

# Case study – Health Inequalities on the Elective Waiting List and factors leading to Emergency Admission

## Future of analysis in the brave new world of digital

**Simon Wellesley-Miller**

*Senior Analytical Manager*

*Performance Analysis Team -South West*

*Elective Recovery Insights Team – National*

**NHS England**

*MSc Graduate*

*Healthcare Data Science*

**University of Exeter**

*South West Lead*

**Association of Professional Healthcare Analysts**

*Fellow*

**NHS-R Community**

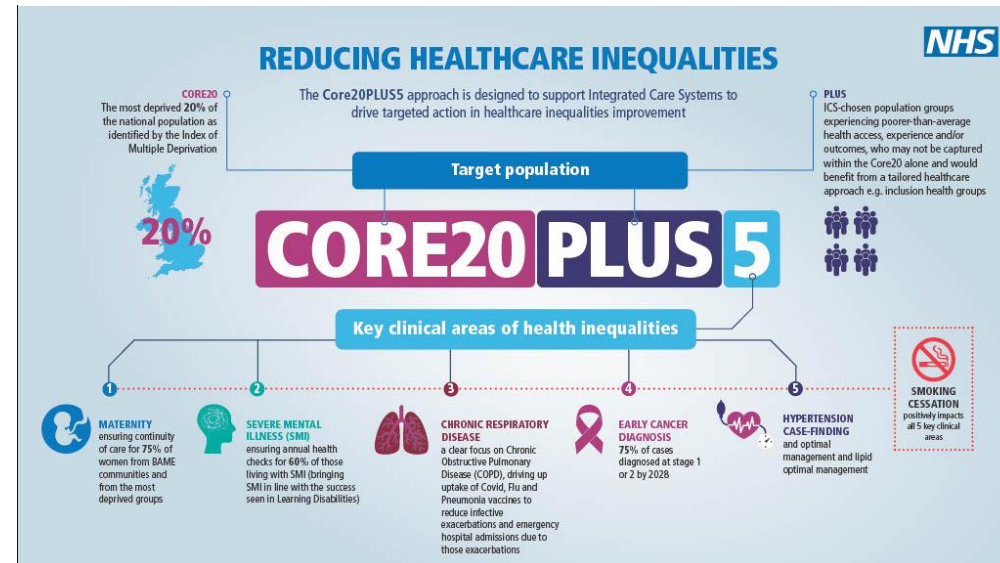
*SPC Analytical Champion*

**NHSE Making Data Count**



# Project objectives

- To understand where there has been significant impacts on health inequalities in the South West, with respect to accessing acute services during Covid 19.
- Outputs of the project will support future areas of focus to address the gap in ensuring accessing services is equitable across the South West.
- Analysis to support this project should be automated and available to enable continuation post MSc and become part of business as usual.
- Look at national schemes and how this work can support national planning



# Definitions

**Health inequalities** are systematic differences in the health status of different population groups. These inequities have significant social and economic costs both to individuals and societies. <sup>(1)</sup>

**Waiting list** - A list of patients waiting to receive a consultative, assessment, diagnosis, care or treatment activity from an organisation.

The list is maintained for an identified care professional or service within an organisation. <sup>(2)</sup>

**Emergency admission** - Patients admitted to hospital when admission is unpredictable and at short notice because of clinical need. <sup>(2)</sup>



Watchdog warns NHS on safety for patients stuck on waiting lists

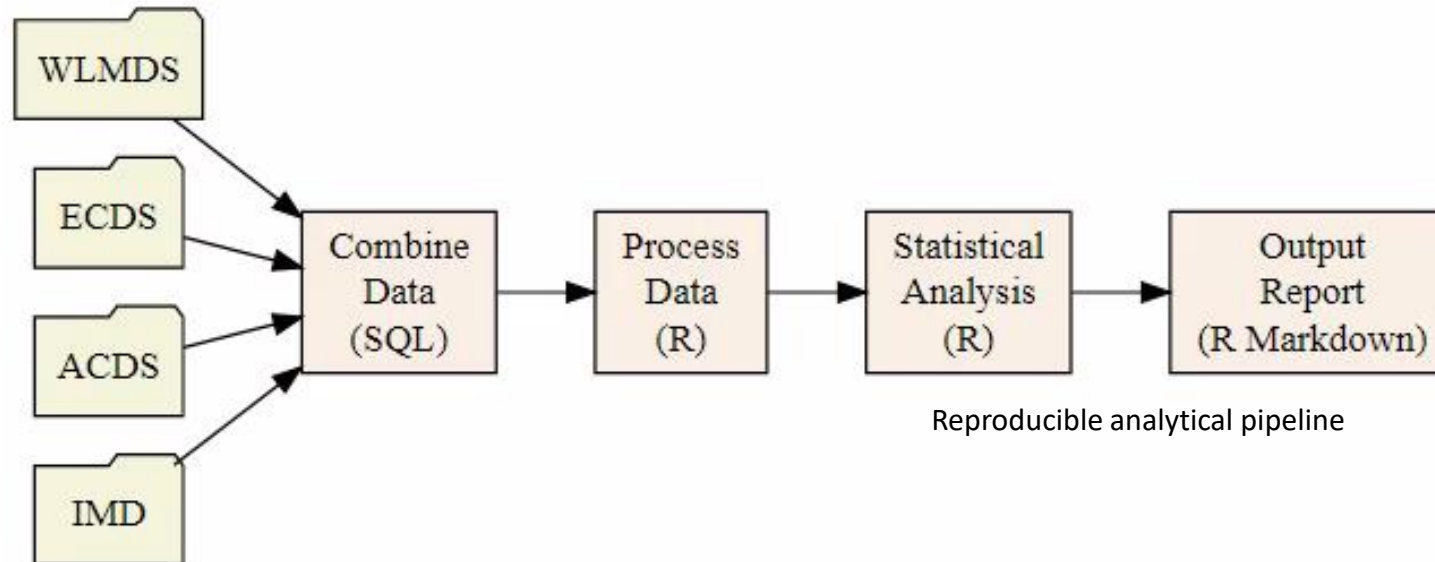


Almost 200,000 patients now waiting at least a year for NHS operations



# Obtaining data

- Main dataset taken from waiting list minimum dataset (WLMDS)
- Emergency care data set (ECDS)
- Admissions data set (ACDS)
- Public Health data for Index of multiple deprivation (IMD) <sup>(4)</sup>
- Public Health data for costal community identification
- Requires a patient level dataset with patient identifiable information
- Appropriate information governance

