PROFESSIONAL DOCTORATES

The Effects of Welfare Reform and Area Level Deprivation on Mental Health and Well-being in the UK

Lawrenson, Jenny

Award date:
2023

Awarding institution:
Bangor University

North Wales Clinical Psychology Programme

The Effects of Welfare Reform and Area Level Deprivation on Mental Health and well-being in the UK

Thesis submitted in part for the award of Doctorate in Clinical Psychology (DClinPsy)

Jenny Lawrenson

June 2023

Declaration

I hereby declare that this thesis is the results of my own investigations, except where otherwise stated. All other sources are acknowledged by bibliographic references. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree unless, as agreed by the University, for approved dual awards.----------

----------Yr wyf drwy hyn yn datgan mai canlyniad fy ymchwil fy hun yw'r thesis hwn, ac eithrio lle nodir yn wahanol. Caiff ffynonellau eraill eu cydnabod gan droednodiadau yn rhoi cyfeiriadau eglur. Nid yw sylwedd y gwaith hwn wedi cael ei dderbyn o'r blaen ar gyfer unrhyw radd, ac nid yw'n cael ei gyflwyno ar yr un pryd mewn ymgeisiaeth am unrhyw radd oni bai ei fod, fel y cytunwyd gan y Brifysgol, am gymwysterau deuol cymeradwy

Contents

“The political and economic order benefits when distress or dysfunction that may connect with its policies and practices is relocated from socio-political space, a public and collective problem, to mental space, a private and individual problem.”

- Dereck Summerfield (2012). Afterword: Against “global mental health”. *Transcultural Psychiatry, 49(3-4)* p 521

Acknowledgements

I wish to extend my deep gratitude to the DClinPsy programme team for sticking with me despite veering off track on multiple occasions. I wish to give special thanks to Dr Chris Saville as my research supervisor, you did not shy away from my big idea, and your statistical wizardry got me to this point. I am also forever grateful for the lockdown lifeline you provided when we were all in the thick of it. Additional thanks must go to Professor Michaela Swales; you stepped in as my training coordinator and you have been a stoic presence ever since. Thank you for allowing me to cry a million tears in your direction!

Additional thanks go to Dr Kate Dickson, my final placement supervisors, who has been pragmatic, supportive and calming when things were getting stressful during the completion of this project. You have become a true friend and mentor.

Closer to home, I am forever grateful to my husband, Craig. When I started training we were newlyweds, fresh off our honeymoon and as I draw to the end of this phase in life, we are stronger than ever although with a few more grey hairs than when I started!

Finally, I wish to dedicate this thesis to my children, Violet and Fox, my two training babies. I could have qualified much sooner if I had not have had you, but my heart would never have known the joy, love and peace you bring to me. Your arrivals made me take the 'scenic route' through training, and whilst this has been a source of frustration at times, the resilience and perseverance it has taught me has made me a better person. Mummy loves you both.

Glossary of Abbreviations

A&E – Accident and Emergency

ATC – Anatomical Therapeutic Compound

BAME – Black and Minority Ethnic

BNF – British National Formulary

CAMHS – Child and Adolescent Mental Health Service

CCG – Clinical Commissioning Group

CI – Confidence Interval

CMD – Common Mental Disorders

CMHT – Community Mental Health Team

CRHT – Crisis Resolution and Home Treatment

DDD – Defined Daily Dose

DV – Dependent Variable

EU – European Union

GP – General Practitioner

IAPT – Improving Access to Psychological Therapies

IMD – Index of Multiple Deprivation

ITS – Interrupted Time Series

IV – Independent Variable

LSOA – Lower Super Output Area

MHA – Mental Health Act

NHS – National Health Service

NICE – National Institute for Health and Care Excellence

OR – Odds Ratio

PTMF – Power Threat Meaning Framework

SES – Socioeconomic Status

SIMD – Scottish Index of Multiple Deprivation

SMI – Severe Mental Illness

UC – Universal Credit

UK – United Kingdom

WHO – World Health Organisation

Thesis Summary

There is a relationship between socioeconomic deprivation and poor mental health outcomes. This thesis explores two separate facets associated with socioeconomic deprivation and the impact this has on mental health and wellbeing in the UK.

Chapter 1 is a systematic literature review looking at the relationship between area level deprivation and the individual's ability to access and use mental health services. Eleven papers are reviewed and four broad themes emerged. These themes are barriers to access in the first instance, use of unplanned routes to receiving mental health care, increased economic burden of mental health care costs linked to living in more deprived areas, and how area level deprivation can hinder successful outcomes once receiving mental health interventions. All studies use administrative data to reach conclusions.

Chapter 2 is a piece of original research that explores trends in antidepressant prescribing rates across Wales during the period of April 2016 to December 2019. During this period, there was a shift in the Welfare benefit system whereby Universal Credit was introduced. Universal Credit was not introduced at a single time point; rather it was introduced on a monthly 'roll out' phase. Taking advantage of the natural pre/post nature of this roll out programme, an Interrupted Time Series model was applied to analyse changes in prescribing trends during a time of policy change. There is a significant increase in antidepressant prescribing rates in each Welsh county in the month when Universal Credit was introduced, and the prescribing rate continued to accelerate beyond the baseline trend over time.

Chapter 3 reflects upon how the research detailed above will influence clinical practice, and what theoretical implications the findings pose. There is also a small reflective narrative discussing some of the challenges associated with completing this piece of research.

Submission Guidelines

Journal of Epidemiology and Community Health (JECH): Impact factor 6.3

Please review the below article type specifications including the required article lengths, illustrations, table limits and reference counts. The word count excludes the title page, abstract, tables, acknowledgements, contributions and references. Manuscripts should be as succinct as possible.

Original research

Manuscripts reporting results of original research should follow the IMRaD style (Introduction, Methods, Results and Discussion) and should have a structured abstract (Background, Methods, Results and Conclusion). All research on human subjects must have been approved by the appropriate ethics committee and must have conformed to the principles embodied in the Declaration of Helsinki (see Ethics Approval for more guidelines). A statement to this effect must be included in the methods section of the paper.

Systematic reviews, meta analyses, rapid and scoping reviews should be submitted as Original research. Other review type articles should be submitted as either an Essay or Research Agenda article.

Reviews should be prepared in strict compliance with MOOSE or PRISMA guidelines or with Cochrane's complementary guidelines for systematic reviews of health promotion and public health interventions. The journal encourages authors to use alternative databases covering scientific literature from low- and middle-income countries not indexed in the traditional international databases (ie, Medline, Web of Science).

Word count: up to 3000 words

Abstract: maximum of 250 words (Background, Methods, Results and Conclusion)

Tables/Illustrations: up to 5

References: up to 40

Please include the key messages of your article after your abstract using the following headings. This section should be no more than 3-5 sentences and should be distinct from the abstract; be succinct, specific and accurate.

What is already known on this topic - summarise the state of scientific knowledge on this subject before you did your study and why this study needed to be done

What this study adds - summarise what we now know as a result of this study that we did not know before

How this study might affect research, practice or policy - summarise the implications of this study

This will be published as a summary box after the abstract in the final published article.

Chapter 1: Literature Review

A Systematic Review of Mental Healthcare Access, Utilisation and Outcomes in the UK in relation to Area Level Deprivation

Abstract

Background: There is an established understanding that there is a social gradient that impacts mental health and wellbeing, with people who have greater levels of socioeconomic adversity in relation to the population level norms being disproportionality impacted by mental health problems. This review aims to synthesise the findings of peer-reviewed articles that explicitly reference area level indices of multiple deprivation as a measure of exposure in their studies.

Methods: Searches of PsychInfo, PubMed and Web of Science where conducted. Studies were included if they were based in the UK, included a UK index of multiple deprivation as a measure of exposure, and had a clearly defined outcome that they were measuring, relating to a facet of service usage.

Results: Eleven studies met the inclusion criteria. A narrative synthesis explores studies which explore how local area deprivation effects access to mental health care services, how local area deprivation can increase risk of unplanned care and how local area deprivation has an impact on the outcomes of individuals attending mental health services.

Conclusion:

Local area deprivation, as defined by national indices of multiple deprivation, is a factor which correlates highly with reduced access to services, unplanned utilisation of services (for example, accessing help via A&E), higher numbers of dropouts in group based interventions and poorer results on service based outcome measures. When studies controlled for area level deprivation by matching people in groups with others from similar areas, there was some evidence to suggest that this leads to better outcomes for individuals who live in more deprived areas.

Keywords: *local area deprivation, index of multiple deprivation, indices of multiple deprivation, access, utilisation, outcomes, mental health care, psychological care, talking*

therapies

Introduction

Mental health as defined by the World Health Organisation is "a state of well-being in which every individual realises his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community". Mental health is not necessarily the absence of a psychiatrically diagnosable 'mental disorder' (WHO, 2014). There is plenty written in existing literature about how mental health and wellbeing exists within a societal context. In terms of prevalence rates, there is an uneven distribution of mental health difficulties, and diagnosable 'disorder' across a social gradient, with those who are socially disadvantaged being disproportionally affected by poor mental health and the adverse consequences associated with poor mental health (Campion et al., 2013). This social gradient is not exclusive to mental health, and can be demonstrated in physical health settings too, however the scope if this review is to look at the impact on Mental Health and wellbeing.

In the UK, area level characteristics are statistically defined, and officially reported upon, using the Index of Multiple Deprivation measure. Each home nation measures and reports independently of one another, meaning there is an index of multiple deprivation (IMD) for England, Wales, Scotland and Northern Ireland. Each index reports upon distinct domains that carry varying weights of importance, in order to determine how deprived an area is, and how it ranks in comparison to other areas. The domains reported on, and the weighting of each domain, do vary between nations as shown is table 1 below. England, Scotland and Northern Ireland report on seven domains, whilst Wales reports on eight (*Northern Ireland Multiple Deprivation Measures*, 2017.; *Scottish Index of Multiple Deprivation (SIMD)*, 2020.; *Welsh Index of Multiple Deprivation (WIMD)e*, 2019.; English Index of Multiple Deprivation, 2019).

The statistics generated within the Indices of Multiple deprivation domains provide a relative rank of deprivation within an area, or neighbourhood. The area or neighbourhood statistics are reported at Lower-layer Super Output Area (LSOA) level. A LSOA is a small geographically determined area that comprise between 400 and 1200 households, with a typical resident population between 1000 and 3000 people, and in England there are 33,755 LSOAs(*Office for National Statistics*, 2021). These individual LSOA areas are then ranked in terms of relative deprivation, and these ranks can be used to determine which areas are the most deprived, or least deprived. The ranks are often clustered into quartiles, quintiles or deciles to compare areas more broadly to one another.

As illustrated in table 1. Area level deprivation encompasses more than just poverty. Poverty relates to the lack of financial resources to meet needs, whereas area level deprivation relates to the lack of many kinds of resources, not just fiscal (i.e. access to healthcare, access to education) (Penney, 2019). However fiscal stability does form the bulk of each domain e.g. income and employment. Deprivation and mental health difficulties are linked (McLean et al., 2014), but what is less clear is whether area level deprivation characteristics impact upon a) a person's ability to access mental health services, b) a person's ability to utilise the services they access and c) a person's ability to obtain a satisfactory outcome from the service they have been using.

Table 1. Differences in Indices of Multiple Deprivation domains across UK home nations, including weighting

England (English Index of Multiple Deprivation, 2019)		Wales (*Welsh Index of Multiple Deprivation (WIMD) 2019*)		Scotland (*Scottish Index of Multiple Deprivation (SIMD), 2020*)		Northern Ireland (*Northern Ireland Multiple Deprivation Measures, 2017.*)	
Income	22.5%	Income	22%	Income	28%	Income	25%
Employment	22.5%	Employment	22%	Employment	28%	Employment	25%
Health Deprivation and Disability	13.5%	Health	15%	Health	14%	Health	15%
Education and Skills Training	13.5%	Education	14%	Education, Skills and Training	14%	Education	15%
Crime	9.3%	Access to Services	10%	Geographic Access to Services	9%	Access	10%
Barriers to Housing and Services	9.3%	Community Safety	5%	Crime	5%	Living environment	5%
Living Environment	9.3%	Housing	7%	Housing	2%	Crime	5%
		Physical Environment	5%				

Aims of the Review

This review aims to synthesise the findings of peer-reviewed articles that explicitly reference area level deprivation as measure of exposure studies looking at mental health service utilisation. The included studies are UK based studies as the measure of exposure for area level deprivation in this study is the use of one of the UK national indices of multiple deprivation.

One of the markers for deprivation within IMD datasets is access to services, which includes access to healthcare. It is of interest to the author of this review to see if any studies explicitly explore access to mental healthcare services in relation to area level deprivation demographics, i.e. do people who live in more deprived areas have equitability of access to mental health services.

A systematic review to find relevant literature and a narrative synthesis will be provided to explore the key findings and to provide context as to the questions being posed.

Method

The design of this review encompasses both a systematic search strategy and a narrative synthesis of the information retrieved following the systematic review. This approach is an established method of exploring data in a text based format in order to address different aspects of the questions being asked (Popay et al., 2006). The evidence gathering broadly followed PRISMA 2020 guidelines, however there were some pragmatic constraints which are discussed in the limitations section of this paper.

Eligibility criteria

Studies to be included in this paper would be pieces of peer reviewed original research, published in the English language, that used home nations indices of multiple deprivation as a dependent variable in their analysis. Papers to be included would be those that explored some facet of mental health service usage. Studies were immediately excluded if: they were not published in the English language; their focus was only physical health care provision (studies that look at both physical and mental health would be included if the mental health component was clearly separate from physical health); studies from outside of the UK; they were not about the provision or utilisation of a defined service.

Search Strategy

An electronic search of articles published in peer-reviewed journals was conducted via PsychInfo, PubMed, Medline and Web of Science. The following search terms were used:

("multiple deprivation" OR "deprived area" OR "area deprivation")

AND

("mental disorder" OR psychology OR psychiatry OR "mental illness" OR "mental health" OR "mental well-being" OR "emotional well-being" OR "psychological well-being" OR psychotherapy)

AND

(Access OR outcome OR utilisation OR utilization OR demand OR availability OR provi*)

Selection Process

Initially duplicate items were removed and then titles and abstracts were screened for inclusion. A second round of screening excluded articles that did not include a measure of area level deprivation as part of the reporting criteria. The remaining articles were read in full and excluded if they failed to report a socioeconomic deprivation outcome measure reported in terms of one of the UK national indices of multiple deprivation (IMD). Papers that were selected for inclusion in this analysis have been summarised and information regarding each study and the areas they were based, number of participants, ages, gender, study designs, sampling methods, study population and IMD prevalence, is presented in table 2 below. Due to pragmatic constraints, no interrater reliability checks were undertaken during this screening process, and the review was not PROSPERO registered.

