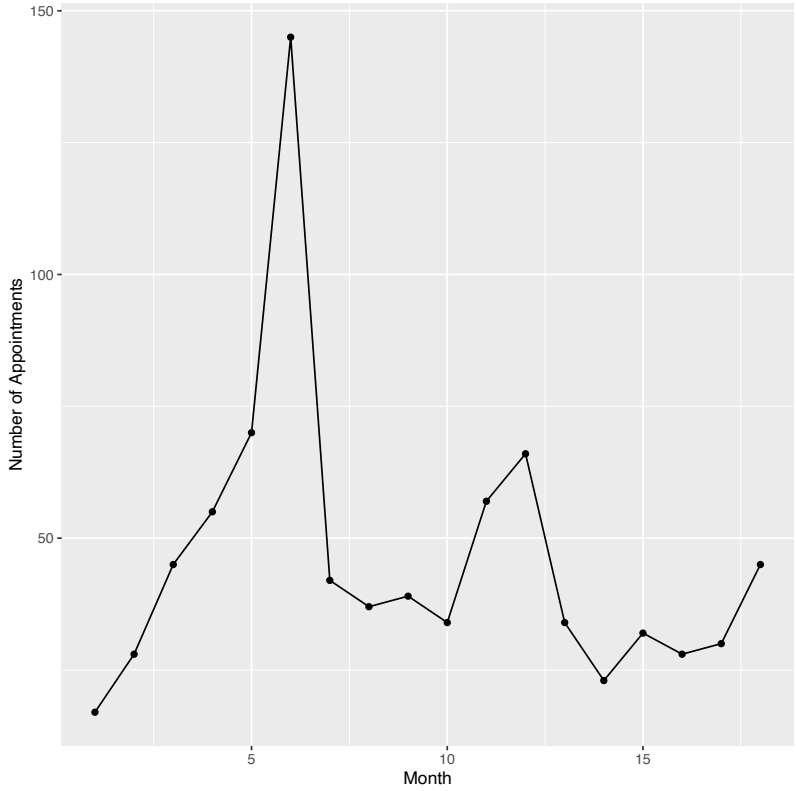


Figure 6.4 Number of follow-up appointments each month.

In order to investigate the timing of appointments more thoroughly we carried out SSA on sequences with two simple states (see Figure 6.1 in the methods section for a visual representation of these types of sequences). We found that the optimal number of clusters was five and descriptions of these groups can be found in Table 6.2. The largest

cluster represents patients who return after 6 months for a second appointment. Further analysis of the patients belonging to each of these clusters revealed few other insights. The only significant result being that patients with movement disorders tended to fall more predominantly into cluster 2, with a second appointment at 3 months followed by further follow up at 6 month intervals. Visualisations of these clusters and a table of patient characteristics for each cluster can be found in the Supplementary Materials.

Cluster	Description
1 (n=163)	Patients return for a second appointment after six months.
2 (n=49)	Patients return for a second appointment after three months and a third appointment after a further six months.
3 (n=89)	Patients return for a second or third appointment at seven or eight months.
4 (n=71)	Patients return for a second appointment after five months.
5 (n=54)	Patients return for a second appointment after four months and a third appointment at eleven months.

Table 6.2 Description of the clusters based on SSA of sequences focused on appointment timing.

6.3.4 Number and type of appointment

State Sequence Analysis of the second set of sequences, those with different appointment types, revealed an optimal cluster solution of 11 distinct clusters (see Figure 6.5), these clusters are described in Table 6.3. The largest cluster is cluster 6 which represents patients with three or more appointments within the 18 month period, mainly of appointments without tests or discharges. It is interesting to note that there are a number of patients who are discharged on their first appointment, yet still return for further appointments during the following 18 months, as seen in cluster 7 for example.

Cluster	Description
1 (n=12)	Two or more unattended appointments in a row.
2 (n=45)	An initial appointment with a test followed by a second standard appointment.
3 (n=25)	Longer sequences of mainly standard appointments.
4 (n=26)	One to three standard appointments, followed by a discharge.
5 (n=65)	Two standard appointments in a row, with some appointments with a test.
6 (n=80)	Three standard appointments in a row.
7 (n=23)	First appointment is a discharge, or a test with a discharge, and the final appointment is also a discharge.
8 (n=29)	End with an unattended appointment.
9 (n=57)	Initial appointment with a test followed by a discharge.
10 (n=52)	Initial appointment with a test followed by an unattended appointment.
11 (n=12)	Initial appointment with a test followed by an appointment with a test and a discharge.

Table 6.3 Description of the clusters based on SSA of sequences focused on appointment type.

Analysis of the characteristics of the patients falling into each cluster reveals that there is no evidence that cluster membership is dependent on sex, age at first appointment, or time to referral. However, there is some evidence that cluster membership is dependent on diagnosis category. Analysis of the individual diagnosis categories shows that there are 3 diagnoses which differ significantly within the clusters, these are seizure/epilepsy, movement disorders, and headache (see Table 6.4). Visualisation of the diagnosis categories within the clusters reveals further patterns (Figure 6.6).

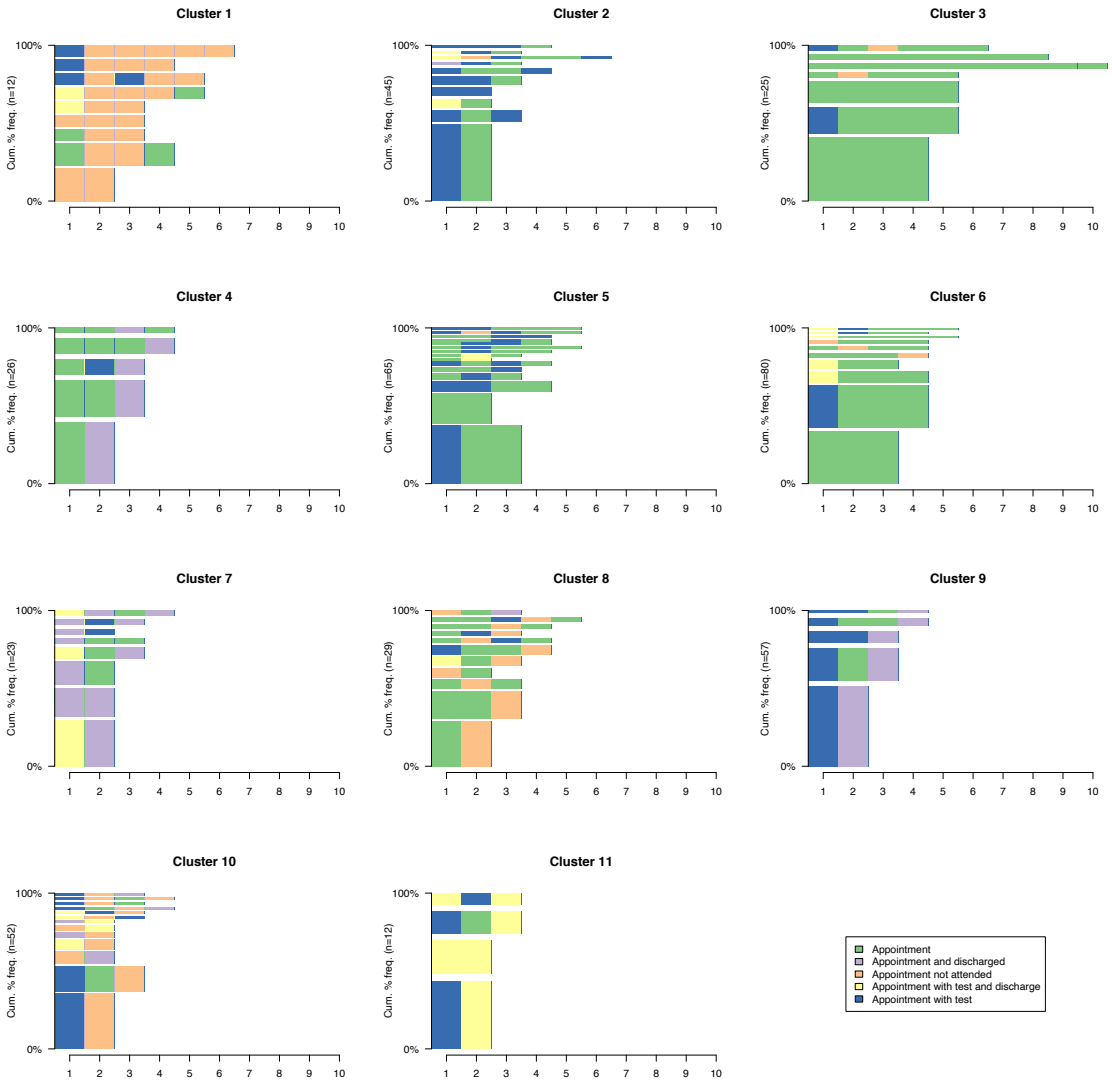


Figure 6.5 Visualisation of the sequences belonging to each of the 11 distinct clusters.

