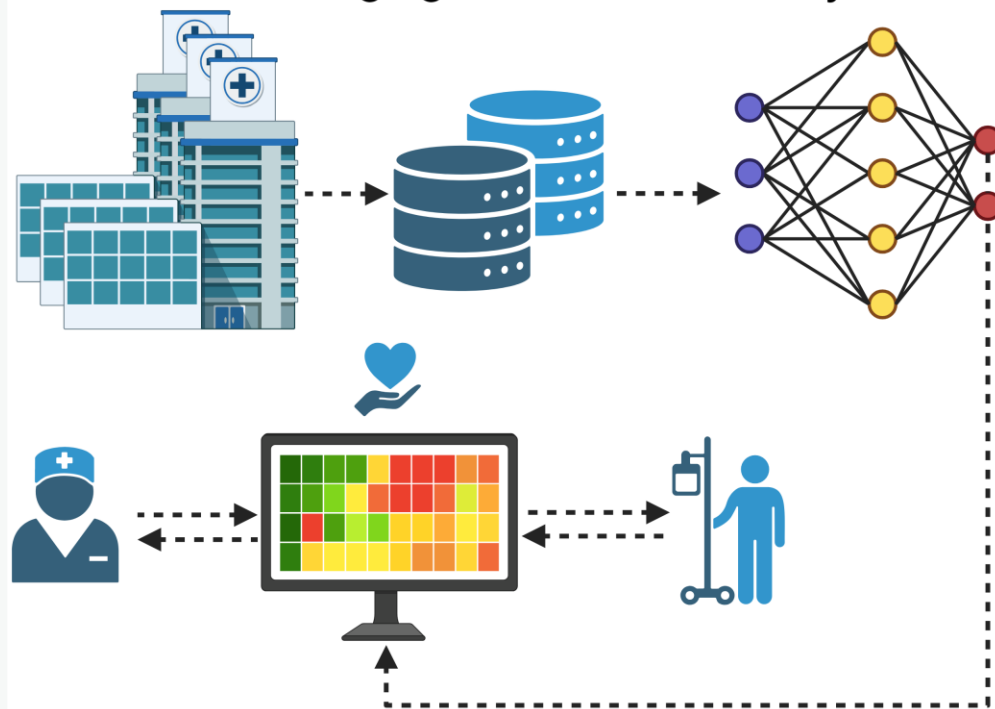


**A routine data-driven approach for
managing healthcare intensity**



Harnessing Machine Learning to Forecast Inpatient Care Intensity in NHS Lothian

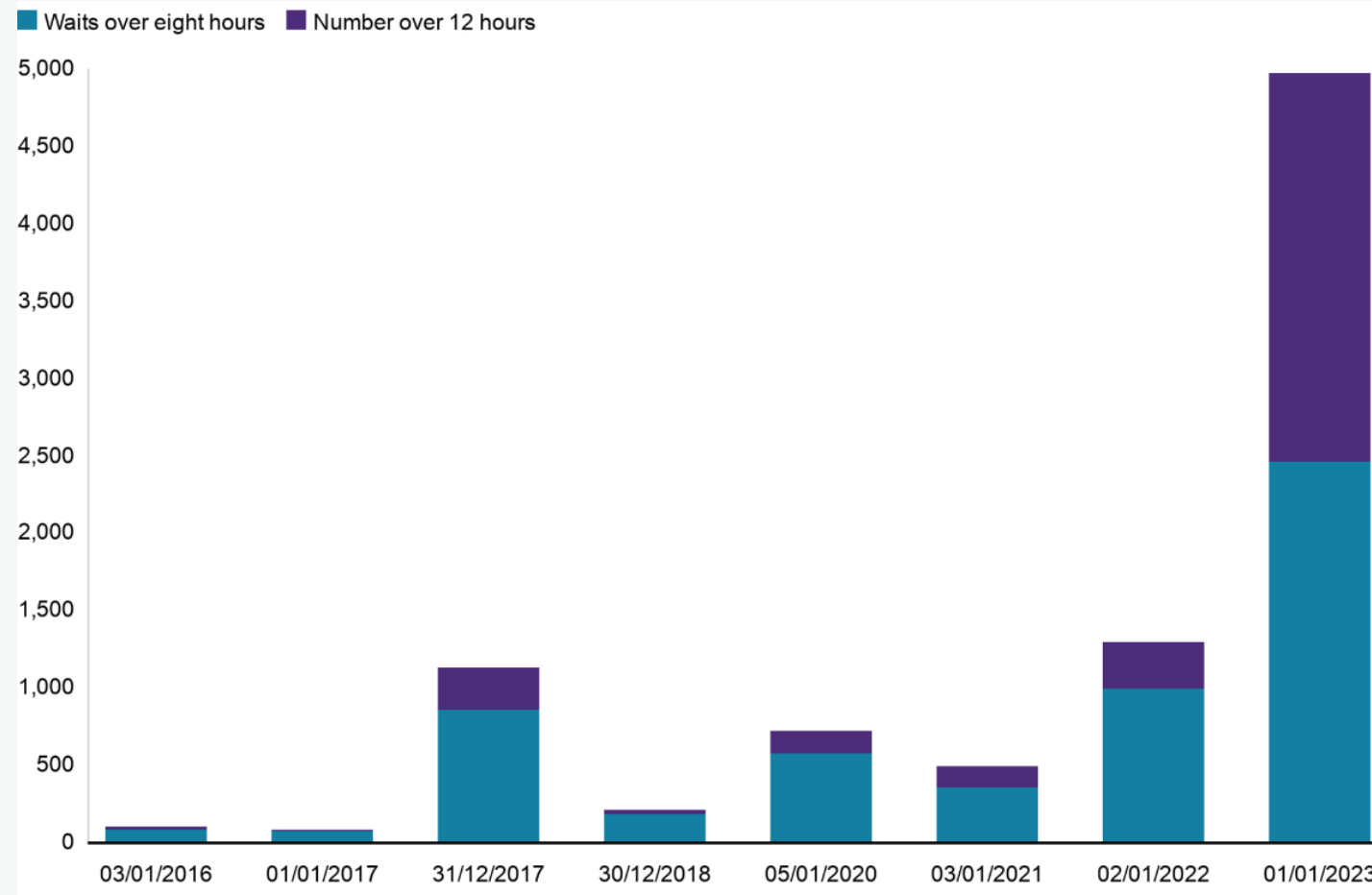
Konstantin Georgiev

*BHF Centre for Cardiovascular Science
University of Edinburgh*

Challenges for Unscheduled Care Systems

- ~40% of ED attendances comprise of older patients with **multiple** long-term conditions (MLTC), and **functional decline**.¹
- Overnight stays in the ED could reduce the likelihood of survival to discharge by ~5%.²
- Our current models in urgent care often **fail** to detect risks between older patients within the 72-hour window after admission.
- **ML-driven** approaches could be used to identify likely care needs early after hospitalisation.

Extended waits in A&E across Scotland



Source: Public Health Scotland

¹Hullick CJ, et al. Silver Book II: an international framework for urgent care of older people in the first 72 hours from illness or injury. *Age and Ageing*. 2021;50(4):1081-1083. doi:[10.1093/ageing/afab062](https://doi.org/10.1093/ageing/afab062) 2