Table 2. Summary of Included Studies including title, authors, year of publication, type of study, geographic area of the study, total number of individuals records analysed, measure of exposure, IV, DV, types of analysis and key findings

	Study Title	**Authors**	**Year**	**Type of Study**	**Geographical Area**	**Service Type**	**Total Individual records analysed, or total n participants**	**Measure of Exposure**	**Other Independent Variables**	**Dependent Variable**	**Type of Analysis**	**Key Findings**
1.	Mental Health in Hospital emergency departments: Cross-sectional analysis of attendances in England	Baracaia, McNulty, Baldwin, Mytton, Evison, Raine, Giacco, Hutchings & Barratt.	2020	Cross-sectional observational study between 1st April 2013 and 31st March 2014 to determine the relationship between Mental Health diagnoses and A&E attendance.	England	Mental health admissions to A&E Departments of English NHS Hospitals	6,262,602	2015 Index of Multiple Deprivation (IMD) rankings using LSOA data derived from patient's home postcodes. Quintile 1 = most deprived, Quintile 5 = least deprived	Age, sex, ethnicity, GP registration	Number of attendances at A&E departments	Descriptive statistics, Logistic regression, cross tabulation and odds ratio calculated.	59.9% of mental health admissions came from most deprived quintiles (4 & 5). Individuals without an IMD (no fixed abode) over four times more likely to have a mental health diagnosis (adjusted OR 4.22, 95% CI 4.11- 4.32).

2.	Detecting referral and selection bias by the anonymous linkage of practice, hospital and clinic data using Secure and Private Record Linkage (SAPREL): Case study from the evaluation of the Improved Access to Psychological Therapy (IAPT) service.	de Lusignan, Navarro, Chan, Parry, Dent-Brown & Kendrick.	2011	Cross-sectional evaluation of linked clinic data to determine selection bias.	Twenty GP practices across England	Improving Access to Psychological Therapies (IAPT) services across England	152,363	2004 IMD rankings using Geographical Information System (GIS) methods. Decile 1 = least deprived, decile 10 – most deprived	Age, Gender, ethnicity	Referral numbers and number of accepted referrals	Descriptive statistics, 95% CI and standard error, t-test, chi square	62.6% of patients of the GP registered population lived in the most deprived 20% areas (9th and 10th decile). Broadly tallied to IAPT referral rates (slight rise in 10th decile, and decrease in 8th decile). Patients accepted from referral to intervention where over represented in less deprived deciles (3rd, 5th and 6th)
3.	On poverty, politics and psychology: The socioeconomic gradient of mental healthcare utilisation and outcomes.	Delgadillo, Asaria, Ali & Gilbody.	2016	Cross-section evaluation of referrals, access and outcomes in IAPT services linked to socioeconomic status	Data from 211 CCG (Clinical Commissioning Group) areas across England, July-September 2014	Access to Psychological Therapies (IAPT) services across England	293,400	IMD rankings calculated for each Clinical Commissioning Group (CCG) area, lower rank = greater deprivation	-	Referrals and clinical outcome data	Descriptive statistics, weighted least squares regression, chi-square and kappa statistics	Significant negative correlation between IMD rank and number of new referrals per CCG area (r=-0.27, P<0.001)

4.	Social inequalities in the demand, supply and utilisation of psychological treatment.	Delgadillo, Farnfield & North.	2018	Cross-section evaluation of the 'access gap' between referral to IAPT and those who did not ultimately receive treatment	Data from 144 IAPT services covering 180 local areas in England, October – December 2015	Access to Psychological Therapies (IAPT) services across England	307,440	2015 Index of Multiple Deprivation (IMD) rankings using LSOA data derived from patients home postcodes. Quintile 1 = most deprived, Quintile 5 = least deprived	Local area prevalence rates of CMD, ethnicity, total number of referrals to the service, workforce size	Accepted referral rates	Step 1- Exploration of inter-correlations between workforce size, population size, IMD score and prevalence of common mental health conditions (Spearman's non-parametric correlations). Rank partial correlation determining association between workforce size and prevalence of CMD's. Step 2 - Weighted Least squares (WLS) regression DV access gap, IVs included IMD score, total	A greater access gap (ratio between cases that did not access treatment and total cases referred for treatment, expressed as a percentage) was associated with living in more deprived areas as defined by IMD (B=.32, p=.01). Work force resourcing (staffing) was not significantly linked to a greater access gap. There was a clear linear trend in CMD prevalence across quintiles as rates of deprivation increase.

											referrals, prevalence of CMDs, workforce size, waiting times	

5.	The influence of socio-demographic similarity and difference on adequate attendance of group psychoeducational cognitive behavioural therapy.	Firth, Delgadillo, Kellett & Lucock.	2020		5 English Primary Care Psychological Therapy services affiliated with the Northern IAPT practice research network	Improving Access to Psychological Therapies (IAPT) services across Northern England	2071 individual patients	2015 Index of Multiple Deprivation (IMD) rankings using LSOA data derived from patient's home postcodes. Deprivation scores ranked between 0-100, with a higher score indicating greater deprivation	Gender, employment status, ethnicity, age, CMD diagnosis	Number of attendances to a group based therapy programme	Development of similarity indices based on age, gender, race and IMD in the first instance. Then analysis of adequate attendance (primary outcome) using logistic multilevel models with rIGLS and logit link function. Post0intervention symptom scores (secondary outcomes) used linear multilevel models with rIGLS estimation.	Age, depression severity, unemployment and IMD were all significant predictors of adequate attendance. Patients who are younger, unemployed, more depressed and living in more deprived neighbourhoods were less likely to attend an adequate dose of treatment (4 out of 6 sessions). The main effect of the IMD similarity index was significant (p=.026) in that patients who came from areas of similar deprivation to the rest of the group where more likely to

												have adequate attendance.

6.	Social gradients in health and social care costs: Analysis of linked electronic health records in Kent, UK.	Jayatunga, Asaria, Belloni, George, Bourne & Sadique.	2019	Cross sectional evaluation of health care costs (including mental health care as a sub category) in relation to neighbourhood deprivation	Kent, UK.	All patient level data across primary, secondary community, mental health and social care	Study restricted to individuals over age 55 due to this group typically incurring higher health costs. Study sample of 323,401, representing 63% of the total population in Kent aged over 55 at the time of the study.	English Index of Multiple Deprivation (IMD). 902 of the 32,844 LSOAs in England are in Kent	Age, gender	Per capita healthcare costs		The impact of deprivation on Mental health care costs for over 55's in Kent is demonstrated by increased spending demands of 27% in the most deprived areas. This is the largest amount of relative additional spending when compared to social care costs (23%), community care (22%), secondary care (12%) and primary care (8%).

7.	Social deprivation and the outcomes of crisis resolution and home treatment for people with mental health problems: A historical cohort study.	Kingsford & Webber.	2010	Historical cohort data used to determine 'successful' or 'unsuccessful' outcomes of CRHT interventions with area level deprivation being considered as part of the analysis	One local authority area in South-East England ranked 85th most deprived out of 354 local authorities. Most deprived authority in its county.	Crisis Resolution and Home Treatment Team (CRHT) - secondary care service	260 cases of episodes of care (some people may have had more than one episode of care during study period)	IMD rankings based on 2004 dataset, all LSOA's in England ranked from 1 (most deprived) to 32482 (least deprived). Ranks ranging from 357 to 27929 in this study, mean rank 8924.6, total 64 LSOA's in area. Arranged in to quartiles.	Age, source of referral, gender, ethnicity, living circumstances	CRHT outcomes (successful vs unsuccessful)	Univariate analysis between predictors and outcomes, chi-square test examining associations between IMD rank, percentage of single occupancy households and CRHT outcomes. Logistic regression to explore associations between significant predictors and CRHT outcomes. Repeat referrals 'clustered'	Between 1 and 9 referrals per LSOA (median 2 per area) distribution skewed towards more deprived areas. IMD rank was significantly associated with CRHT outcome, with people living in more deprived areas having poorer outcomes (($\chi 2$ =4.06, df=1, P = 0.04). Living in the most deprived areas decreased the odd of being referred from a non-enhanced CMHT (OR = 0.22, 95% CI = 0.06-0.91).

8.	Investigating geographical variation in the use of mental health services by area of England: A cross-sectional ecological study.	Maconick, Rains, Jones, Lloyd-Evans & Johnson.	2021	Cross-sectional ecological study using public health England data to explore associations between area characteristics and the number of people in contact with primary and secondary care mental health services	England, 194 CCGs clustered within 62 NHS trusts.	Secondary and primary Care Mental Health Services	Each CCG has catchment of approx. 250,000 people. So approx.	IMD ranking (2015 data) as well as age, gender, prevalence of severe and enduring mental illnesses (SMI_, prevalence of common mental disorder (CMD), unemployment, proportion of population who are black and minority ethnic (BAME), population density, access to and recovery in primary care psychological therapies.	Age, gender, prevalence of SMI, prevalence of CMD, unemployment, ethnicity, population density, access to primary care psychological therapies, recovery in primary care psychological therapies	Contacts with mental health services	Regression analysis (multilevel negative binomial regression models)	Strong evidence that greater area level deprivation and unemployment were associated with a higher number of people In contact with mental health services after controlling for the local prevalence of mental disorders (CMD and SMI) and age (IRR Incidence rate ratio 1.02 (1.01-1.04 p<0.001)

9.	The effect of physical multimorbidity, mental health conditions and socioeconomic deprivation on unplanned admissions to hospital: A retrospective cohort study.	Payne, Abel, Guthrie & Mercer.	2013	Retrospective cohort data study using Scottish GP data to determined mental health comorbidity and/or social deprivation leads to additional unplanned hospital admissions due to long term health disorders	40 general practices across Scotland	Secondary Care services (hospital)	180815 patients aged over 20, medium age 49.	IMD data from Scottish Index of Multiple Deprivation arranged by quintile, with 1 being least deprived, 5 being most deprived. Also sex, age group, physical multi-morbidity count and presence of a mental health condition	Number of physical health conditions, age, sex, number of mental health conditions	Number of hospital admissions	Fixed-effect univariate, and mixed effect multivariate logistic regression models with hospital admissions as the outcome measure.	Prevalence of physical multimorbidity and mental health morbidity increased with deprivation. When compared to people living in the least deprived areas with no mental or physical health conditions, people in the most socioeconomically deprived areas was had a mental health condition and 4 or more physical health admissions had about 18 times the odds of an unplanned admission to hospital (OR 18.34, 95% CI 16.40-

												20.52) and about 50 times the odd of a potentially preventable admission to hospital (OR 51.20, 95% CI 39.06-67.11).

10.	Patterns of referral and waiting times for specialist child and adolescent mental health services.	Smith, Kyle, Daniel, & Hubbard.	2018	Retrospective analysis of referral data looking at referral sources, reasons and outcomes, and cross referencing this with sociodemographic characteristics including deprivation indices	Scotland-one CAMHS service	Child and Adolescent Mental Health service	Data from 476 referrals over 12 month period	Scottish Index of Multiple deprivation quintile (2012 data)	Age, gender, referral reason, referral source	Referral outcomes and waiting times	Regression analysis to determine predictors of referral rejection and waiting times for referrals accepted.	In this study, very few referrals where made from deprived areas, however those who were referred were waiting the longest to be seen.
11.	Variation in compulsory psychiatric inpatient admission in England: A cross-sectional, multilevel analysis.	Welch, McBride, Twig, Keon, Cyhlarova, Crepaz-Keay, Parsons, Scott & Bhui.	2014	Cross sectional analysis of compulsory psychiatric inpatient admissions in England, using multilevel statistical modelling	England	Inpatient mental health care (tertiary services)	1,287,730 patients data (106,719 classed as 'admitted' in study)	English Index of Multiple Deprivation (IMD) 2011 census data.	Age, gender, ethnicity, ethnic density, primary care trust investments in mental health services	Time spent in inpatient mental illness beds subject to Mental Health Act (2007)	Multilevel regression analysis with compulsory admission to hospital under Mental Health Act (MHA) as the main outcome variable	3.5% of psychiatric patients had at least one compulsory admission in 2010/11. There was statistically significant variance at LSOA level [6.6%, 95% CI 6.2%-7.2%] with an apparent dose/response effect i.e. areas with higher levels of deprivation led to

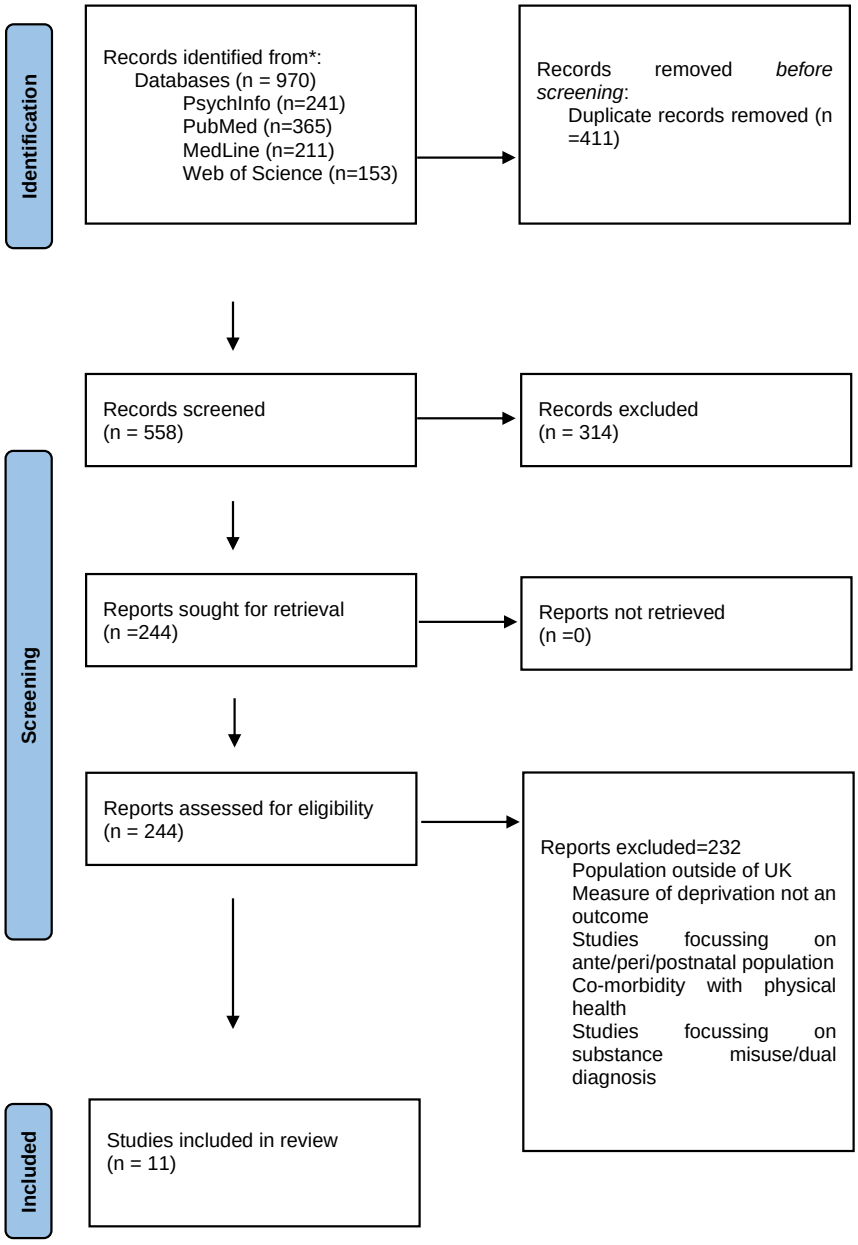
												increased risk of compulsory detention.