The most common sequence in each cluster is oriented at the base of the y-axis and the height of the bars represents the frequency of that sequence within the cluster. Cluster size is included in brackets in the y-axis title.

	1 (n=12)	2 (n=45)	3 (n=25)	4 (n=26)	5 (n=65)	6 (n=80)	7 (n=23)	8 (n=29)	9 (n=57)	10 (n=52)	11 (n=12)	*p-value*
Sex (%):												
Female	7 (58)	22 (49)	10 (40)	9 (35)	36 (55)	31 (39)	14 (61)	15 (52)	36 (63)	25 (48)	6 (50)	*0.186*
Male	5 (42)	23 (51)	15 (60)	17 (65)	29 (45)	49 (61)	9 (39)	14 (48)	21 (37)	27 (52)	6 (50)	
Mean age at first appointment (SD)	43.7 (15.9)	51.9 (17.7)	52.0 (21.9)	54.6 (20.8)	48.8 (18.6)	48.9 (18.4)	54.7 (17.3)	44.4 (20.9)	51.8 (17.9)	40.4 (16.7)	53.4 (15.4)	*0.079*
Time from referral in weeks (SD)	11.5 (9.9)	11.9 (8.8)	12.3 (8.3)	15.5 (9.9)	14.5 (9.1)	13.9 (9.2)	13.8 (8.6)	16.1 (8.5)	9.8 (8.6)	10.7 (7.2)	14.7 (6.6)	*0.204*
Diagnosis Category (%):												
Seizure/epilepsy	3 (25.0)	15 (33.3)	4 (16.0)	3 (11.5)	18 (27.7)	36 (45.0)	2 (8.7)	10 (34.5)	5 (8.8)	12 (23.1)	-	***0.002***
Miscellaneous Neurological Disorders	1 (8.3)	4 (8.9)	4 (16.0)	4 (15.4)	11 (16.9)	8 (10.0)	1 (4.3)	2 (6.9)	6 (10.5)	7 (13.5)	3 (25.0)	*0.797*
Movement Disorders	-	2 (4.4)	9 (36.0)	6 (23.1)	10 (15.4)	12 (15.0)	-	5 (17.2)	2 (3.5)	3 (5.8)	-	***0.003***
Peripheral nerve/neuromuscular	1 (8.3)	4 (8.9)	2 (8.0)	2 (7.7)	3 (4.6)	3 (3.8)	5 (21.7)	4 (13.8)	7 (12.3)	3 (5.8)	4 (33.3)	*0.060*
Stroke	-	3 (6.7)	2 (8.0)	2 (7.7)	4 (6.2)	8 (10.0)	2 (8.7)	-	6 (10.5)	2 (3.8)	-	*0.720*
Headache	-	2 (4.4)	1 (4.0)	5 (19.2)	-	1 (1.3)	4 (17.4)	-	10 (17.5)	5 (9.6)	-	***0.001***
Psychological/functional	1 (8.3)	3 (6.7)	-	2 (7.7)	3 (4.6)	1 (1.3)	2 (8.7)	-	6 (10.5)	6 (11.5)	2 (16.7)	*0.154*
Multiple Sclerosis/demyelination	-	7 (15.6)	-	1 (3.8)	6 (9.2)	4 (5.0)	-	1 (3.4)	2 (3.5)	1 (1.9)	-	*0.079*
No Diagnosis Made	4 (33.3)	-	-	-	1 (1.5)	3 (3.8)	-	5 (17.2)	-	7 (13.5)	-	***0.0005***
Spinal disorders	1 (8.3)	4 (8.9)	-	1 (3.8)	2 (3.1)	1 (1.3)	5 (21.7)	1 (3.4)	3 (5.3)	1 (1.9)	-	*0.020*
Syncope/transient loss of consciousness	-	-	2 (8.0)	-	1 (1.5)	2 (2.5)	-	1 (3.4)	3 (5.3)	3 (5.8)	1 (8.3)	*0.499*
No definite neurological diagnosis	-	1 (2.2)	-	-	1 (1.5)	1 (1.3)	2 (8.7)	-	2 (3.5)	2 (3.8)	2 (25.0)	*0.095*
Dementia	-	-	-	-	2 (3.1)	-	-	-	2 (3.5)	-	-	*0.374*
Muscle	-	-	1 (4.0)	-	2 (3.1)	-	-	-	-	-	-	*0.278*
Motor Neurone Disease	1 (8.3)	-	-	-	1 (1.5)	-	-	-	1 (1.8)	-	-	*0.207*
Brain tumour	-	-	-	-	-	-	-	-	1 (1.8)	-	-	*0.655*
General medical	-	-	-	-	-	-	-	-	1 (1.8)	-	-	*0.641*

Table 6.4 Patient characteristics for all 11 clusters.

After adjusting for multiple testing statistically significant p-values are highlighted in bold.

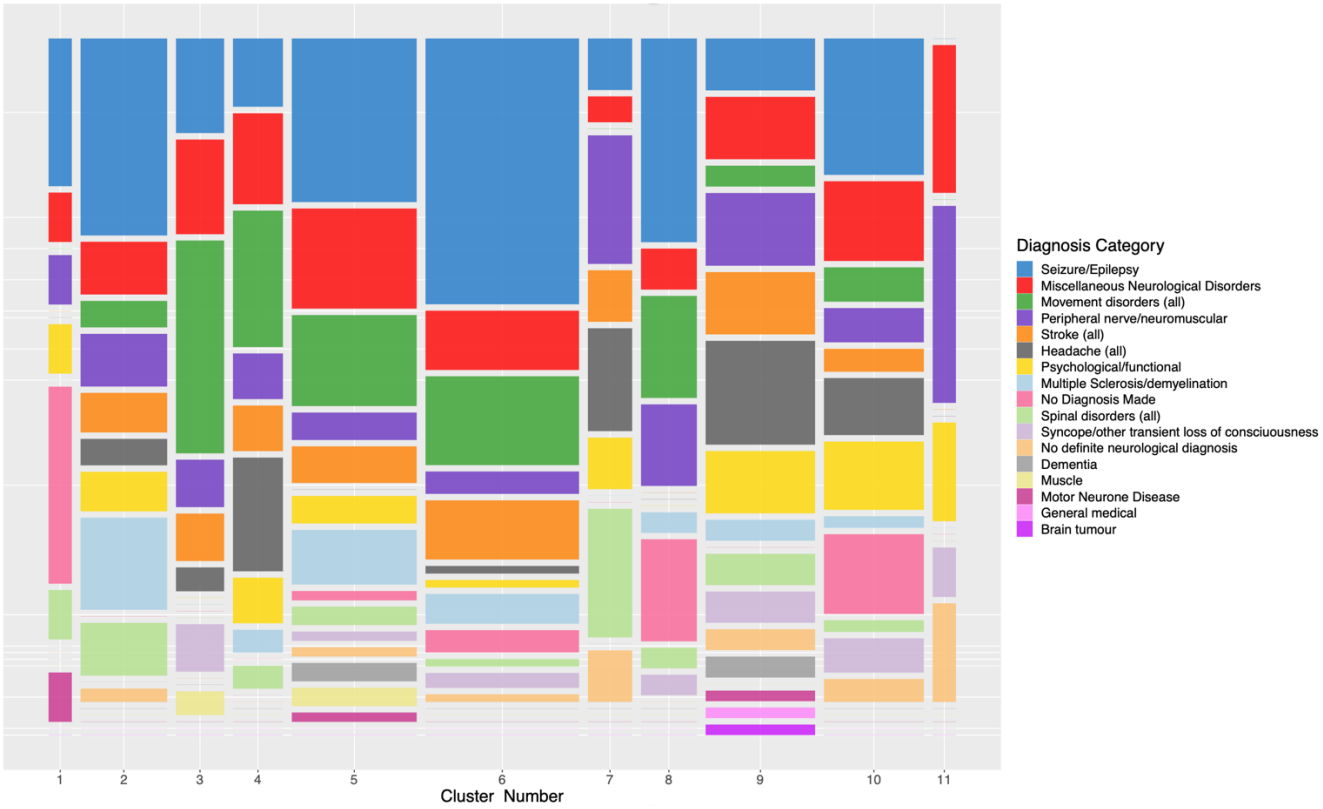


Figure 6.6 Mosaic plot showing the proportion of patients from each diagnosis category falling into each of the 11 clusters.

Note that the width of the vertical columns in the plot represent the relative size of the clusters. Diagnoses with significant results are: Seizure/epilepsy, Movement disorders, Headache, and 'No diagnosis made'.

Figure 6.6 shows that a large proportion of seizure/epilepsy patients fall into cluster 6, the cluster with longer sequences of a standard appointment types, some of whom have tests ordered at their first appointment. Patients with headache disorders fall largely into clusters 4,7,9, all of which are clusters with high rates of discharge. This indicates that those patients with headache disorders who aren't discharged at their first appointment (see Table 6.1), are likely to be discharged at their second appointment. Patients with movement disorders are more likely to fall into cluster 3, with moderate proportions in cluster 4,5, 6 and 8. Cluster 3 contains the patients with the longest sequences and therefore the highest number of appointments in the 18-month period.