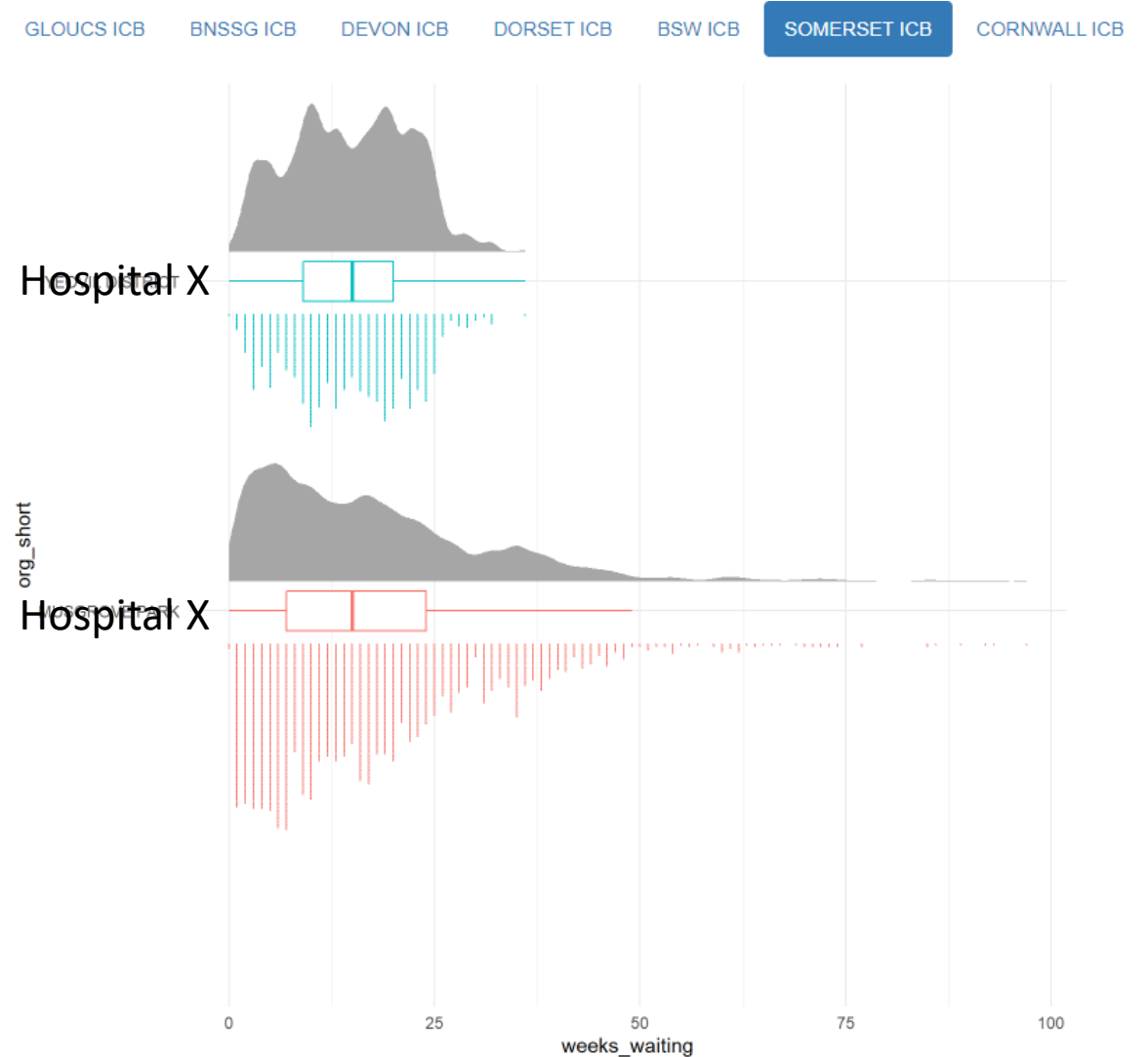


# Data wrangling

- SQL to pull WLMDS with required features
- Linking WLMDS with ECDS and ADCS in SQL across treatment functions
- Pulling public health datasets into analysis
- Calculating local IMD deciles to be able to compare systems
- Collating data into R for analysis and development of pipeline
- Data quality, missing data, assumptions
- Output into automated report

# What does a waiting list look like?

- There is not a single waiting list – is by treatment function and by organisation
- Looking at South West Region, over 50+ organisations, each its own independent lists across 150+ treatment functions
- Waiting lists are far from normally distributed
- There is also an issue that patients that are waiting may become an emergency admission.
- Linking the waiting list dataset to ED attendances and Emergency Admission data, train a model to identify features that may lead to emergency admission



*There are 0 patient outliers over 150 weeks, and 0 patients waiting over 300 weeks.  
The longest wait is 97 weeks.  
Outliers over 200 days have been removed from the graph to maintain scale.*

# What is a health inequality within a waiting list?

- These approaches have flaws as they perhaps simply describe the patients
- Calculate local IMD for comparison
- IMD contains an element of health outcome – risk of self correlation
- Quantitative or descriptive techniques
- Comparison to rates by expected prevalence