Results

The screening process for this review yielded eleven peer reviewed journal articles that met the inclusion criteria. Figure 1 (below) presents this process in the form of a flow chart. The types of studies referred to in the articles where all secondary analyses of routinely collected administrative data. Seven of the studies looked evaluated specific services (Improving Access to Psychological Therapies (IAPT) services (n=4), Accident and Emergency Services (A&E) (n=1), Crisis resolution and home treatment services (n=1), Community mental health teams (CMHT) Child and Adolescent Mental Health services (CAMHs)). The other three studies looked at data across services, linking data across primary care, secondary care (community mental health services) and tertiary care (inpatient mental health services).

Four broad categories emerged; Associations between area level deprivation and access to mental health services, unplanned mental health care and associations with area level deprivation and associations between area level deprivation and successful outcomes following psychological intervention, and healthcare costs associated with deprivation. From the studies selected, the total number of single data cases explored was n≈ 57,310,558 (numbers from one study not specified, but estimated at 48,500,000 based on population information provided (Maconick et al., 2021)) , with the number of single cases in each study ranging from 260 to 48,500,000, median value 293,400. Table 2 (above) evidences how each article reviewed met the criteria of this study.

Figure 1: PRISMA flowchart. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71



Access to services associated with area level deprivation

From the papers reviewed, there was evidence that higher number of referrals for IAPT services are moderately associated with greater levels of local area deprivation. The same level of association was not necessarily representative of people who are on an IAPT caseload, which suggests that whilst need may be higher in more disadvantaged areas, this is not reflected in rates of service access (Delgadillo et al., 2016). Delgadillo et al. (2018) explored potential systemic barriers they termed to be the "Access Gap" between referral to service and starting psychological therapy. They hypothesised that either services in poorer areas were underfunded and therfore unable to meet need based on workforce factors, or that deprivation in and of itself creates obstacles that prevent access to treatment even when it is available. The results of their regression analysis discounted workforce resourcing as the explanation, and suggested instead that people living in more deprived areas are likely to be experiencing higher levels of co-morbidity, disability and role impairment, which may contribute to difficulties in accessing services.

De Lusignan et. al (2011) found that people who had been accepted into IAPT services where from less deprived areas. This was despite the prevelance rates for common mental health problems being higher for those who lived in more deprived areas (de Lusignan et al., 2011). Reasons hypothesised by the authors include the assertion that there may have been an element of selection bias in the early days of evaluation of IAPT services. This selection bias could have led to an unconcious withholding of services for people who lived in more socioeconomically deprived areas as they may also have been less likely to show improved outcomes due to the environmental level factors discussed above (de Lusignan et al., 2011; Delgadillo et al., 2016, 2018; Maconick et al., 2021). The 'unconsious' bias explanation is

speculative at best, as there could be other mechanisms at play e.g appropriateness of referrals; does living in a more deprived area mean the liklihood of requiring mental health support at a level of intesity that is beyond what IAPT services are designed to offer? The design of these studies fails to address clinician decision making processes as they are focussed entirely on administative data and demographic identifiers.

There was some evidence that children and young people in more socioeconomically deprived areas had to wait longer on waiting lists to access mental health support than their counterparts who lived in more affluent areas (Smith et al., 2018). This particular study was looking at just one Child and Adolescent Mental Health service in Scotland, so this finding could just be something specific to this service. Repeating this study and looking at waiting times across multiple CAMHs sites would be needed in order to prove or disprove this claim.

Unplanned use of Mental Health Services associated with area level deprivation

Area level deprivation (adjusted IRR 1.02 95% CI 1.01 to 1.04; $p < 0.001$) is identified as a risk factor for being in contact with primary and secondary mental health services, along with unemployment, and living in an area with a higher Black and Minority Ethnic (BAME) population (Maconick et al., 2021). For each unit increase in area deprivation score using the IMD rank criteria, the odds of needing to access mental health services increase by 2% (Maconick et al., 2021). There is a statistically significant association with area level deprivation and involuntary hospital admission under the Mental Health Act (2007), and the likelihood of admission increased across the quintiles of deprivation, moving from least to most deprived (Weich et al., 2014)

Unplanned mental health care provided in hospital emergency departments shows a similar gradient of increased usage amongst those who live in more deprived areas. In 2013/14, 59.9%

of all mental health attendees to English A&E departments lived in the two most deprived quintiles of the English IMD (Baracaia et al., 2020). As in the Maconick et al. (2021) study, there is a skew towards white British people in deprived areas attending as opposed to those from BAME communities (Baracaia et al., 2020). Non-attendance for mental health appointments with general practitioners in primary care is more likely to occur amongst those living in more deprived areas and is associated with an increased likelihood of unplanned hospital attendance (Payne et al., 2013. There is a known association between physical and mental health comorbidity, and it has been demonstrated that individuals living in the most deprived areas of Scotland have greater levels of physical and mental comorbidities than their more affluent counterparts do. This in turn correlates with higher levels of unplanned hospital admissions, with 23% of unplanned admissions coming from the most deprived quintile compared with 11.8% in the least deprived (Payne et al., 2013)

Mental health care costs and the association with area level deprivation

One paper reviewed focussed on the economic burden associated with the cost of providing mental health care services, and increased spending demands in deprived areas. In Kent, England, it was determined that the mean per capita health care spend in over 55's increased with deprivation across each quintile, with a per capita cost in more affluent areas of £1205 versus £1623 in the most deprived for all areas of health (Jayatunga et al., 2019). Jayatunga and colleagues also report that the socioeconomic inequalities accounted for around 15% of all health and social care costs in their target population, but this increased to 27.1% when looking at mental health care costs by themselves. If the findings from this study were generalizable across England, then it would indicate that £2.63bn of the £9.72bn spent on mental health care in 2019 was a product of socioeconomic inequality; money which could be allocated towards initiatives to reduce inequality.

Outcomes of Mental Health Intervention Associated with Area Level Deprivation

In this review, there was only three studies reported treatment outcomes in the context of area level socioeconomic deprivation. Two of these studies were based in services providing psychological therapies, and the third was a Crisis Resolution home treatment service. People living in the most deprived areas had poorer treatment outcomes, were less likely to reach IAPT "recovery" criteria, and were more likely to drop out of psychological therapy (Delgadillo et al., 2016). Kingsford & Webber (2010) studied outcomes across 260 accepted referrals to a Crisis Resolution and Home Treatment Team service and found that people from the more socioeconomically deprived areas were both more likely to be referred and have poorer treatment outcomes than their counterparts in areas that are more affluent. This group of people were also more likely to be referred to the service from enhanced community mental health teams, indicating a relationship between a greater level of mental health need, social deprivation and poorer crisis resolution home treatment team outcomes (Kingsford & Webber, 2010).

Assertive outreach into more socioeconomically deprived areas, collaborative care between psychological and social care providers or creative approaches to tackling inequality could be beneficial in meeting the needs of individuals from more deprived areas (Delgadillo et al., 2018). One such creative approach is discussed in the case study sample presented by Firth et al. (2020), where participants in a stress reduction programme provided by IAPT who came from similarly deprived areas were more likely to complete an adequate number of sessions to gain the benefit from the intervention ($n \geq 4$ out of 6) than their counterparts who came from more diverse areas (78.6% chance of adequate attendance for similar groups versus 63.5% for groups with a greater mismatch; this result was significant ($p=.026$)). This suggests that sociodemographic comparison may consciously (or unconsciously) impact on attendance to group based psychological interventions (Firth et al., 2020), this may explain some of the variance in attendance and outcomes discussed earlier (Delgadillo et al., 2016, 2018).

Discussion

This review highlights how despite the acknowledged relationship between area level deprivation and psychiatric morbidity, there is a paucity in published studies that consider the local area deprivation in the context of mental health service delivery and accessibility. The studies that are available for scrutiny clearly demonstrate that local area deprivation is a factor which correlates with reduced access to services, unplanned utilisation of services (for example, accessing help via A&E), higher numbers of dropouts in group based interventions and poorer results on service based outcome measures. There are resulting economic costs related to general service demand, but also associated with higher levels of unplanned care and emergency Mental Health Act (2007) admissions to hospital. When studies controlled for area level deprivation by matching people in groups with others from similar areas, there was a limited amount of evidence that suggests this leads to better outcomes for individuals.

What is not explicitly stated, but could be hypothesised based on these findings, is that stress associated with living in socioeconomically deprived areas in and of itself plays a causal role in the development and maintenance of psychological distress, meaning that without tackling the endemic causes of poverty and deprivation, people will remain under stress and experiencing psychological distress.

The primary area of focus in this review has been area level deprivation and the role that plays an individual's ability to access and use mental health services, however it is important to acknowledge how there are multiple other confounding variables which will both contribute to the likelihood of someone living in a more deprived area versus an affluent area, which may also play a role in and of themselves in the likelihood of a person needing or using mental health services. This intersectionality of different demographics e.g., area level deprivation, age, gender, ethnicity, multimorbidity etc is a complex subject. The studies reviewed here had differing levels of attention given to explore some of this intersectionality. Baracaia et al. (2020) gave special mention the those who could not be categorised as having an area level

deprivation quintile due to homelessness, and how these individuals were four times more likely to have a mental health diagnosis than those even in the most deprived areas, and Delgadillo et al. (2018) reported an upwards linear trend in common mental disorder prevalence rates as area level deprivation increased across quintiles. Age and employment status were predictors of attendance to psychological therapy in the study by Firth et al (2020), with younger, unemployed people living in the most deprived areas being the least likely to attend an adequate number of sessions for intervention success. Both area level deprivation and unemployment were associated with the more contact with mental health services when mental health prevalence rates had been controlled for in the Mackonick et al (2021) study, and the presence of physical health conditions further increases the likelihood of contact with mental health services (Payne et al, 2013). Ethnicity was reported on in several studies, but was not singled out as a significant predictor of contact with mental health services in these studies, but there was not much discussion about the relationship between being part of an ethnically marginalised group and the likelihood of living in areas with higher socioeconomic deprivation. Further review would need to be completed to explore the impact of this intersectionality in greater depth.

Limitations of review

As evidenced by the small number of papers reviewed, there is a paucity of published research that explicitly used IMD data as a covariate to explore variations in how individuals are accessing or using mental health services. This means that conclusions reached may not be fully reflective of the lived experience of people. Many of the studies reviewed here were from Scotland or South-East England, so these findings may not be generalizable across the whole of the UK. It is also noteworthy that each home nation has its own IMD, so they are not directly comparable, although it is generally considered that the similarities are great enough to allow for comparison even with the resultant loss of a small amount of data. Whilst the aim of this

review was to explore the impact of geographical variation and service use, it is important to note that individual circumstances within each area will differ. It is not possible to determine how much an individual's circumstances will match the defined level of deprivation for that area.

With the findings of this review looking at a range of services (IAPT, CRHT, CAMHS, Inpatient mental health) it may not be appropriate to assume that findings that relate to a primary care level community based stress reduction programme are applicable to an inpatient who is detained under the Mental Health Act (2007), yet the trend that is common throughout each study is that there is evidence to suggest that people who live in more deprived areas are at a greater risk of not receiving an equitable service, regardless of what type of service.

Further limitations are apparent in the incomplete application of PRISMA guidelines during the selection and screening process of the studies included in this review. Search terms used could have been more inclusive and less confusing. The lack of a critical appraisal tool could have led to appropriate studies being screened out. Discussions have been held regarding these limitations and the author fully accepts that the pragmatic constraints that led to the omission of certain key features of a full systematic review, have impacted upon the quality of this piece of research. Further discussion is had around this in chapter 3. Despite the limitations, these studies do provide evidence that is suggestive that area level deprivation does play a causal role in the way in which individuals are able to access Mental Health Services and how these services are used. Area level deprivation is a multifaceted concept in itself, and there are additional confounding variables that lead to deepening intersectionality which can increase the likelihood of a person living in greater deprivations. The studies that attempted to control for confounding variables did find that area level deprivation was, in itself, accountable for the variations in the outcomes being measured, but not all studies controlled confounding variable in this way. I hope that as more researchers look to utilise administrative data in their studies,

controlling for area deprivation becomes as normalised as controlling for other standard demographic data.

Conclusion

This review highlights how despite the acknowledged relationship between area level deprivation and psychiatric morbidity, there is a paucity in published studies that consider the local area deprivation in the context of mental health service delivery and accessibility. The studies that are available for scrutiny clearly demonstrate that local area deprivation is a factor which correlates with reduced access to services, unplanned utilisation of services (for example, accessing help via A&E), higher numbers of drop outs in group based interventions and poorer results on service based outcome measures. There are a resulting economic costs related to general service demand, but also associated with higher levels of unplanned care and emergency mental health act admission in to hospital. When studies controlled for area level deprivation by matching people in groups with others from similar areas, there was a limited amount of evidence that suggests this leads to better outcomes for individuals.

What isn't explicitly stated, but could be hypothesised based on these findings is that stress associated with living in socioeconomically deprived areas in and of itself plays a causal role in the development and maintenance of psychological distress, meaning that without tackling the endemic causes of poverty and deprivation, people will remain under stress and experiencing psychological distress

Bibliography

Baracaia, S., McNulty, D., Baldwin, S., Mytton, J., Evison, F., Raine, R., Giacco, D., Hutchings, A., & Barratt, H. (2020). Mental health in hospital emergency departments: Cross-sectional analysis of attendances in England 2013/2014. *EMERGENCY MEDICINE JOURNAL*, *37*(12), 744–751. https://doi.org/10.1136/emermed-2019-209105

Barr, B., Kinderman, P., & Whitehead, M. (2015). Trends in mental health inequalities in England during a period of recession, austerity and welfare reform 2004 to 2013. *Social Science & Medicine*, *147*, 324–331. https://doi.org/10.1016/j.socscimed.2015.11.009

Census 2021 geographies—Office for National Statistics. (n.d.). Retrieved 16 June 2023, from https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographies/census2021geographies

Cooper, S. -A., McConnachie, A., Allan, L. M., Melville, C., Smiley, E., & Morrison, J. (2011). Neighbourhood deprivation, health inequalities and service access by adults with intellectual disabilities: A cross-sectional study. *Journal of Intellectual Disability Research*, *55*(3), 313–323. APA PsycInfo®. https://doi.org/10.1111/j.1365-2788.2010.01361.x

Cummins, I. (2018). The Impact of Austerity on Mental Health Service Provision: A UK Perspective. *International Journal of Environmental Research and Public Health*, *15*(6), 1145. https://doi.org/10.3390/ijerph15061145

de Lusignan, S., Navarro, R., Chan, T., Parry, G., Dent-Brown, K., & Kendrick, T. (2011). Detecting referral and selection bias by the anonymous linkage of practice, hospital and clinic data using Secure and Private Record Linkage (SAPREL): Case study from the evaluation of the Improved Access to Psychological Therapy (IAPT) service. *BMC MEDICAL INFORMATICS AND DECISION MAKING*, *11*. https://doi.org/10.1186/1472-6947-11-61

Delgadillo, J., Asaria, M., Ali, S., & Gilbody, S. (2016). On poverty, politics and psychology: The socioeconomic gradient of mental healthcare utilisation and outcomes. *The British Journal of Psychiatry*, *209*(5), 429–430. APA PsycInfo®. https://doi.org/10.1192/bjp.bp.115.171017