6.4 Discussion

There has been very little previous work to examine the types of appointments, and the sequence in which they occur, within outpatient neurology departments. This study helps to fill a gap in current understanding and provides a basis on which future work can be built. It is a starting point for understanding the current situation and provides evidence for the types of change that may be needed.

Using SSA to explore neurology appointments has shown that there are many and varied ways that patients interact with neurology outpatient services. There is, in essence, no 'one-size-fits-all' pattern, even within single diagnostic categories. However, some patterns of similarities can be seen. We found that many patients return for follow-up on an underlying six-monthly cycle. The present study cannot tell us what drives this, but there are several possible explanations such as scheduling based on traditional outpatient pathways, patient behaviour and expectations, and administrative factors. Results in the present study show a 'decay' of the six-monthly cycle suggesting that variation in appointment scheduling emerges over the duration of patient follow up. This could be due to condition-specific differences (for example the timing of particular diagnostic investigations or treatments) or patient-specific differences (for example, patient expectations, or the level of support required) in appointment scheduling. This analysis helps to illustrate these varying patterns and the need for service planning to accommodate a wide range of scheduling patterns.

We found eleven distinct clusters of sequence types which describe within them broadly similar patterns of appointment sequence. Within these clusters there are some patterns common to particular diagnostic categories. For example, those with headache disorders are often discharged at the first appointment. By contrast, patients with movement disorders are seen for regular follow-up appointments. It is likely that such differences reflect condition-specific requirements for ongoing specialist clinic management. Primary headache disorders can often be managed in primary care, although some patients require neurologist input to guide primary care management (115). Other chronic neurological conditions such as Parkinson's disease (PD) are likely to require ongoing neurologist supervision due to the specialist nature of disease management, and National Institute for Health and Care Excellence (NICE) guidelines for PD suggest follow up appointments should be scheduled every 6 to 12 months (116).

Managing the number, frequency and type of individual patient follow-up appointments relies on many different factors, including the type of diagnosis given. This study shows that there are varied ways in which patients interact with neurology services, and although there are some commonalities between patients with the same diagnosis, there are also differences. This indicates the need for a flexible approach to appointment planning, a conclusion which is supported by the Getting It Right First Time (GIRFT) report released in September 2021. This report recommends that, for all patients with chronic neurological conditions, outpatient departments should "consider arranging clinically triggered follow-ups for patients with pending results, personalised patient-initiated follow-ups for patients with disease in remission or with stable disease, as well as the traditional timed follow-up appointments" (101).

This study has also shown that some patients have unexpected sequences, for example being discharged on a first appointment and yet returning for further follow-up. It is likely that a number of factors are responsible for this, such as; an initial discharge being conditional upon the outcome of diagnostic investigations; a further appointment requested by the patient's GP to explain investigation results where the GP may lack capacity to relay such information; or a patient initiating a follow-up appointment through contact with a different member of the booking team. This finding needs further investigation to explore the extent to which the observed appointment sequences deviate from planned sequences, in order to better understand what drives such differences.

6.4.1 Limitations

This study focuses on a single clinic, so it is limited by both the amount of data available and the generalisability of the findings. Even with multiple clinics more work would be required to understand why we see the results we have found. Furthermore, there are many stages during SSA where a different decision, for example to use a different algorithm to measure dissimilarity, could have effects on the results. More work needs to be done to understand the magnitude of the effects of choosing different parameters.

In this study we analyse the results at the level of diagnostic category, even though for some individuals more specific diagnosis will have been made. This is necessary both because the

size of the study limits the amount of detail we can observe, and because specific diagnosis was not routinely coded at neurology outpatient appointments when the data for this study was collected. Routine coding of diagnoses, coupled with larger datasets would allow for a more detailed analysis of the differences in appointment sequences between diagnoses.

6.4.2 Benefits

We have shown that neurology outpatients is a complex environment. Patients have many different diagnoses, with significant variation in multiple dimensions, including patient needs and expectations, as well as a multitude of condition-specific and clinician-directed elements, all of which influence the planned and/or observed number and types of appointments. Using SSA has allowed us to visualise distinct sequences and see which types of sequences are most common. Identifying common patterns, whilst acknowledging the breadth of the differences, can help to inform future planning. This study provides a starting point for understanding neurology outpatients and should offer support in the wider effort to meet targets and standards, and ultimately to improve patient access based on clinical need, as well care delivery.

6.4.3 Future Work

Future work could expand this to a national level which would facilitate much more comprehensive understanding of patterns of outpatient care. With larger datasets more detail could be examined, for example looking in more depth at diagnosis-specific sequences. In addition, national level research could also be used to highlight differences within and between regions, examining variation and its potential causes. This study only looks at a single clinic in a region which has a particularly low consultant to population ratio; it would be informative, for example, to compare this to the types of appointment sequences seen in areas which are better resourced with consultant neurologists.

6.5 Conclusion

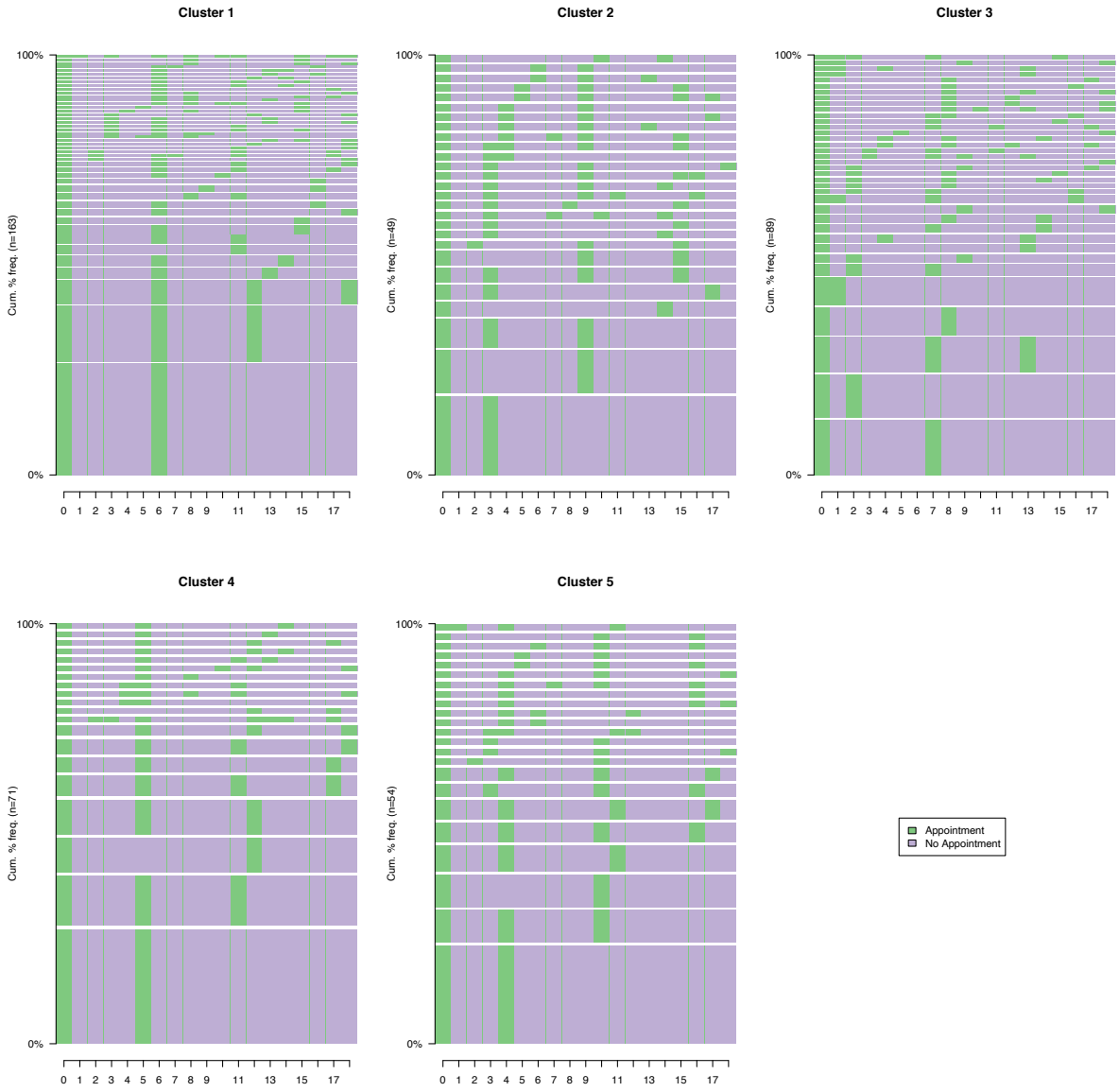
SSA is a useful methodology for exploring patterns of outpatient appointments, especially patterns of appointment type. Neurology outpatient appointments show great diversity across all diagnostic categories, but there are some patterns which are more common within specific

diagnoses. Information about these common patterns could be used to inform the structure of future outpatient appointments, especially when considering initiatives such as the NHS Outpatient Transformation Program