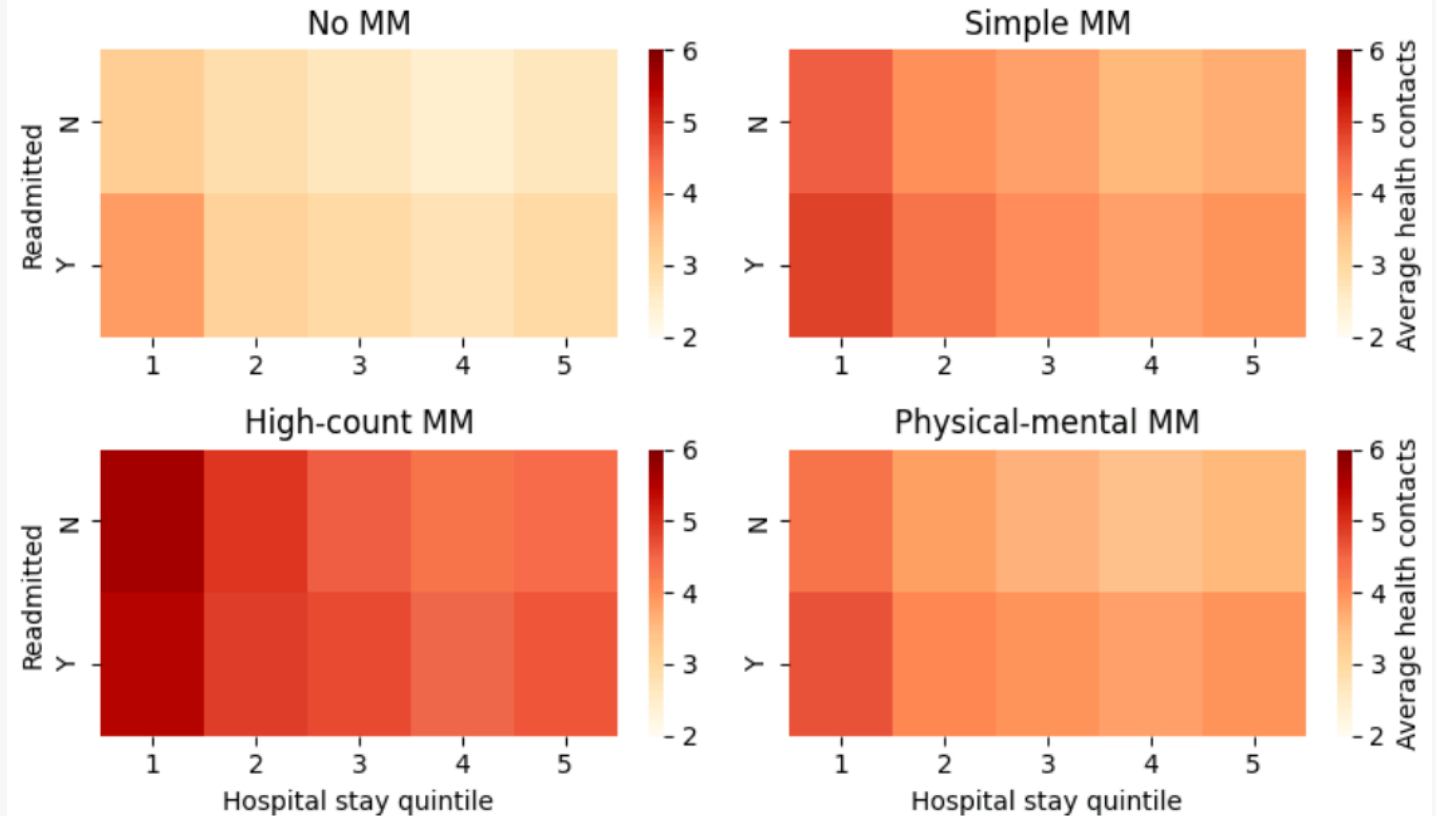
²Roussel M et al. Overnight Stay in the Emergency Department and Mortality in Older Patients. *JAMA Internal Medicine*. 2023;183(12):1378-1385. doi:[10.1001/jamainternmed.2023.5961](https://doi.org/10.1001/jamainternmed.2023.5961)

Previous Work

- **EHR** systems now capture multidimensional indicators of frailty,³ affecting healthcare needs in hospital.
- Each contact can be **timestamped** and recorded for measuring inpatient activity.
- In previous work, we showed associations between **healthcare contact frequency** and **multimorbidity** in NHS Lothian urgent care.⁴

Average health contacts recorded in urgent care by multimorbidity and 30-day readmission

Quintile-binned average total health contacts by multimorbidity group.



