MASTER OF PUBLIC HEALTH

Socioeconomic and other inequalities in unscheduled care admissions and outcomes among the Greater Glasgow and Clyde population

Date of Submission: 27/08/2023

Qualitative (Primary or Secondary Data)		**Systematic Review**		**Other**	
Quantitative (Primary or Secondary Data)	✓	**Meta-analysis**			

2770037B

Supervisor: Jim Lewsey

Principal Investigator: Claire Hastie

Submitted in part fulfilment of the Master of Public Health, College of Medical, Veterinary and Life Sciences, University of Glasgow

Word Count: 11,984

Acknowledgement

I would like to sincerely thank my supervisor, Jim Lewsey, for the invaluable guidance throughout this project. I am extremely thankful for the time and effort he dedicated to overseeing each stage of my thesis. His feedback and motivation pushed me to sharpen my thinking and improve my quality of work.

I would also like to thank Claire Hastie for allowing me to contribute to her impactful oGRE research challenge. Though she is not my direct supervisor, I am grateful for her willingness to provide guidance in each data analysis stage and dissertation writing.

I would like to sincerely thank the entire oGRE team for providing access to NHS Greater Glasgow and Clyde datasets that made this project possible. The dataset required extensive preprocessing before the analysis that the oGRE analyses generously took on. I would also like to extend my gratitude to the NHS Greater Glasgow and Clyde Safe Haven team for reviewing the outputs and their prompt release, ensuring that we were able to meet our deadlines.

I want to thank Alan Stevenson from the Safe Haven support team of the University of Glasgow for his invaluable technical assistance working in the controlled remote workspace. He was tremendously helpful in quickly installing R packages inside the secure workspace whenever I needed additional libraries.

Finally, I want to say thank you to my family for always understanding and supporting me throughout every part of this journey.

Completing my project within the designated timeframe would have been impossible without their invaluable assistance.

Abstract

Background

Unscheduled care encompasses the provision of medical services, including the emergency department of hospitals, out-of-hours services, accident and emergency services and GP-led Walk-in Clinics. These facilities allow patients to seek medical attention without a prior appointment. Current health policies in the United Kingdom aim to reduce its use. Exploring the socioeconomic disparities in unscheduled care usage may help identify the vulnerable population and improve policies.

Aim

The study aims to investigate the presence of inequalities in the unscheduled care outcomes specifically mortality, discharge, immediate hospital admission and repeat presentation within Greater Glasgow and Clyde. This study will specifically focus on how factors such as age, sex, socioeconomic status, and ethnicity might contribute to unscheduled care outcomes.

Methods

This study adopts a retrospective, observational and analytical cohort study design. The analysis was done using Unscheduled care (TRAK A&E) and hospital (SMR01) datasets from NHS Greater Glasgow and Clyde Safe Haven. For each unscheduled care outcome, percentages were predicted based on all the covariates. Binary Logistic regression was used to check the association between demographic variables and unscheduled care outcomes. The covariates year of admission, cause of admission and comorbidities were added to models to see how they change the association. AUC values were used to evaluate the models' ability to discriminate between control and case groups.

Results

Among 3610 patients who visited A&E from 2018-2022, there is 2.8% of mortality within 30 days of an A&E visit. For other three outcomes among 5000 patients admitted to A&E from 2012-2022, there is 87.4% of same-day discharge from A&E (< 24 hours), 53.8% of immediate hospital admission and 39.6 % of repeated visits within 30 days. These percentages serve as general overview without adjusting for other variables. In a detailed analysis using logistic regression, age is a statistically significant predictor and was found to be associated with all outcomes (p-values

<0.001). Patients from least deprived quintile had lower odds of immediate hospital admission (OR: 0.58, 95% CI: 0.47-0.71) and repeat presentation (OR: 0.53, 95% CI: 0.43-0.65) in adjusted models with AUC values of 0.80 and 0.79 (moderate discrimination), respectively in comparision with patients from most deprived quintile. Patients admitted with medical conditions and more than one comorbidity had significantly higher odds of worst outcomes of unscheduled care like short-term mortality, later discharge from A&E, immediate hospitalisation and repeat visits within 30 days (p-values <0.001).

Conclusion

Older, sicker patients admitted for medical conditions experience worst unscheduled care outcomes, like higher mortality, longer stay, hospitalisation and repeat visits. While socioeconomic inequalities are not seen in 30-day mortality, disparities arise in immediate hospital admission and repeat visits, suggesting inequalities in post-discharge support. Exploring clinical severity and cause-specific outcomes can inform public health policymakers in the development of interventions to support vulnerable populations.

List of abbreviations:

A&E: Accident and emergency services

ED: Emergency department

NHS: National Health Service

GGC: Greater Glasgow and Clyde

oGRE: University of Glasgow and NHS Greater Glasgow and Clyde Trusted Research Environment

TRE: Trusted Research Environment

SIMD: Scottish Index of Multiple Deprivation

SMR 01: Scottish Morbidity Record 01

COPD: Chronic Obstructive Pulmonary Disease

OR: Odds Ratio

P-value: Probability value

CI: Confidence Interval

AIDS: Acquired immune deficiency syndrome

ID: Identity document

COVID: Coronavirus Disease

GPOOH: GP out of hours service

GPIH: General Practitioners in hours

EHR: Electronic Health records

RR: Risk ratio

GP: General Practitioner

AOR: Adjusted odds ratio

MIU: Minor Injury Unit

VPN: Virtual Private Network

AUC: Area under the curve

ROC: Receiver operating characteristic

List of Figures

List of Tables

Table of Contents

Chapter 1 Introduction

1.1 Background

1.1.1 Unscheduled care

Unscheduled care refers to medical treatment or advice that is sought for a health issue without making an appointment more than 24 hours in advance (1). While its recognition and terminology might vary across countries, the concept is prevalent in the worldwide healthcare system. In the United Kingdom, the National Health Service (NHS) provides access to numerous health services for unscheduled care. These include the emergency ambulatory service, the accident and emergency (A&E) service, the emergency department in hospitals, out-of-hours services, urgent care centres or walk-in centres (1). NHS Direct is a 24-hour telephone service which directs callers to other services or provides self-care advice (1). The structure and provision of unscheduled care services vary across different regions in the United Kingdom (1). Social determinants of health play a pivotal role in the frequency and nature of unscheduled care admissions (2,3). Despite multiple services in this pathway, approximately 35% of hospital admissions still occur through emergency departments (4). Evidence suggests that many unscheduled care admissions could be avoided through improved primary care intervention (5-7). Routinely collected data can elucidate utilisation patterns across unscheduled care services to identify service gaps and reduce preventable hospital admissions (7).

1.1.2 Inequalities in Unscheduled care admission rates

Health variations are a growing concern in the current national public health agenda (8). Health inequality refers to differences in the health of an individual or group, while health equity refers to health differences that are preventable and unnecessary; allowing them to persist is unjust (8). Although achieving health equity is challenging, it is distinct from health equality, which seeks to eliminate all health differences (8). Despite numerous public health policy interventions, inequalities in accessing health care have been proven to persist (9). Population characteristics like age, sex, area of residence, distance from the hospital and socioeconomic deprivation, play roles in emergency admissions (10). A study conducted during 2006-2008 in England indicated that small shifts in the number of people using primary care services instead of secondary care allow emergency departments to function more efficiently for those most in need of specialists (10). Difficulties in accessing primary care services can be due to socioeconomic status, lack of awareness, and attitude towards health (11). From a systematic review in 2014, it is evident that people from low socioeconomic backgrounds, ethnic minorities, older individuals, lower educational achievement, those with chronic diseases and proximity of patients to healthcare provisions influence the unscheduled care admission rates (12). Another study in 2017-2018, among the Glasgow population, indicated that females have higher admissions rates to the emergency department compared to males (13).

1.1.3 Common causes for Unscheduled care admissions

Many emergency care admissions arise from chronic conditions that have been neglected for an extended period (14). Chronic health conditions like cardiovascular diseases, asthma, dental conditions, epilepsy, and mental health issues can be prevented through timely primary care services (14-17). One common result for all causes from evidence is higher levels of socioeconomic deprivation being associated with delayed treatment for chronic health conditions (14-17). However, certain emergency admissions due to trauma, accidents and anaphylaxis cannot be avoided (14,18). A survey conducted in London showed that international migrants are more likely to utilise A&E services than British Citizens, which can be due to difficulties in registering with general practitioners and receiving timely appointments for healthcare needs (19). Homeless patients might feel difficulties in registering with general practitioner due to lack of address though there are specialist homeless services, which increases the need for emergency admissions (20,21). Dementia is another growing concern in the United Kingdom and one of the common causes for emergency admission in England (22). Dementia is more common among older individuals and people from lower socioeconomic status (22).

1.1.4 Outcomes of Emergency admissions

A national ecological study conducted from 2008-2011 found most of the patients are hospitalised from the emergency department and then discharged after treatment (6). Increase in length of stay in the hospital is noted when the waiting time is more in the emergency department (23). However, the length of stay depends on the type of emergency, but it is shorter for avoidable cases (6). Evidence suggests that very few patients had repeat presentations to an emergency department within 30 days of the initial visit, but this was not explored by population characteristics (6). A research study conducted in England showed that the crude all-cause mortality rate within 30 days after hospital admission from the ED was 8.71% (23). This highlights a concerning proportion of patients passing away in the short term after an emergency visit (23).

1.1.5 The gap

Though there are several studies showing the association between socioeconomic inequalities and unscheduled care in England, literature on its association in the Scottish population is scarce. The NHS in Scotland is devolved by the Scottish Government rather than UK Government; hence understanding and addressing the effects of social determinants of health on unscheduled care admissions becomes an important public health question, influencing policy decisions within the Scottish healthcare system. Few epidemiological studies conducted are looking for individual cause and its association with emergency department admission rate along with factors influencing them. There is no literature analyzing the relationship with demographic variables like sex, age, ethnicity and socioeconomic status and outcomes of emergency department visit like immediate discharge, repeat presentation at A&E within 30 days, immediate hospital admission, later hospitalization, and mortality among the Scottish population. Analyzing the association between these factors can help in building public health policies to achieve health equality among the population. This also helps in understanding the awareness among the population on choosing the right health care services. Hence the present study can respond to this gap in the literature by investigating the association between socioeconomic and other inequalities and Unscheduled care admissions among the Glasgow population which can help in highlighting the potentially avoidable emergencies.

1.2 Structure of the dissertation

There are eight chapters in this dissertation.

Chapter 1 – Background of the study and the gap identified in the literature.

Chapter 2- Search strategy, detailed literature review of inequalities in unscheduled care attendance, and review of the rates of unscheduled care admission and mortality rates post A&E visit reported in previous studies. Also includes a summary of findings from existing literature and rationale for this study.

Chapter 3- Includes a comprehensive summary of the aim and research questions.

Chapter 4- Includes logic model, data sources, ethical consideration, exposure and outcome measurement, data preparation and statistical analysis plan.

Chapter 5- Results of the study, including descriptive tables and logistic regression model outputs.

Chapter 6- Discussion of summary and interpretation of main findings and comparison with wider literature. Also includes strengths, limitations, public health policy suggestions and future research.

Chapter 7- Conclusion

Chapter 8- Includes lessons learned through completion of this study

Chapter 2 Literature Review

2.1 Overview

This chapter presents an overview of the literature unscheduled care admissions in the United Kingdom and their association with patient characteristics and mortality rates post-emergency department visits. This comprehensive literature review will guide in justifying the purpose of this study and shaping the format of statistical analysis that needs to be performed to analyse the association between sociodemographic variables and outcomes of unscheduled care admissions.

2.2 Literature search

Searches were performed using electronic databases from the University of Glasgow library portal. The databases used are OVID Medline, Embase and EBSCOhost (CINAHL). The search was initially performed in January 2023 and was repeated in July 2023 to include the most recent articles. All the map term to subject headings (MESH) were identified and used as search keywords and the most relevant ones were selected to combine using Boolean operators like “OR” and “AND” and truncations. Initially, the articles were screened by their title and abstract, and relevant studies were further screened by reviewing the full article. Endnote was used to manage references and remove duplicate articles.

The inclusion criteria for the project are as follows:

- Articles published from the year 2000.
- Studies which included adults above 18 years of age.
- Studies related to unscheduled care admissions and their differences by patient characteristics.
- Complete articles available for free access.

The exclusion criteria for this project are as follows:

- Study articles which included only participants below 18 years of age.
- Articles published in languages other than English.
- Studies conducted outside the United Kingdom.
- Articles published before the year 2000

The search terms used for socioeconomic factors are living standard, social inequality, socioeconomic factor, standard of living, poverty, or socioeconomic disparity. The search terms used for unscheduled care are Emergency department, emergency ward, emergency medical service, emergency unit, unscheduled care, accident or A&E. The key search terms used for the United Kingdom are UK, United Kingdom, Scotland, England, Northern Ireland or Wales or Great Britain. Only UK-based studies were included so that the findings are closely comparable. *(Search terms are presented in detail in Appendix 1)*

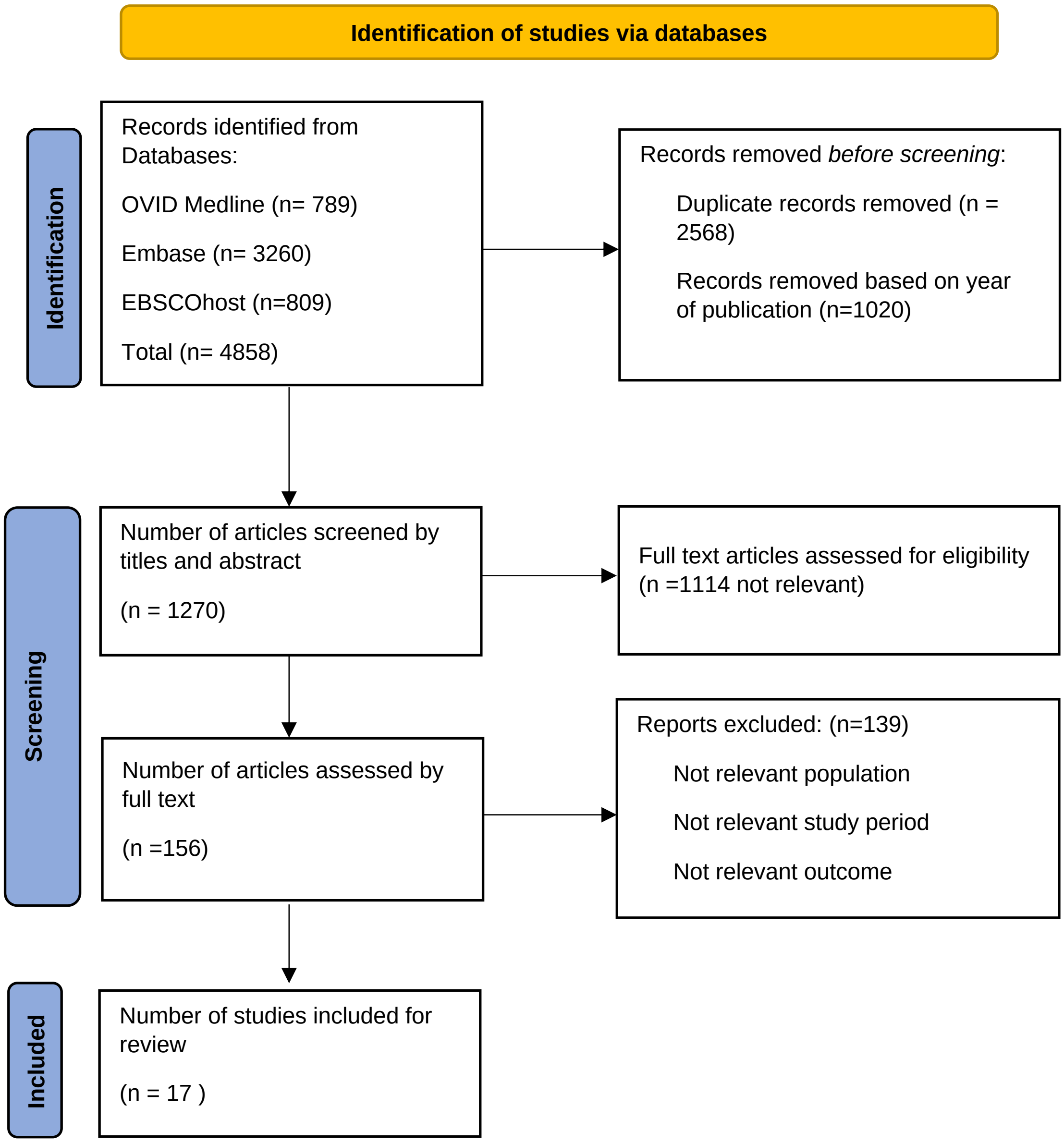

Figure 1 PRISMA flowchart

All the 17 articles included in the literature review are presented in the evidence table with the strengths and limitations of each study (Refer to Appendix 2).

2.3 Inequalities in unscheduled care

2.3.1 Socioeconomic position

An individual's socioeconomic position, as measured by education level, occupation and income has a significant influence on their ability to access healthcare services. This in turn reduces the quality of healthcare choices, creating disparities in health status across different socioeconomic positions. Though achieving health equity is the central objective of many healthcare systems, people from lower socioeconomic positions are less likely to access secondary or tertiary healthcare (11). Not accessing health care services at the right time can increase the need for emergency department visits. This can be due to several reasons like not recognizing the importance of early intervention, obtaining the right diagnosis in primary care and not being aware of the importance of treatment in secondary and tertiary care (11). A study by Allard et al. in 2015 analyzed the characteristics of patients who attended the emergency department with epilepsy in Cornwall, UK over one year period (16). This study showed an association between lower social deprivation and increased emergency department use among people with epilepsy (16). However, the sample size was very small, the recruitment rate was only 54% and included only patients with epilepsy which could limit generalizability (16). This study can be lacking external validity and might not give accurate results on association between socioeconomic deprivation and emergency admission due to smaller sample size (16). Another study conducted in 2014 by Wiseman et al. included 229 general practices in Leicestershire, Northamptonshire and Rutland in England by using publicly available data showed a higher proportion of emergency admissions were among people from higher deprivation. Also, this study involved 229 general practices but did not account for geographical location in the analysis which could confound the results (9). The advantage of this study is involving a large sample size and included the general population, unlike the study by Allard et al. which only involved people with epilepsy which improves the external validity (9,16). In a study conducted by Adamson et al. in 2003, people from lower socio-economic status were more likely to seek emergency healthcare for hypothetical scenarios compared to people from higher socioeconomic status (11). But in this study the Socioeconomic index (SEI) was calculated from SES variables collected from self-reported questionnaires (11). To identify socioeconomic status the questionnaire included questions like car ownership, education level, housing tenure (local authority vs private) and ownership of house which could lead to responder bias (11). A Study conducted in 2019 surveyed 3510 residents of disadvantaged neighbourhoods in Northwest England, showing 36% of the participants were attending accident and emergency (A&E) in the past 12 months. Being unemployed, living in poor-quality housing, and living away from GP practices had increased the likelihood of attending A&E. From the results of this study, it is evident that lower socioeconomic positions play a role in healthcare-seeking behaviour (24). In the above-mentioned study, the disadvantaged neighbourhood was selected by local authorities based on the population size between 5000-10000 (24). Poisson regression was performed to know the relationship between number of visits to A&E in 12 months and socioeconomic status, but this study did not adjust for comorbidities from reliable hospital data instead the health conditions were measured from self-reported questionnaire (24). An observational study compared the sociodemographic factors and attendance characteristics for mental health issues in emergency departments at the NHS, England in 2013 (17). The results of this study showed that 59.9% of residents were from deprivation quintiles 4 and 5 (17). This study did not account for other comorbidities which can be the potential cause of mental health issues (17). Material deprivation and low income were associated with increased casualty and NHS direct use (1), but the data on variables are from self-reported assessments and the severity of illness was not measured.

