Equitable Hospital Length of Stay Prediction for Patients with Learning Disabilities and Multiple Long-term Conditions Using Machine Learning

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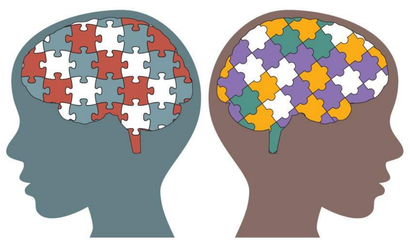
Introduction

Learning disability (LD) in the UK



There are about 1.5 million people with an LD in the UK, including over 1.1 million adults aged ≥18 years [1]

About 9 in 10 adults with LD are likely to develop multiple long-term health conditions (MLTCs)[2].

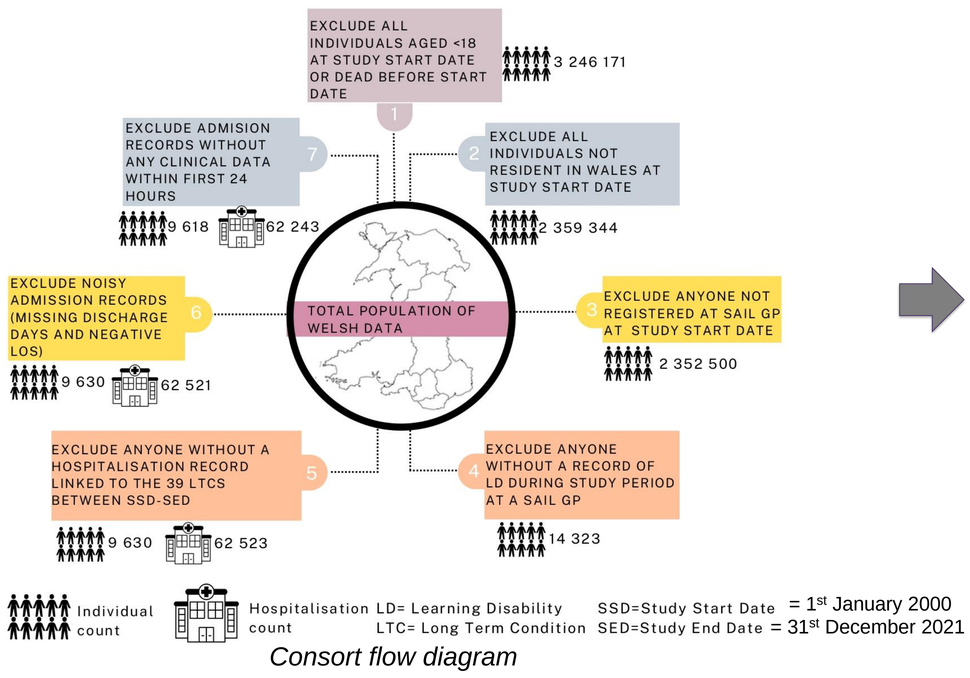
What is the challenge?

Accurately predicting the length of stay (LOS) for patients with LD and MLTCs using machine learning (ML) is essential for improving patient care and optimizing medical resource allocation. Despite its potential, research on the application of ML models to this specific patient population remains limited.