Delgadillo, J., Farnfield, A., & North, A. (2018). Social inequalities in the demand, supply and utilisation of psychological treatment. *Counselling & Psychotherapy Research*, *18*(2), 114–121. APA PsycInfo®. https://doi.org/10.1002/capr.12169

Firth, N., Delgadillo, J., Kellett, S., & Lucock, M. (2020). The influence of socio-demographic similarity and difference on adequate attendance of group psychoeducational cognitive

behavioural therapy. *Psychotherapy Research*, *30*(3), 362–374. APA PsycInfo®. https://doi.org/10.1080/10503307.2019.1589652

Kingsford, R., & Webber, M. (2010). Social deprivation and the outcomes of crisis resolution and home treatment for people with mental health problems: A historical cohort study. *Health & Social Care in the Community*, *18*(5), 456–464. APA PsycInfo®. https://doi.org/10.1111/j.1365-2524.2010.00918.x

Knapp, M. (2012). Mental health in an age of austerity. *Evidence Based Mental Health*, *15*(3), 54–55. https://doi.org/10.1136/ebmental-2012-100758

Maconick, L., Rains, L., Jones, R., Lloyd-Evans, B., & Johnson, S. (2021). Investigating geographical variation in the use of mental health services by area of England: A cross-sectional ecological study. *BMC HEALTH SERVICES RESEARCH*, *21*(1). https://doi.org/10.1186/s12913-021-06976-2

McLean, G., Gunn, J., Wyke, S., Guthrie, B., Watt, G. C., Blane, D. N., & Mercer, S. W. (2014). The influence of socioeconomic deprivation on multimorbidity at different ages: A cross-sectional study. *The British Journal of General Practice*, *64*(624), e440–e447. https://doi.org/10.3399/bjgp14X680545

NIMDM17_Description of Indicators.pdf. (n.d.). Retrieved 16 June 2023, from https://www.nisra.gov.uk/sites/nisra.gov.uk/files/publications/NIMDM17_Description%20of%20Indicators.pdf

Payne, R. A., Abel, G. A., Guthrie, B., & Mercer, S. W. (2013). The effect of physical multimorbidity, mental health conditions and socioeconomic deprivation on unplanned admissions to hospital: A retrospective cohort study. *Canadian Medical Association Journal*, *185*(5), E221–E228. APA PsycInfo®. https://doi.org/10.1503/cmaj.121349

Penney, B. (2019). *The English Indices of Deprivation*. Ministry of Housing, Communities and Local Government. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/835115/IoD2019_Statistical_Release.pdf

Popay, J., Roberts, H., Sowden, A., Petticrew, M., Arai, L., Rodgers, M., & Britten, N. (2006). *Guidance on the Conduct of Narrative Synthesis in Systematic Reviews*. 92.

SIMD+2020+technical+notes.pdf. (n.d.). Retrieved 16 June 2023, from https://www.gov.scot/binaries/content/documents/govscot/publications/statistics/2020/09/sim

d-2020-technical-notes/documents/simd-2020-technical-notes/simd-2020-technical-notes/govscot%3Adocument/SIMD%2B2020%2Btechnical%2Bnotes.pdf

Smith, J., Kyle, R. G., Daniel, B., & Hubbard, G. (2018). Patterns of referral and waiting times for specialist child and adolescent mental health services. *Child and Adolescent Mental Health*, *23*(1), 41–49. APA PsycInfo®. https://doi.org/10.1111/camh.12207

Social determinants of health: Key concepts. (n.d.). Retrieved 16 June 2023, from https://www.who.int/news-room/questions-and-answers/item/social-determinants-of-health-key-concepts

The National Statistics Socio-economic classification (NS-SEC)—Office for National Statistics. (n.d.). Retrieved 16 June 2023, from https://www.ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatisticssocioeconomicclassificationnssecrebasedonsoc2010#category-descriptions-and-operational-issues

United Nations Development Programme. (2020). *Tackling Social Norms: A game Changer for Gender Inequalities*. UN. https://doi.org/10.18356/ff6018a7-en

Weich, S., McBride, O., Twigg, L., Keown, P., Cyhlarova, E., Crepaz-Keay, D., Parsons, H., Scott, J., & Bhui, K. (2014). *Variation in compulsory psychiatric inpatient admission in England: A cross-sectional, multilevel analysis*. NIHR Journals Library. https://doi.org/10.3310/hsdr02490

Welsh Index of Multiple Deprivation (WIMD) 2019: Guidance. (n.d.).

Williamson, A., McQueenie, R., Ellis, D., McConnachie, A., & Wilson, P. (2021). ‘Missingness’ in health care: Associations between hospital utilization and missed appointments in general practice. A retrospective cohort study. *PLOS ONE*, *16*(6). https://doi.org/10.1371/journal.pone.0253163

Chapter 2: Empirical Paper

Depression and Welfare Reform: An Interrupted Time Series Analysis of Antidepressant Prescribing Rates in Wales during the implementation of Universal Credit

Abstract

Background: This study explores trends in antidepressant prescribing in Wales during the phased introduction of Universal Credit to determine if antidepressant prescribing rates in each county, and nationally were altered during the rollout period.

Method: Prescribing data for the study period was gathered for all GP practices across Wales. Data pertaining to antidepressant prescribing plus two control classes of medication (antibiotics and anti-gout medications) was extracted using British National Formulary (BNF) codes and Defined Daily Doses (DDDs) where calculated to create a standardised statistical unit to allow medications of different types and dosages to be compared. An Interrupted Time Series model was then applied to determine if a population level intervention interrupted the underlying trend of prescribing.

Results: Following analysis, it was established that there was a change in the underlying trend of antidepressant prescribing in the post-intervention condition, with an acceleration of antidepressant prescribing rates after Universal Credit was introduced immediately in each county.

Conclusion: By using antidepressant-prescribing rates as a proxy for levels of depression experienced by individuals living through these changes, these findings indicate that the introduction of Universal Credit led to higher rates of diagnosable depression, or exacerbation of pre-existing depressive conditions. The findings from this study support previous qualitative studies that made claim to Universal Credit implementation leading to a worsening of mental health symptoms. It highlights how major policy change led to adverse consequences for the people who were at the greatest risk of being impacted by major fiscal policy and welfare changes.

Keywords: *Welfare reform, Universal credit, antidepressant prescribing, depression, social policy and mental health, Interrupted Time Series Model, impact of austerity*

Introduction

Since 2010, the United Kingdom (UK) government have implemented a series of policies in response to the 2008 global financial crisis, which are referred to as the "austerity agenda" (Mattheys, 2015). Part of the response to the financial crisis was an overhaul of the social security system that provides welfare benefits for people in need, and the introduction of a new welfare benefit called Universal Credit.

According to the Centre for Welfare Reform (2015), fifty percent of the spending cuts fell in within two areas: social security (welfare) benefits and local government spending (Cummins, 2018). These two areas only account for 25% of government spending, thus disproportionately affecting some of the most vulnerable members of our society. One of these policies was to replace and combine six existing social security "benefits" and replace them with a new payment method called Universal Credit (UC). This policy became legislation in 2012 with the creation of the Welfare Reform Act 2012, and in 2013, the new benefit was introduced in selected job centres. On average, austerity led to a 20% reduction in the amount of benefit payment an individual would receive. Part of the aim of Universal Credit was to end a position created by the "legacy" benefits whereby for some people they were better off financially to be out of work, so this would enable people to take up employment without fearing a drop in income. Universal Credit is paid monthly, whereas the older legacy benefits were paid fortnightly. The first payment of Universal Credit is paid in arrears, which can place undue financial hardship on claimants when they must wait up to six weeks for their first payment. In some instances, this has led to people ending up in rent arrears and at risk of eviction from their housing providers (Cummins, 2018).

Many people who are in receipt of state benefits are living with disabilities, mental health problems and are classed as living in poverty (Cummins, 2018). There is an imbalance in the impact of austerity on communities, in that former industrial areas have been worse affected by the impact of austerity cuts and welfare reform (Bambra & Garthwaite, 2015).

There is a well-documented relationship between financial hardship and mental health difficulties (Knapp, 2012) It is thought that the relationship between hardship and mental health is bi-directional or reciprocal; financial poverty can cause stress which leads to mental health problems, and conversely, mental health difficulties can lead to people finding it difficult to manage financial affairs (Knapp, 2012). One important source of evidence for the effects of financial hardship upon mental health is 'natural experiments' based on policy changes or other financial shocks.

Issues of causality with the relationship between poverty, inequality and poor mental health are complex (Cummins, 2018) however there have been studies published, which explore the relationship between economic hardship because of the recession and austerity and increased mental health difficulties. Barr et al., (2015) postulate that the policy changes that came about because of the austerity agenda increased levels of social inequality within the UK and this has contributed to greater rates of self-reported mental health difficulties. Unemployment, a drop in income, unmanageable debt, housing problems and social deprivation are all significant related to higher mental health needs (Knapp, 2012). A 2019 survey of 35 NHS Mental Health service providers in England noted that the biggest external pressure to increased service demand was financial hardship, followed by changes to benefits including universal credit (Evans, 2019). Mental health charities have been particularly critical of the implementation of Universal Credit, stating that it has left many vulnerable people worse off, and this in turn has had a devastating effect on the mental health of its recipients (Evans, 2019).

It is possible to use routinely collected administrative data to assess the impact of an

intervention or event upon mental health at a population level. Wickham et al (2020) used routinely collected data from the "Understanding Society UK Longitudinal Household panel survey" and through responses given on the health questionnaire segment, crosslinked with data regarding employment status, it was determined that since the introduction of universal credit, the population level prevalence of psychological distress had increased by 6.57%, and 63,674 unemployed people reported experiencing psychological distress, with 21,760 meeting the clinical threshold for a depression diagnosis. The conclusion come to by Wickham et al (2020) was that the introduction of Universal Credit has led to an increase in psychological distress amongst those who are affected by the policy.

The health survey data in the Wickham et al (2020) study was self-reported, subjective data. Some studies have utilised prescribing data for psychotropic medication, whereby the number of prescriptions issued acts as a proxy for the level of psychological distress/mental health difficulties being experienced by the populace. Researchers in Spain used prescribing data following the 2008 financial crisis and found that there was an increase in psychotropic drug consumption after the financial crisis, and people who had previously been taking psychotropic medications where more likely to be taking higher doses post crisis (Barceló et al., 2016). In the UK, Vandoros et al., (2019) used drug prescribing data to determine that following the EU referendum vote there was an increase in demand for antidepressant prescriptions.

Hypothesis

When Universal Credit was introduced, it was gradually 'rolled out' on a county-by-county basis. This phased roll out lends itself neatly to exploring if areas that have had Universal Credit introduced have different levels of antidepressant prescribing rates per capita compared to areas that were still on the legacy benefit system. It is hypothesised that the introduction of Universal Credit to an area will lead to an increase and an acceleration of the number of per capita prescriptions for antidepressants being prescribed and dispensed when compared to those areas

using the legacy benefits system in the same times.

Data and Methods

Ethical approval for this study was given by the Research and Ethics Governance Committee at Bangor University (study ref: 2021-16949).

Data pertaining to prescription issuing and medication dispensing in Wales is extracted from Primary Care Dispensing and Information Systems (NWSSP, 2022a) It is updated monthly and contains information about all prescriptions issued in Wales by General Practitioners (GP's) and other none-medical practitioners on behalf of GP surgeries in Wales. Monthly data is published online the NHS Wales Shared Services Partnership website and it contains public sector information licensed under the Open Government Licence v3.0 allowing it to be used freely and flexibly.

The extract shows the total number of prescriptions issued for each drug, and the total number of dosages prescribed for each drug by each individual unique practice ID each month. For the purposes of this study, all data for antidepressant medications, that were prescribed by a GP practice in Wales between April 2016 and December 2019 was used. Any primary care provider that was not a GP practice was excluded from the analysis e.g. community drug and alcohol services, out of hours GP provision and criminal justice system healthcare providers. All data used was population level data; no individual data was extracted from the prescribing records and no individual level demographics were reported.

The number of antidepressant medications being prescribed by GP's was used as a proxy measurement of population level psychological distress on a month-by-month basis. To compare drugs across different brands, types and classes, a statistical unit called the "Defined Daily Dose" (DDD) can be calculated. DDD's provides a fixed unit of measurement to enable research in drug consumption trends irrespective of "price, currencies, package size and strength" DDD's are allocated to drugs based on their "Anatomical Therapeutic Compound" (ATC) code (WHO, 2021). To put this is to context, a 50mg prescription for Sertraline (an

antidepressant) is one DDD, a 200mg prescription of the same drug is four DDD. If you were to compare that to another antidepressant drug, Citalopram, 10mg of Citalopram is one DDD, 200mg of Citalpram would be twenty DDDs. The use of DDDs enables trends over time to be accounted for, so if a person started on 50mg of a drug (one DDD), then ends up on 150mg of that same drug (three DDD) then this would indicate a potential worsening of a condition, but the number of drugs prescribed would not change. Conversely if a person switched from one drug to another, the DDD calculation would determine if the new drug was more potent of not, rather than a change in preparation that comes in a dosage that is a larger number of milligrams. As the drug data published in the GP prescribing index use BNF codes, medication names were manually cross-referenced with ATC codes to enable DDD calculations to be made. See appendix one for the cross-referenced BNF and ACT codes used to gather DDD information for antidepressant drugs included in this study.

Where previous studies have utilised antidepressant-prescribing data as a proxy to measure population level wellbeing, it is common practice to use other classes of drugs as controls. For this study, the control drug classes will be anti-gout medication and antibiotics, the rationale being that anti-gout medication prescribing trends have previously been shown to not be affected by area level changes (Vandoros et al., 2019) and antibiotic prescribing trends have been shown to follow similar patterns in discrete GP prescribing practices as antidepressant prescribing (Spence et al., 2014). Appendix two details the names and BNF code prefixes for all of the drugs used for analysis purposes in this study.

Data relating to numbers of registered patients per GP surgery in Wales is collected annually (NWSSP, 2022b). The mean number of patients per GP surgery was calculated over the duration of the study period as this figure was not static. The number of patients in each GP surgery allowed to calculation of a ‘per capita’ figure for medication prescribing at each surgery and it was this average number of DDD’s per capita per month by GP surgery data

which was used in this analysis.

When an intervention at a population level is implemented over a clearly defined period of time, Interrupted Time Series (ITS) modelling is regarded as a strong method of data analysis (Lopez Bernal et al., 2016). In this instance, the population level 'intervention' is the implementation of Universal Credit. Over a period of two years, each local authority area in Wales introduced Universal Credit; a roll out schedule is available in appendix three (Universal Credit, 2018). In this study, all relevant prescribing data for each county was aggregated and then a dummy variable was assigned to determine in the number of prescriptions was 'pre' or 'post' roll out (0=pre, 1=post). Once each county was started to provide welfare benefits in the form of Universal Credit, that county became a 'post' implementation area. To ensure that there was enough of a pre/post comparison for each county, data was collected for a minimum of 12 months either side of the implementation date. Flintshire was the first Welsh county to implement UC in April 2017, with rollout completion by December 2018.