2.3.2 Age

Many studies have shown age as one of the important predictors of emergency admissions (9,25). Interestingly, a study in England showed fewer older patients (above 65 years of age) were admitted to emergency departments. This study did not adjust for cause for emergency admission and comorbidities which can play an important role in proportion of emergency admissions by age categories (9). The reason behind the decrease in the number of aged people can also be due to routine health check-ups and being under medication (9). Contradicting this another study showed people aged above 85 years had the highest admission rate to the emergency department (AOR 5.53 (95% CI 4.63-6.61, $p<0.001$)) in comparison with other age groups 35-64 and 65-84 years, after adjusting for other demographic variables and hospital characteristics (25). Different from above studies this study was looking at hospital admission rates after visiting A&E (25). This study also included a proxy variable where staffing level at time of arrival to emergency department, which helps in identifying true association between age and proportion of hospital admissions from 3 emergency departments in London. In an ecological study by O'Cathain et al in 2008-2011, a univariable analysis was performed to check if age is a predictor for emergency admissions, but it was not significantly associated (6). The author also stated that age explains lesser variation than socioeconomic deprivation (6). But this study might have an ecological fallacy and might not capture individual-level association between age and emergency admissions (6). There are very few studies showing a clear association between age and emergency department admissions adjusting for confounders.

2.3.3 Sex

A study involving 229 general practices in England states that male patients were more likely to visit the emergency department even after accounting for other practices (staffing levels) and population factors (9). A study by Adamson et al. showed that women are less likely to attend for chest pain scenario that requires immediate medical attention (OR 1.21 95% CI 0.93-1.58), while women were more likely to seek immediate care in case of lumps OR (1.40 95% CI 1.07-1.83). However, this study is a questionnaire survey with clinical vignettes given to patients, which could lead to responder bias (11). Another study in 2020 during the COVID period also showed that men were more likely to get admitted to the emergency department than females (26). Men were more likely to have comorbidities like hypertension, lung disease, heart disease and diabetes (26). This study states the reason can be due to higher rates of comorbidities among the male population, but the author could have considered adjusting for comorbidities while analysing the association between sex and admission rates (26). Contradicting the above studies, a study conducted in London over 1 month period analysing 19734 emergency department attendances in 2017 showed a higher risk for the female population. However, the study duration of a month period may not capture seasonal variations (25).

2.3.4 Other inequalities

Apart from socioeconomic position, age and gender, there are several other inequalities that influence unscheduled care admission rates which include ethnicity, race, and residence. In 2014, among 229 General practices in England, practices with lower white proportions had a higher proportion of emergency admissions indicating ethnic disparities in emergency care utilisation (9). Though white population were fewer in number, the ethnicity data was estimated from hospital inpatients figures and not from community level which can be inaccurate (9). A study analysing 3 emergency departments in London, showed 29% higher odds of black British ethnicity being admitted to the emergency department than white British after adjusting for various factors (adjusted OR 1.29, 95 % CI- 1.16-1.44, $p<0.001$) (25). This shows ethnic minorities might have increased rates of emergency department visits and admissions (25). Living in urban or rural areas can influence the rate of emergency department use, due to the distance of travel to access primary care services or can also increase the admissions rates if they are living close to the emergency department (6). An ecological study in England from 2008-2011 analyzing the potentially avoidable emergency hospital admissions found higher rates of avoidable admissions in urban systems compared to rural ones but also suggests that rural services can keep more patients at home without seeking medical attention due to the distance of travel (6). Though this study reported higher admissions among urban population at ecological level, there are potential chances for ecological fallacy and individual level prediction for relationship even after adjusting for various factors like GP access, staffing availability, health conditions and transportation facility might not be accurate. This study also failed to adjust for bed availability in each area which could confound the admission rates.

2.4 Rates of Unscheduled care admissions

Over 19 million visits were recorded in emergency departments in England during 2007/2008 (24). The estimated cost of emergency departments in England by NHS was over 1.3 billion GBP (24). Evidence by Giebel et al. concludes that distance and access to alternative non-emergency department influence the rate of unscheduled care admissions (24). In a study analysing emergency department visits in 3 hospitals in London showed 19,734 emergency department attendances, out of which 6,263 resulted in admission, representing overall 32% admission rates over one month period (25). However, this one-month period could not capture the potential changes in admission rates over time. A study by O'Cathain et al. looked at the emergency admissions across 152 emergency departments in England from 2008-2011 and showed a mean rate of 2258 per 100,000 population per year for potentially avoidable conditions representing 22% of all emergency admissions (6). Also, this study stated deprivation and urban systems was highly associated with increasing rates of avoidable unscheduled care admissions (6). The most common potentially avoidable emergencies identified in this study are nonspecific chest pain, urinary tract infection, abdominal pain, acute mental health issues, and COPD (6). The authors suggest that effective outpatient management for above conditions could potentially avoid the need for emergency hospital admission (6).

International migrants were found to have increased rates of A&E service attendance rates, accounting for 44.7% of attendance rates in London over a one month period. Among these attenders 32% were admitted (19). Homelessness was another factor increasing the rates of unscheduled care attendance rates (21). Though they are registered with specialist homeless health provider (SHHP), they had higher rates of repeat attendance at emergency departments in Scotland over 2.5 years period with 18% attending more than 5 times (21).

Long waiting time to visit a General Practitioner (GP) is another factor that increases the approach to emergency department. A study surveying 1030 patients at two GP led walk-in centers in England, reported 50% of patients were attending GP led walk-in centers because it allowed quick access without an appointment (27). However, the sample size is very small, and the response rate was 57%. Increasing sample size might help in understanding the impact of increasing GP led walk-in centers on unscheduled care admission rates (27).

2.5 Mortality rates after emergency department visit

A retrospective cohort study by Mason et al. analysed the use of unscheduled care services in the last year of life for all adults (above 18 years of age) in Scotland who died in 2016. The study found 94.9% of 56,407 patients in the cohort used unscheduled care services at least once in the last year of life (28). This study used logistic regression to see the association between unscheduled care services usage and mortality after adjusting for cause of death and other demographic variables. However, this study did not adjust for comorbidities. A study by Jones et al. analysed

5 million NHS patients admitted from emergency department in England from 2016-2018. This study showed statistically significant increase in 30-day mortality for patients delayed 6-8 hours to hospital admission from emergency department (23). This study linked mortality data from death certificates to analyse 30-day mortality after emergency visits for all causes. This study also used logistic regression and adjusted for demographic variables and comorbidities which is an advantage in comparison with a study by Mason et al, but adjusting for cause of death could have made the model more robust.

A large observational study in the United Kingdom described patients presenting to emergency department with suspected COVID-19 during the first wave of the pandemic (26). Among 20,908 adults attending the emergency department with suspected COVID-19, 3246 patients died within 30 days (15.5% mortality) (26). There were increased mortality rates in unscheduled care post-pandemic in comparison with the pre-pandemic period (29). For emergency admissions without COVID-19, in-hospital mortality was 6.9% before the pandemic and 8.1% after the pandemic's first wave (29). Though all the studies were generally looking for mortality rates after emergency department admission, there are limited studies on accessing risk of mortality by age, deprivation quintile, sex and ethnicity in recent periods.

2.6 Summary of the Findings

This literature review scrutinises the impact of socioeconomic position, age, sex, and other demographic variables like ethnicity and residence (urban or rural) and its relationship with unscheduled care attendance and admission. Several studies revealed that socioeconomic status is highly associated with unscheduled care admission which can be due to difficulty in accessing primary care services (11,16,24). This leads to delay in treatment and intervention which increases the need for emergency department visits. Age-related findings were mixed, with few studies showing fewer older patients attending emergency departments and few other studies showing older individuals (more than 85 years) had increased attendance rates in emergency departments (9, 25). Sex-related analysis in unscheduled care was inconsistent with few studies showing male having higher rates of emergency department admissions than females and others showing vice versa (9,25,26). Few studies also reported on ethnic disparities in unscheduled care admission (9,25).

Rates of unscheduled care admission for a particular health condition like mental health issues, epilepsy and dementia respectively were addressed (16,17,22). Mortality rates in unscheduled care pre and post pandemic were clearly differentiated, change in mortality rates due to delay in hospital admissions from emergency department and patterns of utilising ED during last year of life were reported (23,26,28,29). Literature on international migrants and homeless individuals also showed these factors play a role in increasing unscheduled care admission rates and revisit (19,21). Long waiting time for appointments to consult general practitioners is another potential factor for increasing the rates of unscheduled care admission, which is identified in a study analyzing the feedback from people using GP led walk in centers (27). In terms of study design, most studies are retrospective analysis of data as it is relatively quick and easy to involve large samples and to look for association between different sociodemographic variables and unscheduled care at one point of time. Also, most studies used logistic regression to look for associations with outcomes of unscheduled care since it's a binary variable (e.g. Death vs survival, readmission vs no readmission) (21,23,28).

2.7 Rationale for this project

The diversity of findings from the literature review and inconsistent results highlight the need to investigate the socioeconomic and other demographic variables and its relationship with unscheduled care admission rates and outcomes. The role of these factors in unscheduled care is critical. Though there are studies analyzing the association of the socio-demographic variables and unscheduled care admission rates for specific health outcome like mental health issues, epilepsy, and dementia, this limits generalizability to general population (16,17,22). Most of the studies showing association between socioeconomic status and unscheduled care are conducted in England in the United Kingdom and there are limited studies in Scotland. Though Scotland is a part of United Kingdom, healthcare system is under the control of Scottish Government and not the Government of the United Kingdom.

There is limited and fragmented evidence thus, there is a need for analyzing the association between demographic variables like socioeconomic position, age, sex and ethnicity and unscheduled care admission rates and outcomes like discharge, repeat presentation, mortality after emergency department visit and hospital admissions from the emergency department among the Greater Glasgow and Clyde population. In particular, the Greater Glasgow and Clyde region provides an ideal context for this study with diverse and varied population. This area includes wide range of socioeconomic status and various age categories to explore these associations. By employing a retrospective analysis of a large dataset, the study can examine associations between multiple variables and outcomes. Data involving patient details from 2012-2022 ideally captures seasonal variations. While most studies focused on rates of unscheduled care admissions and outcomes, assessing risk of outcomes by population characteristics can provide valuable insight.

This study is a part of the wider oGRE challenge, and this topic was one of 20 to get through a competitive tender on its scientific and public health merit.

Chapter 3 Aims and Objectives

3.1 Aim

This study aims to examine the inequalities in unscheduled care admissions and the outcomes mortality, immediate hospital admission, repeat presentation to A&E and same-day discharge from A&E in relation to age, sex, socioeconomic status and ethnicity.

3.2 Research questions

- How do age, sex, socioeconomic status and ethnicity contribute to inequalities in short-term (30-day) mortality outcomes following an unscheduled care visit?

- To what extent do age sex, socioeconomic status and ethnicity affect same-day discharge from the emergency department and are there identifiable vulnerable populations that experience extended stays after accounting for causes of admission and comorbidities?

- What are the associations between immediate hospital admission rates from A&E department and the population characteristics age, sex, socioeconomic status and ethnicity?

- What factors contribute to disparities in repeat presentation within 30 days to A&E department?

Chapter 4 Methodology

4.1 Study Design

This study adopts a retrospective, observational and analytical cohort study design. In this study, inequalities in unscheduled care admission outcomes are measured alongside different patient characteristics in linked routine healthcare data sets. The study utilises the data over a multi-year period to allow for comparisons across patient exposures. This study enables analysis of relationships between exposure and outcomes using real-world data. It does not influence or modify exposures and outcomes like an interventional study. The main advantage of an observational study is the ability to explore multiple outcomes related to unscheduled care across demographics and time. This study helps in identifying potential inequalities and associated factors, which may be further explored in detail with robust study designs.

The following sections detail the methodology used in this study: logic model, data source, ethical considerations and information governance, key datasets, data preparation, exposure measurement, outcome measurement and statistical analysis.

4.2 Logic model

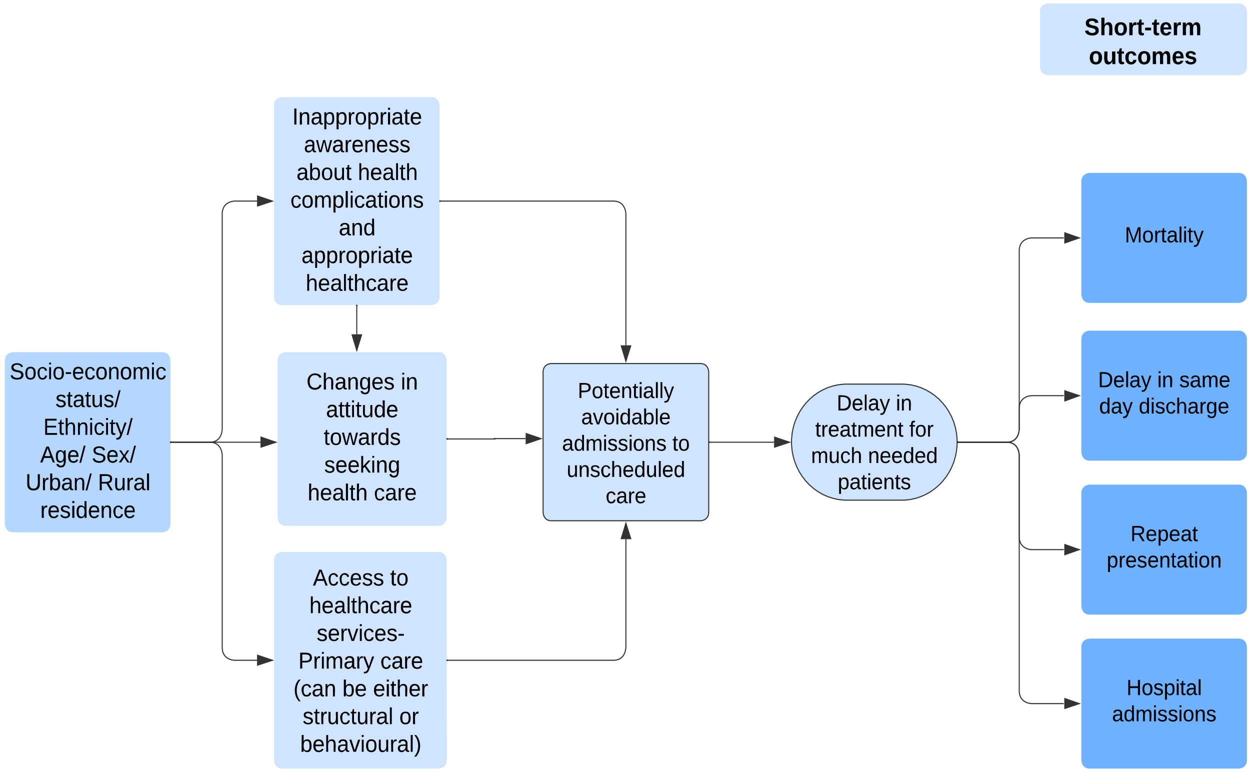

Figure 2 Logic model showing the relationship between Socio-demographic variables and unscheduled care outcomes

A logic model is a conceptual tool used to investigate the relationship between different factors, and it keeps evolving to incorporate new findings and insights (29). In this study, the logic model allows us to hypothesise how demographic variables may lead to certain outcomes of unscheduled care, possibly mediated by certain activities. The above model represents the assumption of this study's selection of exposure and outcome variables. Socio-economic status, ethnicity, urban/rural residence, age, and sex can influence an individual's awareness of health complications and appropriate healthcare needs (11). People living in urban areas may have better access to healthcare services than those living in rural areas (11). Awareness of health complications and appropriate healthcare can influence unscheduled care admission outcomes (11). People unaware of their health complications may not seek care until their condition worsens, leading to unscheduled care admissions (11). Patients unable to access primary care may end up in the emergency department for conditions that could have been managed in a primary care setting (6). Frequent unscheduled care admissions can indicate poor health status (11). This could increase the potentially avoidable emergencies to A&E and increase the burden on the healthcare system (6). Examining the influence of social determinants of health on outcomes of A&E provides valuable insight into preventive strategies that can mitigate adverse events and enhance patient care.

4.3 Data Source

The oGRE challenge aims to develop a health data analysis by leveraging NHS Greater Glasgow and Clyde Safe Haven, Robertson Centre for Biostatistics, and analytical capabilities of University of Glasgow research. The oGRE challenge aims to answer and publish 20 public health questions in Glasgow within 12- month time frame with a team of data analysts and researchers and this study will be one of them.

Local Safe Havens in Aberdeen, Dundee, Glasgow, and Edinburgh along with National Safe Haven managed by Public Health Scotland provide diverse NHS Scotland health data sources for researchers. The NHS GGC Safe Haven provides reference datasets linking patient cohort with routinely collected electronic health record data. The five key datasets provided are unscheduled care, GGC-over 50s, diabetes, COPD, and breast cancer. These datasets were constructed and updated routinely to explore high disease incidence and health inequalities among the population. To speed up access, as there were delays in the wider oGRE team accessing and processing the massive data sets, a random sample of 5000 patients was provided for analysis.

NHS Greater Glasgow and Clyde Safe Haven within the Robertson Centre for Biostatistics, School of Health & Wellbeing, University of Glasgow provides a trusted research environment (TRE) for data analysis. After completing information governance training and obtaining the necessary approval, remote data access was granted to the Safe Haven workspace through a Virtual Private Network (VPN). A unique ID to log into the VPN was provided. Required datasets for this study were loaded into the trusted Safe Haven workspace. Statistical software along with packages required for analysis were loaded inside the workspace upon request. Microsoft Word and Excel were also available inside the Safe Haven workspace for creating output tables. The NHS Safe Haven team reviews all the statistical outputs before release to ensure no disclosure of patient private information. This secure Safe

Haven workspace allows researchers to analyse diverse NHS GGC data safely and efficiently in a controlled environment.

4.4 Ethical Consideration and Information Governance

The West of Scotland provides an approved governance route and secure environment to access anonymised NHS datasets. Access to datasets is provided to researchers in public sector institutions, and all the researchers are bound by data-sharing agreements. As I am a student at the University of Glasgow, and I was a part of oGRE challenge, I was provided access to NHS datasets in a controlled environment. The local Privacy and Advisory Committee (LPAC) offers guidance on data protection. All the datasets are secured according to the University of Glasgow IT standards.

Research analysing disparities in health aligns with principles of justice and fairness. This enables correcting systemic barriers and allocation issues that disadvantage certain groups, making access more equitable (4).

4.5 Key Datasets

4.5.1 Demographics

The demographic dataset provides important insights into the characteristics of the population. This dataset included a sample size of 5000 patients. Population characteristics like date of birth, date of death, deprivation quintile, sex, and postcode were used from this dataset. This demographic dataset included patients admitted to A&E from 2012-2022 in Greater Glasgow and Clyde. Each patient was assigned a unique oGRE ID for linking with different datasets.