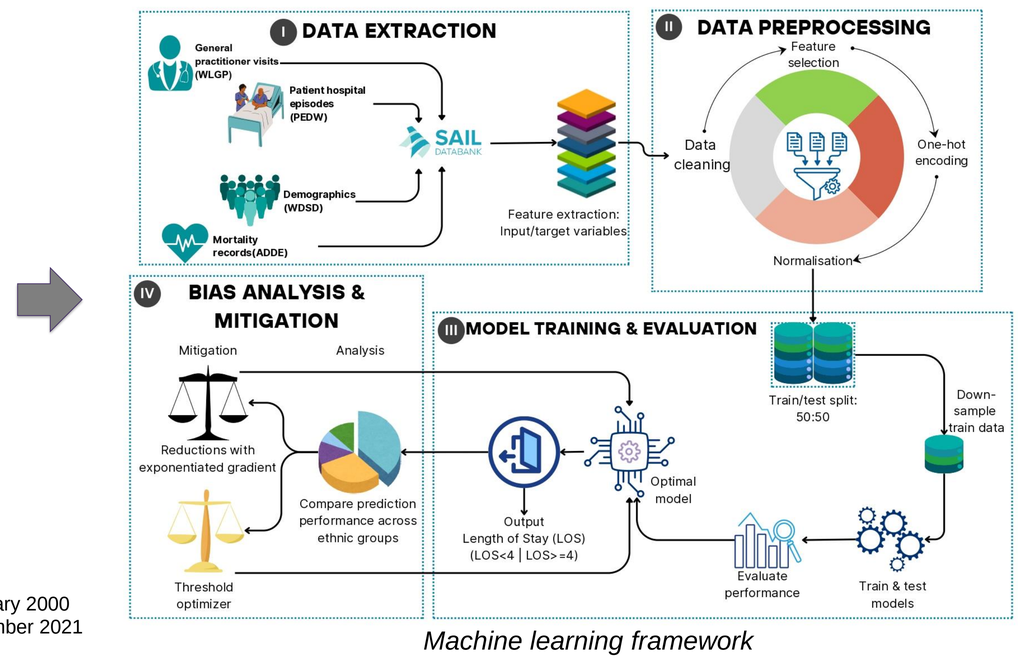
Research Aim

This study employs ML models to predict an LOS of ≥4 days for Welsh patients with LD and MLTCs using clinical, lifestyle, and demographic variables. It also addresses prediction fairness across ethnic groups by implementing two bias mitigation techniques. This highlights the potential of EHR data to support equitable healthcare predictions.

Data Extraction & Machine Learning Framework



Consort flow diagram



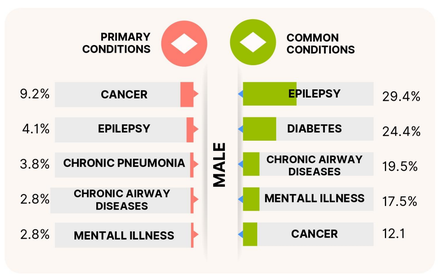
Machine learning framework

Variables used by ML models

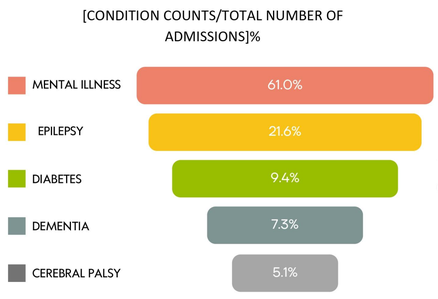
1. Hospital admissions in past 1-3 years
2. Hospital episodes in past 1-3 years
3. Smoking history
4. Alcohol history
5. Autism
6. Medication
7. BMI
8. Physical Activity
9. Presence of any of 40 LTCs
10. MLTC count
11. LTC counts treated in first 24 hours
12. Hospital episodes in first 24 hours
13. Age

Results

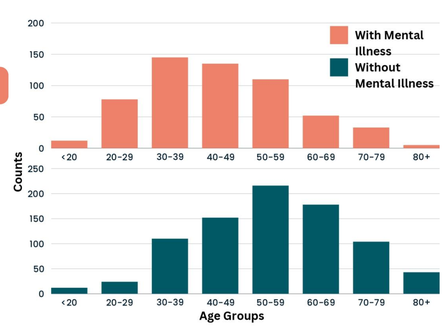
Initial Results



The top five primary conditions and top five prevalent (common) conditions treated or investigated during hospitalisations for the males and females with LD and MLTCs.



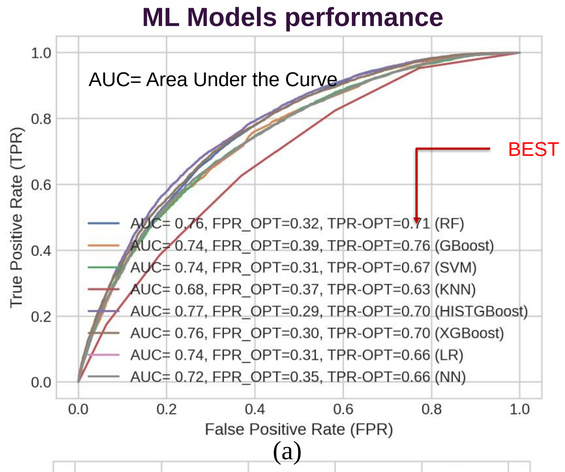
(a)