	Hospital X MUSGRAVE PARK HOSPITAL (N=2361)	Hospital X DODDINGTON HOSPITAL (N=1096)	Overall (N=3457)
<b>Stated gender</b>			
Male	1280 (54.2%)	520 (47.4%)	1800 (52.1%)
Female	1081 (45.8%)	576 (52.6%)	1657 (47.9%)
Other	0 (0%)	0 (0%)	0 (0%)
Not stated	0 (0%)	0 (0%)	0 (0%)
Not known	0 (0%)	0 (0%)	0 (0%)
<b>Ethnicity code</b>			
any_asian	7 (0.3%)	3 (0.3%)	10 (0.3%)
any_black	3 (0.1%)	1 (0.1%)	4 (0.1%)
any_mixed	2 (0.1%)	1 (0.1%)	3 (0.1%)
any_other	9 (0.4%)	0 (0%)	9 (0.3%)
any_white	1788 (75.7%)	583 (53.2%)	2371 (68.6%)
not_known	552 (23.4%)	508 (46.4%)	1060 (30.7%)
<b>Age</b>			
0 to 19	32 (1.4%)	26 (2.4%)	58 (1.7%)
20 to 39	196 (8.3%)	93 (8.5%)	289 (8.4%)
40 to 59	524 (22.2%)	201 (18.3%)	725 (21.0%)
60 to 79	1246 (52.8%)	540 (49.3%)	1786 (51.7%)
80+	363 (15.4%)	236 (21.5%)	599 (17.3%)
<b>IMD quintile</b>			
1-2	521 (22.1%)	130 (11.9%)	651 (18.8%)
3-4	504 (21.3%)	218 (19.9%)	722 (20.9%)
5-6	494 (20.9%)	265 (24.2%)	759 (22.0%)
7-8	366 (15.5%)	294 (26.8%)	660 (19.1%)
9-10	471 (19.9%)	184 (16.8%)	655 (18.9%)
Missing	5 (0.2%)	5 (0.5%)	10 (0.3%)
<b>Waiting list type</b>			
Inpatient	212 (9.0%)	25 (2.3%)	237 (6.9%)
Outpatient	2149 (91.0%)	1071 (97.7%)	3220 (93.1%)
<b>Weeks waiting</b>			
0-18 weeks	1458 (61.8%)	718 (65.5%)	2176 (62.9%)
18-26 weeks	401 (17.0%)	346 (31.6%)	747 (21.6%)
26-40 weeks	355 (15.0%)	32 (2.9%)	387 (11.2%)
40-52 weeks	94 (4.0%)	0 (0%)	94 (2.7%)
52-78 weeks	46 (1.9%)	0 (0%)	46 (1.3%)
78-104 weeks	7 (0.3%)	0 (0%)	7 (0.2%)
104+ weeks	0 (0%)	0 (0%)	0 (0%)

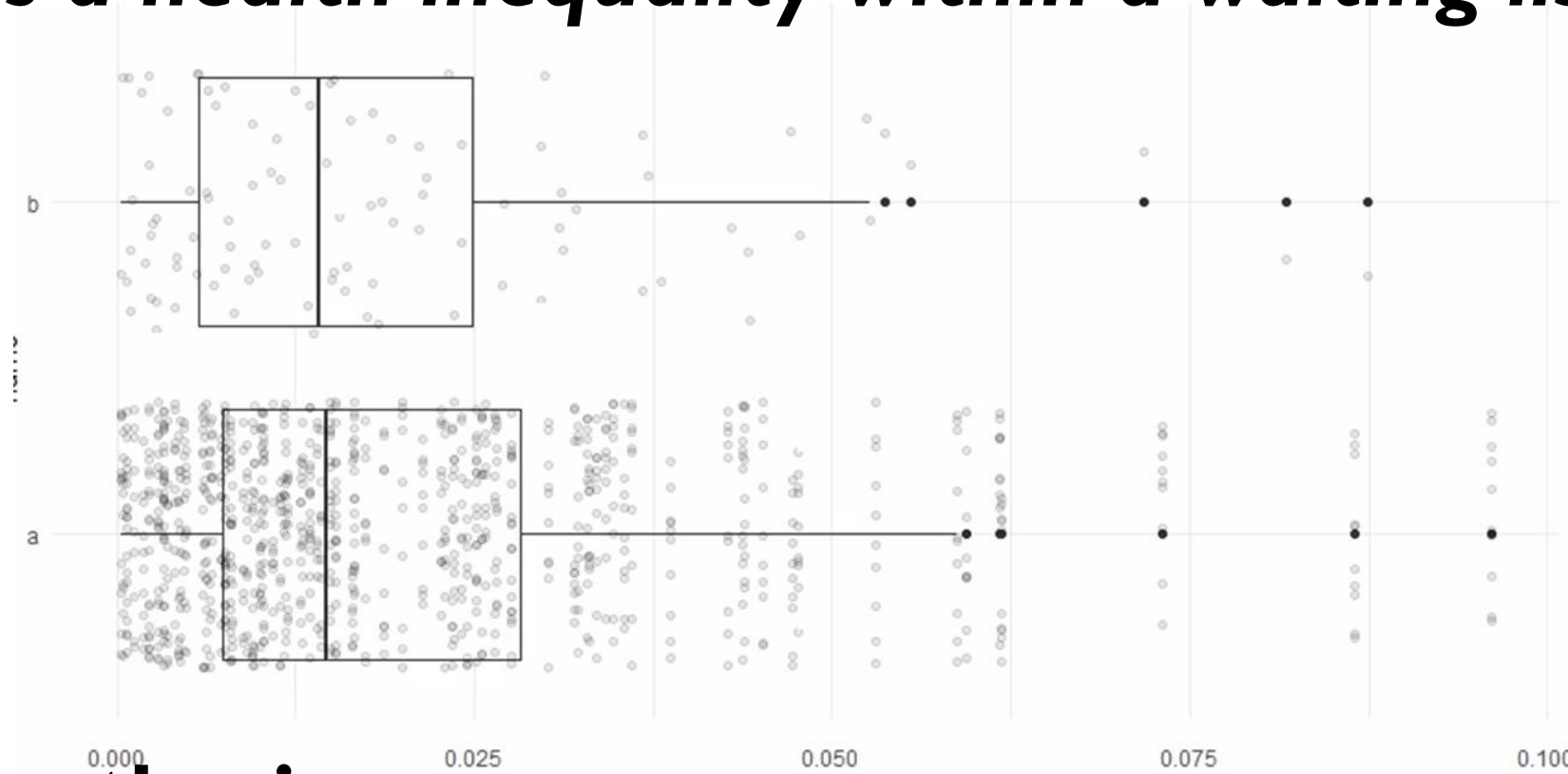
# ***What is a health inequality within a waiting list?***