4.5.2 Trak A&E

Trak A&E dataset contains the patient details from the unscheduled care departments in Greater Glasgow and Clyde. This dataset included admission date, discharge date, cause of admission to A&E, mode of admission, disease types, and ethnicity. This dataset contains information from accident and emergency departments of hospitals in Greater Glasgow and Clyde like Glasgow Royal Infirmary, Inverclyde royal hospital, New Victoria Hospital, Queen Elizabeth university hospital, Royal Alexandra Hospital, Royal Hospital for Children, Stobhill Hospital, West Glasgow ACH - Yorkhill, vale of Leven hospital and few are not mentioned in the dataset due to confidential information. This A&E dataset includes patients admitted from 2012-2022.

4.5.3 Scottish Morbidity Records 01 (SMR01) (Hospital admission)

SMR01 is a national dataset maintained by Public Health Scotland and made available to individual health boards. The SMR01 dataset includes details on admission date to the hospital, length of stay in the hospital and diagnosis. Only the admission date to the hospital was used from this dataset. Like unscheduled care, this included cohorts admitted to the hospital from 2012-2022.

4.5.4 Urban/Rural

The Urban/ Rural dataset contains information on the urban/ rural residence of each patient. According to the Scottish Government Urban Rural classification, the definition of rurality classifies areas with a population of fewer than 3000. All the other areas are coded as urban in this dataset (30). This was calculated based on a two-fold classification of Urban Rural classification in Scotland.

4.5.5 Comorbidities

The oGRE lead analysts pre-processed the comorbidities data. The data shows the date of each comorbidity first recorded in SMR 01, with dates going as far back as 2000. The 17 comorbidities listed in datasets are AIDS, cerebrovascular disease, congestive heart failure, dementia, diabetes organ, uncomplicated diabetes, hemiplegia, malignancy, metastatic, myocardial infarction, mild liver disease, severe liver disease, peptic ulcer, pulmonary disease, peripheral vascular disease, renal disease, and rheumatic disease (31). Each patient might have one or more comorbidity for which they were admitted to hospital. Charlson comorbidity index predicts one year mortality of patients based on burden of diseases (31).

4.6 Data preparation

The data preparation process began by selecting datasets in the Safe Haven workspace. Followed by creating subsets with required variables of interest for this study. The data preparation process will be presented in the flow chart (Figure 3) *(codes in Appendix 3: line numbers, 3-169)*

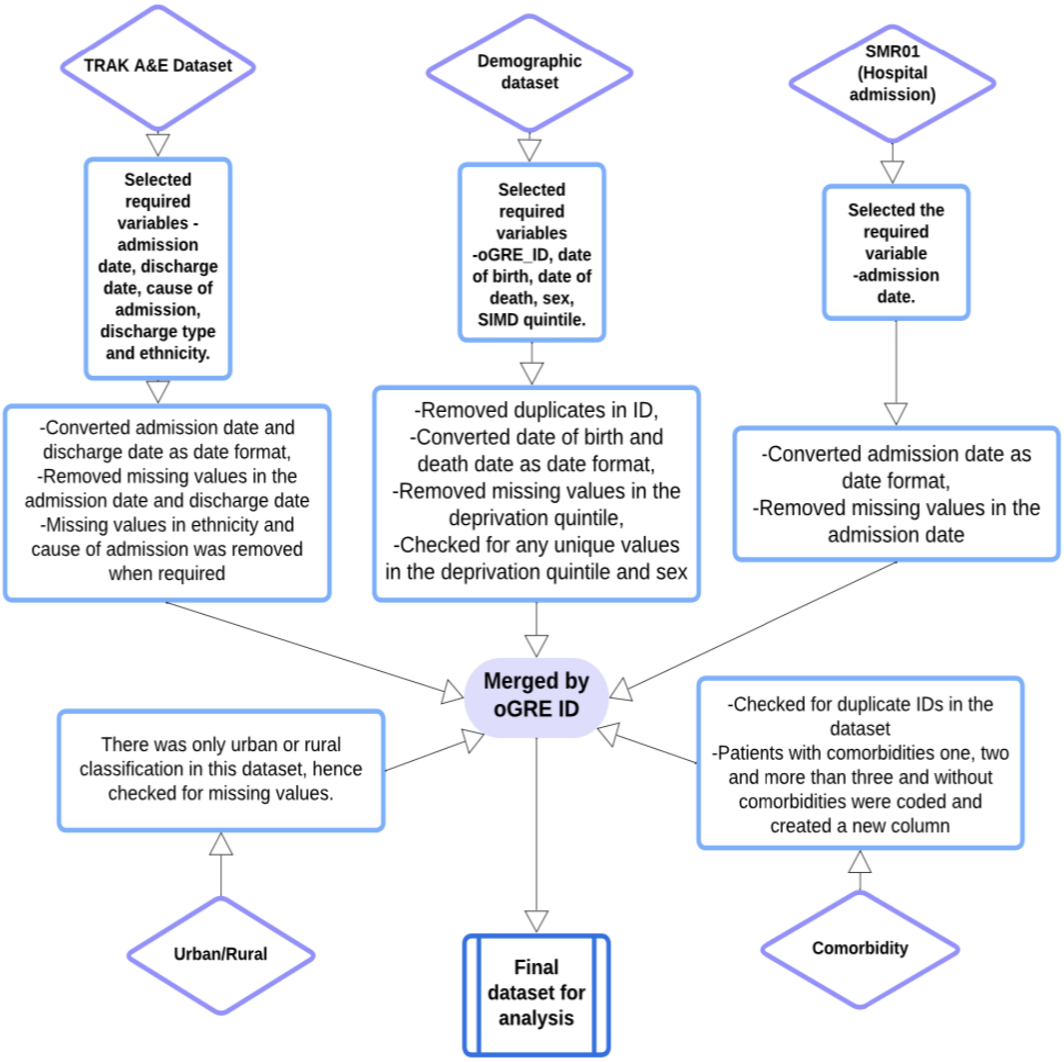

Figure 3 Data cleaning and preparation

4.7 Exposure measurement

4.7.1 Rationale behind the selection of covariates

According to other literature reviewed, socioeconomic status, age, sex, and ethnicity were the four factors influencing emergency department admission (11,13). Hence, I have explored how emergency admission outcomes vary based on these factors. These can be confounded by year of admission, cause of admission and comorbidities (4,26). Hence these covariates are included in the analysis. Years of admission to the emergency department can confound the relationship between exposure and outcome due to changes in medical practices over the years, especially after COVID-19 (26). The cause of admission to A&E can also influence the relationship between exposure and outcome. For instance, consider age as an exposure variable and mortality within 30 days of an A&E visit as the target outcome. A younger individual might be more likely to die from an accident (11). This could bias the relationship between age and unscheduled care outcomes, as the cause of their admission is not directly related to their age but to an external factor (e.g., road traffic accident) (11). As such, it is important to account for the cause of admission when studying the association between age and unscheduled care outcomes to avoid this potential source of bias. Patients with comorbidities can also confound the relationship between A&E outcomes and demographic variables since disease severity can have a significant role in presentation to A&E, and therefore it is important to explore its effects along with demographic variables (13). The following tables shows the categorisation of covariates (Table 1).

Categorical variables	Categories	Data source
Sex	• Male • Female	Trak A&E
Age (years)	• 18-24 • 25-50 • 51-65 • Above 65 years *(Code in appendix 3: line number, 88-92)*	Age calculated from date of birth (demographic dataset) and date of admission (TRAK A&E)
SIMD Deprivation Quintile	• 1-Most deprived • 2 • 3 • 4 • 5- Least deprived	Scottish Index of Multiple deprivation (SIMD) from demographic dataset (32,11)
Ethnicity	• White Scottish population • Other ethnic minorities • Ethnicity Not known or missing *(Code in appendix 3: line number, 107- 109)*	Trak A&E
Year of admission	• 2012-2014 • 2015-2017 • 2018-2020 • 2021-2022 *(Code in appendix 3: line number, 97- 102)*	Trak A&E
Cause of admission	• Medical condition • Injury • Other causes (gynecology/obstetrics condition, accidental poisoning, burns and thermal, non-accidental, fall and collision, sporting injury, self-harm, housework, needle stick injury road traffic accident, COVID 19, firework injury, personal activity, home accident, psychiatric condition and burns • Unspecified *(Code in appendix 3: line number, 103- 106)*	Trak A&E
Comorbidities	• No Comorbidities • One comorbidity present • Two comorbidities present • More than three comorbidities present *(Code in appendix 3: line number, 159- 165)*	Comorbidities from SMR 01

Table 1 Categorisation of co-variates from different data sources

4.8 Outcome measurement

4.8.1 Rationale behind the selection of outcome variables

A previous study in Dublin investigated in-hospital mortality (2002-2017) in 30 days after emergency visit (33). However, the aim of the current study is to examine inequalities in 30 days of mortality after A&E visit, including deaths occurring in the hospital and shortly after discharge. Focusing on mortality across the full 30 days after an ED visit, rather than restricting to just in-hospital deaths, provides a more comprehensive look at short-term outcomes and helps capture any inequalities leading to death soon after discharge from A&E (23). This helps in exploring quality and continuity of care provided both during and post-hospital visit. Overcrowding in hospital negatively impact on patient care quality and overall efficacy of the healthcare system (34). Due to overcrowding in hospitals patients are kept in ED for longer periods which leads to bed blocking (34). Analysing same-day discharges from A&E by population characteristics helps in highlighting the groups most affected by extended emergency department stay. It also indicates potentially avoidable emergencies that could be managed outside the A&E setting. This analysis further enables assessing the effect of the 4-hour target policy launched by NHS, which requires ED treatment, transfer or discharge within 4 hours of admission to A&E. A study has shown less night bed occupancy at A&E after a 4-hour target intervention. Hence, exploring discharge on the same day of A&E visit by patient characteristics can provide insight on inequalities in discharge (35). Immediate hospital admission from ED indicates the high-risk patients and timeliness of admissions (35). It helps in understanding how social determinants of health influence hospital admissions, which is proven to be related in previous studies (4). Patients discharged from the emergency department may return within 30 days to emergency department if there is premature discharge, insufficient post-discharge care planning, complex chronic disease management needs and limited health literacy (36). A study reported repeated emergency department visits within 30 days indicates the treatment quality and decision to seek right health care service (36). Since this study period also includes COVID-19 pandemic these outcomes can provide insights into burden on emergency department before and after the pandemic (37). The following table shows the calculation of outcome variables from different datasets (Table 2).

Outcome	Binary Categories	Calculation
Mortality within 30 days (2018-2021)	• Patients died from 2018-2021 within 30 days (coded as 1) • Rest of the cohort visiting A&E from 2018-2021 (coded as 0)	(Date of death - Admission date to A&E) *(Code in appendix 3: line number, 118- 121)*
Discharge on the same day as A&E admission	• Discharged on the same day (coded as 1) • Rest of the cohort visiting A&E from 2012-2014 (coded as 0)	(Admission date to A&E = Discharge to A&E) *(Code in appendix 3: line number, 123- 129)*
Immediate hospital admission	• Discharged from A&E and admitted to hospital on same day (coded as 1) • Rest of the cohort not admitted to hospital on same day (coded as 0)	(A&E discharge date = Hospital admission date from SMR 01) *(Code in appendix 3: line number, 147- 155)*
Repeat presentation within 30 days	• Repeat presentation to A&E within 30 days for at least one visit (coded as 1) • Rest of the cohort who did not have repeat presentations in 30 days (coded as 0)	Each admission date to A&E is subtracted from the previous admission date; a Repeat visit within 30 days for each patient at least once was considered as a positive outcome. (*Code in appendix 3: line number, 131- 145)*

Table 2 Calculation of outcome variables from different datasets

4.9 Statistical analysis

R statistical software version 4.3.0 inside the Safe Haven was used for all the analysis in this study.

4.9.1 Descriptive statistics

The number of patients by population characteristics calculated using the “table” function in R. Cross tabulation was done for each outcome (binary variable) with all population characteristics like age, sex, ethnicity, SIMD quintile, year of admission to A&E, and cause of admission to A&E to record the number and percentage. *(Code in appendix 3: line number, 171- 265)*

4.9.2 Logistic regression models

Logistic regression was used to model the log-odds of outcomes in A&E admissions. Also, to check the association between each exposure variable, which are categorical or continuous and the binary outcome variables with and without adjusting for other factors. *(Code in appendix 3: line number, 270- 486)*

The rationale for using logistic regression in this study is to estimate the odds ratio for each predictor (independent) variables. This measures how each covariate impacts the odds of unscheduled care outcomes (dependant variable). It can be useful for understanding the risk factors that contribute to unscheduled care outcomes. In Summary, logistic regression offers a robust framework for understanding and predicting binary outcomes in A&E admissions, making it suitable to answer my research questions.

Unadjusted logistic regression model:

- Age with all four outcomes of unscheduled care admission
- SIMD quintile with all four outcomes of unscheduled care admission
- Sex and all four outcomes of unscheduled care admission
- Ethnicity and all four outcomes of unscheduled care admission
- Year of admission to A&E and all four outcomes of unscheduled care admission
- Cause of admission to A&E and all four outcomes of unscheduled care admission
- Comorbidities and all four outcomes of unscheduled care admission
- Urban/ Rural residence and all four outcomes of unscheduled care admissions

Adjusted logistic regression models:

- Adjusted models with all seven variables like age, sex, SIMD quintile, ethnicity, year of admission to A&E, cause of admission to A&E and comorbidities and each outcome of interest.

Hypotheses:

Null hypothesis - There is no association between the demographic exposure variables and unscheduled care outcomes in the population (OR=1)

Alternative hypothesis - There is an association between the demographic exposure variables and unscheduled care outcomes in the population (OR $\neq 1$).

Year of admission, cause of admission and comorbidities were added to models to see how it changes the association between demographic variables and unscheduled care outcomes. The odds ratio was calculated for each coefficient estimate in logistic regression models. Associations were considered statistically significant if the p-value for coefficients was less than 0.05. The p-value corresponds to the type 1 error of the two-tailed 0.05 level. For smaller values of standard errors and if the p values are slightly above 0.05, though it cannot be interpreted as statistical significance, there can be an association between exposure and outcome. When these analyses are repeated with the full data set in the wider oGRE project, the p-values will become smaller and the 95% CIs narrower.

4.9.3 Area under curve (AUC)

AUC values are used to assess how well the logistic regression model can predict/ classify the outcomes of unscheduled care. Using AUC values from adjusted logistic regression models gives a more accurate way to interpret how well the model predicts outcomes after adjusting for all other variables.

Chapter 5 Results

5.1 Overview

The results chapter includes descriptive statistics of patients included in the dataset by population characteristics and percentage of outcomes by patient characteristics. Also includes regression models to show its association with outcomes of A&E before and after adjusting for other factors, including year, causes for admission to unscheduled care and comorbidities for which patient had been admitted to the hospital, and AUC values.

5.2 Descriptive statistics

5.2.1 Proportion of Sociodemographic Variables

Characteristics		Count (N)	Percentage (%)
Sex	Male	2582	51.6%
	Female	2317	46.3%
	Missing values (excluded)	101	2.0%
Age groups (years)	18-24	539	10.7%
	25-50	2028	40.5%
	51-65	1080	21.6%
	Above 65	1216	24.3%
	Below 12 years and missing values (excluded)	137	2.7%
Deprivation quintile	1-Most deprived	2007	40.1%
	2	911	18.2%
	3	637	12.7%
	4	594	11.8%
	5- Least deprived	750	15.0%
	Missing values(excluded)	101	2.0%
Ethnicity	White Scottish	3741	74.8%
	Others	688	13.7%
	Not known	310	6.2%
	Missing	261	5.2%
Urban / Rural residence	Urban	4918	98.3%
	Rural	82	1.6%
Year of admission	2012-2014	791	15.8%
	2015-2017	912	18.2%
	2018-2020	2487	49.7%
	2021-2022	673	13.4%
	Missing	137	2.7%
Cause of admission	Medical condition	1367	27.3%
	Injury	1159	23.1%
	Other causes	784	15.6%
	unspecified	1481	29.6%
	Missing	209	4.1%
Comorbidities	No comorbidity	3093	61.8%
	One	806	16.1%
	Two	464	9.2%
	More than three	500	10%
	Missing	137	2.7%

Table 3 Population characteristics of 5000 patients in the dataset visiting A&E

The Table 3 summarises the number of patients and percentage of patients who visited A&E from 2012- 2022 in Greater Glasgow and Clyde by population characteristics. Almost equal number of males and females were included in the study and for patients with missing sex details were excluded for complete analysis. Patients below 18 years of age were excluded so that the outcomes are analysed only for adults. Maximum number of attendance to A&E were by people who are above 65 years of age (24.3%) and also by people aged between 25-50 years (40.5%). Patient were also categorised based on deprivation quintiles from the demographics dataset and the highest number of attendance was from most deprived group (40.1%). The majority of the population in Greater Glasgow and Clyde are white Scottish (74.84%). When proportion of urban and rural residence of patients was analysed from the dataset, 98% of population are from urban residence visiting A&E. Hence including 98% urban population and 2% rural population might not have enough data to make estimates of rural status.

5.2.2 Mortality within 30 days of A&E visit

Mortality outcome within 30 days of A&E visit		Total observations	Number of deaths	Percentage of deaths (%)
Sex	Male	1483	45	3.0
	Female	1677	43	2.5
Age groups (year)	18-24	290	Not disclosed- small numbers	
	25-50	1262	Not disclosed- small numbers	
	51-65	750	Not disclosed- small numbers	
	Above 65	858	76	8.5
Deprivation quintile	1-Most deprived	1251	39	3.1
	2	579	18	3.1
	3	432	Not disclosed- small numbers	
	4	383	Not disclosed- small numbers	
	5- least deprived	515	Not disclosed- small numbers	
Ethnicity	White Scottish	2297	66	2.8
	Others	455	Not disclosed- small numbers	
	Not known	242	Not disclosed- small numbers	
Year of admission	2018-2020	2487	67	2.6
	2021-2022	673	21	3.1
Cause of admission	Medical condition	935	50	5.3
	Injury	701	Not disclosed- small numbers	
	Other	464	Not disclosed- small numbers	
	Unspecified	1051	35	3.3
Comorbidity	No comorbidity	2053	Not disclosed- small numbers	
	one	514	Not disclosed- small numbers	
	two	296	Not disclosed- small numbers	
	More than three	297	31	10.4
Total		3160	88	2.8

Table 4 Mortality within 30 days of A&E visit by population characteristics

After analysing Table 4, since the date of death details were available only for patients who died after 2018, patients who visited A&E only after 2018 were included in the analysis for this particular outcome so that mortality within 30 days of A&E visit can be calculated reliably. Only 3160 patients admitted from 2018 were identified in the dataset. There was not much difference between males and females in mortality within 30 days, but number of death was significantly higher among people aged 65 years

(8.5%). In the case of deprivation quintile, people from most deprived areas had higher percentage (3.1%) of mortality compared to other groups. Since this dataset involves majority of white Scottish population, there was higher number of death cases (2.8%) identified among them, but their relationship with mortality in 30 days of A&E visit can be analysed from regression model. Patients admitted from 2021-2022 had higher percentage of death than those admitted from 2018-2020. Patients admitted for medical conditions had a higher death percentage (5.3%) in comparison with other causes of admission to A&E. Patients with more than three comorbidities had a higher risk of death in comparison with other categories of comorbidities (10.4%).