Data Analysis

R. statistical modelling software, version 4.0.2 was used to analyse the aggregated prescribing data. Defined daily doses for each class of drugs (antidepressants, antibiotics and anti-gout preparations) where calculated and summed for each month (April 2016 – December 2019), then divided by the number of registered patients in the surgery, then multiplied by 30 to determine a 'monthly per capita' level of prescribing for each GP practice within each local authority area (22 in total). For every month, each local authority area was ascribed a dummy variable to indicate if the prescribing data was from pre-universal credit roll out (pre=0) or post-roll out (post =1).

Results

The Interrupted time series regression model was applied and figure one shows a scatter plot of the time series for each drug class over time, with the orange line indicating measures taken pre intervention, and the blue representing post intervention. Figure 2 shows the data for

antidepressants only. Figure 1 shows that for the control classes of medication there is very little change in prescribing trends generally, nor is there an impact from the introduction of universal credit. Figure 2 shows the antidepressant-prescribing trend in detail. There is a general upwards trend regarding the number of antidepressant medications being prescribed over time, Strikingly, there is evidence of both step change and slope change in the number of antidepressants being prescribed post-universal credit roll out which indicates an acceleration of antidepressant prescribing rates which is significantly higher than the baseline trend (Table 1).

Antidepressant prescribing trends increased over the time period of this study, which corroborates other evidence of increasing antidepressant prescribing (Lalji et al., 2021; Mars et al., 2017). It also shows that the difference in prescribing rates between the pre-roll out areas and the post-roll out areas was significant, indicating that there was a marked increase of Defined Daily Doses of antidepressant medication following the introduction of universal credit within a local authority area, compared to other counties in the same time period who were not yet on the Universal Credit system. This methodology controls for the upward linear trend of antidepressant prescribing, so differences between the ‘pre’ and ‘post’ conditions could feasibly be attributed to a change in condition, which is hypothesised here to be the change in the method of receiving state welfare benefits. This step change plus acceleration of prescribing occurs at each conditional change point in all 22 counties as visualised in figure 3.

Table 1: Time series regression data for Antidepressant, Antibiotic and Anti-Gout medication prescribing in Wales. Data was collected monthly for the period April 2016-December 2019. Data consists of the average number of defined daily doses of each medication prescribed per capita every month by each individual GP practice. Per capita figure represents the mean number registered patients during the study period. Each month, the GP practice was assigned a dummy variable to define if the surgery sat within a pre Universal credit roll out area, or a post universal credit roll out area. Significance at 0.001 is indicated with *** asterisks.

	Antidepressants			*Antibiotics (control 1)*			*Anti-Gout (control 2)*		
	Estimate	*SE*	*Z value*	*Estimate*	*SE*	*Z value*	*Estimate*	*SE*	*Z value*
Intercept	4.270e+00 ***	1.959e-01	21.80 ***	5.808e-01	1.132e-02	51.32	2.381e-01	9.852e-03	24.169
Pre/post UC roll out	-5.420e-03	4.877e-03	-1.11	-3.851e-03	1.294e-03	-2.98	-2.585e-04	4.096e-04	-0.631
Tine point (month/year)	7.625e-04***	1.159e-05	65.77 ***	-1.500e-05	3.075e-06	-4.88	2.891e-05	9.736e-07	29.694
Pre/post Universal credit rollout * time point interaction	9.862e-05***	1.098e-05	8.98 ***	-1.1196-05	2.915e-06	-4.10	3.931-06	9.225e-07	4.261

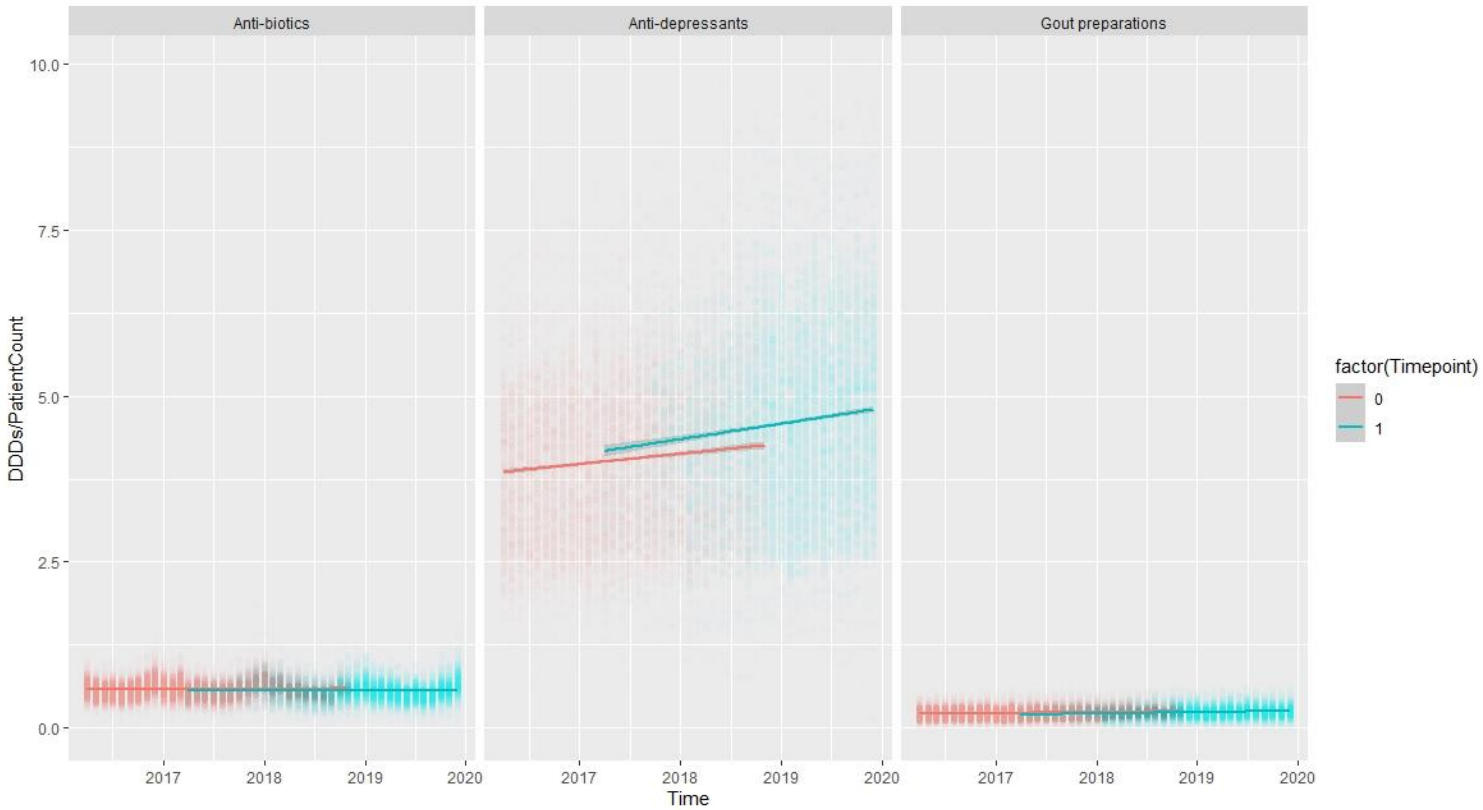


Figure 1. Scatter plots for average number of Defined Daily Doses per capita for each drug class within each GP surgery in Wales (each datapoint at each timepoint represents prescribing average DDD per capita for the population served by individual GP practices, with changes over time being noted). Orange points represent data from GP surgeries in pre-Universal Credit roll out areas and blue indicates data from prescribers in post-universal credit roll out areas. The orange regression line is for pre-universal credit roll out trends (timepoint 0), blue is post universal credit roll out regression line (timepoint 1). Prescribing rates for the control classes of drugs did not significantly alter over the period of this study.

Figure 2. Scatter plot highlighting antidepressant data only. It shows the average number of defined daily doses of antidepressant medication per patient for each GP/prescriber on a month by month basis. Each datapoint at each time point represents the data from an individual GP practice, with changes over time being noted. The prescribing data is count of all antidepressant drug prescribed across all areas only. Orange points represent the GP surgery's in areas in that are pre-universal credit roll out, blue is post roll out. The orange line is the regression line for the pre-universal credit roll out condition, the blue line is the regression line for the post universal credit roll ot condition. The gap between the lines shows a step wise increase in antidepressant DDD prescribing between the pre and post conditions. The gradient of the post implementation line is steeper than pre implementation indicating an acceleration in prescribing rates compared to pre intervention conditions

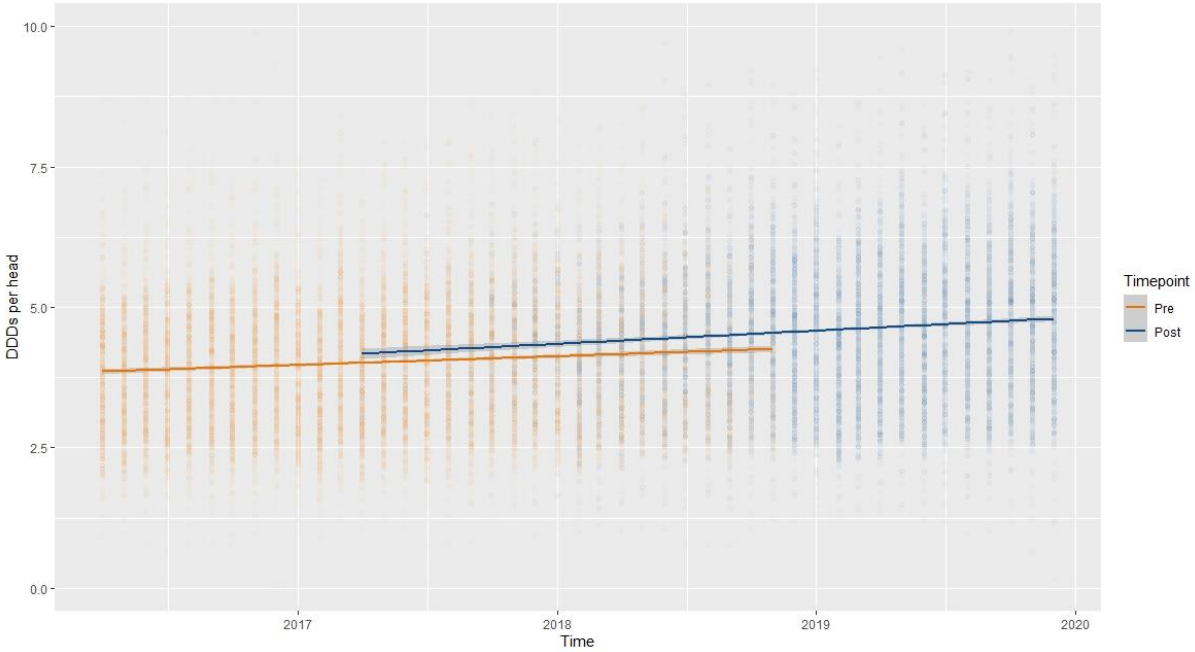
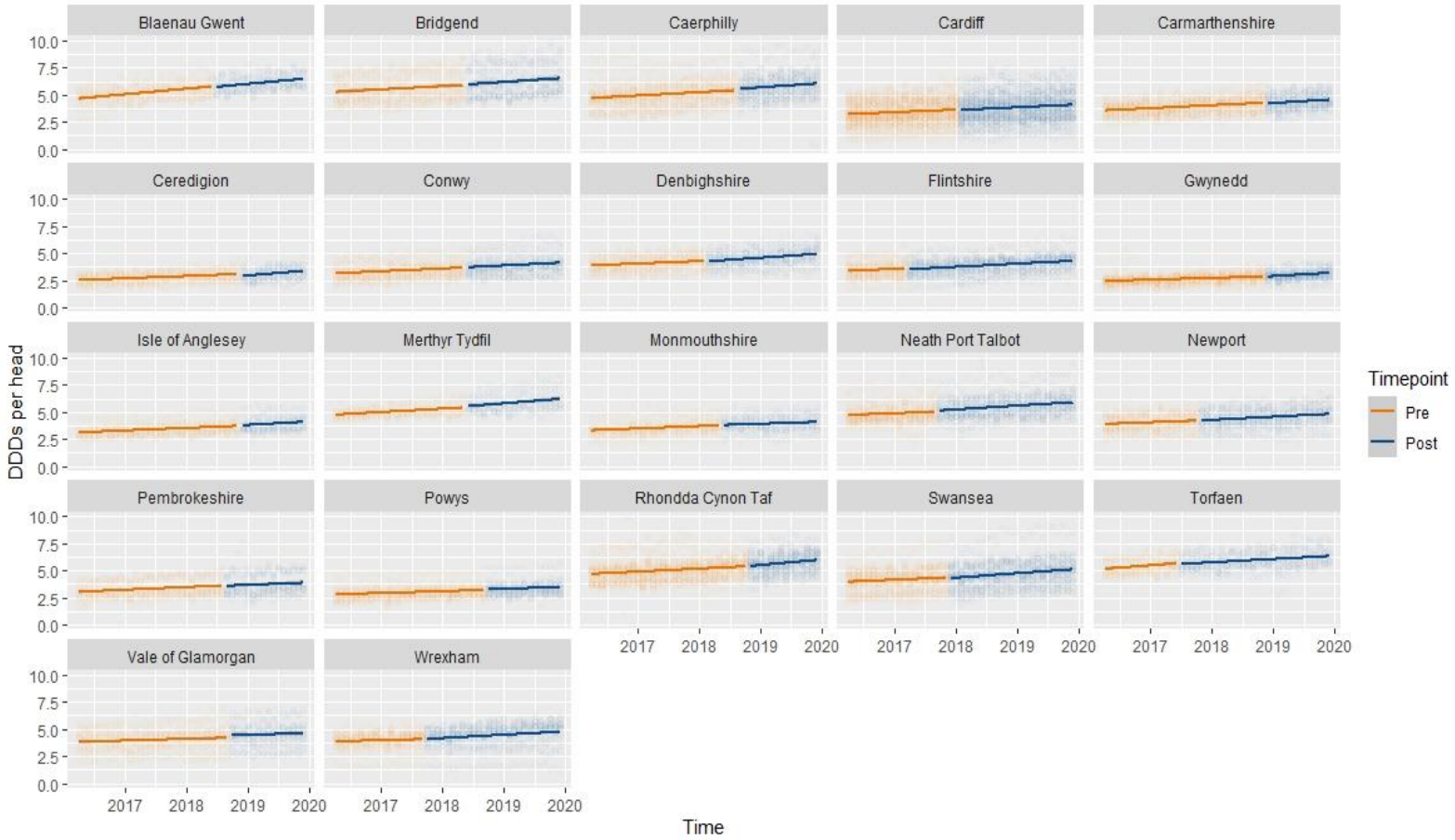


Figure 3. Scatter plots showing the average number of defined daily doses of antidepressant medication prescribing rates per capita for each GP surgery within that county area. Graphs show the data for each county in Wales, the orange regression line represents prescribing rates during the legacy benefit period, and the blue line representing antidepressant prescribing rates in the Universal Credit period.