- What if there was a 95% to 5% percent split by gender on a waiting list?
- Would we consider that to be a health inequality?
- Conditions and disease do have a demographic prevalence
- Literature review identified some previous work to look at distribution of waits, this mainly looked at the difference in mean and median, or via a survival analysis, many others tried to link to prevalence rates <sup>(5)</sup> <sup>(6)</sup>

## **My hypothesis**

*If a waiting list is equitable, then the distribution of patient cohorts within the overall distribution would be the same*

# What is a health inequality within a waiting list?



## My hypothesis

*If a waiting list is equitable, then the distribution of patient cohorts within the overall distribution would be the same*



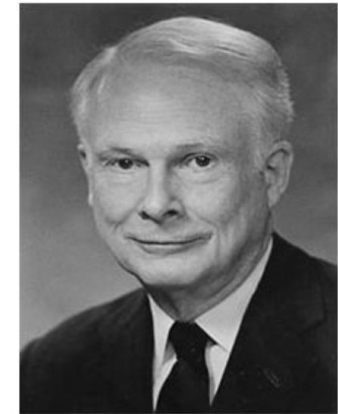
# What is a health inequality within a waiting list?

- Identified a statistical test to compare distributions of cohorts within a waiting list
- Utilises a rank sum approach to compare sample significance across non parametric distributions <sup>(7)</sup>
- Created analytical pipeline to examine waiting lists by treatment code, by organisation and by health inequality demographic
- Runs at scale and only return those that reach statistical significance with a p value < 0.05
- Where statistical significance identified run further pairwise comparisons to identify significance between pairs within cohorts
- Dynamically create exception report for analysis and discussion
- Can be run for any treatment function (with slight tweaks could be run for other regions)

**William Kruskal**



**Wilson Allen Wallis**



$$H = \frac{12}{N(N+1)} \left( \sum \frac{R_i^2}{n_i} \right) - 3(N+1) \text{ where,}$$

$n_i$  = the total number of points in the  $i^{th}$  sample

$R_i$  = the rank sums the  $i^{th}$  sample

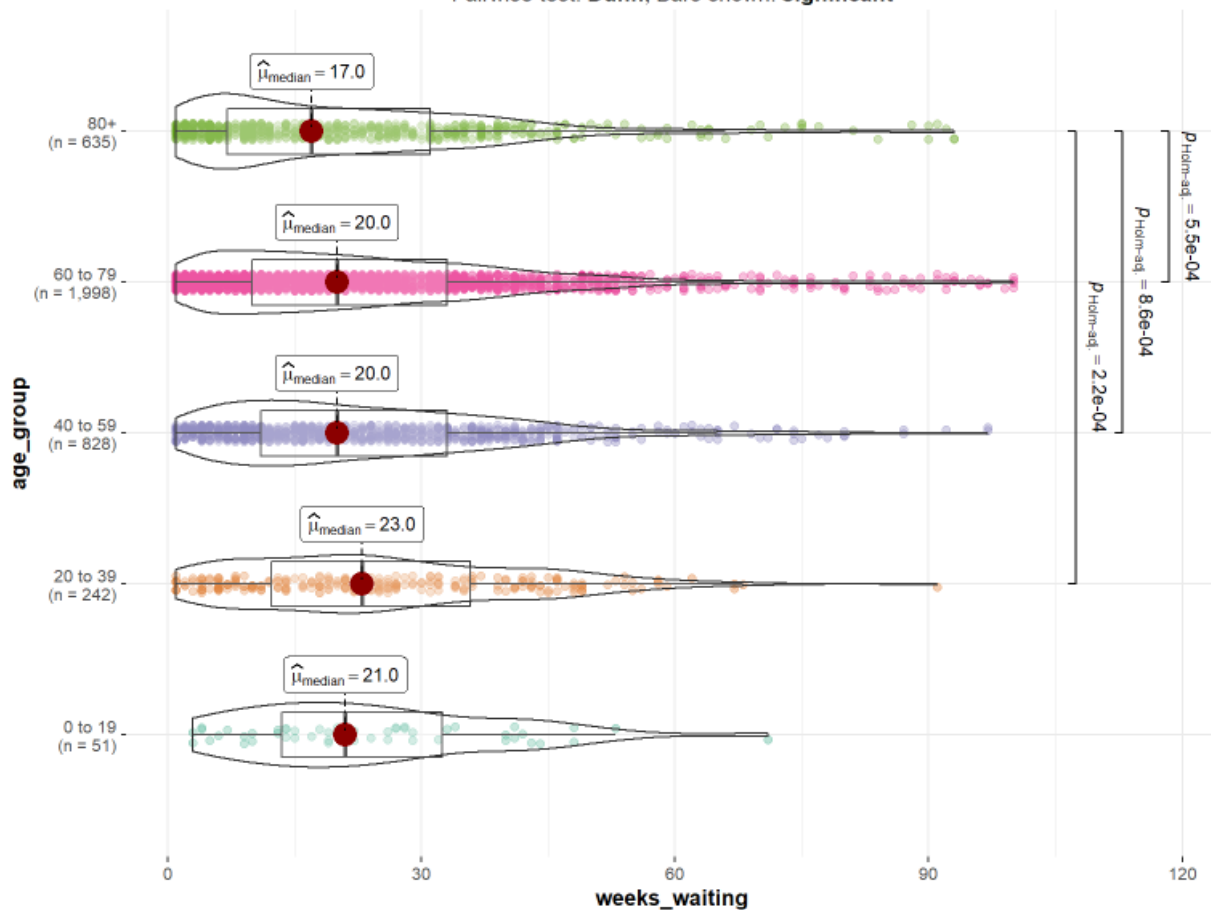
$N$  = the total number of sample points