5.2.3 Discharge on the same day as A&E visit

Discharge on same day of A&E visit		Total observations	Discharged on same day from A&E	Pecentage of same-day discharge from A&E (%)
Sex	Male	2560	2010	78.5
	Female	2303	2241	97.3
Age groups (years)	18-24	539	467	86.6
	25-50	2028	1826	90.0
	51-65	1080	948	87.7
	Above 65	1216	1010	83.0
SIMD deprivation Quitntile	1- Most deprived	1993	1744	87.5
	2	906	796	87.8
	3	633	537	84.8
	4	592	526	88.8
	5- Least deprived	739	648	87.6
Ethnicity	White Scottish	3668	3194	87.0
	Others	688	602	87.5
	Not known	310	274	88.3
Year of admission	2012-2014	791	726	91.7
	2015-2017	912	816	89.4
	2018-2020	2487	2156	86.6
	2021-2022	673	553	82.1
Cause of admission	Medical condition	1367	1115	81.5
	Injury	1159	1099	94.8
	Other	784	704	89.7
	Unspecified	1481	1333	90.0
Comorbidity	**No comorbidity**	3093	2780	89.8
	One	806	693	85.9
	Two	464	383	82.5
	More than three	500	395	79.0
Total		4863	4251	87.4

Table 5 Discharge on same day of A&E visit by population characteristics

From Table 5, after excluding patients below 18 years of age and patients whose deprivation quintile and admission dates were missing, 4863 patients were included in the analysis. Maximum number of patients (87.4%) were discharged on the same day of the A&E visit. For analysing how it varies by population characteristics, higher proportion of females were discharged on the same day than males. But from this descriptive table 5, not much information about inequalities in groups can be accessed because a maximum number of patients are discharged on the same day. As these are just unadjusted risk percentages, the relationship between population characteristics and discharge on the same day of A&E visit can be understood from the regression model after adjusting for other factors.

5.2.4 Immediate hospital admission from A&E

Immediate hospital admission from A&E		Total observations	Number of immediate hospital admission from A&E	Percentage of immediate hospital admission from A&E (%)
Sex	Male	2560	1199	46.8
	Female	2303	1421	61.7
Age groups (years)	18-24	539	153	28.3
	25-50	2028	865	42.6
	51-65	1080	614	56.8
	Above 65	1216	988	81.2
SIMD Deprivation quintile	1-Most deprived	1993	1145	57.4
	2	906	512	56.5
	3	633	343	54.1
	4	592	282	47.6
	5- Least deprived	739	338	45.7
Ethnicity	White Scottish	3668	2121	57.8
	Others	688	346	50.2
	Not known	310	153	49.3
Year of admission	2012-2014	791	463	58.5
	2015-2017	912	557	61.0
	2018-2020	2487	1146	46.0
	2021-2022	673	454	67.4
Cause of admission	Medical condition	1367	1130	82.6
	Injury	1159	124	10.6
	Other	784	465	59.3
	Unspecified	1481	901	60.8
Comorbidity	No comorbidity	3093	1114	36.0
	One	806	604	74.9
	Two	464	416	89.6
	More than three	500	486	97.2
Total		4863	2620	53.8

Table 6 Immediate hospital admission from A&E by population characteristics

In table 6, after linking two datasets of patients who visited emergency department and patients who have been admitted to hospital from SMR 01 dataset, 2620 (53.8%) of patients were immediately admitted to hospital from A&E. From Table 4 it is evident that females were admitted to hospital immediately than male (61.7%) . People who are aged more than 65 were more likely to get immediately admitted to hospital (81.2%). One interesting fact from table 4 is patients admitted from 2021-2022 were more likely to get admitted to hospital immediately than in previous years. Patients visiting A&E for injury had least percentage of admission to the hospital (10.6%). Patients with more than three comorbidities had 97.2% of for immediate hospital admission.

5.2.5 Repeat presentation to A&E within 30 days

Repeat presentation within 30 days of A&E visit		Total observations	Number of patients had repeat presentation to A&E within 30 days	Percentage of patients had repeat presentation (%)
Sex	Male	2560	911	35.5
	Female	2303	1019	44.2
Age groups (years)	18-24	539	220	40.8
	25-50	2028	768	37.8
	51-65	1080	391	36.2
	Above 65	1216	551	45.3
SIMD Deprivation quintile	1-Most Deprived	1993	878	44.0
	2	906	370	40.8
	3	633	241	38.0
	4	592	223	37.6
	5-Least Deprived	739	218	29.4
Ethnicity	White Scottish	3668	1567	42.7
	Others	688	279	40.5
	Not known	310	84	27.0
Year of admission	2012-2014	791	508	64.2
	2015-2017	912	423	46.3
	2018-2020	2487	727	29.3
	2021-2022	673	272	40.4
Cause of admission	Medical condition	1367	599	43.8
	Injury	1159	359	30.9
	Other	784	322	41.0
	Unspecified	1481	650	43.8
Comorbidity	No comorbidity	3093	1001	32.3
	One	806	374	46.4
	Two	464	236	50.8
	More than three	500	319	63.8
Total		4863	1930	39.6

Table 7 Repeat presentation within 30 days of A&E visit

In table 7, among the patients who visited A&E, 1930 had repeat presentations to A&E within 30 days (39.6%) from 2012-2022. Females were higher in proportion for repeat presentation to A&E within 30 days (44.2%). Like other outcomes, patients aged 65 years and above and people aged between 25-50 had higher chances of repeated admission to A&E. People from most deprived areas had higher percentage (44%) of repeated admissions to A&E within 30 days. Patients admitted for medical conditions had higher percentage of repeat presentation (43.8%) than those admitted for injury (30.9%).

5.3 Logistic regression models

5.3.1 Mortality within 30 days of A&E admission

Characteristics	Unadjusted model				Adjusted model			
	OR	95% CI		P-value	OR	95% CI		P-value
Sex								
Female	Reference							
Male	1.18	0.77	1.81	0.423	1.11	0.70	1.76	0.649
SIMD								
1	Reference							
2	0.99	0.56	1.75	0.992	1.00	0.54	1.85	0.995
3	0.66	0.31	1.37	0.269	0.680	0.30	1.50	0.343
4	0.83	0.41	1.68	0.612	0.935	0.43	2.01	0.864
5	0.74	0.38	1.42	0.371	0.922	0.45	1.88	0.825
Age								
	1.08	1.07	1.10	<0.001	1.091	1.07	1.10	<0.001
Ethnicity								
White Scottish	Reference							
Other ethnic groups	0.45	0.19	1.04	0.063.	0.627	0.26	1.48	0.2901
Not known	1.15	0.54	2.43	0.7039	2.072	0.92	4.62	0.0751
Year of admission								
2018-2020	Reference							
2021-2022	1.16	0.70	1.91	0.551	0.982	0.58	1.65	0.947
Cause of admission								
Medical condition	Reference							
Injury	0.02	0.00	0.18	<0.001	0.075	0.01	0.55	<0.05
Other	0.07	0.01	0.31	<0.001	0.145	0.03	0.60	<0.01
Unspecified	0.60	0.39	0.94	<0.001	0.842	0.52	1.36	0.483
Comorbidity								
No comorbidity	Reference							
One	14.53	5.83	36.19	<0.001	11.517	4.24	31.28	<0.001
Two	38.47	15.86	93.29	<0.001	29.953	11.26	79.66	<0.001
More than three	39.76	16.43	96.18	<0.001	31.700	11.92	84.29	<0.001

Table 8 Regression outputs for mortality within 30 days of A&E visit

In table 8 it shows that age, the cause for admission and comorbidity had statistically significant associations with mortality within 30 days of A&E visit. For every one-year increase in age, there is 1.08 times higher odds of mortality in 30 days. When comparing other ethnic groups with white Scottish patients, after adjustment, this is showing a 37% reduction (OR = 0.63) in the odds of dying within 30 days with a p-value of 0.29. The confidence interval is wider due to small sample size (and small numbers of events). Patients admitted from 2021-2022 had 1.163 times higher odds of dying when compared to 2018-2020, but after adjusting for other variables, it becomes closer to a null association (OR= 0.98). When comparing with patients admitted for medical condition, patients admitted for injury and other causes like road traffic accidents, surgical conditions had lower odds of dying within 30 days of A&E visit where the odds ratio is less than 1 (p-value <0.05). Patients with one or more than one comorbidity had significantly higher odds of dying than patients with no comorbidities after adjusting for all the other factors. Age is used as a continuous variable in all four models as it had a linear relationship with all outcomes.

5.3.2 Discharge on the same day as A&E visit

Characteristics	Unadjusted model				Adjusted model			
	OR	95% CI		P-value	OR	95% CI		P-value
Sex								
Female(reference)	Reference							
Male	0.97	0.82	1.15	0.784	0.95	0.80	1.13	0.606
SIMD								
1	Reference							
2	1.03	0.81	1.31	0.789	1.03	0.81	1.32	0.762
3	0.79	0.61	1.03	0.083	0.80	0.61	1.03	0.095.
4	1.13	0.85	1.51	0.379	1.08	0.80	1.45	0.590
5	1.01	0.78	1.31	0.899	0.98	0.75	1.28	0.910
Age								
	0.99	0.98	0.99	<0.001	0.99	0.99	0.99	<0.05
Ethnicity								
White Scottish	Reference							
Other ethnic groups	1.03	0.81	1.32	0.761	1.01	0.79	1.30	0.907
unknown	1.12	0.78	1.61	0.508	1.146	0.795	1.650	0.463
Year of admission								
2012-2014	Reference							
2015-2017	0.76	0.54	1.05	0.105	0.75	0.53	1.06	0.111
2018-2020	0.58	0.44	0.77	<0.001	0.62	0.47	0.84	<0.001
2020-2022	0.41	0.29	0.56	<0.001	0.48	0.34	0.67	<0.001
Cause								
Medical condition	Reference							
Injury	4.13	3.08	5.55	<0.001	3.80	2.82	5.12	<0.001
Other causes	1.98	1.52	2.60	<0.001	1.86	1.42	2.45	<0.001
Unspecified	1.33	1.09	1.63	<0.01	1.32	1.08	1.62	<0.01
Comorbidity								
No comorbidity	Reference							
One	0.69	0.54	0.86	<0.001	0.759	0.591	0.975	<0.05
Two	0.69	0.40	0.69	<0.001	0.577	0.426	0.782	<0.001
More than three	0.42	0.33	0.54	<0.001	0.46	0.345	0.632	<0.001

Table 9 Regression outputs discharge on same day of A&E visit

From table 9, for every one year increase in age, there is significant decrease in the odds of being discharged on the same day of A&E visit. As age increases people are less likely to get discharged on the same day of A&E visit (p value<0.05). Though none of the deprivation quintiles were significant deprivation quintile 3 had only 8% probability (p-value- 0.08) of null hypothesis were the odds ratio will be one (i.e the odds of getting discharged are similar in all deprivation quintiles). There is no significant difference observed in discharge in sex categories and among different ethnic groups. When looking for inequalities in discharge over time with 2012-2014 as reference category, patients visiting A&E from 2018-2020 and 2020-2022 had lesser odds of getting discharged on the same day than people who were admitted in 2012-2014 (p-value<0.0001). Than patients getting admitted for medical conditions people admitted for injury and other causes had higher odds 3.80 and 1.86 times respectively for discharge on same day of A&E visit after adjusting for other factors (p-value<0.0001). For patients whose cause of admission were unspecified the odds of getting discharged on the same day is 1.3 times higher (p- value <0.05). Patients with one or more comorbidities had lower odds of getting discharged on the same day of admission to A&E than patients with no comorbidities.

5.3.3 Immediate hospital admission from A&E

Characteristics	Unadjusted model				Adjusted			
	OR	95% CI		P-value	OR	95% CI		P-value
Sex								
Female(reference)	Reference							
Male	0.87	0.77	0.97	<0.05	0.97	0.84	1.11	0.674
SIMD								
1	Reference							
2	0.96	0.82	1.12	0.636	0.98	0.81	1.19	0.896
3	0.87	0.73	1.04	0.149	0.85	0.68	1.06	0.156
4	0.67	0.56	0.80	<0.001	0.65	0.52	0.82	<0.001
5	0.62	0.52	0.73	<0.001	0.58	0.47	0.71	<0.001
Age group								
	1.04	1.03	1.04	<0.001	1.02	1.01	1.02	<0.001
Ethnicity								
White Scottish	Reference							
Other ethnic groups	0.73	0.62	0.86	<0.001	0.90	0.74	1.10	0.330
Not known	0.40	0.31	0.51	<0.001	0.53	0.40	0.71	<0.001
Year of admission								
2012-2014	Reference							
2015-2017	1.11	0.91	1.34	0.285	1.06	1.06	1.34	0.606
2018-2020	0.60	0.51	0.71	<0.001	0.53	0.43	0.65	<0.001
2021-2022	1.46	1.18	1.81	<0.001	1.04	0.81	1.35	0.718
Cause								
Medical Condition	Reference							
Injury	0.23	0.19	0.27	<0.001	0.33	0.27	0.41	<0.001
Other	0.58	0.49	0.70	<0.001	0.84	0.68	1.04	0.116
Unspecified	0.58	0.50	0.68	<0.001	0.66	0.55	0.79	<0.001
Comorbidity								
No comorbidity	Reference							
One	5.31	4.45	6.33	<0.001	3.52	2.90	4.26	<0.001
Two	15.39	11.31	20.94	<0.001	8.92	6.41	12.40	<0.001
More than three	61.66	36.06	105.4	<0.001	30.43	17.19	53.87	<0.001

Table 10 Regression outputs for immediate hospital admission from A&E

From table 10 , deprivation quintile 5 indicates that the least deprived population have 0.58 times lesser odds (95%CI- 0.47 -0.71; P-value <0.001) of immediate hospital admission when compared with the reference group which includes patients from most deprived socioeconomic status after adjustments. Patients from deprivation quintile 4 also have lesser odds of getting admitted to hospital in comparison to reference group. For every one unit increase in age there is 1.02 times (2%) higher the odds of getting admitted to hospital. As age increases, patients are more likely to get admitted to hospital from A&E (p-value<0.05). For patients whose ethnic group is not known and for other ethnic minorities the odds of getting admitted to hospital is lesser when compared to White Scottish population. Patients visited A&E from 2021-2022 after adjusting for other factors had 1.04 times higher the odds of getting admitted to hospital in comparison with the reference group (2012-2014). Patients visiting A&E for injury and other causes had lesser odds of getting admitted to hospital than patients visiting for medical conditions (p-value<005). As number of comorbidities increases the odds of getting admitted to hospital significantly increases with higher odds even after adjusting for other factors (<0.001). But the confidence interval for comorbidities are wider indicating lack of precision.

5.3.4 Repeat presentation to A&E within 30 days

Characteristics	Unadjusted model				Adjusted model			
	OR	95%CI		P-value	OR	95%CI		P-value
Sex								
Female(reference)	Reference							
Male	0.98	0.88	1.11	0.86	1.06	0.93	1.21	0.322
SIMD								
1	Reference							
2	0.87	0.74	1.02	0.105	0.89	0.75	1.07	0.230
3	0.78	0.65	0.93	<0.01	0.79	0.65	0.98	<0.05
4	0.76	0.63	0.92	<0.01	0.812	0.65	1.00	0.05.
5	0.53	0.44	0.63	<0.001	0.53	0.43	0.65	<0.001
Age group								
	1.00	1.00	1.011	<0.001	0.99	0.98	0.99	<0.001
Ethnicity								
White Scottish	Reference							
Other ethnic groups	0.91	0.77	1.07	0.291	0.89	0.74	1.07	0.224
Not known	0.33	0.25	0.44	<0.001	0.33	0.24	0.46	<0.001
Year of admission								
2012-2014	Reference							
2015-2017	1.40	1.19	1.64	<0.001	1.52	1.28	1.82	<0.001
2018-2020	1.31	1.14	1.50	<0.001	1.72	1.48	2.02	<0.001
2021-2022	64.78	33.09	126.8	<0.001	82.37	41.70	162.72	<0.001
Causes								
Medical condition	Reference							
Injury	0.48	0.40	0.56	<0.001	0.55	0.45	0.66	0.156
Others	0.78	0.65	0.93	<0.001	0.86	0.70	1.05	<0.01
Unspecified	0.72	0.62	0.84	<0.001	0.77	0.65	0.91	<0.001
Comorbidity								
No Comorbidity	Reference							
One	1.80	1.54	2.11	<0.001	2.00	1.67	2.41	<0.001
Two	2.16	1.77	2.63	<0.001	2.60	2.04	3.30	<0.001
More than three	3.68	3.02	4.48	<0.001	4.53	3.5	5.82	<0.001

Table 11 Regression output for repeat presentation to A&E within 30 days

From table 11, patients from deprivation quintile 5 which is the least deprived category had 0.5 times (50%) lesser odds of repeated presentation to A&E within 30 days of A&E visit in comparison with the most deprived group. Age was significantly associated with repeat presentation to A&E within 30 days (p value<0.05). Patients had a null association (OR=1) of repeat presentation to A&E within 30 days for every one-unit increase in age. For patients from other ethnic minority groups and for patients whose ethnicity is not known, there is lesser odds of repeat presentation to A&E within 30 days in comparison with the White Scottish population (p-value<0.005). Patients admitted to A&E between 2015-2017 and 2018-2020 had higher odds of repeat presentation in comparison with the reference group (2012-2014). Patients admitted to A&E from 2021-2022 had significantly very high odds of repeat presentation to A&E in comparison to 2012-2014. Patients visiting A&E for other causes like injury had lesser odds (OR=0.55) of repeat presentation to A&E in comparison with patients who visited A&E for medical conditions. Patients who had more than three comorbidities had 4.53 times higher odds of repeat presentation to A&E in comparison with patients with no comorbidities as reference category. The odds ratio for repeat presentation had increased after adjusting for other factors.

5.3.5 AUC values

Models (Adjusted for multiple variables)	AUC value	95% confidence interval	
Mortality within 30 days of A&E visits	0.84	0.80	0.87
Discharge on the same day as A&E visit	0.76	0.74	0.79
Immediate hospital admission from A&E	0.80	0.79	0.82
Repeat presentation to A&E within 30 days	0.79	0.77	0.89

Table 12 Area under the curve values for all the adjusted logistic regression models

AUC of 0.7-0.8 for all four adjusted logistic regression models suggests that models have acceptable to good discriminatory capabilities.

Chapter 6 Discussion

6.1 Summary and interpretation of findings

6.1.1 Mortality within 30 days of A&E visit

Mortality within 30 days after an emergency department visit is a short-term outcome which is an indicator of the quality of a health care system (38). This research found no evidence of a significant association between mortality within 30 days after an emergency department visit and each deprivation quintile in comparison with people residing in the most deprived areas group after adjusting for age, sex, ethnicity, cause of admission, year of admission and comorbidities. This shows that in terms of socio-economic deprivation and for the time period 2018-2022, data indicates equal access to healthcare services in Greater Glasgow and Clyde (39). For every one-year increase in age, there is 9% increased odds of mortality in 30 days after an A&E visit after adjusting for other variables. People admitted for medical conditions and with comorbidities higher had odds of mortality within 30 days.