Discussion

The results of this interrupted time series multilevel regression analysis indicate that there is a relationship between the introduction of Universal Credit, and an increase in antidepressant prescribing accelerated relative to the underlying upward trend of antidepressant prescribing more generally. This reinforces the position of previous studies which have used survey self-report data as an indicator of depressed mood in individuals who have been transferred to the new Universal Credit system from the old legacy system (Barr et al., 2015, Wickham et al., 2020). The findings of this study are rooted in objective data as opposed to self-report data which is subjective and potentially liable to reporting bias, or missing responses from populations who are most in need (Goodman & Gatward, 2008). There was no significant changes in prescribing rates for both control classes of medications, antibiotic and anti-gout preparations, with prescribing rate remaining stable. This would indicate that changes in antidepressant prescribing rates were influenced by an external variable rather than changes in prescriber practices, as discussed earlier in this paper.

Strengths

A particular strength of this study is how the naturally occurring repeated measures structure that comes from the staggered implementation of universal credit by administrative area allows for a robust interpretation of findings, given that the trend of an acceleration in antidepressant prescribing rates occurred in every county immediately in the month(s) following the introduction of Universal Credit. This suggests that populations that were the most affected by the introduction of Universal Credit (i.e. people who are out of work or are on low incomes) may have needed to seek medical attention with associated depression or low mood, and have either had more antidepressant medications prescribed than previously, or dosages have increased as captured by the number of DDD's reported per drug per surgery per month.

Seeing the replication of the same trend occur in each county where the data was broken down to local authority areas is a particular strength of this study design, as it was the natural experiment conditions of the universal credit rollout programme within each local authority that allow the conclusions made by the study to be so robust.

In Wales, NHS prescriptions for all drugs are dispensed free of charge, and not means tested as in other parts of the UK. There is evidence to suggest that paying for prescriptions can affect the way in which patients take prescribed medication and make health choices in relation to medication seeking and medication management ((Norris et al., 2015; Schafheutle, 2008; Schafheutle et al., 2002). For this reason, utilising data from Welsh GP practices means that issues such as cost barriers to accessing medication can be mitigated.

An additional strength of this study design is how it lends itself to continued longitudinal surveillance of prescribing trends. This study period ends in December 2019, which was just at the start of the COVID-19 pandemic, and pre-lockdown measures. This study design could be utilised to look at antidepressant prescribing trends when social distancing measures where enforced, to determine if there was any change in antidepressant prescribing rates during this unprecedented period.

Limitations

A limitation of using prescribing data in this manner is the underlying assumption that antidepressant prescriptions can be used as a proxy for an individual experiencing depression or emotional distress. Whilst there are clear guidelines surrounding the prescribing of antidepressant medication (NICE, 2009) some antidepressants that sit within the tricyclic category are commonly used as an adjunct to pain medications in cases of chronic pain or other medical disorders. Using prescribing data as a proxy for mental distress could also be under inclusive as there will be people who would meet the threshold for antidepressant medication but may choose not to seek medical assistance, may decline pharmacotherapy or may be engaged in psychological therapies instead. This study design does not capture this population.

With that in mind, it may be the case that this sample under-represents what could be a larger issue.

A further consideration must be given to the need for individuals to potentially evidence 'disability' in order to access benefits. This new regime pushed people to having to medicalise their difficulties in order to justify 'deservingness' (Delgadillo et al., 2016). This could in effect muddy the waters when using antidepressant-prescribing data as a pure measure of need or misery.

A point of caution needs to been raised in that not every welfare benefit recipient has yet been transferred from the old legacy system to universal credit. There have been multiple delays in the implementation of the system and whilst all new claimants and so called, 'simple' cases e.g. single people without dependents or additional health needs, were scheduled to transition first. This means that in each 'post' condition, there will be a mix of recipients receiving both the legacy benefits and some on the Universal Credit system, although it could be hypothesised that the looming impending changes once switched to a UC area could also contribute to a reduction in psychological wellbeing.

Conclusion

In the period April 2016-December 2019, antidepressant-prescribing rates in Wales continued to trend upwards on a month-by-month basis. In each county, at differing time points, there was an external event; the introduction of Universal Credit. Universal Credit changed the way in which welfare benefits would be paid to recipients, and was reported as being a source of concern for many of its intended recipients (Cummins, 2018; Evans, 2019; Mattheys et al., 2018; Thomas et al., 2018) . Using an Interrupted Time Series model to take advantage of a staggered nature of the implementation period of the Universal Credit. Rollout, this study determined that in each county there was a stepwise increase in antidepressant prescribing rates at the point of implementation for Universal Credit. This higher rate of prescribing was maintained post roll out and the rates of prescribing were accelerated in the post-roll out areas.

These findings indicate that the introduction of Universal Credit led to higher rates of diagnosable depression, or exacerbation of pre-existing depressive conditions. This in turn led to people seeking additional mental health support from general practitioners and this is demonstrated by the increase in defined daily doses of antidepressant medications prescribed, and the acceleration of increases in the areas where Universal credit had been rolled out versus the areas still on the legacy system. This trend was not replicated in the control drug classes of antibiotic medication and anti-gout medications. The findings from this study support previous qualitative studies that made claim to Universal Credit implementation leading to a worsening of mental health symptoms (Barr et al. 2015) and quantitative studies that used self-report data (Wickham et al. 2020). It highlights how major policy change led to adverse consequences for the people who were at the greatest risk of being impacted by major fiscal policy and welfare changes.

Bibliography

Bambra, C., & Garthwaite, K. (2015). Austerity, welfare reform and the English health divide. *Area*, *47*(3), 341–343. https://doi.org/10.1111/area.12191

Barceló, M. A., Coll-Negre, M., Coll-de-Tuero, G., & Saez, M. (2016). Effects of the Financial Crisis on Psychotropic Drug Consumption in a Cohort from a Semi-Urban Region in Catalonia, Spain. *PLOS ONE*, *11*(2), e0148594. https://doi.org/10.1371/journal.pone.0148594

Barr, B., Kinderman, P., & Whitehead, M. (2015). Trends in mental health inequalities in England during a period of recession, austerity and welfare reform 2004 to 2013. *Social Science & Medicine*, *147*, 324–331. https://doi.org/10.1016/j.socscimed.2015.11.009

Biglan, A., Ary, D., & Wagenaar, A. C. (n.d.). *The Value of Interrupted Time-Series Experiments for Community Intervention Research*. 19.

Cummins, I. (2018). The Impact of Austerity on Mental Health Service Provision: A UK Perspective. *International Journal of Environmental Research and Public Health*, *15*(6), 1145. https://doi.org/10.3390/ijerph15061145

Delgadillo, J., Asaria, M., Ali, S., & Gilbody, S. (2016). On poverty, politics and psychology: The socioeconomic gradient of mental healthcare utilisation and outcomes. *The British Journal of Psychiatry*, *209*(5), 429–430. APA PsycInfo®. https://doi.org/10.1192/bjp.bp.115.171017

Evans, N. (2019). In the balance: Austerity and its toll on mental health services. *Mental Health Practice*, *22*(3), 8–10. https://doi.org/10.7748/mhp.22.3.8.s7

Goodman, A., & Gatward, R. (2008). Who are we missing? Area deprivation and survey participation. *EUROPEAN JOURNAL OF EPIDEMIOLOGY*, *23*(6), 379–387. https://doi.org/10.1007/s10654-008-9248-0

Joint Formulary Committee (Ed.). (2021). *British National Formulary* (Vol. 81). BMJ Publishing and the Royal Pharmaceutical Society.

Knapp, M. (2012). Mental health in an age of austerity. *Evidence Based Mental Health*, *15*(3), 54–55. https://doi.org/10.1136/ebmental-2012-100758

Lalji, H. M., McGrogan, A., & Bailey, S. J. (2021). An analysis of antidepressant prescribing trends in England 2015-2019. *Journal of Affective Disorders Reports*, *6*, 100205. https://doi.org/10.1016/j.jadr.2021.100205

Lopez Bernal, J., Cummins, S., & Gasparrini, A. (2016). Interrupted time series regression for the evaluation of public health interventions: A tutorial. *International Journal of Epidemiology*, dyw098. https://doi.org/10.1093/ije/dyw098

Mars, B., Heron, J., Kessler, D., Davies, N. M., Martin, R. M., Thomas, K. H., & Gunnell, D. (2017). Influences on antidepressant prescribing trends in the UK: 1995-2011. *Social Psychiatry and Psychiatric Epidemiology*, *52*(2), 193–200. https://doi.org/10.1007/s00127-016-1306-4

Mattheys, K. (2015). The Coalition, austerity and mental health. *Disability & Society*, *30*(3), 475–478. https://doi.org/10.1080/09687599.2014.1000513

Mattheys, K., Warren, J., & Bambra, C. (2018). "Treading in sand": A qualitative study of the impact of austerity on inequalities in mental health. *Social Policy & Administration*, *52*(7), 1275–1289. https://doi.org/10.1111/spol.12348

NWSSP. (n.d.-a). *General Practice Prescribing Data Extract—NHS Wales Shared Services Partnership*. Retrieved 17 February 2022, from https://nwssp.nhs.wales/ourservices/primary-care-services/general-information/data-and-publications/general-practice-prescribing-data-extract/

GP Practice Analysis—NHS Wales Shared Services Partnership. (2022). Retrieved 17 February 2022, from https://nwssp.nhs.wales/ourservices/primary-care-services/general-information/data-and-publications/gp-practice-analysis/

Soumerai, S. B., Starr, D., & Majumdar, S. R. (2015). How Do You Know Which Health Care

Effectiveness Research You Can Trust? A Guide to Study Design for the Perplexed. *Preventing Chronic Disease*, *12*, E101. https://doi.org/10.5888/pcd12.150187

Spence, R., Roberts, A., Ariti, C., & Bardsley, M. (n.d.). *Focus On: Antidepressant prescribing*. 43.

Thomas, F., Hansford, L., Ford, J., Wyatt, K., McCabe, R., & Byng, R. (2018). Moral narratives and mental health: Rethinking understandings of distress and healthcare support in contexts of austerity and welfare reform. *Palgrave Communications*, *4*(1), 39. https://doi.org/10.1057/s41599-018-0091-y

Vandoros, S., Avendano, M., & Kawachi, I. (2019). The EU referendum and mental health in the short term: A natural experiment using antidepressant prescriptions in England. *Journal of Epidemiology and Community Health*, *73*(2), 168–175. https://doi.org/10.1136/jech-2018-210637

Wagner, A. K., Soumerai, S. B., Zhang, F., & Ross-Degnan, D. (2002). Segmented regression analysis of interrupted time series studies in medication use research. *Journal of Clinical Pharmacy and Therapeutics*, *27*(4), 299–309. https://doi.org/10.1046/j.1365-2710.2002.00430.x

WHO Collaborating Centre for Drug Statistics Methodology. (2021). Guidelines for ATC classification and DDD assignment 2021. Oslo, Norway, 20

Wickham, S., Bentley, L., Rose, T., Whitehead, M., Taylor-Robinson, D., & Barr, B. (2020). Effects on mental health of a UK welfare reform, Universal Credit: a longitudinal controlled study. *Lancet Public Health*, *5*, e157-164.

Chapter 3 – Reflections of Research and Implications for Theory Development and Clinical Practice

Reflections of Research and the Implications for Theory Development and Clinical Practice

This thesis attempts to contribute to existing research broadly relating to socioeconomic deprivation and the impact this has on mental health and wellbeing. Chapter 1 details a narrative systematic review of existing peer reviewed published literature, which explores the relationship between area level deprivation and mental health service access, usage and outcomes in the UK. Chapter 2 consists of an original piece of empirical research, exploring changes in antidepressant prescribing rates in Wales during a 45-month period when the welfare benefit system was changing to the new Universal Credit system. This final chapter summarises the main findings, discusses the implications for clinical practice, its potential contribution to wider developments, recommendations for future research, and reflections of the research process as a whole, including why this topic felt personally important to highlight.

Summary of thesis findings

Chapter 1 is a systematic literature review with narrative commentary, exploring if there is a relationship between area level deprivation and the ability to access and use mental health services in the UK, and if this area level deprivation can play a role in the outcomes achieved after receiving mental health support. Area level deprivation was measured using the Index of Multiple Deprivations which reports at lower super-output area (LSOA) which is a geographically determined area containing between 400 and 1200 households Eleven peer reviewed journal articles met criteria for inclusion in the review. Area level deprivation encompasses several domains, Income, Employment, Health, Education, Crime, Barriers to housing and services, and living environment. All of the reviews where secondary data analyses of routinely gathered administrative data. There was a pooled sample of approximately 57,310,558 data cases, covering a range of different services that provide mental health intervention options or varying intensities; Improving Access to Psychological Therapies services, Accident and Emergency services, Crisis Resolution and Home Treatment

teams, Child and Adolescent Mental Health Services, General Practitioner surgeries and Inpatient mental health services. Four themes emerged from the review that supported the hypothesis that area level deprivation plays a role in a person's ability to access mental health support plays a role in unplanned care and increased costs, and can influence outcomes of mental health interventions such as psychological therapies.

Chapter 2 is an original piece of quantitative research using an Interrupted Time Series analysis to assess trends in antidepressant prescribing rates in Wales, during the roll out of Universal Credit. The study aimed to corroborate previous quantitative reports of how the introduction of Universal Credit led to people feeling more depressed. Antidepressant prescribing rates were used as a proxy measure for depression prevalence, although this is likely to be an underestimation on the impact of mental wellbeing, due to not everyone who is experiencing clinically diagnosable depression taking medication to manage his or her symptoms. The staggered introduction of Universal Credit provided natural experiment conditions, so the Interrupted time series model with multiple baseline design would provide robust evidence. There was a statistically significant change in antidepressant prescribing trends in all areas after the introduction of Universal Credit, with all counties demonstrating an immediate step change followed by an acceleration in prescribing rates from the underlying baseline trend, which already demonstrated an increase in prescribing rates over time.

Implications for clinical practice and future research

Both chapters highlight important topics that could have implications in clinical practice. Chapter 1 determined that living in more deprived areas has a negative impact when accessing mental health services through traditional referral routes, increased the risk of accessing care via unplanned routes, and is related to unsatisfactory outcomes when psychosocial interventions are accessed. From a clinical practice perspective, understanding the context of the area that a person lives in may be helpful in understanding why there may be barriers to engagement and improvement. In terms of service related evaluation, when screening referrals,

recording postcode data and mapping that with IMD data regarding the area level deprivation of the LSOA could help to determine patterns of rejected referrals, to see if they come from similar areas. This could open up discussions about why those referrals are seen to be inappropriate. Is there bias towards people living in certain areas, as suggested by De Lusignan. et al. 2011, or are people who are living in these more deprived areas being referred to mental health services when the need is actually linked to social needs, housing, employment or finances? It could be that the services that receive referrals from more deprived areas are not designed to work with the intensity of the presenting mental health difficulties. For example, IAPT services in England, and Primary Care Mental Health services in Wales, have a clear remit of working with 'common mental disorders' e.g. mild to moderate depression and anxiety. Given the links between area level deprivations and psychiatric morbidity, it could well be that the level of need required is beyond what a primary care service could safely offer. There was not enough literature that met the inclusion criteria available to draw conclusions, as there was no studies undertaken in community mental health teams for example, only crisis resolution services.