6.6 Supplementary Materials

	1 (n=163)	2 (n=49)	3 (n=89)	4 (n=71)	5 (n=54)	*p-value*
Sex (%):						
Female	86 (53)	22 (45)	37 (42)	37 (52)	29 (54)	*0.42*
Male	77 (47)	27 (55)	52 (58)	34 (48)	25 (46)	
Mean age at first appointment (SD)	47.1 (18.9)	50.9 (16.9)	52.4 (19.7)	50.6 (17.2)	46.3 (19.4)	*0.31*
Time from referral in weeks (SD)	12.2 (9.1)	14.7 (9.3)	13.9 (8.7)	12.7 (8.5)	12.3 (8.3)	*0.85*
Diagnosis Category (%):						
Seizure/epilepsy	45 (27.6)	12 (24.5)	15 (16.9)	22 (31.0)	14 (25.9)	*0.441*
Miscellaneous Neurological Disorders	18 (11.0)	4 (8.2)	12 (13.5)	8 (11.3)	9 (17.7)	*0.820*
Movement Disorders	15 (9.2)	14 (28.6)	11 (12.4)	6 (8.5)	3 (5.5)	***0.003***
Peripheral nerve/neuromuscular	14 (8.6)	1 (2.1)	15 (16.9)	6 (8.5)	2 (3.7)	*0.041*
Stroke	12 (7.4)	3 (6.1)	6 (6.7)	6 (8.5)	2 (3.7)	*0.888*
Headache	12 (7.4)	4 (8.2)	5 (5.6)	4 (5.6)	3 (5.5)	*0.955*
Psychological/functional	10 (6.1)	2 (4.1)	4 (4.5)	6 (8.5)	4 (7.4)	*0.865*
Multiple Sclerosis/demyelination	6 (3.7)	4 (8.2)	3 (3.4)	6 (8.5)	3 (5.5)	*0.446*
No Diagnosis Made	10 (6.1)	-	6 (6.7)	2 (2.8)	2 (3.7)	*0.355*
Spinal disorders	7 (4.3)	1 (2.1)	5 (5.6)	4 (5.6)	2 (3.7)	*0.912*
Syncope/transient loss of consciousness	5 (3.1)	1 (2.1)	2 (2.2)	-	5 (9.3)	*0.051*
No definite neurological diagnosis	4 (2.5)	3 (6.1)	1 (1.1)	1 (1.4)	2 (3.7)	*0.399*
Dementia	1 (0.6)	-	1 (1.1)	-	2 (3.7)	*0.234*
Muscle	1 (0.6)	-	1 (1.1)	-	1 (1.9)	*0.919*
Motor Neurone Disease	2 (1.2)	-	1 (1.1)	-	-	*0.870*
Brain tumour	1 (0.6)	-	-	-	-	*0.803*
General medical	-	-	1 (1.1)	-	-	*0.641*

Supplementary Table 1. Patient characteristics for the 5 clusters resulting from SSA on the sequences focussed on appointment timing. After adjusting for multiple testing statistically significant p-values are highlighted in bold.



Supplementary Figure 1. Visualisation of the 5 clusters resulting from SSA on the sequences focussed on appointment timing. The most common sequence in each cluster is oriented at the base of the y-axis and the height of the bars represents the frequency of that sequence within the cluster. Cluster size is included in brackets in the y-axis title.

7 Discussion and Conclusion

7.1 Neurology Lessons

In this thesis we have used a routinely collected data set to address questions and issues relating to neurology outpatient services in the North-West of England. The four papers which make up this thesis address different areas of neurology research, and discussion points from each paper are summarised in this section.

7.1.1 Answers to the research questions

The paper presented in Chapter 3 explored the ways in which routinely collected data have been used in neurology research. We found that previous neurology research using RCD focused on a small number of conditions and there were few studies into common conditions such as migraine and headache. There were also very few studies which included multiple conditions in the same research and looked at neurology services as a whole. This directed the subsequent research we conducted, as we focused on these two gaps in the current research landscape.

Our second paper, presented in Chapter 4, aimed to answer questions relating to who visits the outpatient neurology clinic, how long they wait for a new appointment, and what resources are being used. We found that the principal working diagnoses in more than 60% of patients referred to the clinic fell into one of five diagnostic categories; that differences in waiting times showed variable access between diagnostic categories; and that diagnosis also influenced what resources patients used in terms of tests and follow-up appointments.

The third paper, presented in Chapter 5, examined the single diagnostic category of headache. The aim of this paper was to identify unexpected number of referrals from GP surgeries to the outpatient clinic for headache patients. We found that it was possible to identify GP surgeries with unexpected numbers of referrals using residuals from a Poisson model. The model also showed that the distance of a GP surgery from the

clinic, and the number of other types of neurology referral made were significant predictors of headache referrals.

The final paper, presented in Chapter 6, explored the ways in which State Sequence Analysis could be used to identify patterns in appointment sequences. We were able to show that neurology outpatient appointment sequences are diverse across all diagnostic categories, but there are some patterns which are more common within specific diagnoses.

7.1.2 Research contribution and impact

This research has used a unique dataset to produce insights into a neurology outpatient clinic that have been rarely seen before. Chapter 4 replicated and extended work by Stevens and Stone (43,65) showing that routinely collected data can be used to shed light on the types of patients who visit a neurology clinic and the resources they use. Chapter 5 demonstrates how it is possible to use common modelling methods to identify the location of variability in referrals. Although there is a large body of research on the existence of variation in referral rates, very little has been done previously to identify its location. Chapter 6 uses a methodology that is relatively new to health research to identify the existence of specific patterns in appointment sequences which is useful for resource planning.

The area where this research has had most impact to date is in the implementation of outpatient coding. Using the most common diagnoses found in the research presented in chapter 4 the outpatient neurology clinic in Preston have created a diagnostic list within their electronic health record. The creation of this list has also prompted discussion at a national level within forums such as the National Neuroscience Advisory Group (NNAG). The discussion centres around how best to implement national level coding, and what type of system to use. Our research is contributing greatly to this debate in providing both the evidence base for the utility of coding and the most common diagnostic categories that would be most useful to highlight. Any electronic system for capturing diagnoses needs to be detailed enough to capture a useful differentiation between diagnoses, but also simple enough to enable ease of input for clinicians. Our

research is contributing to the debate on which diagnoses are most beneficial to include in such lists.

The issue of diagnostic coding in neurology outpatient clinics has also been addressed in two additional papers which arose from the work carried out for this thesis, and can be found in the appendices (117,118). These two papers bring the issue of coding to a wider academic audience and have contributed to the debate on how best to proceed with a national outpatient coding project. The first of these two papers arose from work done during the COVID-19 pandemic to identify patients who needed to 'shield' (117). The difficulties encountered when trying to identify these patients prompted the publication of this editorial discussing the obstacles and highlighting the utility of recording diagnostic categories. The second of the papers discusses in more depth not just the benefits of outpatient coding, but also the practicalities of introducing a diagnostic coding system (118).

7.2 Routinely Collected Data Lessons

The introduction to this thesis explored the benefits and limitations of using routinely collected data that had been previously identified by other researchers. This discussion section will highlight the specific experiences of using RCD for our research into neurology services.

7.2.1 Benefits of using RCD

One of the many benefits of using RCD, mentioned by a number of researchers, is the availability of the data and the relative low cost of this type of research (2–4), and this is a benefit that was apparent through this research. It was not necessary to collect large amounts of bespoke data and, as the data were available once ethical agreements were in place, more time could be spent on analysis of the data instead of on data collection. Although bespoke data collection was not necessary, the use of online open-source data enhanced the data received from the hospital. Linking routinely collected data to other freely available sources such as the Index of Multiple Deprivation, census data, and NHS Digital data on GP surgeries expanded and enriched the research undertaken.

The longitudinal nature of the data meant that it was possible to examine temporal patterns such as the sequences of appointments explored in chapter 6. The ability to look at a series of appointments over time enabled a greater understanding of the patient experience than simply looking at the number of people attending appointments, for example. The longitudinal nature of the data could be used in further research to examine changes over time, or to compare pre-Covid appointment structures to those experienced post-covid, for example.

One of the most beneficial aspects of analysing routinely collected data in this thesis was the ability to work closely with the clinician who generated the data. This allowed for deeper insights into the data than if it had simply been downloaded from an online database, for example. Understanding how and why the data were collected is incredibly useful when it comes to analysis. One of the accepted limitations of working with RCD is that it is not collected for research, and that the statisticians and analysists who work with the data lack understanding of the data generating process (2). However, working closely with the clinician allowed for a deeper understanding of the data and therefore an appreciation of how best to analyse it.

7.2.2 Limitations of using RCD

The data used in this thesis had some limitations common to other researchers' experiences of using routinely collected data. There was missing data, data from different sources which was contradictory, and accessing the data required a long ethical review process. There were also limitations in the amount and type of data that was available, for example the data only included information from neurology outpatient services and not from other hospital departments.