6.1.2 Discharge on the same day of the A&E visit

In this study, more than 85% of the population are discharged on the same day from A&E. This can prevent bed blocking at A&E and allow A&E services to provide immediate care for patients in need (34). The emergency department is used as a route for securing tertiary care services and for bypassing long outpatient waiting hours, as reported in a study by Buja et al. in 2013 (40). Exploring immediate hospital admission after discharge and cause of admissions in detail from A&E helps identify factors driving avoidable admissions. In my study, as age increases, there is lower odds of getting discharged on the same day. Patients admitted for medical conditions and patients with more than three comorbidities have higher odds of getting admitted at A&E and not being moved to in-patient hospital beds.

6.1.3 Immediate hospital admission from A&E

Socioeconomic disparity was observed in hospital admission in this study. Patients from deprivation quintiles 4 and 5 have lesser odds of immediate hospital admission in comparison with patients from the most deprived quintile 1, which is statistically significant (p-value <0.05) after adjusting for comorbidities, cause of admission and year of admission. This may indicate better access to primary care among patients from higher socioeconomic status, which enables them to be managed in the emergency setting rather than needing hospitalisation. This disparity can highlight that the social determinants of health significantly influence hospital admission. The white Scottish population had higher odds of getting admitted to the hospital, while patients visiting A&E for medical conditions and patients with at least one comorbidity had significantly higher odds of immediate hospital admission. In this study, males had significantly lesser odds of getting admitted to a hospital from A&E than females.

6.1.4 Repeat presentation to A&E within 30 days

Patients from the most deprived quintile 1 have higher odds of repeated visits to A&E within 30 days in comparison with other quintiles. This may be due to difficulties in accessing other primary care services for the most vulnerable population. This can also be due to a lack of awareness and understanding about choosing the right healthcare service. Low socioeconomic status often correlates with various social determinants of health that can increase the risk of injury and illness. As age increases there is higher odds of repeat presentation to A&E within 30 days. There were significantly higher odds of repeat presentation to A&E in 2021-2022 even after adjusting for other factors. Patients admitted for medical conditions and with comorbidities had higher odds of repeat presentation to A&E within 30 after adjusting for other variables.

6.2 Comparison with wider literature

6.2.1 Mortality in 30 days of A&E visit

This study had 2.8% mortality within 30 days of A&E visit (2018-2022). The current study had a smaller sample size compared to the Baker et al. study, which analysed data on over 59,000 emergency department patients in a year period (41). Due to its large National dataset, Baker et al. was able to calculate 30-day mortality rates, finding a 0.19% death rate after ED visit (41). With a limited sample size the current study did not calculate the overall mortality rate but rather focused on examining risk factors associated with mortality. Though a random sample of 3160 patients who visited A&E from 2018-2022 can predict inequalities in mortality without bias after adjusting for other factors, using all the GG &C data as planned in the near future will assist in measuring the true effect with greater precision, leading to smaller p-values and narrower confidence intervals in the statistical inference. This can also improve the statistical power of the study. The death rate due to COVID-19 was higher, irrespective of patient characteristics (26,37). Since the study period includes the COVID-19 pandemic, adjusting for death due to COVID 19 may help reduce bias when examining cause-specific trends in mortality. In a study by Katikireddi et al., analysing mortality records from 2001-2013 in Scotland, in-hospital mortality is higher in the white Scottish population than in other ethnic minorities (42). In his study ethnicity was linked from the Scotland census 2001 rather than hospital recording which minimizes missing values (42). In contrast, ethnicity information was inconsistently recorded in the hospital dataset used for my study. Though my study included mortality of all patients after ED visit and was not restricted to in-hospital mortality, the results of my study were similar to the result in a previous study by Katikireddi et al., where ethnic minorities had lower odds of dying than the White Scottish population. Elderly patients and patients with comorbidities have higher odds of dying, which is similar to previous findings (42,33). Many studies use logistic regression to analyse mortality outcomes, which is appropriate for a binary outcome and allows adjusting for confounders (33). However, some studies rely on chi-square tests or t-tests (i.e., they are univariable), which do not allow adjusting for other variables (43,44). Though some studies have adjusted for comorbidities, other demographic factors have not been adjusted for (33). In this study, both comorbidity, year, cause for admission and all the demographic variables were adjusted, which improves the validity of results.

6.2.2 Discharge on the same day as A&E visit

In this study, 15% of patients stay in the emergency department for more than a day. The same-day emergency care programme and 4-hour target to treat and discharge patients from ED by NHS may have an influence on this (45, 46). This outcome mainly indicates the efficiency of the emergency department or potentially avoidable admission (6). However, this trend also raises concerns about premature discharge and follow-up care gaps (45,46). After adjustment, older and sicker patients had lower odds of same-day discharge, suggesting patients required complex treatment and were kept in ED without shifting to the hospital. Similar studies indicate that elderly patients with comorbidities stay in ED for more than 24 hours (47). The reason behind this can be due to staff shortage, poor efficiency of the health care system or lack of bed availability in hospitals to move the patient immediately. Studies show that when the length of stay in ED is more than 24 hours, the crude mortality rate is 31.8% and shows a significantly increased risk of death (48). This study also shows that patients admitted for the injury had significantly higher odds (OR= 4.13) of being discharged on the same day than those admitted for medical conditions. This outcome can be related to mortality like previous studies to check for an association between length of stay in ED and mortality (48). Exploring this outcome with more clinical details helps better understand the potentially avoidable admissions and overall management of ED. Furthermore, it is notable that the odds of same-day discharge was lesser during 2018-2020 and 2021-2022 during the first and second wave of COVID-19 and associated lockdowns when patients stayed longer in ED due to bed shortage in hospitals. This is similar to previous studies showing longer lengths of stay in ED during that period (49). The use of logistic regression with multiple confounder adjustments is a strength in looking at the trends of same-day discharge over the years, different causes, and comorbidities, along with demographic variables that highlight the vulnerable population compared to basic analysis in other studies (47,48).

6.2.3 Immediate hospital admission from A&E

Patients from more deprived area had higher odds of getting admitted to the hospital from A&E after adjusting for other variables. This increases unplanned avoidable hospital admissions. This aligns with previous studies showing fewer avoidable hospital admission from A&E among patients from less deprived areas (6,9). However, some contradicting findings suggest that most affluent groups get admitted to hospital immediately than others (16). This can be very cause-specific, and the studies which say most deprived do not have higher odds, did not adjust for comorbidities and cause for admission like this study (16). In this study, ethnic minorities had higher odds of getting admitted to the hospital after adjusting for other factors, which is similar to another study conducted in 2017 in London by Ismail et al. with larger sample (25). As age increases, the odds of immediate admission to the hospital increases, which is similar to other studies after adjusting for other factors (6,9,16,25). Patients admitted for injury had lesser odds of getting admitted to the hospital from A&E in comparison with patients visiting with medical conditions since immediate care is given at A&E and do not require hospital admission. This could also indicate potentially avoidable hospital admissions that could have been treated outside emergency care settings like minor injury unit (MIU) treated by nurses (16,50). Patients with more than three comorbidities had significantly higher odds which is similar to a previous systematic study that analysed potentially avoidable hospital admission (16). The observed disparities in immediate hospital admissions from A&E indicate potential inequalities in access to primary care and chronic disease management (16). Improving primary care services could help reduce reliance on emergency services (27).

6.2.4 Repeat Presentation to A&E within 30 days

This study showed that patients from the most deprived quintile had 53% higher odds of repeat presentation to A&E within 30 days compared to the least deprived quintile. However, previous studies have found that repeat visit had decreased after adjusting for comorbidities, but in this study, the odds of repeat presentation by deprivation quintile doesn't change after adjusting for comorbidities (51). But since the disease severity is not known with accuracy from routine health records, this indication of inequalities cannot be conclusive. As in other studies, older age, and male sex were associated with a higher likelihood of repeat visits to A&E in 30 days (52). Patients admitted for medical conditions and with more comorbidities also had higher odds of returning to A&E within 30 days after adjusting for other variables, which is consistent with previous studies (51,52,53). The overall percentage of revisit in this sample was high at 39.6% compared to previous analyses with 22% (52). This may relate to selection of patients visiting A&E for 10-year (2012-2022) period involving the COVID period, unlike a previous study which involved participants visiting A&E for two years period (2014-2016) (52). The study by Gelder et al. used more advanced predictive modelling approaches like Kaplan Maier curves and Cox regression models to identify association between predictors and revisit within 30 days to A&E and built a logistic regression model with significant predictors (52). An advantage of survival analysis is that, censoring of a patient who died is possible, which might obviously influence the odds of an A&E revisit. Poisson Regression was also used in a previous study for similar outcome were number of visits to A&E was taken into account (24). However, logistic regression is suitable for the aim of this analysis, since this study focuses only on the inequalities in the binary outcome of repeat presentation (yes/no) within 30 days of A&E visit. Additional predictive modelling could be considered in future work with a larger sample.

6.3 Strengths

A major strength of this study is the use of routinely collected Electronic Health Record (EHR) from NHS Greater Glasgow and Clyde Safe Haven. EHR data reflects real-world data as it captures information about patients from hospital records. The retrospective and observational nature of this study is cost-effective and efficient and allows for longitudinal analysis. The random sample of 5000 over an extensive period of 10 years allows for robust analysis in analysing trends and utilisation of emergency departments and outcomes. This study leverages the ability to link multiple datasets from NHS Safe Haven Greater Glasgow and Clyde which includes demographic details of patients, emergency department visits, hospital admissions, urban/rural classification and comorbidities. This linkage provides comprehensive data to explore multiple exposures and outcomes.

A key strength is a clearly pre-specified statistical analysis plan, which helps in addressing the study's aims of exploring inequalities in unscheduled care. Appropriate descriptive statistics were used to characterise the sample. By adjusting for variables like cause of admission, comorbidities and year of admission, this study accounts for important potential confounding factors. This is the key strength not present in all observation studies. Also model discrimination was done using Area Under Curve (AUC) values to establish the predictive ability of models.

6.4 Limitations

While routinely collected health records (Real World Data) provide many advantages, the retrospective observational nature of the study limits the ability to infer a causal relationship between exposure and outcome. There can be information bias expected in EHR, like data entry errors, inconsistency in coding for different diseases and missing values.

Though important confounders are measured and adjusted, residual confounders like disease severity cannot be eliminated. In this study, socioeconomic status is measured by area-level deprivation quintile, but individual-level health behaviours, socioeconomic status details and level of education may influence outcomes. Measuring and controlling for all the confounders is infeasible. The absence of ethnicity for numerous patients limited the precision of interpretations from the models, which is a popular concern in electronic health records (42). Reverse causation is another concern in this study since the dates for hospital admission were not considered for comorbidities and their association with outcomes of A&E services. Patients might have developed comorbid conditions after an A&E visit, which could bias the results.

Date of death was available only from 2018-2022, which limits the analysis of mortality outcomes before that period. Due to a delay in data arrival from Safe Haven NHS, we were unable to conduct a survival analysis for 30-day mortality based on population characteristics in this study.

Addressing cause-specific outcomes might have been more appropriate to predict the mortality and potentially avoidable admissions. The rate of unscheduled care admissions among Glasgow population could not be calculated from this subsample.

After the analyses, since the outputs have to be approved by NHS GGC Safe haven team and due to information governance reasons, small numbers for few outcomes could not be disclosed.

6.5 Public Health Policy Implications

This analysis of emergency department utilisation reveals concerning indicators among the most deprived population, including immediate hospital admission and repeated visits that warrant further investigation. The findings suggest there may be opportunities to optimise health service usage and improve outcomes through targeted community-level intervention. However, more research is needed to understand the drivers of these trends before making conclusions. Monitoring trends in same-day discharge from the A&E department is crucial for evaluating policies like same-day emergency care and the 4-hour target at A&E by NHS. This result also helps in highlighting the additional requirements of public health campaigns like the “Choose well” campaign by NHS to create awareness on potentially avoidable A&E visits to reduce the burden on the healthcare system. This increased hospital admissions through A&E might indicate emergency departments being used to bypass the waiting time at the hospital, which must be considered by policymakers and healthcare systems to reduce waiting times for appointments. Future studies combining qualitative inquiry could help elucidate any issues relating to health literacy, inappropriate healthcare usage, and other barriers to care among vulnerable groups. Community-based educational programs accessing appropriate levels of care could be implemented once we better understand the needs of the population.

6.6 Future research

This analysis was conducted on a small random subsample (N=5000) due to time constraints and additional duration required for preprocessing larger datasets. As this study is a part of the oGRE challenge, it will be expanded in future work using full datasets of approximately 400,000 emergency visits. The University of Glasgow will publish this study, and I will be contributing to the bigger project. With the full dataset rate of unscheduled care admission among the Greater Glasgow and Clyde population will be calculated. With a larger sample size more robust survival analysis can be performed to evaluate the association between each exposure variable (age, sex and socioeconomic status, ethnicity) and time to mortality and hospitalisation after an emergency visit. Kaplan Maier survival analysis will be done to analyse cumulative incidence i.e., time to mortality and hospitalisation following the initial visit to A&E, and the Cox regression hazard model to analyse the factors associated with it. These methods are more appropriate for predicting mortality and hospitalisation over time by population characteristics. Additionally, cause-specific analyses, i.e., by type of disease, would be more beneficial for outcomes like discharge on the same day, immediate hospital admission, and repeat A&E visits within 30 days to identify preventable and avoidable A&E visits. Charlson's comorbidity index will be calculated, and its association with outcomes of unscheduled care will be analysed. Also, linking primary care data on prescriptions, appointments and health status with hospitalisation records could provide a better picture of patients' illness severity. This could strengthen risk adjustment and help determine if admissions were potentially avoidable. A qualitative approach could also build a richer understanding of preventable admissions to A&E.

Chapter 7 Conclusion

This retrospective analysis of patients visiting the emergency department provides valuable insight into patterns and outcomes of unscheduled care. The lack of socioeconomic disparities in 30-day mortality signals that “end-stage” emergency care is likely comparable across groups after controlling for other factors. However, gaps by deprivation status in immediate hospital admission from A&E and repeat visits to A&E in 30 days indicate potential inequalities in preventive services. Older age and sicker patients (i.e. those admitted for medical conditions and more than three comorbidities) consistently conferred with higher risks of mortality within 30 days of A&E visit, later discharge from A&E (>24 hours), immediate hospitalisation and repeat visits within 30 days, after adjusting for other factors. These findings demonstrate the value of monitoring emergency department outcomes through an equity lens rather than equality. Monitoring key emergency department outcomes by population characteristics remains crucial for holistic understanding and improvements in the health care system.

Chapter 8 Lessons Learned

This oGRE project provided me growth opportunities I could not have gotten from other projects. Performing statistical coding in a shorter period was challenging. Each time when I wanted a new package in R, I required help from the Safe Haven support team to install it. Working in the Safe Haven remote desktop was time-consuming due to performance lag. Also, exporting results from R was challenging since most advanced packages were unavailable, so tables had to be made manually. All outputs had to go through a disclosure review process by the NHS team before being released externally, which added time and complexity. Despite the difficulties, the experience provided an opportunity for meaningful professional and personal growth. Hands-on experience with real-world data analysis provided growth in practical skills.

Data cleaning, data manipulation, and data linking through R coding in a controlled environment are the skills I have acquired after this project. Creating a statistical analysis plan to answer the research question was a valuable learning experience for my future research.

Writing my thesis helped improve my academic writing skills, especially by analysing sources thoroughly for the literature review to summarise the evidence. Throughout the writing process, I improved my skills in articulating ideas clearly and cohesively.

One of the most valuable insights I gained was the ability to compare and contrast existing literature critically. I learned the importance of critically evaluating rather than accepting the viewpoints presented in existing literature.

The insights gained and methodologies learned from this project will undoubtedly serve as a strong foundation as I continue to pursue research oppoutunities involving data analysis.

References

1. O'Cathain A, Knowles E, Munro J, Nicholl J. Exploring the effect of changes to service provision on the use of unscheduled care in England: population surveys. BMC health services research. 2007 Dec;7:1-7.
2. Downing A, Wilson R. Regional surveillance of accident and emergency department attendances: experiences from the West Midlands. Journal of Public Health. 2005 Mar 1;27(1):82-4.
3. Carlisle R, Groom LM, Avery AJ, Boot D, Earwicker S. Relation of out of hours activity by general practice and accident and emergency services with deprivation in Nottingham: longitudinal survey. Bmj. 1998 Feb 14;316(7130):520.
4. Blunt I, Bardsley M, Dixon J. Trends in emergency admissions in England 2004–2009: is greater efficiency breeding inefficiency?. Emergency. 2000;1000:0.
5. Bindman AB, Grumbach K, Osmond D, Komaromy M, Vranizan K, Lurie N, Billings J, Stewart A. Preventable hospitalizations and access to health care. Jama. 1995 Jul 26;274(4):305-11.
6. O'Cathain A, Knowles E, Maheswaran R, Pearson T, Turner J, Hirst E, Goodacre S, Nicholl J. A system-wide approach to explaining variation in potentially avoidable emergency admissions: national ecological study. BMJ quality & safety. 2014 Jan 1;23(1):47-55.
7. O'Cathain A, Coleman P, Nicholl J. Characteristics of the emergency and urgent care system important to patients: a qualitative study. Journal of Health Services Research & Policy. 2008 Apr 2;13.
8. Huff N, Macleod C, Ebdon D, Phillips D, Davies L, Nicholson A. Inequalities in mortality and illness in Trent NHS Region. Journal of Public Health. 1999 Mar 1;21(1):81-7.
9. Wiseman CE, Baker R. Exploration of population and practice characteristics explaining differences between practices in the proportion of hospital admissions that are emergencies. BMC Family Practice. 2014 Dec;15(1):1-9.
10. Bankart MJ, Baker R, Rashid A, Habiba M, Banerjee J, Hsu R, Conroy S, Agarwal S, Wilson A. Characteristics of general practices associated with emergency admission rates to hospital: a cross-sectional study. Emergency Medicine Journal. 2011 Jul 1;28(7):558-63.