Chapter 2 highlighted how a major change in social policy implemented at government level had an impact on the mental health of a nation. A natural area to expand this research would be to use the same methodology to examine antidepressant-prescribing trends in the other home nations during the Universal Credit rollout to determine if this trend was unique to Wales, or if it the finding are just as applicable in England, Scotland and Northern Ireland. A further area of interest would be to determine if the trends began to settle again after Universal Credit became the norm, rather than the new system. If this would even be possible though is a question I have asked myself, as not long after the period where this study ended, the global Covid-19 pandemic struck and I would be interested to determine if this methodology could be used to assess antidepressant prescribing trends during the pandemic, paying particular

attention to lockdown periods, where social isolation became problematic for many and some households experienced unexpected unemployment, or had to adjust to furlough conditions. I would suspect that this could confound findings regarding antidepressant prescribing.

From a clinical practice perspective, the findings from this research did cause feelings of concern. To meet the criteria set out by NICE guidelines for the treatment of depression, antidepressant prescribing is not recommended as a first-line treatment for less severe depression, unless it is the persons preference (N*ICE*, 2022). Understanding the severity of depression, or personal preference regarding psychotropic medication, was beyond the remit of this study; but a logical leap to make would be to say that if antidepressant prescribing rates had increased significantly in such a short time period, the level of distress displayed by those seeking help must have been greater than 'less severe'.

Taking antidepressant medication comes with risks. Common side effects can include increased feeling of anxiety, digestive disorders, loss of appetite, dizziness, insomnia, hypersomnia, loss of libido and erectile dysfunction amongst other symptoms (*MIND-2020*) It can initially cause an increase in suicidality, with young adults being at increased risk of experiencing suicidal feelings upon commencement of antidepressant medication. Older adults are at increased risk of falls and hyponatraemia. (*NICE, 2022)*. Stopping antidepressants puts a person at risk of experiencing uncomfortable withdrawal symptoms which include vertigo, dizziness, altered sensations, altered feelings, restlessness and agitation, problems sleeping, sweating, abdominal symptoms, palpitations, headaches and joint pains. Practicing mental health clinicians need to be aware of the physical impact of antidepressant medication.

There is a risk that by focussing on individual responses to the pressures associated with financial instability and changes to the welfare system, by considering them to be mentally unwell and in need of medicine, we are turning a blind eye to the wider system and the cruelty it has imposed upon some of the people who are in most need in society.

Contribution to theory development

The studies detailed in this work focus on broader societal level findings rather than digging down to explore individual lived experiences. As a psychologist we tend to work at the individual, small group or family/system level, with a nod to how external pressures impact on the day-to-day lived experience. We may include it in a formulation, as an outside influence, but not necessarily place enough value on the real impact that these external pressures pose on day-to-day functioning. Despite this, there has long been understanding that in order for people to feel safe, secure, and achieve full potential, basic needs such as housing, food security, and access to fiscal means need to ideally be in place and be secure to allow for 'self-actualisation' (Maslow, 1945). Critics of this theory point out that there in inherent privilege in this model in stating that all of the lower levels of the hierarchy pyramid must be achieved before a person can meet their full potential, when there are many people who come from insecure and disadvantaged backgrounds to become very successful and personally fulfilled in their lives. If we embrace this theory unquestioningly then this could lead to people not being permitted access to psychotherapeutic services if they are deemed to not have their basic needs met, therefore they "could not possibly" engage with psychological therapy.

The theoretical framework in which I feel that this research makes a positive contribution to the understanding and further development, is the Power, Threat, Meaning Framework (PTMF) (*Johnstone & Boyle*, 2018). Johnstone and Boyle developed this framework to provide an alternative to functional psychiatric diagnosis, working on the premise that a disease based model for human suffering in the context of experience, is not the approach to take. I am acutely aware that throughout my own research, using terminology such as 'Depression'; which is a functional psychiatric diagnosis, and focussing entirely on the use of pharmacotherapy as a treatment option to 'fix' the problem has left me with feelings of discomfort at times, as I do not naturally lean towards the medical model of functional psychiatric diagnoses. I have found myself using the language of disorder but trying to reiterate the harm being perpetuated by

wider societal influences, which does not fully ‘fit’ with the psychiatric model. This approach fits with a critical realism ideology; I inherently reject the terminology of ‘depression’ as being meaningful it its own right, however the experienced feelings of chronic low mood and its associated physiological phenomena are real, and need to be addressed as real concerns for the person, but this is much more than just a label. Some of this ideological stance stems strongly from my own experiences, which are briefly explored later in this chapter.

Psychiatric diagnosis relies on clustering subjective experiences rather than clinical signs to determine a pattern cluster that best matches an established label. These clusters of behaviours are often insensitive to individual cultures and experiences. What this fails to do is consider contextual issues, firmly rooting the illness (in this case depression) in the person. That is not to say that the other end of the spectrum is also true, in terms of causality, it is too crude to determine that poverty *causes* depression, instead it is shown to exert influence in the development of internal feelings that could traditionally be characterised as ‘depression’ as per the psychiatric model.

The PTMF model allows for nuance and understanding of how POWER (in this instance, government led changes to the welfare system) that manifests through social structures leads to THREAT (worry about financial instability, concerns about sanctions, worry about food stability, housing concerns, experiencing mental distress as a consequence), and the personal MEANING of that threat can then be considered. This meaning will be idiosyncratic, based on a person’s beliefs and experiences leading to how they make sense of a situation. This could be from a number of sources including media driven narratives such as ‘scroungers’ and ‘Benefits Britain’, feeling lack of self-worth when lived experience does not align to capitalist driven ideologies whereby paid work is viewed as being the marker of success, when paid work does not pay enough to live, where greater economic wealth equals success, to feeling depersonalised when your ability to access means is reduced to a national insurance number

and a claim in the system, to feel dehumanised when you have to get a professional to deem you 'too sick' to work, a sense of shame; to speculate a few examples of potential meanings. How a person then responds to this feeling of threat is key. The current psychiatric driven model of depression effectively lumps all of the above to a passive suffering of biological defects, whereas the PTMF model acknowledges all of the above as activating a threat response designed for survival. However, there is not a medication on the market designed to overcome internal feelings coming from external threats, so it is much easier to attribute this to 'depression' and provide a medication to help alleviate the sensations in the course of a 10 minute GP appointment. I am by no means denigrating the work of other caring professionals, more highlighting the enormity of how much influence the wider societal threat has adversely affected the mental wellbeing of so many people.

Personal reflections of Research Process

Completion of this project was not a path than ran smoothly. I returned to training after a second maternity leave in May 2020. I returned to a world in chaos due to Covid-19 pandemic lockdown restrictions. Not only was I figuring out how to work from home with two very young children around due to childcare facilities being closed, I had to get creative with how to tackle my thesis project, not knowing how long restrictions could last. I had been inspired by a previous trainee's thesis presentation at a previous Stakeholders Event, where they spoke about how they successfully utilised secondary data sources to produce a piece of epidemiological research. Despite my natural urge to eschew quantitative research methods, as I do not consider myself comfortable with numerical data, I thought that this approach could resolve the immediate problems associated with accessing people during lock down.

This is, however a thesis of two halves. After the empirical component was nearing completion, I began to undertake the systematic literature review. Determining this topic was less about a passion project, but trying to make a positive contribution to existing literature whilst keeping the topics broadly related, and not replicating previous work. As I started to get underway with

this, I began to experience ill health, which culminated in having to press pause on my training and take time off whilst I learnt to adapt to life with an unexpected neurological condition. This condition affected my vision, my mobility, my cognition and levels of fatigue. Completing the remainder of this thesis in these unexpected circumstances has been less than ideal, resulting in a lot of frustration linked to my own perceived altered cognitive functioning. Despite these tremendous setbacks, I am now in a position where I AM submitting a thesis, a position I did not expect to be in a year ago when I was at the height of my ill health. For that alone, I am proud.

Throughout the process of completing this thesis, I have been keenly aware of my personal background and the closeness I have felt to some of the situations I have sought to bring focus to. My own journey in to Clinical Psychology has not followed the "traditional" trajectory of a-levels, undergraduate degree, master's degree, work experience, doctorate. I started to think about psychology as a career when I was in my early twenties, living in a very deprived area, relying on state benefits (the old legacy system), medicated with antidepressants as there was not much more my GP could provide to try and reduce the sense of constant doom that came with food insecurity, fear of the bailiffs and rent arrears! I was provided the opportunity to work one day a week under the old 'permitted work' scheme, as a service user consultant within a therapeutic community. This opened up doors that I never dreamed would be possible. This role gave me a seat at the table and I was able to take part in the design of new, psychologically informed, services designed for people who had experienced complex trauma as I had. My voice and my experiences were valuable, and my contributions were welcomed, and respected. I vividly recall speaking with the head of psychological services for the NHS trust I was working with, and almost sheepishly expressing a desire to go to college to do a psychology course "so I can understand more". Her absolute enthusiasm and encouragement gave me to push to take that first step, and after a year of night school, I successfully started my

undergraduate Psychology degree.

I consider myself to have been hugely fortunate to access the services I needed to help me to understand myself at a time in my life when I was vulnerable and insecure. Having a group of people who I could relate to on multiple levels, including coming from a similar background, made a huge difference. These people could relate to trying to manage a life on a very small amount of money.

After spending the early part of my career living in fear of being 'found out'. Carrying around a misplaced shame at having lived experience of mental health difficulties, the stigma of spending six years of my life 'on benefits', I began to realise that these experiences have actually contributed positively to how I work with other people. I am now more outspoken about the need to diversify Clinical Psychology as a profession, and instead of being ashamed of these experiences, I am proud of how resilient they made me.

Speaking out, conducting research and dissemination of gained knowledge is just another step to take in raising awareness of the psychological consequences of area level deprivation and having to rely on the welfare system in order to live. Giving someone an antidepressant will not cure a system that is threatening, confusing, stigmatising and dehumanising, but maybe it does highlight a need, as this thesis has clearly demonstrated.

Bibliography

Antidepressants (2020). Retrieved 28 June 2023, from https://www.mind.org.uk/media/6474/antidepressants-2020.pdf

Baracaia, S., McNulty, D., Baldwin, S., Mytton, J., Evison, F., Raine, R., Giacco, D., Hutchings, A., & Barratt, H. (2020). Mental health in hospital emergency departments: Cross-sectional analysis of attendances in England 2013/2014. *EMERGENCY MEDICINE JOURNAL*, *37*(12), 744–751. https://doi.org/10.1136/emermed-2019-209105

de Lusignan, S., Navarro, R., Chan, T., Parry, G., Dent-Brown, K., & Kendrick, T. (2011). Detecting referral and selection bias by the anonymous linkage of practice, hospital and clinic data using Secure and Private Record Linkage (SAPREL): Case study from the evaluation of the Improved Access to Psychological Therapy (IAPT) service. *BMC MEDICAL INFORMATICS AND DECISION MAKING*, *11*. https://doi.org/10.1186/1472-6947-11-61

Delgadillo, J., Asaria, M., Ali, S., & Gilbody, S. (2016). On poverty, politics and psychology: The socioeconomic gradient of mental healthcare utilisation and outcomes. *The British Journal of Psychiatry*, *209*(5), 429–430. APA PsycInfo®. https://doi.org/10.1192/bjp.bp.115.171017

Delgadillo, J., Farnfield, A., & North, A. (2018). Social inequalities in the demand, supply and utilisation of psychological treatment. *Counselling & Psychotherapy Research*, *18*(2), 114–121. APA PsycInfo®. https://doi.org/10.1002/capr.12169

Firth, N., Delgadillo, J., Kellett, S., & Lucock, M. (2020). The influence of socio-demographic similarity and difference on adequate attendance of group psychoeducational cognitive behavioural therapy. *Psychotherapy Research*, *30*(3), 362–374. APA PsycInfo®. https://doi.org/10.1080/10503307.2019.1589652

Johnstone, L. & Boyle, M. with Cromby, J., Dillion, J., Harper,D ., Kinderman, P., Longden, E., Pilgrim, D. & Dread, J. (2018). *The Power Threat Meaning Framework: Towards the identification of patterns in emotional distress, unusual experiences and troubled or troubling behaviour, as an alternative to functional psychiatric diagnosis.*. Leicester: British Psychological Society.

Jayatunga, W., Asaria, M., Belloni, A., George, A., Bourne, T., & Sadique, Z. (2019). Social gradients in health and social care costs: Analysis of linked electronic health records in Kent, UK. *PUBLIC HEALTH*, *169*, 188–194. https://doi.org/10.1016/j.puhe.2019.02.007

Maslow, A. H. (1943). A Theory of Human Motivation. Psychological Review, 50, 370-396.

https://doi.org/10.1037/h0054346

Maconick, L., Rains, L., Jones, R., Lloyd-Evans, B., & Johnson, S. (2021). Investigating geographical variation in the use of mental health services by area of England: A cross-sectional ecological study. *BMC HEALTH SERVICES RESEARCH*, *21*(1). https://doi.org/10.1186/s12913-021-06976-2

Payne, R. A., Abel, G. A., Guthrie, B., & Mercer, S. W. (2013). The effect of physical multimorbidity, mental health conditions and socioeconomic deprivation on unplanned admissions to hospital: A retrospective cohort study. *Canadian Medical Association Journal*, *185*(5), E221–E228. APA PsycInfo®. https://doi.org/10.1503/cmaj.121349

Recommendations | Depression in adults: Treatment and management | Guidance | NICE. (2022, June 29). NICE. https://www.nice.org.uk/guidance/ng222/chapter/recommendations#less-severe-depression

Smith, J., Kyle, R. G., Daniel, B., & Hubbard, G. (2018). Patterns of referral and waiting times for specialist child and adolescent mental health services. *Child and Adolescent Mental Health*, *23*(1), 41–49. APA PsycInfo®. https://doi.org/10.1111/camh.12207

Weich, S., McBride, O., Twigg, L., Keown, P., Cyhlarova, E., Crepaz-Keay, D., Parsons, H., Scott, J., & Bhui, K. (2014). *Variation in compulsory psychiatric inpatient admission in England: A cross-sectional, multilevel analysis*. NIHR Journals Library.

https://doi.org/10.3310/hsdr02490
Maslow, A. H. (1943). A Theory of Human Motivation. Psychological Review, 50, 370-396.

https://doi.org/10.1037/h0054346

Appendices

Appendix 1: Table showing BNF codes, Drug names, Defined Daily Doses and ATC codes for all antidepressant class drugs analysed in Chapter 2.