# What is a health inequality within a waiting list?

## Distribution of waiting times

$\chi^2_{\text{Kruskal-Wallis}}(4) = 25.8, p = 3.5e-05, \hat{\epsilon}^2_{\text{ordinal}} = 6.9e-03, \text{CI}_{95\%} [3.8e-03, 1.0], n_{\text{obs}} = 3,754$

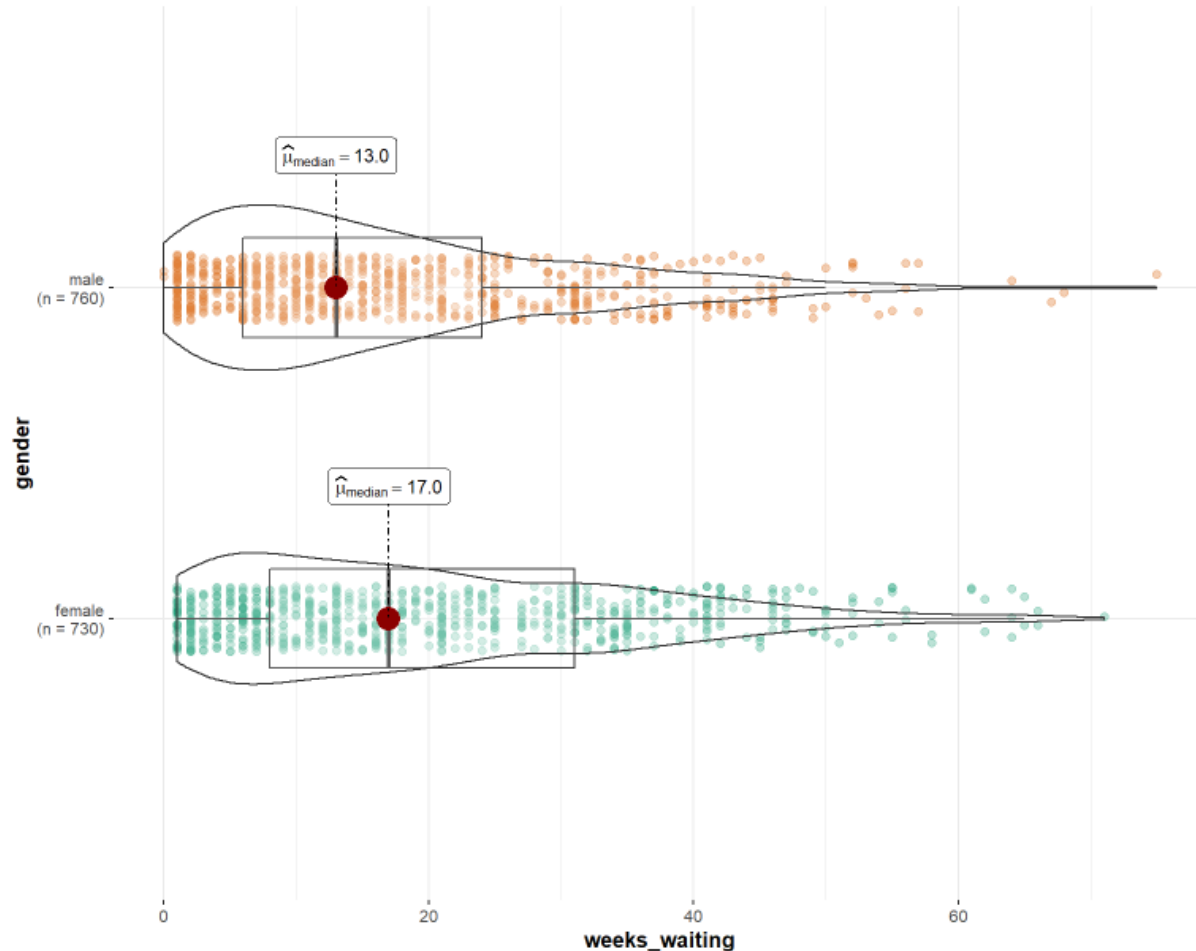
Pairwise test: **Dunn**, Bars shown: **significant**



There are 3,754 patients waiting at Royal Cornwall (Treliske).  
 The longest median wait by group is 23 weeks and the shortest is 17 weeks.  
 A difference of 6 weeks. Overall, the median wait is 20 weeks.  
 Waiting lists are not normally distributed and so this is only a crude indication of central tendency.  
 The most significant difference between groups is between age group 20 to 39 and age group 80+

## Distribution of waiting times

$W_{\text{Mann-Whitney}} = 3.2e+05, p = 1.5e-06, \hat{r}_{\text{rank biserial}} = 0.1, \text{CI}_{95\%} [8.6e-02, 0.2], n_{\text{obs}} = 1,490$



There are 1,490 patients waiting at North Devon District.  
 The longest median wait by group is 17 weeks and the shortest is 13 weeks.  
 A difference of 4 weeks. Overall, the median wait is 15 weeks.  
 Waiting lists are not normally distributed and so this is only a crude indication of central tendency.  
 There are only two groups within this analysis and so only a pairwise comparison has been carried out.