The amount of missing data was not significant (under 5%) and did not have any inherent structure and so we did not use any complex methodologies to resolve this issue, and just removed the small number of records with missing data. However, this is an area in which care must be taken as missing data can be structured in such a way that bias is introduced into a study if it is not handled correctly (119). Where differing sources were contradictory it was necessary to find a third source to corroborate the

correct information. This can be a time-consuming procedure and can detract from one of the main benefits of using routine data – that of the convenience of its availability.

The data analysed in this thesis was limited by the fact that there was no information on patient interactions outside of neurology outpatient services. There was no data from other hospital departments, visits to the GP, or other useful health and lifestyle information such as smoking status or employment. It was possible to link our data to other sources such as the Index of Deprivation, but this only gave context for the geographical area in which patients lived, not information at the individual patient level. Having more data on other patient interactions and their health could help better understand the drivers of visits to health care and to neurology clinics in particular (3).

Research using RCD differs from other types of research as the ability to answer research questions is restricted by the data that is available. In more traditional research environments, the research question is first determined, and this then informs specific data collection strategies. We found that in research using RCD this is necessarily reversed and it is the data which informs the types of questions that can be asked and answered. This presented a limitation during this thesis as the initial ethical review restricted which data were accessible. It was not possible to view the data in advance of applying for the ethical review, and so it was not possible to know which questions it would be possible to answer. This inability to foresee what questions would be feasible and what extra data might be required limited the research to questions which could be answered by the data we initially requested.

7.2.3 Potential solutions and recommendations

It is important to understand that ethical agreements place necessary limitations on the data that a researcher can access, however it may be possible to request a more flexible agreement; for example, including in the ethics agreement a clause which allows the data to be updated during the time period of the study. It may also be possible to make amendments to the ethical agreement during the study to enable activities such as gathering data from other hospital departments. Developing relationships with people within relevant departments at the Trust is essential for both facilitating the initial ethical application process and enabling any future amendments. We also found it to be

greatly beneficial to attend the Research Ethics Committee in person to directly answer questions that were raised.

Gathering data on interactions from outside of neurology services would greatly enhance the research. However, obtaining data from other sources such as GP surgeries, for example, would be more complex than requesting extension of data collection within the hospital and would probably necessitate the creation of bespoke databases combining data from primary and secondary care. Some NHS Trusts have begun to do this, a prime example is the 'community data warehouse' at Morecambe Bay Trust, and these initiatives should be supported, advertised, and expanded to other Trusts.

Care must be taken not to put extra pressure on clinicians to collect data for research purposes, as their focus necessarily remains on the diagnosis, treatment, and management of patients. However, electronic health records could be streamlined to enable easier use by both clinicians and researchers. Combining records into a data warehouse at Trust level is a good example of this as it makes the most of the data available without putting unnecessary pressure on clinicians to collect more data, or to radically alter their current practices.

It is necessary to work with clinicians and managers within the NHS to ensure that the data collected is suitable for different types of purpose, and from a researchers' point of view it is necessary to collaborate with clinicians in order to understand the data they are using in their research. Forming collaborations between researchers and NHS Trusts, with both clinicians and analytical staff, is a key way in which future research using routinely collected NHS data can be improved and moved forward.

7.3 General study limitations

One of the main limitations faced throughout this thesis was the lack of diagnostic coding of outpatient neurology appointments. Although the dataset contained a diagnosis field it was recorded as free text, and therefore it was necessary to use a bespoke categorisation system to render it useable in analysis. Recording of standardised diagnostic codes at outpatient appointments would allow for easier analysis and, more importantly, comparison of analyses across different geographical

areas and timeframes. As mentioned in section 7.1.2 the issue of diagnostic coding has been explored in greater depth in the papers found in the Appendix. As a result of the work done in this thesis, and the publication of these separate papers, coding practices at a local and national level have begun to change. The neurology clinic at Preston, whose data was analysed in this thesis, have integrated a diagnosis list into their electronic health records that is based on the most common diagnoses presented in chapter 4.

Another limitation is the fact that the data used in this thesis were from a single clinic. This limits conclusions to a small geographical area and makes it difficult to generalise further without more research. However, the methodologies that have been demonstrated using this data could be used elsewhere, either in other geographical areas or within the same clinic but using more current data, to either compare results or to corroborate and extend our findings.

Despite these limitations we have demonstrated that routinely collected data can be successfully used to gain a greater understanding of how a neurology clinic is structured and how its resources are being utilised. This will help inform future management of resources for the benefit of both clinicians and patients.

7.4 Future Research

7.4.1 Future neurology research

We found that many patients attend only one appointment, and often that appointment does not result in any testing or follow up. Future research could be designed to identify patients that are likely to need only one appointment. If this were possible then potentially these patients could be seen in primary care thus freeing up resources within the outpatient clinic and saving the patient the unnecessary difficulties of traveling to a hospital appointment only to be discharged from the clinic on the same day.

Our research also points towards other possibilities that could be explored such as offering patients testing before they attend their first appointment. In 2015 NICE introduced a recommendation for suspected CNS cancer patients to be referred ‘direct-to-scan’ rather than to a consultant appointment first (68). Research is needed to

determine if this pathway results in better outcomes for the patient, but it could potentially be expanded to patients with other types of diagnosis. If a patient is first offered a scan or other test, then these results can be discussed at a first appointment rather than having to wait. This would lessen the stress on the patient as they are waiting less time for results, and it also frees up consultant time as there is no initial consultation. In addition, if the results of the scan or test are negative and easily explained, then this could be communicated to the patient's GP, saving the patient the consultant appointment.

This type of treatment pathway would need a triage system in place to determine the most appropriate option for each patient as it is not always clear from referral letters what testing might be needed. An initial appointment may be needed in some cases in order for the consultant to determine which tests may be necessary. Further research is needed to determine which neurological referrals would benefit most from a 'direct-to-testing' model. Future research from a health economic perspective would also be interesting in order to determine the cost-benefit of different pathways.

As routine diagnostic coding practices are taken up more widely it will be possible to extend this research to other geographical areas allowing for analysis of larger datasets and comparison across different NHS Trusts and Integrated Care Boards (the replacement for CCGs). This type of research would be of great benefit as there remains a large variability in neurology services across England and the UK. The ability to compare the way services are used, and to identify areas of variability, would allow for more targeted research into specific issues.

Expanding this research from the level of one trust to a national scale would require a large, federated dataset which would be difficult to obtain currently. The development of a national Secure Data Environment (SDE) in line with the Goldacre report would hopefully allow for this, but that may be some way in the future. The first step to expanding this research may lie in using a regional SDE to expand the research to a regional level such as Lancashire and South Cumbria. Such an SDE is currently under development at an Integrated Care System level within Lancashire and South Cumbria ICS, and this should provide the data platform required to undertake such research.

This thesis has highlighted potential issues in the variability of referrals for a single diagnosis, that of headache. However, with the data available, it was only possible to identify the existence and location of variability and not any cause for it. Further research would need to be undertaken to uncover any potential causes for the variation. Extending this research into the area of causation would necessitate new analyses using other types of data. It would be useful to gather data on all patients who seek care from their GP for symptoms of headache and compare those who are referred to the neurology clinic with those whose symptoms are managed within the primary care setting.

If it were possible to source larger data sets this would allow for more focused research into the experiences of different subsets of patients. In particular it would be of great interest to explore in more detail the types of appointment sequences experienced by patients with the same diagnosis. Focusing a State Sequence Analysis on patients within a single diagnostic category would be of interest for both resource allocation and for the ability to understand the patient experience in more depth.

We chose to use State Sequence Analysis to study sequences of appointments, however there are a number of different approaches that have been taken by others to study care trajectories, patient pathways and visit patterns. Future research in the area of appointment sequences could take advantage of these other methodologies. Williams et al used graphical representations of care pathways and string matching to match patient records with particular care pathways (120). This work could be used to understand common pathways and which patients take which routes through the hospital system. A different study approached the problem of identifying re-visit patterns in cerebrovascular patients by using sequential pattern mining (121). This approach uses the concept of a ‘minimum support’ to identify which patterns can be classified as common within the dataset. Nuemi et al added a spatial component to their analysis of hospital pathways in lung cancer patients (122), which allowed them to visualise physical journeys as well as conceptual ones. There has also been research into care trajectories in COVID-19. Thygesen et al used event trajectory networks to study the rates of transition frequency and duration between different events (123). These examples of other types of sequence analysis show that there are numerous possibilities

for future research which focus on different aspects of the sequence, pathway or trajectory being studied.

7.4.2 The future of research using RCD

There are currently a number of ways of accessing routinely collected health data in the UK through data curated by organisations such as Open SAFELY and the HDR UK Research Innovation Gateway (124,125). These data sources provide access for researchers to large secure datasets, but there are also limitations to working with these types of data. For example, the researcher is limited to the types of data held and the type of research allowed. The HDR UK gateway holds very specific datasets such as Parkinson's Audit data and an Epilepsy tissue bank, making accessing data an option only if the datasets held are relevant to the research being conducted. Open SAFELY contains primary care data and is currently only available for COVID research but will hopefully be available for other types of research in the future. The Goldacre report recommends investment in Secure Data Environments, at both a regional and national level which will help to mitigate some of these limitations (14). A national secure data repository would be the ideal way to access health data for research, but this option may be a long way in the future.