Drug Code Prefix	Drug Name	Drug classification		
0403040	Agomelatine	Antidepressant		
1001040	Allopurinol	Gout Preparation		
0501040	Amikacin	Antibiotics		
0501090	Aminosalicylic Acid	Antibiotics		
0403010	Amitriptyline	Antidepressant		
0403010	Amoxapine	Antidepressant		
0501013	Amoxicillin	Antibiotics		
0501013	Ampicillin	Antibiotics		
0501050	Azithromycin	Antibiotics		
0501023	Aztreonam	Antibiotics		
0501090	Bedaquiline	Antibiotics		
1001040	Benzbromarone	Gout Preparation		
0501011	Benzylpenicillin	Antibiotics		
0501090	Capreomycin	Antibiotics		
0501021	Cefadroxil	Antibiotics		
0501021	Cefalexin	Antibiotics		
0501020	Cefamandole	Antibiotics		
0501020	Cefazolin	Antibiotics		
0501020	Cefepime	Antibiotics		
0501021	Cefixime	Antibiotics		
0501021	Cefotaxime	Antibiotics		
0501021	Cefoxitin	Antibiotics		
0501020	Cefpirome	Antibiotics		
0501021	Cefpodoxime	Antibiotics		
0501020	Cefprozil	Antibiotics		
0501021	Cefradine	Antibiotics		
0501021	Ceftazidime	Antibiotics		
0501021	Ceftriaxone	Antibiotics		
0501021	Cefuroxime	Antibiotics		
0501021	Celaclor	Antibiotics		
0501070	Chloramphenicol	Antibiotics		
0501120	Ciprofloxacin	Antibiotics		
0403030	Citalopram	Antidepressant		

0501050	Clarithromycin	Antibiotics		
0501060	Clindamycin	Antibiotics		
0501100	Clofazimine	Antibiotics		
0403010	Clomipramine	Antidepressant		
0501013	Co-amoxiclav	Antibiotics		
0501013	Co-fluampicil	Antibiotics		
1001040	Colchicine	Gout Preparation		
0501070	Colistimethate	Antibiotics		
0501070	Colistin	Antibiotics		
0501080	Co-trimoxazole	Antibiotics		
0501090	Cycloserine	Antibiotics		
0501070	Dalbavancin	Antibiotics		
0501100	Dapsone	Antibiotics		
0501070	Daptomycin	Antibiotics		
0501090	Delamanid	Antibiotics		
0501030	Demeclocycline	Antibiotics		
0501030	Deteclo	Antibiotics		
0501022	Doripenem	Antibiotics		
0403010	Dosulepin	Antidepressant		
0403010	Doxepin	Antidepressant		
0501030	Doxycycline	Antibiotics		
0403040	Duloxetine	Antidepressant		
0501022	Ertapenem	Antibiotics		
0501050	Erythromycin	Antibiotics		
0403030	Escitalopram	Antidepressant		
0501090	Ethambutol	Antibiotics		
0501090	Ethionamide	Antibiotics		
1001040	Febuxostat	Gout Preparation		
0501070	Fidaxomicin	Antibiotics		
0501012	Flucloxacillin	Antibiotics		
0403030	Fluoxetine	Antidepressant		
0403040	Flupentixol	Antidepressant		
0403030	Fluvoxamine	Antidepressant		
0501070	Fosfomycin	Antibiotics		
0501070	Fusidic Acid	Antibiotics		
0501040	Gentamicin	Antibiotics		
0501022	Imipenem	Antibiotics		

0403010	Imipramine	Antidepressant		
0403020	Isocarboxazid	Antidepressant		
0501090	Isoniazid	Antibiotics		
0501120	Levofloxacin	Antibiotics		
0403040	Levomilnacipran	Antidepressant		
0501070	Linezolid	Antibiotics		
0403010	Lofepramine	Antidepressant		
0501030	Lymecycline	Antibiotics		
0403010	Maprotiline	Antidepressant		
0501022	Meropenem	Antibiotics		
0501130	Methanamine hippurate	Antibiotics		
0501110	Metronidazole	Antibiotics		
0403010	Mianserin	Antidepressant		
0501120	Mictral	Antibiotics		
0403040	Milnacipran	Antidepressant		
0501030	Minocycline	Antibiotics		
0403040	Mirtazapine	Antidepressant		
0403020	Moclobemide	Antidepressant		
0501120	Moxifloxacin	Antibiotics		
0501120	Nalidixic Acid	Antibiotics		
0403040	Nefazodone	Antidepressant		
0501040	Neomycin	Antibiotics		
0501040	Netilmicin	Antibiotics		
0501070	Nitazoxanide	Antibiotics		
0501130	Nitrofurantoin	Antibiotics		
0403010	Nortriptyline	Antidepressant		
0403040	Oxitriptan	Antidepressant		
0501030	Oxytetracycline	Antibiotics		
0403030	Paroxetine	Antidepressant		
0403020	Phenelzine	Antidepressant		
0501011	Phenoxymethylpenicillin	Antibiotics		
0501014	Piperacillin	Antibiotics		
0501015	Pivmecillinam	Antibiotics		
0501070	Pristinamycin	Antibiotics		
1001040	Probenecid	Gout Preparation		
0501090	Pyrazinamide	Antibiotics		
0501070	Quinupristin	Antibiotics		

1001040	Rasburicase	Gout Preparation		
0403040	Reboxetine	Antidepressant		
0501090	Rifabutin	Antibiotics		
0501090	Rifampicin	Antibiotics		
0501090	Rifater	Antibiotics		
0501070	Rifaximin	Antibiotics		
0403030	Sertraline	Antidepressant		
0501070	Sodium fusidate	Antibiotics		
0501090	Streptomycin	Antibiotics		
0501080	Sulfadiazine	Antibiotics		
0501080	Sulfamethoxypyridazine	Antibiotics		
0501080	Sulfapyridine	Antibiotics		
1001040	Sulfinpyrazone	Gout Preparation		
0501070	Taurolidine	Antibiotics		
0501070	Tedizolid	Antibiotics		
0501070	Teicoplanin	Antibiotics		
0501050	Telithromycin	Antibiotics		
0501012	Temocillin	Antibiotics		
0501090	Terizdone	Antibiotics		
0501030	Tetracycline	Antibiotics		
0501100	Thalidomide	Antibiotics		
0501014	Ticarcillin	Antibiotics		
0501030	Tigecycline	Antibiotics		
0501110	Tinidazole	Antibiotics		
0501040	Tobramycin	Antibiotics		
0403020	Tranylcypromine	Antidepressant		
0403010	Trazodone	Antidepressant		
0501080	Trimethoprim	Antibiotics		
0403010	Trimipramine	Antidepressant		
0403040	Typtophan	Antidepressant		
0501070	Vancomycin	Antibiotics		
0403040	Venlafaxine	Antidepressant		
0501090	Voractiv	Antibiotics		
0403040	Vortioxetine	Antidepressant		

Appendix 2: Table of all drugs analysed for study in Chapter 2, including generic name, BNF code and drug classification – listed in alphabetical order

Drug Code Prefix	Drug Name	Drug classification
0403040	Agomelatine	Antidepressant
1001040	Allopurinol	Gout Preparation
0501040	Amikacin	Antibiotics
0501090	Aminosalicylic Acid	Antibiotics
0403010	Amitriptyline	Antidepressant
0403010	Amoxapine	Antidepressant
0501013	Amoxicillin	Antibiotics
0501013	Ampicillin	Antibiotics
0501050	Azithromycin	Antibiotics
0501023	Aztreonam	Antibiotics
0501090	Bedaquiline	Antibiotics
1001040	Benzbromarone	Gout Preparation
0501011	Benzylpenicillin	Antibiotics
0501090	Capreomycin	Antibiotics
0501021	Cefadroxil	Antibiotics
0501021	Cefalexin	Antibiotics
0501020	Cefamandole	Antibiotics
0501020	Cefazolin	Antibiotics
0501020	Cefepime	Antibiotics
0501021	Cefixime	Antibiotics
0501021	Cefotaxime	Antibiotics
0501021	Cefoxitin	Antibiotics
0501020	Cefpirome	Antibiotics
0501021	Cefpodoxime	Antibiotics
0501020	Cefprozil	Antibiotics
0501021	Cefradine	Antibiotics
0501021	Ceftazidime	Antibiotics
0501021	Ceftriaxone	Antibiotics
0501021	Cefuroxime	Antibiotics
0501021	Celaclor	Antibiotics
0501070	Chloramphenicol	Antibiotics
0501120	Ciprofloxacin	Antibiotics

0403030	Citalopram	Antidepressant
0501050	Clarithromycin	Antibiotics
0501060	Clindamycin	Antibiotics
0501100	Clofazimine	Antibiotics
0403010	Clomipramine	Antidepressant
0501013	Co-amoxiclav	Antibiotics
0501013	Co-fluampicil	Antibiotics
1001040	Colchicine	Gout Preparation
0501070	Colistimethate	Antibiotics
0501070	Colistin	Antibiotics
0501080	Co-trimoxazole	Antibiotics
0501090	Cycloserine	Antibiotics
0501070	Dalbavancin	Antibiotics
0501100	Dapsone	Antibiotics
0501070	Daptomycin	Antibiotics
0501090	Delamanid	Antibiotics
0501030	Demeclocycline	Antibiotics
0501030	Deteclo	Antibiotics
0501022	Doripenem	Antibiotics
0403010	Dosulepin	Antidepressant
0403010	Doxepin	Antidepressant
0501030	Doxycycline	Antibiotics
0403040	Duloxetine	Antidepressant
0501022	Ertapenem	Antibiotics
0501050	Erythromycin	Antibiotics
0403030	Escitalopram	Antidepressant
0501090	Ethambutol	Antibiotics
0501090	Ethionamide	Antibiotics
1001040	Febuxostat	Gout Preparation
0501070	Fidaxomicin	Antibiotics
0501012	Flucloxacillin	Antibiotics
0403030	Fluoxetine	Antidepressant
0403040	Flupentixol	Antidepressant
0403030	Fluvoxamine	Antidepressant
0501070	Fosfomycin	Antibiotics
0501070	Fusidic Acid	Antibiotics
0501040	Gentamicin	Antibiotics

0501022	Imipenem	Antibiotics
0403010	Imipramine	Antidepressant
0403020	Isocarboxazid	Antidepressant
0501090	Isoniazid	Antibiotics
0501120	Levofloxacin	Antibiotics
0403040	Levomilnacipran	Antidepressant
0501070	Linezolid	Antibiotics
0403010	Lofepramine	Antidepressant
0501030	Lymecycline	Antibiotics
0403010	Maprotiline	Antidepressant
0501022	Meropenem	Antibiotics
0501130	Methanamine hippurate	Antibiotics
0501110	Metronidazole	Antibiotics
0403010	Mianserin	Antidepressant
0501120	Mictral	Antibiotics
0403040	Milnacipran	Antidepressant
0501030	Minocycline	Antibiotics
0403040	Mirtazapine	Antidepressant
0403020	Moclobemide	Antidepressant
0501120	Moxifloxacin	Antibiotics
0501120	Nalidixic Acid	Antibiotics
0403040	Nefazodone	Antidepressant
0501040	Neomycin	Antibiotics
0501040	Netilmicin	Antibiotics
0501070	Nitazoxanide	Antibiotics
0501130	Nitrofurantoin	Antibiotics
0403010	Nortriptyline	Antidepressant
0403040	Oxitriptan	Antidepressant
0501030	Oxytetracycline	Antibiotics
0403030	Paroxetine	Antidepressant
0403020	Phenelzine	Antidepressant
0501011	Phenoxymethylpenicillin	Antibiotics
0501014	Piperacillin	Antibiotics
0501015	Pivmecillinam	Antibiotics
0501070	Pristinamycin	Antibiotics
1001040	Probenecid	Gout Preparation
0501090	Pyrazinamide	Antibiotics

0501070	Quinupristin	Antibiotics
1001040	Rasburicase	Gout Preparation
0403040	Reboxetine	Antidepressant
0501090	Rifabutin	Antibiotics
0501090	Rifampicin	Antibiotics
0501090	Rifater	Antibiotics
0501070	Rifaximin	Antibiotics
0403030	Sertraline	Antidepressant
0501070	Sodium fusidate	Antibiotics
0501090	Streptomycin	Antibiotics
0501080	Sulfadiazine	Antibiotics
0501080	Sulfamethoxypyridazine	Antibiotics
0501080	Sulfapyridine	Antibiotics
1001040	Sulfinpyrazone	Gout Preparation
0501070	Taurolidine	Antibiotics
0501070	Tedizolid	Antibiotics
0501070	Teicoplanin	Antibiotics
0501050	Telithromycin	Antibiotics
0501012	Temocillin	Antibiotics
0501090	Terizdone	Antibiotics
0501030	Tetracycline	Antibiotics
0501100	Thalidomide	Antibiotics
0501014	Ticarcillin	Antibiotics
0501030	Tigecycline	Antibiotics
0501110	Tinidazole	Antibiotics
0501040	Tobramycin	Antibiotics
0403020	Tranylcypromine	Antidepressant
0403010	Trazodone	Antidepressant
0501080	Trimethoprim	Antibiotics
0403010	Trimipramine	Antidepressant
0403040	Typtophan	Antidepressant
0501070	Vancomycin	Antibiotics
0403040	Venlafaxine	Antidepressant
0501090	Voractiv	Antibiotics
0403040	Vortioxetine	Antidepressant

Appendix 3: Table detailing rollout schedule for Universal Credit Implementation in all 22 Welsh Counties

2017	
April	Flintshire
May	
June	
July	Torfaen
August	
September	
October	Neath Port Talbot Wrexham
November	Newport
December	Swansea
2018	
January	
February	Cardiff
March	Denbighshire
April	
May	
June	Bridgend Conwy Merthyr Tydfil Monmouthshire
July	Blaenau Gwent
August	
September	Caerphilly Pembrokeshire
October	Powys Vale of Glamorgan
November	Rhondda Cynon Taf
December	Carmarthenshire Ceredigion Gwynedd Isle of Anglesey

Appendix 4: Word Count Details

Main Substance of thesis:

Thesis Summary: 293

Chapter 1: 2997 plus abstract 245

Chapter 2: 2989 plus abstract 246

Chapter 3: 3041

Total of the main substance of the thesis: 9810

Tables, figures, references and appendices:

Chapter 1:

References: 716

Tables and Figures: 2232

Chapter 2:

References: 601

Tables, Figures and Appendices: 1171

Chapter 3:

References: 492

Total of the tables, figures, references and appendices of the thesis: 5212

Appendix 5: Bangor University Ethics approval confirmation.

Fw: Ethical approval granted for 2021-16949 Depression and Welfare Reform: An Interrupted Time Series analysis of antidepressant prescribing rates in Wales during the implementation of Universal Credit - Jen...

about:blank

Report Block Delete Archive Reply Reply all Forward Meeting Rules Read / Unread Categorise Flag / Unflag Assign policy Print Immersive reader

Delete Respond Move Tags Print Immersive reader

Fw: Ethical approval granted for 2021-16949 Depression and Welfare Reform: An Interrupted Time Series analysis of antidepressant prescribing rates in Wales during the implementation of Universal Credit

Dear Jenny,

2021-16949 Depression and Welfare Reform: An Interrupted Time Series analysis of antidepressant prescribing rates in Wales during the implementation of Universal Credit

Your research proposal number 2021-16949
has been reviewed by the [Pre-Aug 2021] School of Psychology Ethics and Research Committee
and the committee are now able to confirm ethical and governance approval for the above research on the basis described in the application form, protocol and supporting documentation. This approval lasts for a maximum of three years from this date.

Ethical approval is granted for the study as it was explicitly described in the application

If you wish to make any non-trivial modifications to the research project, please submit an amendment form to the committee, and copies of any of the original documents reviewed which have been altered as a result of the amendment. Please also inform the committee immediately if participants experience any unanticipated harm as a result of taking part in your research, or if any adverse reactions are reported in subsequent literature using the same technique elsewhere.

Mae croeso i chi gysylltu gyda'r Brifysgol yn Gymraeg neu Saesneg. Ni fydd gohebu yn Gymraeg yn arwain at oedi.

Type here to search 12:59 30/06/2023