11. Adamson J, Ben-Shlomo Y, Chaturvedi N, Donovan J. Ethnicity, socio-economic position and gender—do they affect reported health—care seeking behaviour?. Social science & medicine. 2003 Sep 1;57(5):895-904.
12. Huntley A, Lasserson D, Wye L, Morris R, Checkland K, England H, Salisbury C, Purdy S. Which features of primary care affect unscheduled secondary care use? A systematic review. BMJ open. 2014 May 1;4(5):e004746.
13. Levin K, Crighton E. Sex, age and socioeconomic inequalities in older people's unscheduled care. European Journal of Public Health. 2019 Nov 1;29(Supplement_4):ckz185-142.
14. Busby J, Purdy S, Hollingworth W. How do population, general practice and hospital factors influence ambulatory care sensitive admissions: a cross sectional study. BMC Family Practice. 2017 Dec;18:1-9.
15. Watson JP, Cowen P, Lewis RA. The relationship between asthma admission rates, routes of admission, and socioeconomic deprivation. European Respiratory Journal. 1996 Oct 1;9(10):2087-93.
16. Allard J, Shankar R, Henley W, Brown A, McLean B, Jadav M, Parrett M, Laugharne R, Noble AJ, Ridsdale L. Frequency and factors associated with emergency department attendance for people with epilepsy in a rural UK population. Epilepsy & Behavior. 2017 Mar 1;68:192-5.
17. Baracaia S, McNulty D, Baldwin S, Mytton J, Evison F, Raine R, Giacco D, Hutchings A, Barratt H. Mental health in hospital emergency departments: cross-sectional analysis of attendances in England 2013/2014. Emergency Medicine Journal. 2020 Dec 1;37(12):744-51.
18. Buka RJ, Crossman RJ, Melchior CL, Huissoon AP, Hackett S, Dorrian S, Cooke MW, Krishna MT. Anaphylaxis and ethnicity: higher incidence in British South Asians. Allergy. 2015 Dec;70(12):1580-7.
19. Hargreaves S, Friedland JS, Gothard P, Saxena S, Millington H, Eliahoo J, Le Feuvre P, Holmes A. Impact on and use of health services by international migrants: questionnaire survey of inner city London A&E attenders. BMC health services research. 2006 Dec;6(1):1-7.
20. Aldridge RW, Story A, Hwang SW, Nordentoft M, Luchenski SA, Hartwell G, Tweed EJ, Lewer D, Katikireddi SV, Hayward AC. Morbidity and mortality in homeless individuals, prisoners, sex workers, and individuals with substance

use disorders in high-income countries: a systematic review and meta-analysis. The Lancet. 2018 Jan 20;391(10117):241-50.
21. Reilly J, Hassanally K, Budd J, Mercer S. Accident and emergency department attendance rates of people experiencing homelessness by GP registration: a retrospective analysis. BJGP open. 2020 Dec 1;4(5).
22. Watson J, Green MA, Giebel C, Darlington-Pollock F, Akpan A. Social and spatial inequalities in healthcare use among people living with dementia in England (2002–2016). Aging & Mental Health. 2022 Aug 6:1-2.
23. Jones S, Moulton C, Swift S, Molyneux P, Black S, Mason N, Oakley R, Mann C. Association between delays to patient admission from the emergency department and all-cause 30-day mortality. Emergency Medicine Journal. 2022 Mar 1;39(3):168-73.
24. Giebel C, McIntyre JC, Daras K, Gabbay M, Downing J, Pirmohamed M, Walker F, Sawicki W, Alfirevic A, Barr B. What are the social predictors of accident and emergency attendance in disadvantaged neighbourhoods? Results from a cross-sectional household health survey in the north west of England. BMJ open. 2019 Jan 1;9(1):e022820.
25. Ismail SA, Pope I, Bloom B, Catalao R, Green E, Longbottom RE, Jansen G, McCoy D, Harris T. Risk factors for admission at three urban emergency departments in England: a cross-sectional analysis of attendances over 1 month. BMJ open. 2017 Jun 1;7(6):e011547.
26. Goodacre S, Thomas B, Lee E, Sutton L, Loban A, Waterhouse S, Simmonds R, Biggs K, Marincowitz C, Schutter J, Connelly S. Characterisation of 22445 patients attending UK emergency departments with suspected COVID-19 infection: Observational cohort study. PLoS One. 2020 Nov 25;15(11):e0240206.
27. Arain M, Nicholl J, Campbell M. Patients' experience and satisfaction with GP led walk-in centres in the UK; a cross sectional study. BMC health services research. 2013 Dec;13:1-9.
28. Mason B, Kerssens JJ, Stoddart A, Murray SA, Moine S, Finucane AM, Boyd K. Unscheduled and out-of-hours care for people in their last year of life: a retrospective cohort analysis of national datasets. BMJ open. 2020 Nov 1;10(11):e041888.

29. Joly BM, Polyak G, Davis MV, Brewster J, Tremain B, Raevsky C, Beitsch LM. Linking accreditation and public health outcomes: a logic model approach. Journal of Public Health Management and Practice. 2007 Jul 1;13(4):349-56.
30. Overview - Scottish Government Urban Rural Classification 2016 - gov.scot https://www.gov.scot/publications/scottish-government-urban-rural-classification-2016/pages/2/
31. Sharabiani MT, Aylin P, Bottle A. Systematic review of comorbidity indices for administrative data. Medical care. 2012 Dec 1:1109-18.
32. Scottish Index of Multiple Deprivation 2020 - https://www.gov.scot/collections/scottish-index-of-multiple-deprivation-2020/
33. Byrne D, Browne JG, Conway R, Cournane S, O'Riordan D, Silke B. Mortality outcomes and emergency department wait times—The paradox in the capacity limited system. Acute Med. 2018 Jan 1;17(3):130-6.
34. Pellico-López A, Cantarero D, Fernández-Feito A, Parás-Bravo P, Cayón de las Cuevas J, Paz-Zulueta M. Factors associated with bed-blocking at a university hospital (Cantabria, Spain) between 2007 and 2015: A retrospective observational study. International Journal of Environmental Research and Public Health. 2019 Sep;16(18):3304.
35. Keogh B, Culliford D, Guerrero-Ludueña R, Monks T. Exploring emergency department 4-hour target performance and cancelled elective operations: a regression analysis of routinely collected and openly reported NHS trust data. BMJ open. 2018 May 1;8(5):e020296.
36. Rising KL, LaNoue MD, Gerolamo AM, Doty AM, Gentsch AT, Powell RE. Patient uncertainty as a predictor of 30-day return emergency department visits: an observational study. Academic Emergency Medicine. 2019 May;26(5):501-9.
37. Reschen ME, Bowen J, Novak A, Giles M, Singh S, Lasserson D, O'Callaghan CA. Impact of the COVID-19 pandemic on emergency department attendances and acute medical admissions. BMC Emergency Medicine. 2021 Dec;21(1):1-4.
38. Oliver G, Reynard C, Martin GP, Body R. Association between delays to patient admission from the emergency department and all-cause 30-day mortality. Emergency Medicine Journal. 2022 Nov 1;39(11):876-7.

39. Frank J, Bromley C, Doi L, Estrade M, Jepson R, McAteer J, Robertson T, Treanor M, Williams A. Seven key investments for health equity across the lifecourse: Scotland versus the rest of the UK. Social Science & Medicine. 2015 Sep 1;140:136-46.
40. Buja A, Fusco M, Furlan P, Bertoncello C, Baldovin T, Casale P, Marcolongo A, Baldo V. Characteristics, processes, management and outcome of accesses to accident and emergency departments by citizenship. International journal of public health. 2014 Feb;59:167-74.
41. Baker M, Clancy M. Can mortality rates for patients who die within the emergency department, within 30 days of discharge from the emergency department, or within 30 days of admission from the emergency department be easily measured?. Emergency medicine journal. 2006 Aug 1;23(8):601-3.
42. Katikireddi SV, Cezard G, Bhopal RS, Williams L, Douglas A, Millard A, Steiner M, Buchanan D, Sheikh A, Gruer L. Assessment of health care, hospital admissions, and mortality by ethnicity: population-based cohort study of health-system performance in Scotland. The Lancet Public Health. 2018 May 1;3(5):e226-36.
43. Dabrera G, Allen H, Zaidi A, Flannagan J, Twohig K, Thelwall S, Marchant E, Aziz NA, Lamagni T, Myers R, Charlett A. Assessment of mortality and hospital admissions associated with confirmed infection with SARS-CoV-2 Alpha variant: a matched cohort and time-to-event analysis, England, October to December 2020. Eurosurveillance. 2022 May 19;27(20):2100377.
44. Pearse RM, Moreno RP, Bauer P, Pelosi P, Metnitz P, Spies C, Vallet B, Vincent JL, Hoeft A, Rhodes A. Mortality after surgery in Europe: a 7 day cohort study. The Lancet. 2012 Sep 22;380(9847):1059-65.
45. Mason S, Weber EJ, Coster J, Freeman J, Locker T. Time patients spend in the emergency department: England's 4-hour rule—a case of hitting the target but missing the point?. Annals of emergency medicine. 2012 May 1;59(5):341-9.
46. Weber EJ, Mason S, Freeman JV, Coster J. Implications of England's four-hour target for quality of care and resource use in the emergency department. Annals of emergency medicine. 2012 Dec 1;60(6):699-706.
47. Choi W, Woo SH, Kim DH, Lee JY, Lee WJ, Jeong S, Cha K, Youn CS, Park S. Prolonged length of stay in the emergency department and mortality in critically

ill elderly patients with infections: a retrospective multicenter study. Emergency Medicine International. 2021 Jul 19;2021.
48. Zhang Z, Bokhari F, Guo Y, Goyal H. Prolonged length of stay in the emergency department and increased risk of hospital mortality in patients with sepsis requiring ICU admission. Emergency Medicine Journal. 2019 Feb 1;36(2):82-7.
49. Savioli G, Ceresa IF, Novelli V, Ricevuti G, Bressan MA, Oddone E. How the coronavirus disease 2019 pandemic changed the patterns of healthcare utilization by geriatric patients and the crowding: A call to action for effective solutions to the access block. Internal and Emergency Medicine. 2022 Mar;17(2):503-14.
50. Byrne G, Richardson M, Brunsdon J, Patel A. An evaluation of the care of patients with minor injuries in emergency settings. Accident and emergency nursing. 2000 Apr 1;8(2):101-9.
51. Vest JR, Ben-Assuli O. Prediction of emergency department revisits using area-level social determinants of health measures and health information exchange information. International journal of medical informatics. 2019 Sep 1;129:205-10.
52. de Gelder J, Lucke JA, de Groot B, Fogteloo AJ, Anten S, Heringhaus C, Dekkers OM, Blauw GJ, Mooijaart SP. Predictors and outcomes of revisits in older adults discharged from the emergency department. Journal of the American Geriatrics Society. 2018 Apr;66(4):735-41.
53. Slankamenac K, Zehnder M, Langner TO, Krähenmann K, Keller DI. Recurrent emergency department users: two categories with different risk profiles. Journal of clinical medicine. 2019 Mar 9;8(3):333.

Appendices

Appendix 1. Search tables

OVID Medline

#	Searches	Results
1	(living standard* or social inequality* or socioeconomic factor* or standard of living or poverty or socioeconomic disparit*or socioeconomic deprivation).ti,ab.	13390
2	("ethnicity" or "ethnic group*" or "nationalit*").ti,ab.	43256
3	(urban residence* or urban population*).ti,ab.	2416
4	(rural residence* or rural population*).ti,ab.	2918
5	(sex or male or female).ti,ab.	549226
6	(age factor or age categor* or age).ti,ab.	805151
7	1 or 2 or 3 or 4 or 5 or 6	1157350
8	(emergency department* or emergency ward* or emergency medical service* or emergency unit* or unscheduled care or accident* or A&E).ti,ab.	98461
9	(UK or United Kingdom* or Scotland or England or Northern Ir* or wales or Great Britain).ti,ab.	126703
10	7 and 8 and 9	789

Embase

#	Searches	Results
1	(living standard* or social inequality* or socioeconomic factor* or standard of living or poverty or socioeconomic disparit* or socioeconomic deprivation).ti,ab.	55166
2	("ethnicity" or "ethnic group*" or "nationalit*").ti,ab.	175905
3	(urban residence* or urban population*).ti,ab.	11164
4	(rural residence* or rural population*).ti,ab.	12956
5	(sex or male or female).ti,ab.	2778394
6	(age factor or age categor* or age).ti,ab.	4082925
7	1 or 2 or 3 or 4 or 5 or 6	5667293
8	(emergency department* or emergency ward* or emergency medical service* or emergency unit* or unscheduled care or accident* or A&E).ti,ab.	380359
9	(UK or United Kingdom* or Scotland or England or Northern Ir* or wales or Great Britain).ti,ab.	415250
10	7 and 8 and 9	3260

EBSCOhost (CINAHL)

Search ID	Search terms	Results
S1	TI ((living standard* or social inequality* or socioeconomic factor* or standard of living or poverty or socioeconomic disparit* or socioeconomic deprivation)) OR AB ((living standard* or social inequality* or socioeconomic factor* or standard of living or poverty or socioeconomic disparit* or socioeconomic deprivation))	28,558
S2	TI (("ethnicity" or "ethnic group*" or "nationalit*")) OR AB (("ethnicity" or "ethnic group*" or "nationalit*"))	51,551
S3	TI ((urban residence* or urban population*)) OR AB ((urban residence* or urban population*))	6,291
S4	TI ((rural residence* or rural population*)) OR AB ((rural residence* or rural population*))	7,554
S5	TI ((sex or male or female)) OR AB ((sex or male or female))	540,871
S6	TI ((age factor or age categor* or age)) OR AB ((age factor or age categor* or age))	793,246
S7	S1 OR S2 OR S3 OR S4 OR S5 OR S6	1,119,607
S8	TI ((emergency department* or emergency ward* or emergency medical service* or emergency unit* or unscheduled care or accident* or A&E)) OR AB ((emergency department* or emergency ward* or emergency medical service* or emergency unit* or unscheduled care or accident* or A&E))	109,459
S9	TI ((UK or United Kingdom* or Scotland or England or Northern Ir* or wales or Great Britain)) OR AB ((UK or United Kingdom* or Scotland or England or Northern Ir* or wales or Great Britain))	157,862
S10	S7 AND S8 AND S9	809

Appendix 2. Evidence Table

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
1	Ethnicity, socio-economic position, and gender—do they affect reported healthcare seeking behaviour?	Adamson et al.	2003	Cross-sectional survey	Adults aged 18-75 selected from 2 general practices in Southwest England. Included 191 Black and 1146 White respondents.	Total number of participants are 1350.	Black people, those of lower socioeconomic status, and women were at least as likely, if not more likely, to report seeking immediate healthcare for hypothetical scenarios compared to White people, those of higher socioeconomic status, and men.	Large sample size (n=1350), used standardized hypothetical scenarios/vignettes	Self-reported intended behavior may not reflect actual behavior, limited measures of potential mediating factors.
2	Socio-economic determinants of casualty and NHS Direct use	Shah et al	2004-2005	Cross-sectional study using secondary analysis of data from the 2004-2005 British General Household Survey.	General population of Great Britain, sampled from private households.	20,421 participants for casualty analysis, 7,634 households for NHS Direct analysis	1) Lower income, material deprivation, and lower socioeconomic position were associated with higher casualty (A&E) use. 2) Lower income, material deprivation, and low socioeconomic position were associated with lower household use of NHS Direct. 3) NHS Direct was underutilized by older people, ethnic minority households, and people born outside the UK.	1) Uses national survey data representing the general population. 2) Able to examine determinants of casualty and NHS Direct use in the same population. 3) Large sample size (over 20,000 individuals for casualty analysis, over 7,600 households for NHS Direct analysis).	1) Relies on self-reported utilization data which may be subject to recall bias. 2) Unable to account for frequency of utilization. 3) Limited measures of health need (self-reported illness). 4) Unable to examine NHS Direct use at individual level.

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
3	Impact on and use of health services by international migrants: questionnaire survey of inner-city London A&E attenders	Hargreaves et al.	2006	Questionnaire survey	- Patients attending an inner city London A&E department over 1 month	- 1611 A&E patients	- The study surveyed 1611 patients attending an inner-city London A&E department over 1 month. - 44.7% of respondents were born overseas, representing 87 nationalities. - Overseas born patients were overrepresented compared to the local population (44.7% vs 33.6%). - Recently arrived migrants (≤10 years in UK) comprised 73.9% of overseas born respondents. - GP registration rates differed between migrant groups but did not affect mode of access to the A&E.	- Surveyed consecutive A&E patients over 1 month period - High response rate (49.4%) - Available in 6 languages to improve access	- Single centre study limits generalizability - Excluded patients brought in by ambulance who may differ
4	The Combined Influence of Distance and Neighbourhood Deprivation on Emergency Department Attendance in a Large English Population: A Retrospective Database Study	Rudge et al	2007/08	Retrospective cohort	Residents of a region in central England attending EDs	1.4 million ED visits captured in the database.	- ED attendance decreased by 1.5% per km distance for adults and 2.2% for children. - Attendance was more than double in the most deprived neighbourhoods compared to the least deprived. - The effect of distance was greater in more deprived areas. - Proximity to minor injury units reduced ED attendance.	Large regional population, used road distance not straight-line distance.	Did not adjust for case severity, ecological design.

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
5	A system-wide approach to explaining variation in potentially avoidable emergency admissions: national ecological study	O'Cathain et al	2008-2011	ecological study in England	152 emergency and urgent care systems in England.	3.3 million potentially avoidable emergency admissions.	- 22% of emergency admissions were for the 14 potentially avoidable conditions. - There was 3.4-fold variation in age-sex adjusted admission rates for these conditions across systems. - Most variation (75%) was explained by population factors - deprivation and urban/rural status. - Additional variation was explained by emergency department attendances and conversion rate to admissions, ambulance calls not transported, and perceived GP access.	National data across multiple years, looked at system-wide factors beyond just primary care.	Ecological study design, many factors tested for small number of systems.
6	Using routine clinical and administrative data to produce a dataset of attendances at Emergency Departments following self-harm	Polling et al	2009-2011	Retrospective cohort	ED attendances for self-harm at 4 hospitals in South London.	10,688 self-harm ED attendances in the EHR dataset.	- The linked EHR dataset had 10,688 self-harm ED attendances, over double the 4491 admissions for self-harm. Did not analyse by population characteristics.	Novel use of linked data, compared to manual audit.	Single health system, incomplete capture in EHR data.

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
7	Patients' experience and satisfaction with GP led walk-in centres in the UK; a cross sectional study	Arain et al	2011	cross-sectional study of patients	Patients attending two GP-led walk-in centres in England.	1030 patients completed the main survey.	- 93% of patients at Centre A and 86% at Centre B were highly or fairly satisfied with the GP walk-in service. - 50% of patients reported coming to the walk-in centre for quick GP access without an appointment. - 9% came because their regular GP office was closed. - 20% could not see their regular GP due to work hours.	Validated questionnaire, compared two models of GP walk-in centres.	Only surveyed two centres, moderate response rate (57%).
8	Exploration of population and practice characteristics explaining differences between practices in the proportion of hospital admissions that are emergencies	Wiseman and Baker	2014	Retrospective cohort	General practices in Leicestershire, Northamptonshire and Rutland, England	229 general practices	Population characteristics and practice characteristics both predicted the proportion of admissions that were emergency. Deprivation, fewer white patients, more male patients, lower hypertension prevalence, more outpatient appointments, and smaller practice size were associated with a higher proportion of emergency admissions.	Used publicly available data on 229 practices, multivariate regression analysis	Observational study so can only show associations, some data limitations.