Along with the administrative data warehousing previously mentioned in section 7.2.3 and the large, federated datasets mentioned above, the future of research using RCD could be enhanced using data mining methods such as NLP. Work is currently being undertaken on the use of NLP to extract information from discharge letters from the neurology clinic at Preston (126). This type of research could lead to better classification of diagnoses, and the extraction of clinical and administrative information without the explicit need for a clinician to record it in a database, or a member of administrative staff to manually extract data from the letter. This would both provide more data for research using RCD and alleviate some of the administrative burden on staff.

The general future of NHS data is far beyond the scope of this thesis, but it is worth mentioning that in an ideal world the NHS in England would have a system similar to

that in Scotland or Scandinavia, where health data is much more coherent. Ideally all Trusts would use the same electronic systems allowing for the application of the FAIR data principles – better findability, accessibility, and interoperability, which enable more efficient reuse of data (127).

There are currently several organisations involved in making health data in England more accessible to researchers. The Health Foundation support analysts and researchers through their Advancing Applied Analytics programme (128); Health Data Research (HDR) UK host a Research Innovation Gateway for access to UK health datasets, and are also involved in trusted research environments and the Data Analytics Research Environments (DARE) UK programme (129); and NHS digital host the Secure Data Environments service (130).

It is also important to note that research and analysis also takes place within the NHS both at Trust level, with the emergence of data science teams in many Trusts, and at a national level with NHS digital. The future of research using routinely collected data may well lie in the ability to train and engage with these teams which are embedded within the health services. That is not to say that academic research will not play its part, but that there is a great deal of talent and opportunity available within the NHS if they can be given the right tools and training.

7.5 Conclusion

This thesis has shown that routinely collected data can be used to explore and understand health services in a neurology outpatient setting in the northwest of England. We first outlined the current gaps in the literature and research by conducting a systematic mapping review, and from this presented three research papers which developed the themes identified in that review.

The research presented in chapter 4 demonstrates the utility of understanding who is visiting the neurology clinic, how long they must wait for appointments and what resources are used in terms of tests ordered and follow up appointments offered. The longitudinal nature of routinely collected data mean that this research could be

expanded by extracting current data and comparing the pre-pandemic waiting times and resource utilisation presented in this thesis to those being experienced post pandemic.

Variation in referral rates from GP surgeries to specialist consultant care is acknowledged as an issue in healthcare. Chapter 5 of this thesis presented a method for identifying the location of extremes of variability which could be then used to target further research or interventions.

Using state sequence analysis in chapter 6 allowed us to demonstrate that there are a number of different types of appointment sequence, and that there are some common patterns in the types of appointments that patients attend. This type of research is useful for resource planning and for understanding the patient experience.

Routinely collected data has many limitations as outlined throughout this thesis, however we have shown that it can be used to great effect to understand outpatient services. Although we have used the specific case study of a neurology outpatient clinic this type of research could be applied in other areas of healthcare. Understanding the limitations of RCD and working within them is key, however it should not be overlooked as an excellent resource for research. The future of research using routinely collected data looks bright as there are several organisations working to make data more accessible, and many researchers are working on ways to make the use of RCD more rigorous. There is a vast scope for the future use of routinely collected data both in health research in general and within neurology outpatient services specifically.

Appendices

BMJ Neurology Open

COVID-19 exposes the urgent need for coding of outpatient neurology episodes

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Early in the COVID-19 pandemic response, the Chief Medical Officer for England commissioned the National Health Service (NHS) Digital to identify vulnerable people at 'high risk' of complications from COVID-19, who should be 'shielded' for at least 12 weeks (shielded patient list (SPL)). The SPL was defined as a subset of circa 1.5 million patients in certain categories deemed to be 'extremely vulnerable' and who were advised to practice 'shielding', not leaving the home other than for essential healthcare needs and stopping all contact with those outside their home; these patients would need additional support from local government and health services. A larger 'at-risk' group (circa 19 million) normally at risk from influenza was advised to practice strict social distancing. The SPL categories included people on immunosuppression therapies sufficient to significantly increase the risk of infection, which would encompass some patients with neurological conditions (eg, multiple sclerosis), but otherwise patients with neurological diagnoses were not initially included in the SPL.

NHS Digital has acknowledged challenges in deriving the SPL, including that existing datasets did not hold data in the required form to identify the SPL, and data held in clinical codes did not directly map to the requirements in the SPL (the absence of clinical coding for many outpatient episodes does not seem to have been acknowledged). The lack of direct mapping to the SPL led to expert clinicians (via clinical specialty organisations) being asked to 'translate' (or map) so that individual patients could be identified. The Association of British Neurologists (ABN) produced stratification guidance at the request of organisations coordinating the identification of these patients. However, the lack of routine outpatient coding to underpin this exercise was not, seemingly, acknowledged. The general limitations of the approach, however, were apparently recognised, including the inaccuracy of the underlying centrally held administrative data, the incompleteness of the underlying data, and the speed at which the list was required (initially within 48 hours). These limitations were to be mitigated by local clinical services and general practitioners being able to add to the SPL directly.

Deficiencies in neurology informatics in the UK have been recognised for some time. The majority of clinical neurology activity takes place in the outpatient setting, but despite this, clinical coding of outpatient episodes is not mandatory. This, and the nuanced nature of identifying whether patients with particular neurological diagnoses were 'extremely vulnerable' based on certain specific clinical features and/or disease severity, meant that clinicians were required to manually review thousands of individual case records. Inevitably, each clinician will have approached this task somewhat differently, including the determination of 'extremely vulnerable', given the ABN risk stratification guidance, although detailed, did require interpretation at an individual patient level. The ABN guidance on risk stratification was, by necessity, revised repeatedly during the risk stratification exercise due to evolving information available, adding a layer of complexity. Risk stratification, although essential, represented an enormous demand (ultimately spanning several weeks) just as clinician time became even more scarce due to factors such as sickness, self-isolation and redeployment. With the benefit of coded outpatient episodes, the entire process could have been streamlined, probably with partial automation, and with a targeted approach to stratification based on diagnostic coding. The multitude of information systems, lack of consistency in file systems, names and formats, and so on further hampered efforts at the local level to automate any aspect of the process.

Pre-COVID-19, neurology outpatient coding had been recognised as a priority by

the Neurology Intelligence Collaborative, a subcommittee of the National Neuroscience Advisory Group. Preliminary efforts were already underway, with the support of the Association of British Neurologists. Coding is also deemed to be complementary to the Getting It Right First Time NHS improvement programme. This exercise is now more pressing. It needs to be clinically led and driven, a crucial aspect to develop and maintain clinician 'buy in'. There is recognition that different hospitals are at very different points in their digital maturity; the diversity of electronic patient record systems, independent or commercial, freedom of local IT teams to implement changes and so on all add to the challenge of implementation. Commitment from clinicians will be key in order to drive the process of integration of a pragmatic system of clinical classification of outpatient episodes.

Neurology services in the UK are in the midst of a 'perfect storm': an ageing population, burgeoning neurodegenerative disease, growing societal expectations, diminishing confidence among non-neurologists to manage neurological conditions, all conspiring to outstrip clinical neurology capacity. There was already a pressing need to implement outpatient neurology coding. COVID-19 has exposed just how urgent this issue has become. Hopefully, widespread clinical engagement will be forthcoming.

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OPEN ACCESS

Outpatient neurology diagnostic coding: a proposed scheme for standardised implementation

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ABSTRACT

Clinical coding uses a classification system to assign standard codes to clinical terms and so facilitates good clinical practice through audit, service design and research. However, despite clinical coding being mandatory for inpatient activity, this is often not so for outpatient services, where most neurological care is delivered. Recent reports by the UK National Neurosciences Advisory Group and NHS England's 'Getting It Right First Time' initiative recommend implementing outpatient coding. The UK currently has no standardised system for outpatient neurology diagnostic coding. However, most new attendances at general neurology clinics appear to be classifiable with a limited number of diagnostic terms. We present the rationale for diagnostic coding and its benefits, and the need for clinical engagement to develop a system that is pragmatic, quick and easy to use. We outline a scheme developed in the UK that could be used elsewhere.

INTRODUCTION

Clinical coding is the assignment of standard codes to clinical terms using a classification system. Having an accurate description of outpatient activity coded by diagnosis, rather than simply the number of patients seen, would help to understand how neurology outpatient clinics are used and this would inform service design. Outpatient coding has the potential to improve neurology services (see box 1), for example, to anticipate the necessary capacity to develop headache pathways, or to ensure sufficient specialist nursing or advanced practitioner support.

Clinical coding requires a reliable, robust system to capture the diagnoses of patients seen, as well as when they were seen, by whom and where.