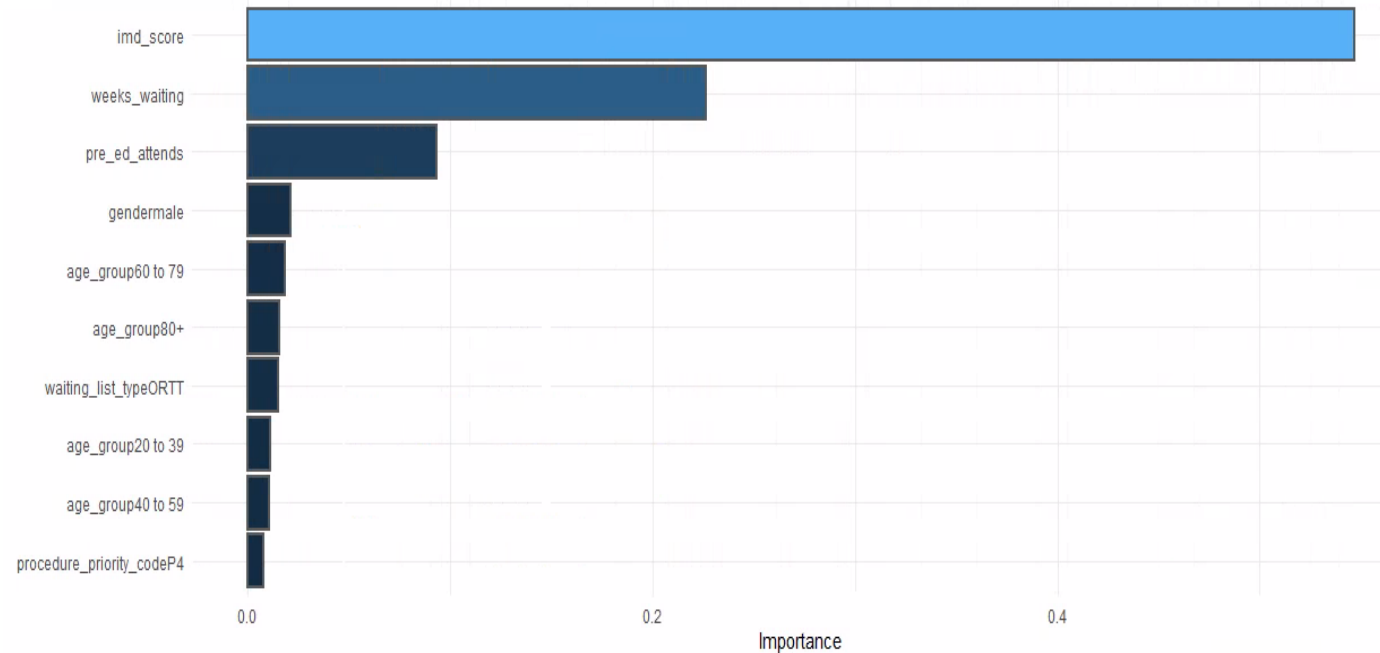
# ***What are the risks leading to emergency admission?***

- Chose to train a machine learning XGBoost<sup>(8)</sup> model
- Flexible
- In built capacity for missing values
- Good performance
- Interpretability of results, can give explainable feature importance
- Rather than specific prediction, determining feature importance is the goal
- Useful for risk stratification of patients and potential support of clinical triage

*dmlc*  
**XGBoost**

# XG Boost Model

- No need to scale or centre data
- Creates a decision tree
- Utilises a space filling parameter grid to try various hyper parameters in the model itself and selects best AOC
- Uses 10 fold cross-validation using stratification for tuning the model
- Returns interpretable feature importance



# Results

- Reproducible analytical pipeline – code to be published
- Feedback from operational leads, clinicians and analysts
- Does identify elements of inequality
- Risk factors – hardly breaking new ground but good to support intuition with data

# Discussion

- Not all inequalities picked up are necessarily an issue
- Element of clinical decision making and ongoing risk stratification
- Not all disparities are clinically meaningful – there may clinical need to prioritise treatment
- Data quality is poor – especially around ethnicity
- The pipeline is built so that additional features can easily be added to the analysis, things such as serious mental illness (SMI), learning disability (LD), long term conditions (LTC) etc
- IMD is very crude and covers an area of up to 3,000 people (better measures being developed)