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
9	Frequency and factors associated with emergency department attendance for people with epilepsy in a rural UK population	Allard et al.	2015	Observational cross-sectional study	Adults with epilepsy living in Cornwall, UK who attended the ED after a seizure over a 1-year period. Predominantly white British sample.	46 people with epilepsy	Around one-third of people with epilepsy attended ED more than twice, accounted for the majority (65%) of emergency department (ED) visits. Seizure frequency and lower social deprivation were associated with increased ED use.	- Used standardized questionnaires - Had NHS ethical approval - Compared to an urban study	- Small sample size (n=46) - Recruitment rate only 54% which could bias results - Excluded cognitively impaired patients which limits generalizability
10	Social and spatial inequalities in healthcare use among people living with dementia in England (2002–2016)	Watson et al	(2002 – 2016)	Retrospective cohort study using electronic health records	People diagnosed with dementia in England, identified through electronic medical records from the Clinical Practice Research Datalink.	142,302 people diagnosed with dementia in England between 2002-2016	- Men and people from more deprived and rural areas had higher rates of A&E attendances and emergency hospital admissions. - People from Asian and Black ethnic groups had lower likelihood of emergency hospital admissions compared to White ethnic groups.	- Large sample size (n=142,302) - Used robust statistical analyses - Included multiple types of healthcare utilization as outcomes	- Relied on clinical diagnosis of dementia in medical records, which may underestimate true prevalence - Lacked data on dementia severity and informal care, which may impact healthcare utilization

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
11	Demographic and socioeconomic patterns in healthcare-seeking behaviour for respiratory symptoms in England: a comparison with non-respiratory symptoms and between three healthcare services	Morrison et al	2015-2016	ecological study	People contacting NHS111, GPIH and GPOOH for respiratory symptoms in England.	1.5 million respiratory contacts to GPOOH.	- There were more respiratory contacts to GPOOH for females (RR 1.73), and those in the most deprived areas (RR 2.70) compared to the least deprived areas.	Large dataset, explored multiple services, compared respiratory and non-respiratory contacts.	Ecological study so can't infer causality, no comorbidity data.
12	Accident and emergency department attendance rates of people experiencing homelessness by GP registration: a retrospective analysis	Reilly et al	2015-2017	Retrospective cohort	Homeless patients attending A&E in one health board area in Scotland.	4408 A&E attendances by homeless patients.	- There were 4408 A&E attendances by 1225 homeless patients over 2.5 years. - 62% were registered with the specialist practice and 38% with mainstream GPs. - There was no significant difference in attendance rates or urgency of attendance between the groups. - Around 70% of attendances in both groups were urgent or very urgent.	Used multiple methods to identify homeless patients, complete A&E attendance data.	Lacked detailed medical history, underestimates true homeless population.

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
13	Risk factors for admission at three urban emergency departments in England: a cross-sectional analysis of attendances over 1 month	Ismail et al.	2017	Cross-sectional analysis of routine data	- Adults attending 3 inner London EDs over 1 month period	- 19,734 ED attendances	- Analyzed 19,734 attendances at 3 emergency departments (EDs) in London over 1 month - Overall admission rate was 32%, but ranged from 23% to 44% across the 3 EDs - Admission risk was higher in those who were older, female, of black ethnicity, and living in more deprived areas - Leaving the ED just before the 4-hour target was strongly associated with admission	- Used routine ED data to examine range of demographic, presentation, and ED factors - Controlled for multiple potential confounders in regression models	- Unable to include diagnosis due to coding inconsistencies - Single month may not capture seasonal variations - ED workload factors taken at fixed timepoints rather than dynamically
14	What are the social predictors of accident and emergency attendance in disadvantaged neighbourhoods?	Giebel et al.	2019	Cross-sectional survey	- Residents of disadvantaged neighbourhoods in Northwest England	3,510 residents of disadvantaged neighbourhoods	- 31.6% of the sample reported attending accident and emergency (A&E) in the past 12 months. - Being out of work and living in poor quality housing increased likelihood of attending A&E. - Living further from a GP practice increased likelihood of attending A&E. - Living closer to an A&E department increased likelihood of attending A&E.	- Surveyed residents from a wide geographical area of disadvantaged neighbourhoods - Comprehensive assessment of range of predictors including health, socioeconomic factors, social support, proximity to services	- Cross-sectional design limits causal inference - Self-reported A&E attendance could lead to recall bias

Number	Title	Authors	Year	Study type	Population	Sample size	Main findings	Strengths	Limitations
15	Mental health in hospital emergency departments: cross-sectional analysis of attendances in England 2013/2014	Baracaia et al.	2020	Cross-sectional analysis of national data	- Relied on routine coding data which can be inaccurate - Unable to identify all self-harm related attendances	- 6,262,602 ED attendances	- Analyzed over 6 million emergency department (ED) attendances in England in 2013/2014 - 4.2% of attendances were due to mental health conditions - 33% of mental health attendances required admission to hospital	- National data on all NHS ED attendances over 1 year period - Large sample size	- Relied on routine coding data which can be inaccurate - Unable to identify all self-harm related attendances
16	Characterisation of 22445 patients attending UK emergency departments with suspected COVID-19 Infection: Observational cohort study	Goodacre et al.	2020	Observational cohort study	Patients attending 70 EDs in the UK with suspected COVID-19 from March to May 2020	20908 adults	- The study included 22445 patients attending 70 emergency departments (EDs) in the UK with suspected COVID-19 from March to May 2020. - 31.6% of adults and 27.4% of children were admitted to hospital at initial assessment in the ED - Admission rates were higher in men (72.9%) than women (61.4%) -Adults with confirmed COVID-19 after admission were more likely to die or require organ support compared to those admitted without confirmed COVID-19.	- Large, multi-centre cohort across 70 EDs in the UK - Prospective and retrospective data collection - 30-day follow-up on outcomes	- Reliance on clinical records led to some missing data - Did not collect reasons for ED attendance or admission
17	Impact of the COVID-19 pandemic on emergency department attendances and acute medical admissions	Reschen et al	2019-2021	Retrospective cohort	Adult ED attendances and acute medical admissions at a hospital in England.	243,667 ED attendances, 82,899 medical admissions.	- In the first COVID wave, ED attendances fell 37% and medical admissions fell 30%, but rebounded within a year. - ED attendances dropped most in younger adults while admissions dropped most in older adults. - Non-COVID medical admissions had more co-morbidities compared to pre-pandemic. - Low acuity ED attendances and admissions across all severities fell in the pandemic. - 7-day mortality rose for ED attendances but not medical admissions.	Detailed clinical data, covered pre-pandemic to one year into pandemic.	Single hospital site, retrospective observational design.

Appendix 3 Codes

Data Cleaning And Manipulation

```
#Loading  required packages
library(mosaic)
library(ggplot2)
library(descr)
library(haven)
library(lubridate)
library(dplyr)
library(tidyverse)
library(pROC)
library(ResourceSelection)

#Cleaning demographic dataset
#Importing demographics dataset
demo<- Demographics_subsample_v1_20230626
#Creating subset with required variables
newdemo<- demo %>% select (oGRE_ID, OBF_DOB, SEX, SIMD_2016_QUINTILE, DATE_OF_DEATH)
#Remove duplicates in ogre ID
newdemo<- newdemo %>% distinct(oGRE_ID,.keep_all=TRUE)
# Convert date of birth and date of death to date type
newdemo$OBF_DOB<- as.Date(newdemo$OBF_DOB, "%Y-%m-%d")
newdemo$DATE_OF_DEATH<- as.Date(newdemo$DATE_OF_DEATH, "%Y-%m-%d")
```

```
summary(newdemo$DATE_OF_DEATH)
#Removing missing values in deprivation quintile
sum (is.na (newdemo$SIMD_2016_QUINTILE))
newdemoclean <- newdemo [complete.cases(newdemo$SIMD_2016_QUINTILE),]
summary(newdemoclean$SIMD_2016_QUINTILE)
head(newdemoclean)
#Check for unique values other than 1-5 deprivation quintile
newdemoclean2<- newdemoclean%>% filter(SIMD_2016_QUINTILE %in% 1:5)
#Check for values other than M and F
newdemoclean3<- newdemoclean%>% filter(SEX %in% c("M", "F"))
#Cleaning TRAK A and E dataset
# Renaming second trak A and E dataset
TRAKAANDE <- TRAK_AandE_subsample_v1_20230719
#Creating a subsample with required columns
NEWTRAK <- TRAKAANDE %>% select(oGRE_ID, DISCHARGE_TYPE_DESCRIPTION, CAUSEOFINJURY_DESCRIPTION, ADMISSION_DATE, DISCHARGE_DATE, ETHNICITY_DESCRIPTION)
#Check for missing values
sum (is.na (NEWTRAK$DISCHARGE_TYPE_DESCRIPTION))
sum (is.na (NEWTRAK$CAUSEOFINJURY_DESCRIPTION))
sum (is.na (NEWTRAK$ADMISSION_DATE))
sum (is.na (NEWTRAK$DISCHARGE_DATE))
sum (is.na (NEWTRAK$ETHNICITY_DESCRIPTION))
#Remove missing values from discharge date
NEWTRAK2 <- NEWTRAK [complete.cases(NEWTRAK$DISCHARGE_DATE),]
```

```r
#Check if all the date of birth and date of death are in date format
NEWTRAK2$ADMISSION_DATE<- as.Date(NEWTRAK2$ADMISSION_DATE, "%Y-%m-%d")
NEWTRAK2$DISCHARGE_DATE<- as.Date(NEWTRAK2$DISCHARGE_DATE, "%Y-%m-%d")

#Cleaning SMR 01 dataset
#Importing and renaming SMR dataset
SMR<- SMR01_subsample_v1_20230626
#Creating a subsample with required columns
NEWSMR <- SMR %>% select(oGRE_ID, ADMDATE)
# Check if admission date are in date format
NEWSMR$ADMDATE<- as.Date(NEWSMR$ADMDATE, "%Y-%m-%d")
sum (is.na (NEWSMR$ADMDATE))
summary(NEWSMR$ADMDATE)

#Cleaning urban or rural dataset
#importing and renaming the dataset
Urbanandrural<- Urban_Rural_subsample_v1_20230721
#Check for missing values
sum (is.na (Urbanandrural$Current_UC))

#Merging all the datasets with required variables
MERGEDDATA <- merge(newdemoclean3, NEWTRAK2, by= "oGRE_ID", all = TRUE)
MERGEDDATA2<- merge(MERGEDDATA, Urbanandrural, by= "oGRE_ID", all = TRUE)
descriptivedata<-MERGEDDATA2 %>% distinct(oGRE_ID, .keep_all = TRUE)
```

```
summary(descriptivedata$SEX)
sum (is.na (descriptivedata$SEX))
summary(MERGEDDATA2)
head(MERGEDDATA2)
#Cleaning the merged dataset
FINALMERGEDDATA<- MERGEDDATA2 %>% drop_na(SIMD_2016_QUINTILE, OBF_DOB, ADMISSION_DATE, DISCHARGE_DATE)
summary(FINALMERGEDDATA)
summary(FINALMERGEDDATA$DATE_OF_DEATH)

#Calculating age of the patients
FINALMERGEDDATA$AGE <- as.numeric(difftime(FINALMERGEDDATA$ADMISSION_DATE, FINALMERGEDDATA$OBF_DOB, units = "weeks"))/ 52.25
FINALMERGEDDATA$AGE <- round (FINALMERGEDDATA$AGE)
summary(FINALMERGEDDATA$AGE)
#Removing patients below who are below 18 years of old
MERGEDSUBSETABOVE18 <- subset(FINALMERGEDDATA, AGE>=18)
summary(MERGEDSUBSETABOVE18$AGE)
#Categorising age
MERGEDSUBSETABOVE18$agegroup<- cut(MERGEDSUBSETABOVE18$AGE,
                        breaks= c(17,24,51,65,Inf),
                        labels=c('18-24', '25-50', '51-65', 'above65'),
                        right= TRUE, include.lowest=TRUE)
#Categorising year of admission
#Add year column
MERGEDSUBSETABOVE18<- MERGEDSUBSETABOVE18 %>% mutate(year= year(as.Date(ADMISSION_DATE)))
```

```
#Categorise year
MERGEDSUBSETABOVE18<- MERGEDSUBSETABOVE18%>% mutate(yearcategorised=case_when(year>=2012& year<=2014~ "2012-2014",
                                                    year>=2015& year<=2017~ "2015-2017",
                                                    year>=2018& year<=2020~ "2018-2020",
                                                    year>=2021& year<=2022~ "2021-2022",
                                                    TRUE~ "OTHER"))
#Recoding cause of admission into three categories
MERGEDSUBSETABOVE18$CAUSEOFINJURY<- recode(MERGEDSUBSETABOVE18$CAUSEOFINJURY_DESCRIPTION, "Medical Condition"= 1,
                            "Injury (Other Mechanism)"= 2,
                            "Unspecified"= 4, .default = 3)
#Recoding ethnicity into three categories
MERGEDSUBSETABOVE18$ETHNICITY<- recode(MERGEDSUBSETABOVE18$ETHNICITY_DESCRIPTION, "White Scottish"= 1, "Not Known"= 3, .default = 2)
summary(MERGEDSUBSETABOVE18$ETHNICITY)

#Calculating mortality within 30 days of A and E visit
#Creating a subset after removing duplicates in id column
mortality<-MERGEDSUBSETABOVE18%>% distinct(oGRE_ID, .keep_all = TRUE)
#Creating a subset of population from A and E for whom admission is only after 2018 since the death dates are only from then
mortality<- mortality %>% mutate(year= year(as.Date(ADMISSION_DATE)))
mortality<- mortality %>%filter(year>=2018)
#Creating a new column in the dataset by substracting admission date and date of death
mortality$mortalitydays<- as.numeric(mortality$DATE_OF_DEATH- mortality$ADMISSION_DATE)
mortality$mortalityin30days<- ifelse(mortality$mortalitydays<=30,1,0)
```

```
mortality$mortalityin30days[is.na(mortality$mortalityin30days)]<-0
sum(mortality$mortalityin30days==1)

#Creating a variable for people Discharged on the same day
MERGEDSUBSETABOVE18$dischargedays<-  as.numeric(MERGEDSUBSETABOVE18$DISCHARGE_DATE- MERGEDSUBSETABOVE18$ADMISSION_DATE)
sum(MERGEDSUBSETABOVE18$dischargedays==0)
summary(MERGEDSUBSETABOVE18$dischargedays)
MERGEDSUBSETABOVE18$dischargedsameday<- ifelse(MERGEDSUBSETABOVE18$dischargedays<=0,1,0)
dischargebyID<-MERGEDSUBSETABOVE18%>% distinct(oGRE_ID, .keep_all = TRUE)
sum(dischargebyID$dischargedsameday==1)

#Creating a variable to see repeat presentation to A and E within 30 days of previous visit
repeatpresentationwithin30days<- MERGEDSUBSETABOVE18 %>%
arrange(oGRE_ID, ADMISSION_DATE) %>%
group_by(oGRE_ID) %>%
mutate(repeatvisitdays= as.numeric(ADMISSION_DATE-lag(ADMISSION_DATE)))
repeatpresentationwithin30days$ repeatvisitin30days <-  ifelse(repeatpresentationwithin30days$repeatvisitdays <=30, 1, 0)
repeatpresentationwithin30days$repeatvisitin30days[is.na(repeatpresentationwithin30days$repeatvisitin30days)]<-0

#Removing multiple enteries of patients to calculate the number of patients
patientidnoduplicate4<-repeatpresentationwithin30days %>%
arrange(oGRE_ID, desc(repeatvisitin30days))%>%
group_by(oGRE_ID) %>%
mutate(repeatvisitin30days1 = ifelse(any(repeatvisitin30days==1),
```

```
                        1,0)) %>% distinct(oGRE_ID, .keep_all = TRUE)
sum(patientidnoduplicate4$repeatvisitin30days==1)

#To check for immediate hospital admission
MERGEDSUBSETABOVE18<- MERGEDSUBSETABOVE18 %>% mutate(year= year(as.Date(ADMISSION_DATE)))
MERGEDDATA8 <- merge(MERGEDSUBSETABOVE18, NEWSMR, by= "oGRE_ID")
MERGEDDATA8$datematch<- ifelse (MERGEDDATA8$DISCHARGE_DATE==MERGEDDATA8$ADMDATE,1,0)
HOSPADM<-MERGEDDATA8 %>% group_by(oGRE_ID)%>%
                         summarise(HOSADM= ifelse(any(datematch==1), 1, 0),)
patientidnoduplicateforhospitalisationFINAL<-dischargebyID %>% left_join(HOSPADM, by="oGRE_ID")
patientidnoduplicateforhospitalisationFINAL$HOSADM[is.na(patientidnoduplicateforhospitalisationFINAL$HOSADM)]<-0
sum(patientidnoduplicateforhospitalisationFINAL$HOSADM==1, na.rm=TRUE)

#Loading comorbidity dataset
comorbDATA<-Comorbidities_subsample_v1_20230728
#Adding Comorbidity to all merged datasets
df<- comorbtrial%>% rowwise() %>% mutate (comcount= sum(!is.na(c_across(-oGRE_ID))))%>% ungroup()
df<- df%>% mutate( comgroup= case_when(comcount==0~ 0,
                        comcount==1~1,
                        comcount==2~2,
                        comcount>=3~3))
newcomorb2 <- df%>% select(oGRE_ID, comgroup)
comorbfinaldis<- dischargebyIDfinal %>% left_join(newcomorb2, by="oGRE_ID")
comorbfinalmor<-mortalityfinal%>% left_join(newcomorb2, by="oGRE_ID")
```

```
comorbfinalhosp<-patientidnoduplicateforhospitalisationFINAL%>% left_join(newcomorb2, by="oGRE_ID")
comorbfinalrepeat<-patientidnoduplicate4%>% left_join(newcomorb2, by="oGRE_ID")
```