Internationally, clinical coding is used to record clinical activity and for billing. Billing systems vary around the world, capturing data relevant to the payment system, generally focusing on the type of activity rather than the clinical diagnosis. There is variable central collation of clinical activity and diagnostic codes.

In the UK, inpatient admissions in the National Health Service (NHS) are coded by diagnosis (see box 2) but hospitals and primary care use different coding systems. Most neurology care is delivered in outpatient clinics where there is no mandatory coding of diagnosis.

Diagnostic coding of outpatients is likely to become part of UK clinical commissioning in the future, and may well become mandatory; thus, clinicians should consider engaging with (and so shaping) the process from the outset.

This paper summarises the current situation, describes relevant pilot work, discusses potential barriers and outlines a proposed standardised scheme for implementing outpatient neurology diagnostic coding.

Outpatient neurology diagnostic coding

In the UK, the National Neuroscience Advisory Group report[1] and Getting It Right First Time—an NHS improvement programme focused on improving access to care for patients with neurological disorders across England[2]—both recommended developing outpatient coding to support service planning and to enable benchmarking between different neurology services.

We currently have no standardised mechanism for outpatient neurology diagnostic coding. Some centres are adopting local implementation systems, and some individual neurologists keep their own

Box 1 Benefits of outpatient coding for patients, clinicians and neurology services

- Allowing more effective use of available resources, thus improving patient access and care. Improved access to neurology outpatient clinics could prevent hospital admission and improve clinical outcomes.
- Improving understanding of the service being delivered. Examples include the proportion of patients with multiple sclerosis receiving disease-modifying therapies or the frequency of brain imaging for people with headache.
- Paving the way for monitoring of clinical outcomes, for example, measurable changes in health, function or quality of life as a result of clinical care. Review of clinical outcomes establishes standards against which clinical practice can be continuously improved.
- Potentially standardising and so enabling closer working with other clinicians and services, service planning, audit and research.
- Opportunity for understanding disparities in neurological care, for example, through linkage with patient demographic and Index of Multiple Deprivation data.
- Outpatient neurology diagnostic coding would inform healthcare planning and resource allocation, as illustrated by the recent study of the burden of neurological disorders across the USA.[10]

records, but often the only standardised information recorded is whether the outpatient visit was for a new or follow-up appointment. Despite a longstanding recognition of the need for neurology outpatient coding, there has been no appetite for its standardised implementation, seemingly because of workload pressures and lack of administrative support. In short, the process needs to be clinically driven and pragmatic to avoid excessively burdening clinicians.

The COVID-19 pandemic brought the lack of outpatient coding into sharp focus because of the difficulty in risk stratifying patients with neurological conditions.[3] Data held centrally by NHS Digital were recognised to be inaccurate and incomplete, and so the task of risk stratification was delegated to individual clinicians, who themselves were severely hampered by the lack of outpatient diagnostic coding data.

The clinician-friendly Systematised Nomenclature of Medicine-Clinical Terms (SNOMED CT; see box 3) is the clinical vocabulary with the greatest momentum with respect to direct care and its readiness for use in clinical research. SNOMED CT permits entry of concepts familiar to clinicians, including symptoms, procedures, clinical measurements, diagnoses and medications. Concepts have unique IDs, but SNOMED CT supports synonyms, allowing the same concept to be expressed in multiple ways. The Wales neurology

Box 2 UK inpatient diagnostic coding

In the UK, National Health Service (NHS) inpatient data are assigned Healthcare Resource Group codes based on procedure codes and International Classification of Diseases 10th Revision (ICD-10 diagnosis codes, enabling hospitals to be reimbursed for activity. Coding data from inpatient records contribute to commissioning datasets, which are sent by the hospital to the Secondary Uses Service (SUS), an external national data warehouse hosted by NHS Digital. Hospital episode statistics data are derived from cleaned SUS data extracts, and used for a range of analytics, planning services, monitoring and payment.

The coding is done by non-medical coders from their analysis of the medical notes and discharge summary.

Box 3 The Systematised Nomenclature of medicine-clinical terms (SNOMED CT)

The SNOMED CT is a medical terminology designed for input into electronic health records. It comprises concepts organised into hierarchies, descriptions linking human readable terms to concepts and relationships linking concepts to related concepts. SNOMED CT is not an alternative to ICD-10. However, SNOMED CT terms are better suited to clinician use, and can be mapped to ICD-10. More widespread clinical use of SNOMED CT should also facilitate its continued development and ensure that it remains up to date and suitable for use in specialist settings such as neurology. SNOMED CT addresses the requirement for robust interoperability between different systems with the use of appropriate information and data standards.

The FAIR (findability, accessibility, interoperability and reusability) principles[11] aim to make data findable, accessible, interoperable and reusable in order to maximise its usefulness. Outpatient neurology diagnostic coding requires a standardised approach, which individual hospital information technology (IT) systems and end users will need to adopt. This would include assignment of relevant patient identifiers including NHS number (findable), using a standardised protocol to permit retrieval by identifier (accessible), and use SNOMED CT terms (ensuring interoperability and reusability). A 2002 Audit Commission report entitled 'Data remember: improving the quality of patient-based information in the NHS'[12] recommended implementation of SNOMED CT, not least because this system permits clinicians to use familiar diagnostic and procedure terms at the point of care. SNOMED CT terms are a mixture of 'disorder', 'finding' and other term types based on the commonly used clinical nomenclature (eg, headache is a symptom as well as a disorder, epilepsy is a syndrome). Although other administrative systems such as ICD-10 will still be widely used, ICD-10 coding or similar could be generated automatically from SNOMED CT terms, reducing the burden on the end user.

NHS, National Health Service.

database has demonstrated SNOMED CT can be used to code for neurological practice.[4] Wardle and Spencer reported key benefits to be: the ability to understand patient cohorts; recording accurate clinician-derived diagnostic information informs clinical services and facilitates epidemiological work. Comparisons of data between individual patients and whole patient cohorts can be made in real time (eg, comparing the clinical course of multiple sclerosis of an individual versus peers while taking disease-modifying therapy). SNOMED CT also offers the flexibility to add functionality, for example, monitoring botulinum toxin administration including structured data capture. SNOMED CT has other important advantages including interoperability and the ability to encode metadata. In the UK, the National Information Board, charged with developing strategic priorities for data and technology in health and care across NHS, public health, clinical science, social care and local government, endorses the move to SNOMED CT as a single clinical terminology to support direct management of care.

The Sentinel Stroke National Audit Programme illustrated the impact of good data, helping to transform stroke care in the NHS. Stroke teams are active in this audit and the related coding and assessments. Similar principles could apply to neurology with clinicians appreciating the benefits of having open and transparent access to their own data, as well as to data from other users. Box 4 shows some practical applications of outpatient neurology diagnostic coding. By demonstrating the value of data collection, clinicians will increasingly see the value of accurate diagnostic coding, and the importance of their taking ownership of it.

Outpatient neurology diagnostic coding: how?

A 2006 Royal College of Physicians survey found that 80% of UK clinicians had little or no contact with coding departments[5]; clinical disengagement seems an important contributor to poor data quality.[6 7]

Factors facilitating clinician engagement with outpatient neurology diagnostic coding include speed, simplicity and ease of use. Above all, for successful implementation in a live clinical setting, the time commitment must be minimal and the payback worthwhile. Local implementation requires support by individual Trusts and Health Boards, owing to the diversity of clinical information systems, but should follow a standardised approach that adheres to some basic principles. This will ensure the system is 'user-friendly' with the fewest possible steps or 'clicks' to assign a code, and minimal time per entry. Our experience shows that this is readily achievable, although by interested clinicians. We need a pragmatic approach, with a focus on the main neurological condition. Where a patient has been coded once, it should be quicker to code at subsequent appointments providing the diagnosis is unchanged.

Box 4 Practical applications of outpatient neurology diagnostic coding: some examples

Patient safety.
Despite the widespread lack of outpatient coding and the adverse impact this had on recent COVID-19 risk stratification exercises,[8] those clinicians with locally held diagnostic category data benefited from more rapid identification of patients with diagnoses likely to be deemed extremely vulnerable (eg, conditions associated with bulbar dysfunction). There are likely to be many similar situations. For example, being able to identify particular patient cohorts rapidly might help where there is a safety alert, or a need to track patients taking a particular medication (such as sodium valproate).

Disease monitoring to support clinical decision making.
'Live' use of SNOMED CT in Wales[4] has shown how it is possible to compare individual patient performance with the whole cohort over time, in real time. Thus clinical coding, with filtering (eg, by disease) and linkage to other relevant clinical data (eg, linking data on patients with multiple sclerosis with Expanded Disability Status Scale (EDSS) scores and use of disease-modifying drugs) can compare disease progression or activity and support clinical decision making.

Addressing capacity and demand: identifying unexpected rates of referral, using headache as an example.
In a recent retrospective observational study, we prospectively assigned diagnostic categories.[13] We collected data from a single consultant outpatient neurology clinic and 202 General Practitioner (GP) surgeries across seven clinical commissioning groups in the northwest of England, and identified 388 new referrals for headache. We applied statistical modelling to identify GP surgeries with unexpected rates of referral, thereby permitting relevant targeted intervention, education and/or support.