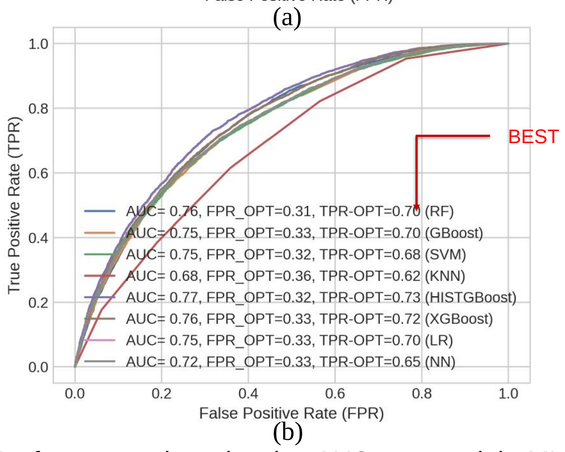
(b)

Distribution of patients with long hospital LOS ≥ 129 days. (a) The 4 most common conditions and (b) age distribution of patients with and without mental illness.

ML Models performance



(a)



(b)

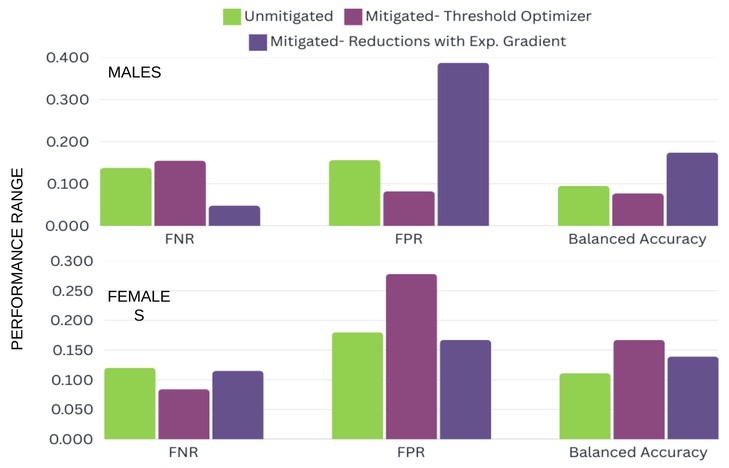
Performance plots showing AUC across eight ML models, highlighting optimal False Positive Rates (FPR) and True Positive Rates (TPR) for (a) male and (b) female cohorts. Models with lower FPR and higher AUC/TPR are optimal; RF was selected as the best model.

Bias Mitigation Across Ethnic Groups

	Ethnic Group	FNR	FPR	Balanced Accuracy
Males	Asian	0.195	0.547	0.629
	Black	0.273	0.533	0.597
	Other	0.333	0.423	0.622
	Unknown	0.234	0.392	0.687
	White	0.222	0.394	0.692

	Ethnic Group	FNR	FPR	Balanced Accuracy
Females	Asian	0.216	0.320	0.732
	Black	0.167	0.500	0.667
	Other	0.111	0.333	0.778
	Unknown	0.219	0.398	0.692
	White	0.231	0.393	0.688

Tables showing performance discrepancies of the unmitigated RF model across ethnic groups for males and females. The unmitigated model refers to the classifier without any bias mitigation algorithms applied.



Performance range (difference between the highest and lowest metrics across ethnic groups) for the unmitigated RF model and bias-mitigated RF models (threshold optimizer and exponentiated gradient reduction), for males and females. ***A lower performance range indicates reduced discrepancies across ethnic groups.***

Conclusions

Prolonged hospital stays and premature discharge increase patient risks such as infections, falls, cognitive and physical decline, and emergency readmissions. Accurate LOS prediction is essential for optimizing resource allocation and preventing these adverse outcomes.

This study develops ML models to predict hospital LOS for patients with LD and MLTCs while addressing fairness across ethnic groups. The RF model outperformed others, achieving an AUC of 0.759 (males) and 0.756 (females), with balanced accuracy of 0.690 and 0.689, respectively. Bias mitigation reduced disparities, with the threshold optimizer showing the most significant improvements.

The findings highlight the potential for equitable healthcare predictions using EHR data, paving the way for improved clinical decision-making and resource management.

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