Descriptive Statistics

```
table(descriptivedata$SEX)
table(descriptivedata$ETHNICITY_DESCRIPTION)
table(descriptivedata$Current_UC)
table(dischargebyID$agegroup)
table(descriptivedata$SIMD_2016_QUINTILE)
table(dischargebyID$CAUSEOFINJURY_DESCRIPTION)
table(TRAKAANDE$HOSPITAL_DESCRIPTION)
table(dischargebyIDfinal$yearcategorised)
table(dischargebyIDfinal$CAUSEOFINJURY)
table(comorbfinalhosp$comgroup)
table(comorbfinalhosp$ETHNICITY)
#Mortalitywithin 30 days
#SIMD
crosstabmortality<- crosstab(mortalityfinal$mortalityin30days, mortalityfinal$SIMD_2016_QUINTILE,chisq = FALSE)
print(crosstabmortality)
#Age
crosstabage<- crosstab(mortalityfinal$mortalityin30days, mortalityfinal$agegroup)
print(crosstabage)
#Sex
crosstabsex<- crosstab(mortalityfinal$mortalityin30days, mortalityfinal$SEX)
```

```
print(crosstabsex)
#Ethnicity
crosstabmortality<- crosstab(mortalityfinal$mortalityin30days, mortalityfinal$ETHNICITY)
print(crosstabmortality)
#Cause
crosstabmortality<- crosstab(mortalityfinal$mortalityin30days, mortalityfinal$CAUSEOFINJURY)
print(crosstabmortality)
#Year categorised
crosstabmortality<- crosstab(mortalityfinal$mortalityin30days, mortalityfinal$yearcategorised)
print(crosstabmortality)
#Comorbidity
crosstabmortality<- crosstab(comorbfinalmor$mortalityin30days, comorbfinalmor$comgroup)
print(crosstabmortality)

#Discharged on same day of A and E visit
# SIMD
crosstabdischarge<- crosstab(dischargebyIDfinal$dischargedsameday, dischargebyIDfinal$SIMD_2016_QUINTILE)
print(crosstabdischarge)
#Age
crosstabdischargeage<- crosstab(dischargebyID$dischargedsameday, dischargebyID$agegroup)
print(crosstabdischargeage)
#Sex
crosstabdischargesex<- crosstab(dischargebyID$dischargedsameday, dischargebyID$SEX)
```

```
print(crosstabdischargesex)
#year
crosstabyear<- crosstab(dischargebyIDfinal$dischargedsameday, dischargebyIDfinal$yearcategorised)
print(crosstabyear)
# Ethnicity
crosstabdischarge<- crosstab(dischargebyID$dischargedsameday, dischargebyID$ETHNICITY)
print(crosstabdischarge)
# Cause
crosstabdischargecause<- table(dischargebyID$dischargedsameday, dischargebyID$CAUSEOFINJURY)
print(crosstabdischargecause)
#Comorbidity
crosstabdischarge<- crosstab(comorbfinaldis$dischargedsameday, comorbfinaldis$comgroup)
print(crosstabdischarge)

#Immediate hospital admission
#SIMD
crosstabadmsimd<- crosstab(patientidnoduplicateforhospitalisationFINAL$HOSADM, patientidnoduplicateforhospitalisationFINAL$SIMD_2016_QUINTILE)
print(crosstabadmsimd)
#Age
crosstabadmage<- crosstab(patientidnoduplicateforhospitalisation4$datematch, patientidnoduplicateforhospitalisation4$agegroup)
print(crosstabadmage)
#Comorbidity
crosstabadmcom<- crosstab(comorbfinalhosp$HOSADM, comorbfinalhosp$comgroup)
print(crosstabadmcom)
```

```
#Sex
crosstabadmsex<- crosstab(patientidnoduplicateforhospitalisationFINAL$HOSADM, patientidnoduplicateforhospitalisationFINAL$SEX)print(crosstabadmsex)
#Ethinicity
crosstabadmETHN<- crosstab(patientidnoduplicateforhospitalisationFINAL$HOSADM, patientidnoduplicateforhospitalisationFINAL$ETHNICITY)
print(crosstabadmETHN)
#Year
crosstabadmyear<- crosstab(patientidnoduplicateforhospitalisationFINAL$HOSADM, patientidnoduplicateforhospitalisationFINAL$yearcategorised)print(crosstabadmyear)
#Cause
crosstabadmcause<- crosstab(patientidnoduplicateforhospitalisation4$datematch, patientidnoduplicateforhospitalisation4$CAUSEOFINJURY)
print(crosstabadmcause)

#Repeat presentation to A&E
#SIMD
crosstabRPSIMD<- crosstab(patientidnoduplicate4$repeatvisitin30days, patientidnoduplicate4$SIMD_2016_QUINTILE)print(crosstabRPSIMD)
#Age
crosstabRPage<- crosstab(patientidnoduplicate4$repeatvisitin30days, patientidnoduplicate4$agegroup)print(crosstabRPage)
#Sex
crosstabRPsex<- crosstab(patientidnoduplicate4$repeatvisitin30days, patientidnoduplicate4$SEX)print(crosstabRPsex)
#Ethnicity
crosstabRPethn<- crosstab(patientidnoduplicate4$repeatvisitin30days, patientidnoduplicate4$ETHNICITY)print(crosstabRPethn)
#Year
crosstabRPyear<- crosstab(patientidnoduplicate4$repeatvisitin30days, patientidnoduplicate4$yearcategorised)
print(crosstabRPyear)
```

```
#Cause
summary(patientidnoduplicate4$CAUSEOFINJURY)crosstabRPcause<- crosstab(patientidnoduplicate4$repeatvisitin30days, patientidnoduplicate4$CAUSEOFINJURY)print(crosstabRPcause)
#Comorbidity
crosstabRPcause<- crosstab(comorbfinalrepeat$repeatvisitin30days, comorbfinalrepeat$comgroup)print(crosstabRPcause)
```

Regression Models

```
#Mortality model building
#SIMD
mortalityfinal$SIMD_2016_QUINTILE <-factor(mortalityfinal$SIMD_2016_QUINTILE)
MortalitymodelSIMD <- glm(mortalityin30days ~ SIMD_2016_QUINTILE , data=mortalityfinal, family="binomial")
summary(MortalitymodelSIMD)
confint.default(MortalitymodelSIMD)
exp(cbind(OR=coef(MortalitymodelSIMD), confint.default(MortalitymodelSIMD)))
#Age
Mortalitymodelage <- glm(mortalityin30days ~ AGE , data=mortalityfinal, family="binomial")
summary(Mortalitymodelage)
confint.default(Mortalitymodelage)
exp(cbind(OR=coef(Mortalitymodelage), confint.default(Mortalitymodelage)))
#Sex
Mortalitymodelsex <- glm(mortalityin30days ~ SEX, data=mortalityfinal, family="binomial")
summary(Mortalitymodelsex)
confint.default(Mortalitymodelsex)
```

```
exp(cbind(OR=coef(Mortalitymodelsex), confint.default(Mortalitymodelsex)))
#Ethnicity
mortalityfinal$ETHNICITY <-factor(mortalityfinal$ETHNICITY)
Mortalitymodelethn <- glm(mortalityin30days ~ ETHNICITY , data=mortalityfinal, family="binomial")
summary(Mortalitymodelethn)
confint.default(Mortalitymodelethn)
exp(cbind(OR=coef(Mortalitymodelethn), confint.default(Mortalitymodelethn)))
# Cause
mortalityfinal$CAUSEOFINJURY <-factor(mortalityfinal$CAUSEOFINJURY)
Mortalitymodelcause <- glm(mortalityin30days ~ CAUSEOFINJURY , data=mortalityfinal, family="binomial")
summary(Mortalitymodelcause)
confint.default(Mortalitymodelcause)
exp(cbind(OR=coef(Mortalitymodelcause), confint.default(Mortalitymodelcause)))
#Year
mortalityfinal$yearcategorised <-factor(mortalityfinal$yearcategorised)
Mortalitymodelyear <- glm(mortalityin30days ~ yearcategorised , data=mortalityfinal, family="binomial")
summary(Mortalitymodelyear)
confint.default(Mortalitymodelyear)
exp(cbind(OR=coef(Mortalitymodelyear), confint.default(Mortalitymodelyear)))
#Comorb
comorbfinalmor$comgroup <-factor(comorbfinalmor$comgroup)
Mortalitymodelcomorb <- glm(mortalityin30days ~ comgroup , data=comorbfinalmor, family="binomial")
summary(Mortalitymodelcomorb)
confint.default(Mortalitymodelcomorb)
```

```
exp(cbind(OR=coef(Mortalitymodelcomorb), confint.default(Mortalitymodelcomorb)))
#Adjusted model
mortalityfinal$SIMD_2016_QUINTILE <-factor(mortalityfinal$SIMD_2016_QUINTILE)
mortalityfinal$ETHNICITY<-factor(mortalityfinal$ETHNICITY)
mortalityfinal$yearcategorised <-factor(mortalityfinal$yearcategorised)
mortalityfinal$CAUSEOFINJURY <-factor(mortalityfinal$CAUSEOFINJURY)
mortalityfinal$comorbidity <-factor(mortalityfinal$comorbidity)
MortalitymodelADJ <- glm(mortalityin30days ~ SIMD_2016_QUINTILE+ SEX+ yearcategorised+ AGE+ CAUSEOFINJURY+ ETHNICITY+ comgroup, data=comorbfinalmor, family="binomial")
summary(MortalitymodelADJ)
confint.default(MortalitymodelADJ)
exp(cbind(OR=coef(MortalitymodelADJ), confint.default(MortalitymodelADJ)))
#Fit check
Predict1<- MortalitymodelADJ, newdata= comorbfinalmor, type=”response”)
Roc1<- roc(comorbfinalmor$mortalityin30days, Predict1 , ci= TRUE)
print(Roc1)
plot(Roc1)

#Discharge model
#SIMD
dischargemodelSIMD <- glm(dischargedsameday ~ SIMD_2016_QUINTILE , data=dischargebyID, family="binomial")
summary(dischargemodelSIMD)
confint.default(dischargemodelSIMD)
exp(cbind(OR=coef(dischargemodelSIMD), confint.default(dischargemodelSIMD)))
#Age
```

```
dischargemodelAGE <- glm(dischargedsameday ~ AGE , data=dischargebyID, family="binomial")
summary(dischargemodelAGE)
confint.default(dischargemodelAGE)
exp(cbind(OR=coef(dischargemodelAGE), confint.default(dischargemodelAGE)))
#Sex
dischargemodelsex <- glm(dischargedsameday ~ SEX , data=dischargebyID, family="binomial")
summary(dischargemodelsex)
confint.default(dischargemodelsex)
exp(cbind(OR=coef(dischargemodelsex), confint.default(dischargemodelsex)))
#Cause
dischargemodelcause <- glm(dischargedsameday ~ CAUSEOFINJURY , data=dischargebyID, family="binomial")
summary(dischargemodelcause)
confint.default(dischargemodelcause)
exp(cbind(OR=coef(dischargemodelcause), confint.default(dischargemodelcause)))
#Ethnicity
dischargemodelethn <- glm(dischargedsameday ~ ETHNICITY , data=dischargebyID, family="binomial")
summary(dischargemodelethn)
confint.default(dischargemodelethn)
exp(cbind(OR=coef(dischargemodelethn), confint.default(dischargemodelethn)))
#Year
dischargemodelyear <- glm(dischargedsameday ~ yearcategorised , data=dischargebyID, family="binomial")
summary(dischargemodelyear)
confint.default(dischargemodelyear)
exp(cbind(OR=coef(dischargemodelyear), confint.default(dischargemodelyear)))
```

```
#Comorbidity
comorbfinaldis$comgroup <-factor(comorbfinaldis$comgroup)
dischargemodelcom <- glm(dischargedsameday ~ comgroup , data=comorbfinaldis, family="binomial")
summary(dischargemodelcom)
confint.default(dischargemodelcom)
exp(cbind(OR=coef(dischargemodelcom), confint.default(dischargemodelcom)))
#Adjusted Model
comorbfinaldis$SIMD_2016_QUINTILE <-factor(comorbfinaldis$SIMD_2016_QUINTILE)
comorbfinaldis$ETHNICITY<-factor(comorbfinaldis$ETHNICITY)
comorbfinaldis$yearcategorised <-factor(comorbfinaldis$yearcategorised)
comorbfinaldis$CAUSEOFINJURY <-factor(comorbfinaldis$CAUSEOFINJURY)
dischargemodel <- glm(dischargedsameday ~ SIMD_2016_QUINTILE + AGE+ SEX + yearcategorised+ ETHNICITY+ CAUSEOFINJURY+ comgroup, data=comorbfinaldis, family="binomial")
summary(dischargemodel)
confint.default(dischargemodel)
exp(cbind(OR=coef(dischargemodel), confint.default(dischargemodel)))
#Fit check
Predict2<- dischargemodel, newdata= comorbfinaldis, type=”response”)
Roc2<- roc(comorbfinaldis $ dischargedsameday, Predict2 , ci= TRUE)
print(Roc2)
plot(Roc2)

#Repeat Presentation Model
#SIMD
repeatpresentationmodelsimd <- glm(repeatvisitin30days ~ SIMD_2016_QUINTILE , data=patientidnoduplicate4, family="binomial")
```

```
summary(repeatpresentationmodelsimd)
confint.default(repeatpresentationmodelsimd)
exp(cbind(OR=coef(repeatpresentationmodelsimd), confint.default(repeatpresentationmodelsimd)))
#Sex
repeatpresentationmodelsex <- glm(repeatvisitin30days ~ SEX , data=patientidnoduplicate4, family="binomial")
summary(repeatpresentationmodelsex)
confint.default(repeatpresentationmodelsex)
exp(cbind(OR=coef(repeatpresentationmodelsex), confint.default(repeatpresentationmodelsex)))
#Age
repeatpresentationmodelage <- glm(repeatvisitin30days ~ AGE , data=patientidnoduplicate4, family="binomial")
summary(repeatpresentationmodelage)
confint.default(repeatpresentationmodelage)
exp(cbind(OR=coef(repeatpresentationmodelage), confint.default(repeatpresentationmodelage)))
#Ethnicity
patientidnoduplicate4$ETHNICITY<-factor(patientidnoduplicate4$ETHNICITY)
repeatpresentationmodelethn <- glm(repeatvisitin30days ~ ETHNICITY , data=patientidnoduplicate4, family="binomial")
summary(repeatpresentationmodelethn)
confint.default(repeatpresentationmodelethn)
exp(cbind(OR=coef(repeatpresentationmodelethn), confint.default(repeatpresentationmodelethn)))
#Year
patientidnoduplicate4$yearcategorised<-factor(patientidnoduplicate4$yearcategorised)
repeatpresentationmodelyear <- glm(repeatvisitin30days ~ yearcategorised , data=patientidnoduplicate4, family="binomial")
summary(repeatpresentationmodelyear)
confint.default(repeatpresentationmodelyear)
```

```r
exp(cbind(OR=coef(repeatpresentationmodelyear), confint.default(repeatpresentationmodelyear)))
#Cause
patientidnoduplicate4$CAUSEOFINJURY<-factor(patientidnoduplicate4$CAUSEOFINJURY)
repeatpresentationmodelcause <- glm(repeatvisitin30days ~ CAUSEOFINJURY , data=patientidnoduplicate4, family="binomial")
summary(repeatpresentationmodelcause)
confint.default(repeatpresentationmodelcause)
exp(cbind(OR=coef(repeatpresentationmodelcause), confint.default(repeatpresentationmodelcause)))
#Comorbidity
repeatpresentationmodelcom <- glm(repeatvisitin30days ~ comgroup , data=comorbfinalrepeat, family="binomial")
summary(repeatpresentationmodelcom)
confint.default(repeatpresentationmodelcom)
exp(cbind(OR=coef(repeatpresentationmodelcom), confint.default(repeatpresentationmodelcom)))
#Adjusted Model
patientidnoduplicate4$SIMD_2016_QUINTILE <-factor(patientidnoduplicate4$SIMD_2016_QUINTILE)
patientidnoduplicate4$ETHNICITY<-factor(patientidnoduplicate4$ETHNICITY)
patientidnoduplicate4$yearcategorised <-factor(patientidnoduplicate4$yearcategorised)
patientidnoduplicate4$CAUSEOFINJURY <-factor(patientidnoduplicate4$CAUSEOFINJURY)
comorbfinalrepeat$comgroup <-factor(comorbfinalrepeat$comgroup)
repeatpresentationmodel <- glm(repeatvisitin30days ~ SIMD_2016_QUINTILE + AGE+ SEX+ yearcategorised+ CAUSEOFINJURY+ ETHNICITY+ comgroup, data=comorbfinalrepeat,
family="binomial")
summary(repeatpresentationmodel)
confint.default(repeatpresentationmodel)
exp(cbind(OR=coef(repeatpresentationmodel), confint.default(repeatpresentationmodel)))
#Fit check
```

```
Predict3<- repeatpresentationmodel, newdata= comorbfinalrepeat, type=”response”)
Roc3<- roc(comorbfinalrepeat$repeatvisitin30days, Predict3 , ci= TRUE)
print(Roc3)
plot(Roc3)

#Immediate hospital admission model
#Age
immediatehospitalisationmodelage<- glm( HOSADM ~ AGE , data=patientidnoduplicateforhospitalisationFINAL, family="binomial")
summary(immediatehospitalisationmodelage)
confint.default(immediatehospitalisationmodelage)
exp(cbind(OR=coef(immediatehospitalisationmodelage), confint.default(immediatehospitalisationmodelage)))
#Sex
immediatehospitalisationmodelsex<- glm(HOSADM  ~  SEX , data=patientidnoduplicateforhospitalisationFINAL, family="binomial")
summary(immediatehospitalisationmodelsex)
confint.default(immediatehospitalisationmodelsex)
exp(cbind(OR=coef(immediatehospitalisationmodelsex), confint.default(immediatehospitalisationmodelsex)))
#SIMD
immediatehospitalisationmodelsimd<- glm( HOSADM ~ SIMD_2016_QUINTILE , data=patientidnoduplicateforhospitalisationFINAL, family="binomial")
summary(immediatehospitalisationmodelsimd)
confint.default(immediatehospitalisationmodelsimd)
exp(cbind(OR=coef(immediatehospitalisationmodelsimd), confint.default(immediatehospitalisationmodelsimd)))
#Ethnicity
immediatehospitalisationmodelethn<- glm( HOSADM ~ ETHNICITY , data=patientidnoduplicateforhospitalisationFINAL, family="binomial")
summary(immediatehospitalisationmodelethn)
```

```
confint.default(immediatehospitalisationmodelethn)
exp(cbind(OR=coef(immediatehospitalisationmodelethn), confint.default(immediatehospitalisationmodelethn)))
#Cause
immediatehospitalisationmodelcause<- glm( HOSADM~ CAUSEOFINJURY , data=patientidnoduplicateforhospitalisationFINAL, family="binomial")
summary(immediatehospitalisationmodelcause)
confint.default(immediatehospitalisationmodelcause)
exp(cbind(OR=coef(immediatehospitalisationmodelcause), confint.default(immediatehospitalisationmodelcause)))
#Year
immediatehospitalisationmodelyear<- glm( HOSADM ~ yearcategorised , data=patientidnoduplicateforhospitalisationFINAL, family="binomial")
summary(immediatehospitalisationmodelyear)
confint.default(immediatehospitalisationmodelyear)
exp(cbind(OR=coef(immediatehospitalisationmodelyear), confint.default(immediatehospitalisationmodelyear)))
#Comorbidity
immediatehospitalisationmodelcom<- glm( HOSADM ~ comgroup , data=comorbfinalhosp, family="binomial")
summary(immediatehospitalisationmodelcom)
confint.default(immediatehospitalisationmodelcom)
exp(cbind(OR=coef(immediatehospitalisationmodelcom), confint.default(immediatehospitalisationmodelcom)))
#Adjusted model
patientidnoduplicateforhospitalisationFINAL$SIMD_2016_QUINTILE <-factor(patientidnoduplicateforhospitalisationFINAL$SIMD_2016_QUINTILE)
patientidnoduplicateforhospitalisationFINAL$ETHNICITY <-factor(patientidnoduplicateforhospitalisationFINAL$ETHNICITY)
patientidnoduplicateforhospitalisationFINAL$yearcategorised <-factor(patientidnoduplicateforhospitalisationFINAL$yearcategorised)
patientidnoduplicateforhospitalisationFINAL$CAUSEOFINJURY <-factor(patientidnoduplicateforhospitalisationFINAL$CAUSEOFINJURY)
comorbfinalhosp$comgroup <-factor(comorbfinalhosp$comgroup)
```

```
immediatehospitalisationmodel<- glm( HOSADM ~ SIMD_2016_QUINTILE + AGE + SEX + yearcategorised+ ETHNICITY+ CAUSEOFINJURY+ comgroup, data=comorbfinalhosp, family="binomial")
summary(immediatehospitalisationmodel)
confint.default(immediatehospitalisationmodel)
exp(cbind(OR=coef(immediatehospitalisationmodel), confint.default(immediatehospitalisationmodel)))
#Fit check
Predict4<- immediatehospitalisationmodel, newdata= comorbfinalhosp, type=”response”)
Roc4<- roc(comorbfinalhosp$HOSADM, Predict4 , ci= TRUE)
print(Roc4)
plot(Roc4)
```