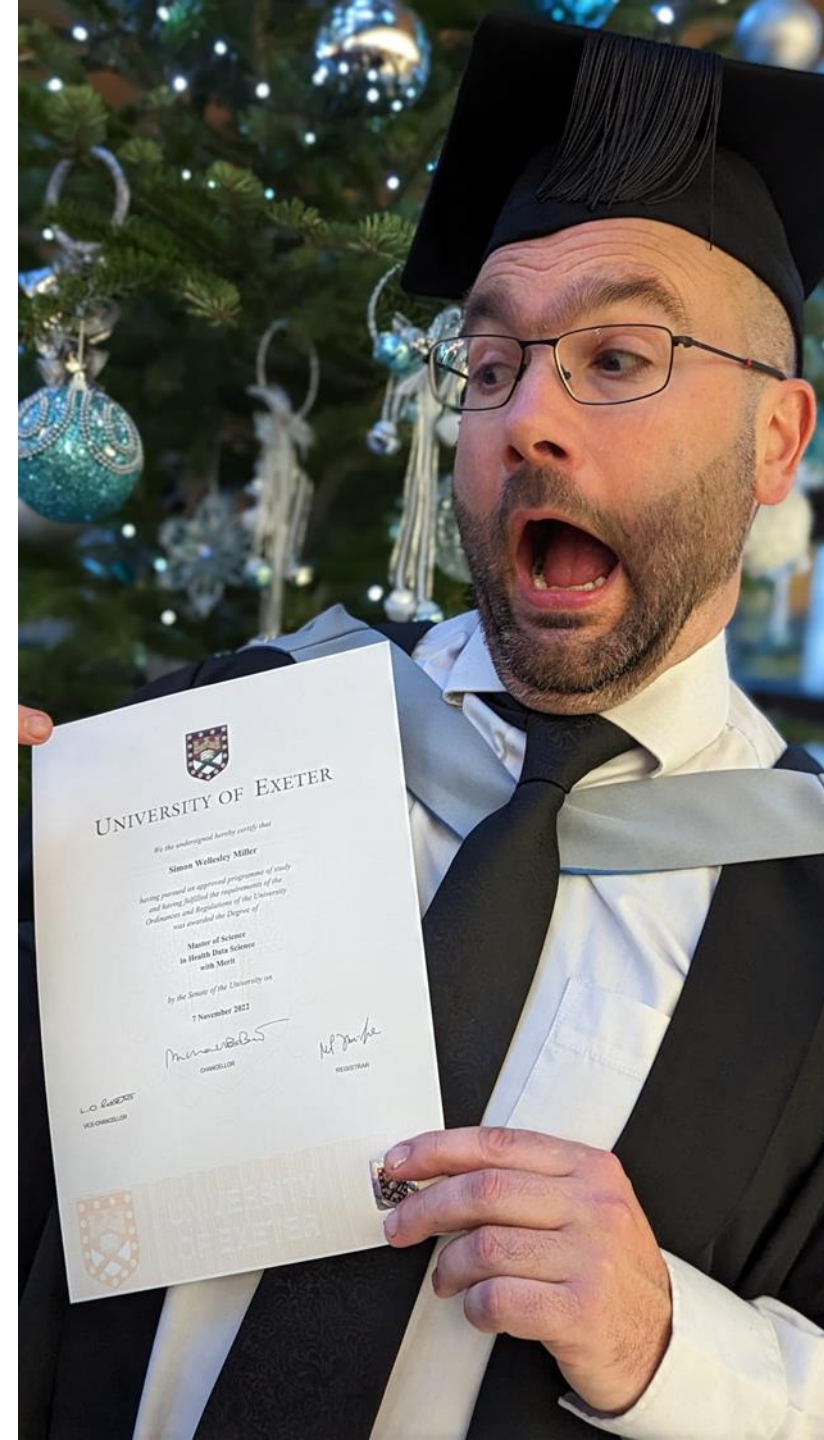


# Conclusion

- So much time wrangling the data
- Report is just a snapshot
- Additional features to be added, serious mental illness, learning disability, long term conditions, coastal status etc
- More features, better analysis, better model!
- Code written to be a simple adaption to add new features – have transferred to UDAL to be one workflow
  - Choose a site and one click to produce report
  - Can be run with local WLMDS
- Utilised at local level to stratify risk and support clinical decision making
- Starting to be used at a regional level to support strategic decision making and inequalities oversight

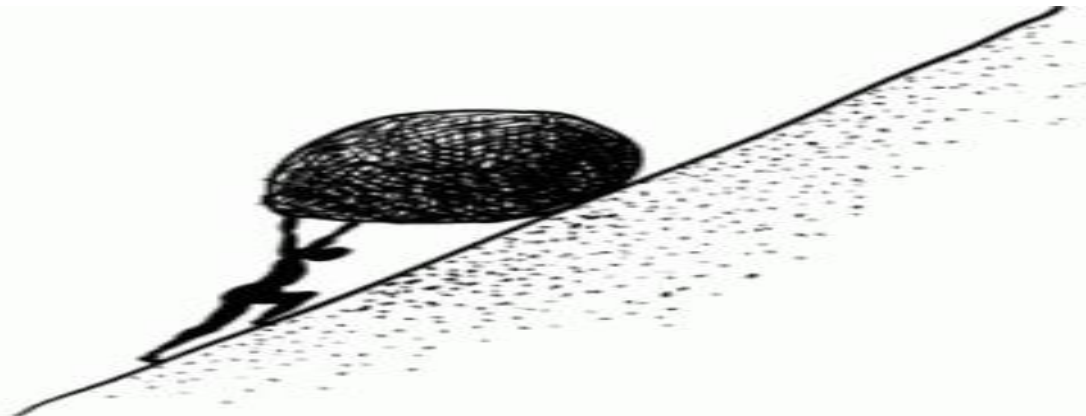


# End of my MSc Project



# Continuing work

- Really fortunate to have opportunity to work with ERIC and to continue work with wider team of data engineers and scientists.
- Current work is linking to master patient index to improve data quality - clearer picture of who is waiting
- Additional features from master patient index and stratification datasets – additional inequalities to add such as MH, LD, co morbidities, care home etc etc
- Developed robust statistical analysis of those waiting longest. Are certain demographics being adversely affected?
- Work is conducted at massive scale across treatment functions by ICBs and potentially provider level.






# Continuing work

- Conversion of raw numbers into population rates built from master patient index at LSOA level and building up. Will allow standardised comparison of rates by population.
- This will enable comparisons across systems to identify genuine statistical outliers.
- Looking to compare more wider public health measures to compare prevalence on lists
- Machine Learning cluster analysis of long waits – find out truly what are the most common profiles for patients waiting – to build insight and design targeted interventions
- Time series analysis – looking at statistical change over time



# Continuing work

- Process mining – extract patient pathways from data to identify bottlenecks
- Demand and capacity modelling to predict future waiting list
- Identify key areas of concern and apply targeted interventions
- Evaluate targeted interventions

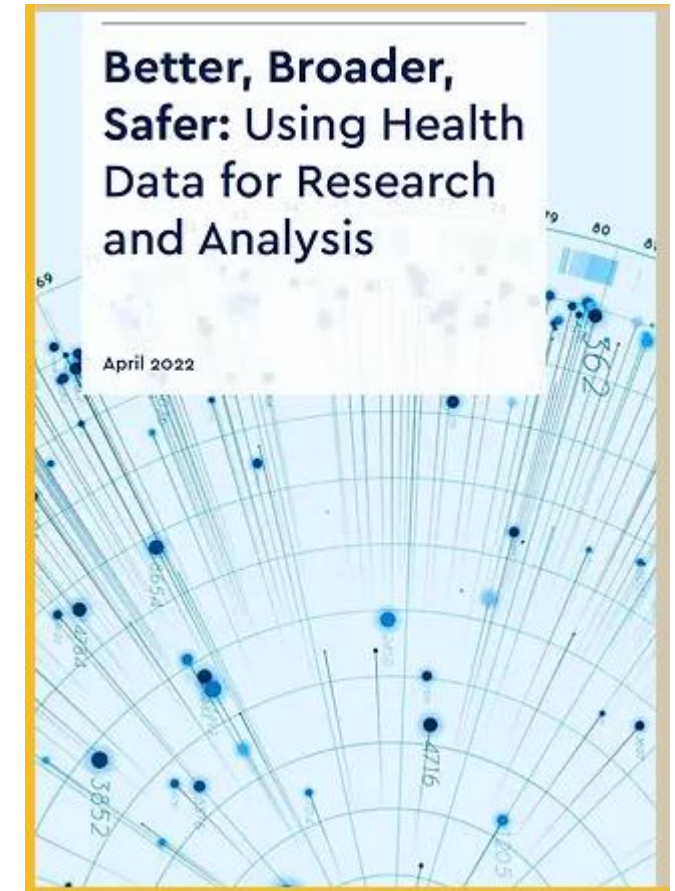
An illustration on a blue background with a white grid. A magnifying glass with a black handle and silver frame is positioned over a small square graph. The graph shows a bell-shaped curve. Two question marks are floating around the graph: one above and to the left, and another to the right. A small square icon with a similar bell curve is located below the graph.