Specialised commissioning.
While most healthcare is planned and arranged locally, NHS England plans specialised treatment services nationally and regionally for people with rare and complex conditions. However, NHS England is currently transitioning to place-based and population-based commissioning. Such a networked approach—enabling complex patients to be seen locally and yet ensuring funding reflects their needs—depends on having accurate diagnostic coding.

NHS, National Health Service; SNOMED CT, Systematised Nomenclature of Medicine-Clinical Terms.

It is unrealistic to expect to implement a perfect system immediately, enabling complete coding of all patients. Indeed, it would be preferable that a system captures coding for 80% of all outpatients (new and follow-up) using a small number of codes than to

Table 1 Diagnostic category frequencies from two large neurology referral studies

Diagnostic category	Biggin *et al*[8] percentage n=1951	Stone *et al*[9] percentage n=3781	Combined percentage n=5732
Headache (all)	19.4	19.2	19.3
Seizure/epilepsy	14.5	13.6	13.9
Psychological/functional	9.7	15.5	13.5
Peripheral nerve/neuromuscular	8.5	10.5	9.8
Movement disorders (all)	9.2	5.9	7.0
Spinal disorders	5.0	6.2	5.8
Multiple sclerosis/demyelination	2.2	6.7	5.1
Syncope/transient loss of consciousness	5.0	4.1	4.4
Stroke (all)	4.7	3.4	3.9
General medical	1.5	2.4	2.1
Dementia	1.0	0.6	0.7
Brain tumour	0.5	0.6	0.5
Muscle	0.5	0.6	0.5
Motor neurone disease	0.4	0.2	0.3
Miscellaneous neurological disorders	13.9	10.4	11.6
No definite neurological diagnosis	4.0	0.0	1.4
Total	1951	3781	5732

continue to fail to capture coding for 100% of patients. Thus, we should order the specified list of core diagnoses according to their frequency, minimising the time spent scrolling/searching. Many clinicians might wish only to enter minimal 'high level' diagnostic categories, while others may wish to enter more detailed 'granular' diagnostic information. We should facilitate both approaches.

Decisions regarding the level of coding could be made locally, although it will be sensible to prioritise a minimum core dataset (eg, headline diagnostic category) and include this automatically in clinic letters. Clinicians need to retain the option to enter more granular diagnostic data, preferably by using SNOMED-CT (box 3) and that those choosing to do this should not be penalised with extra work—the 'high level' category should be assigned automatically. Essentially, we recommend keeping the system as simple and as quick as possible, to avoid any sense of additional clinician burden.

In order to determine a reliable estimate of diagnostic category frequencies, we combined the data from two large neurology referral studies.[8 9] Table 1 shows the diagnostic categories and frequencies in the two studies, as well as the combined frequencies and combined proportions.

This exercise showed that four of the top five diagnostic categories were common to both studies. We could classify 63.5% of new patients' working diagnoses into these five diagnostic categories. For simplicity, in the proposed scheme shown below (table 2) we have rounded the indicative percentage frequencies to 20% (headache), 15% (psychological/functional), 15% (seizure/epilepsy), 10%–15% (peripheral nerve/neuromuscular), followed by 5%–10% (demyelination/inflammation, spinal degenerative disease, movement disorder) and 5%–25% (other). Table 2, therefore, includes the headline diagnostic categories arranged in order of frequency in a general neurology clinic, acting as a 'gateway' to the SNOMED CT terms.

Local implementation must allow the automatic population of headline (super-ordinate) diagnostic categories where users choose to enter SNOMED CT terms (eg, 'SUNCT' would automatically be assigned to 'headache' without the clinician making additional steps). Full implementation of the proposed scheme for coding would involve assignment of SNOMED CT terms, thus minimising the proportion of conditions assigned to 'other'. Inevitably, clinicians will vary in their degree of granularity during routine coding.

During prospective paper-based piloting of this approach locally during the COVID-19 pandemic, we benefited from feedback as well as peer engagement and iterative discussion as it developed. This pragmatic approach balances simplicity (for those wishing only to enter the highest level diagnostic categories—perhaps the only element that would be mandated) with the scope for additional diagnostic granularity where desired, indeed as far as SNOMED CT permits.

Early feedback to clinicians, for example, through dashboards, will be important to maintain motivation and interest. Greater use of SNOMED CT by neurologists should encourage ongoing development of the system. We have included three case

Table 2 Proposed coding scheme

Indicative proportion of new outpatient attendances	Headline categories (10 categories, preferred option)	Subcategories (28 categories)	SNOMED CT terms	
20%	Headache	Migraine	Migraine (finding)	(Multiple SNOMED CT terms)
		Idiopathic intracranial hypertension	Benign intracranial hypertension (disorder)	
		Headache (other)	(multiple SNOMED CT terms)	
15%	Functional/psychological disorder	Functional	(multiple SNOMED CT terms)	
		Anxiety	Anxiety (disorder)	(multiple SNOMED CT terms)
		Depression	Depressive disorder (disorder)	(multiple SNOMED CT terms)
15%	Epilepsy/seizure	Epilepsy	Epilepsy (disorder)	(multiple SNOMED CT terms)
		Seizure	Seizure disorder (disorder)	(Multiple SNOMED CT terms Including non-epileptic attack disorder)
10%–15%	Neuromuscular disorder	Peripheral neuropathy	Peripheral nerve disorder (disorder)	(Multiple SNOMED CT terms)
		Myopathy	Disorder of skeletal and/or smooth muscle (disorder)	(Multiple SNOMED CT terms)
		Myasthenia gravis	Myasthenia gravis (disorder)	(multiple SNOMED CT terms)
5%–10%	Demyelination/inflammation	Multiple sclerosis	Multiple sclerosis (disorder)	(Multiple SNOMED CT terms)
		Other CNS demyelination/ inflammation	Demyelinating disorder of the CNS (disorder)	(Multiple SNOMED CT terms)
5%–10%	Spinal degenerative disease	Spinal degenerative disease	Degeneration of spine (disorder)	(Multiple SNOMED CT terms)
5%–10%	Movement disorder	Parkinsonism	Parkinsonism (disorder)	(Multiple SNOMED CT terms)
		Essential tremor	Essential tremor (disorder)	
		Other movement disorder	Movement disorder (disorder)	(Multiple SNOMED CT terms)
5%–25%	Other	Ataxia	Ataxia (finding)	(Multiple SNOMED CT terms)
		Cerebrovascular disease	Cerebrovascular disease (disorder)	(Multiple SNOMED CT terms)
		Cranial nerve palsy	(Multiple SNOMED CT terms)	
		Dementia	Dementia (disorder)	(Multiple SNOMED CT terms)
		Faints/blackouts	(multiple SNOMED CT terms)	
		Traumatic brain injury	Traumatic brain injury (disorder)	(Multiple SNOMED CT terms)
		Sleep disorder	(multiple SNOMED CT terms)	
		Encephalopathy	(multiple SNOMED CT terms)	
		Other	(multiple SNOMED CT terms)	
	Suspected neurological diagnosis	Suspected neurological diagnosis		
	No definite neurological diagnosis made	Symptoms	(Multiple SNOMED CT terms) for example, dizziness, diplopia, multiple symptoms, sensory symptoms, visual disturbance, weakness	
	Not coded			

SNOMED CT, Systematised Nomenclature of Medicine-Clinical Terms.

studies based on experiences from early implementation (see online supplemental appendix).

CONCLUSION

Outpatient neurology diagnostic coding will provide opportunities to improve delivery of neurological services. Coding is best led by clinicians, and needs to be quick, simple and pragmatic. Our proposed scheme takes account of diagnostic category frequency. Local implementation should permit the clinician to identify only the 'headline' diagnostic category if they wish, and perhaps this should be the only mandatory element. However, clinicians must have the option to enter more granular diagnostic data using SNOMED CT terms. The use of SNOMED CT should promote engagement, data completeness, consistency, accuracy and permit adherence to FAIR principles.

The process needs to be clinically led, and the data openly available. Maximising clinical engagement in the process of outpatient neurology coding will depend on implementation that allows for speed, simplicity and ease of use.

Key points

- Outpatient diagnostic coding has the potential to improve service delivery and patient care.
- Successful implementation requires the process to be pragmatic and quick.
- A standardised approach will enhance the impact of coding.
- Clinical engagement will be crucial to the success of outpatient neurology diagnostic coding.

Further reading

- National Neurosciences Advisory Group (2021) Lessons learnt from the COVID-19 pandemic. Priorities in care for people with neurological conditions after the pandemic. https://www.neural.org.uk/wp-content/uploads/2021/04/Lessons-learnt-from-the-COVID-19-pandemic-Priorities-in-care-for-people-with-neurological-conditions-A-report-by-the-National-Neurosciences-Advisory-Group-NNAG-April-2021.pdf
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