**P-Value**  
*[ˈpē ˈvæl-(.)yü]*

A statistical measure used to determine the likelihood that an observed outcome is the result of chance.

# Future of analytics

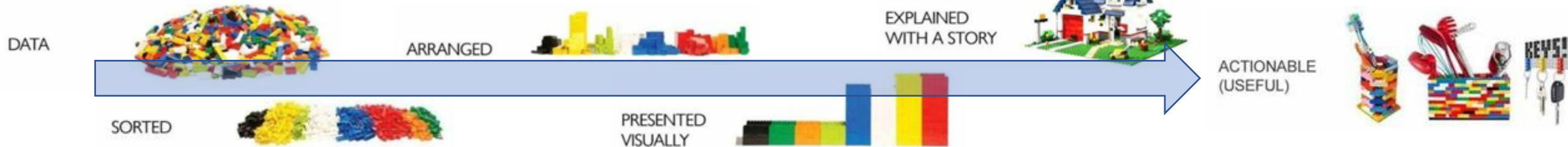
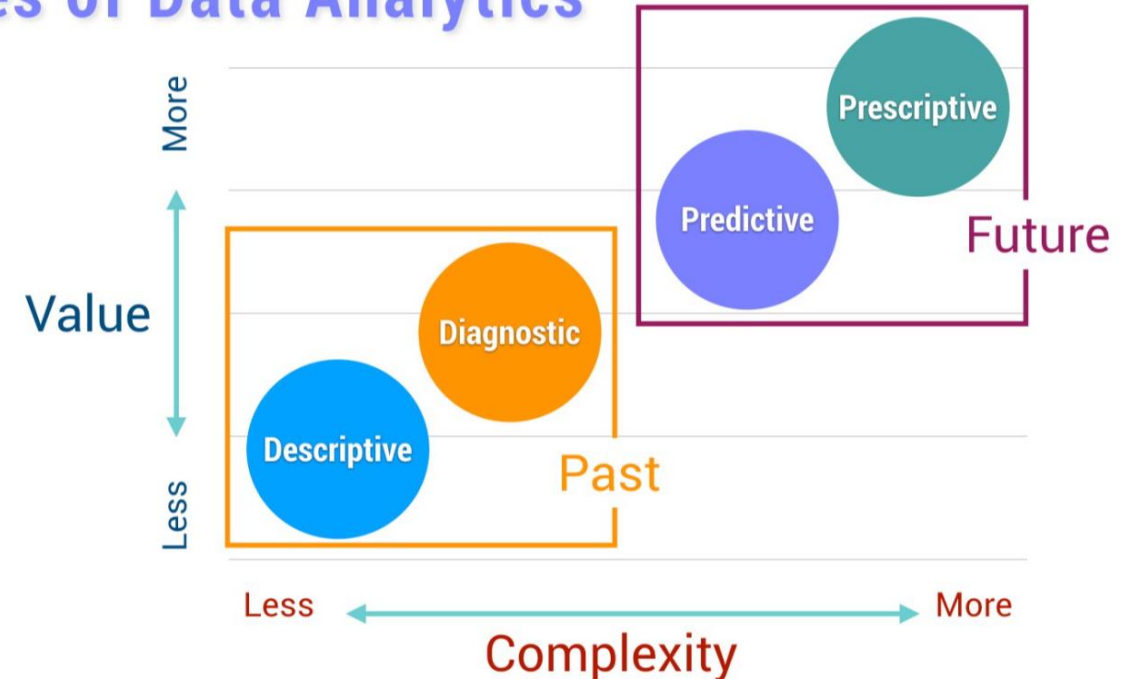
- Really exciting
- Blue widget counting – **NO!**
- Change the analytical questions and conversations
- Stop analysts producing data and get them producing analysis
- New ways of working – new tools
- Accept Goldacre review
- Default is to share code



# How digital can help

- Allow analysts tools and infrastructure to do this cool stuff
- We need data linkages and environments
- Change the analytical questions and conversations
- Accept Goldacre review
- Default is to share code
- Stop analysts producing data and get them producing analysis
- Upskill our workforce – competency framework

## 4 Types of Data Analytics



# Any questions?

# Thank you!

## References

- (1) <https://www.who.int/news-room/facts-in-pictures/detail/health-inequities-and-their-causes>
- (2) NHS Data Model and dictionary - [https://www.datadictionary.nhs.uk/classes/waiting\\_list.html](https://www.datadictionary.nhs.uk/classes/waiting_list.html)
- (3) <https://www.england.nhs.uk/about/equality/equality-hub/national-healthcare-inequalities-improvement-programme/core20plus5/>
- (4) <https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019>
- (5) Dimakou, S., Dimakou, O. & Basso, H.S. Waiting time distribution in public health care: empirics and theory. *Health Econ Rev* **5**, 25 (2015).
- (6) Dimakou, S., Parkin, D., Devlin, N. et al. Identifying the impact of government targets on waiting times in the NHS. *Health Care Manag Sci* **12**, 1 (2009)
- (7) Kruskal, W. H., & Wallis, W. A. (1952). Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical Association*, **47**, 583-621.
- (8) Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). New York, NY, USA: ACM.

## Thanks to

Lucy Wellesley-Miller, Vicki Cruize, Tobin Savage, Jo Mcsweeney, Martin Huscroft, Julia Gonzalez-Esquerre, Fiona Leat, Prof. Martin Pitt, Prof. William Henley and many others for support with the project