No MM: <2 long-term conditions

Simple MM: 2-3 long-term conditions

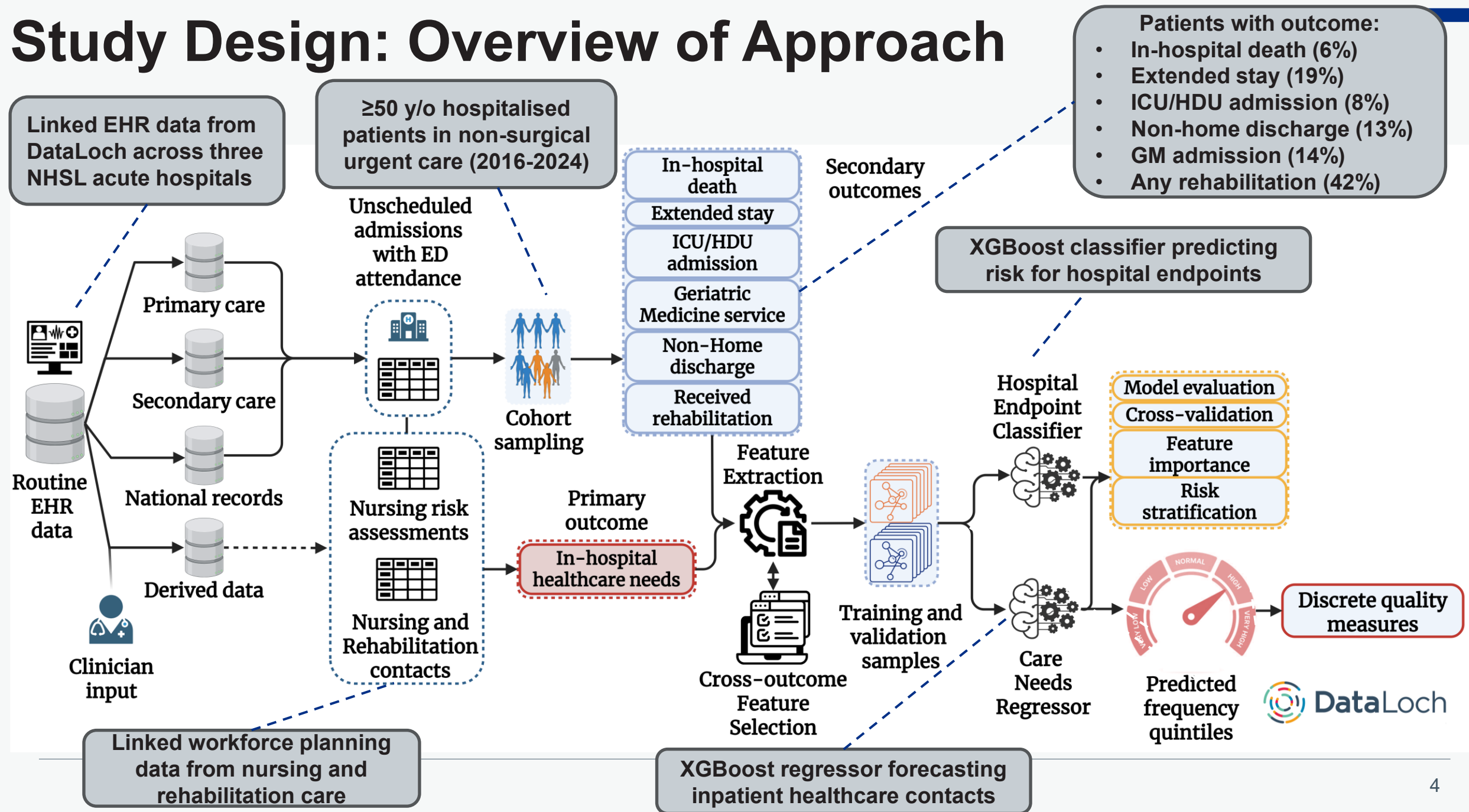
High-count MM: ≥4 long-term conditions

Physical-mental MM: >1 physical + >1 mental condition

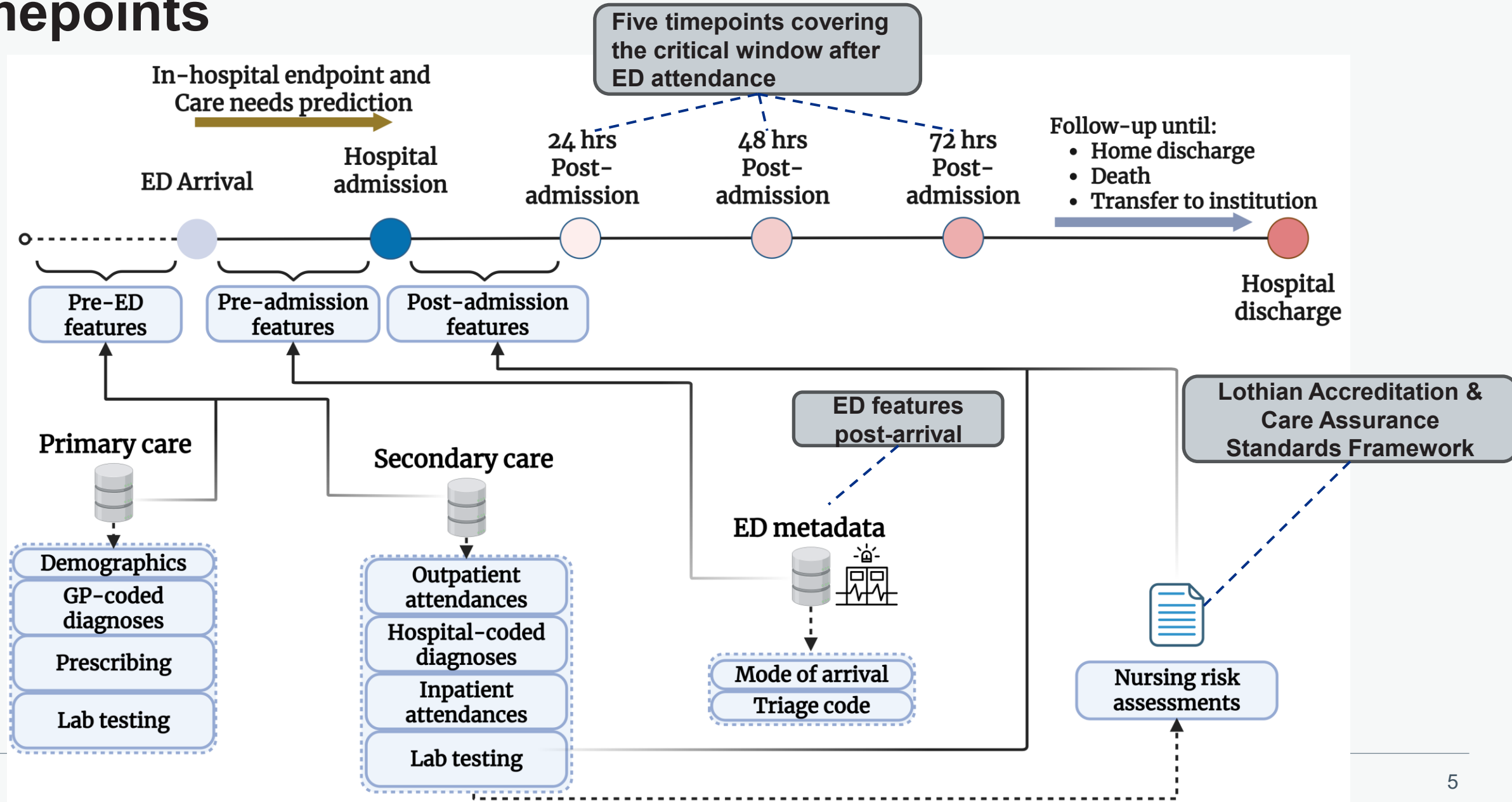
³Clegg A et al. Development and validation of an electronic frailty index using routine primary care electronic health record data. *Age Ageing*. 2016;45(3):353-360. doi:[10.1093/ageing/afw039](https://doi.org/10.1093/ageing/afw039)

⁴Georgiev K et al. Understanding hospital activity and outcomes for people with multimorbidity using electronic health records. *Scientific Reports*. 2025;15(1):8522. doi:[10.1038/s41598-025-92940-7](https://doi.org/10.1038/s41598-025-92940-7)

Study Design: Overview of Approach



Study design: Data Collection and Prediction Timepoints



Patient Characteristics

Intensity quintiles based on
nursing/rehab contacts

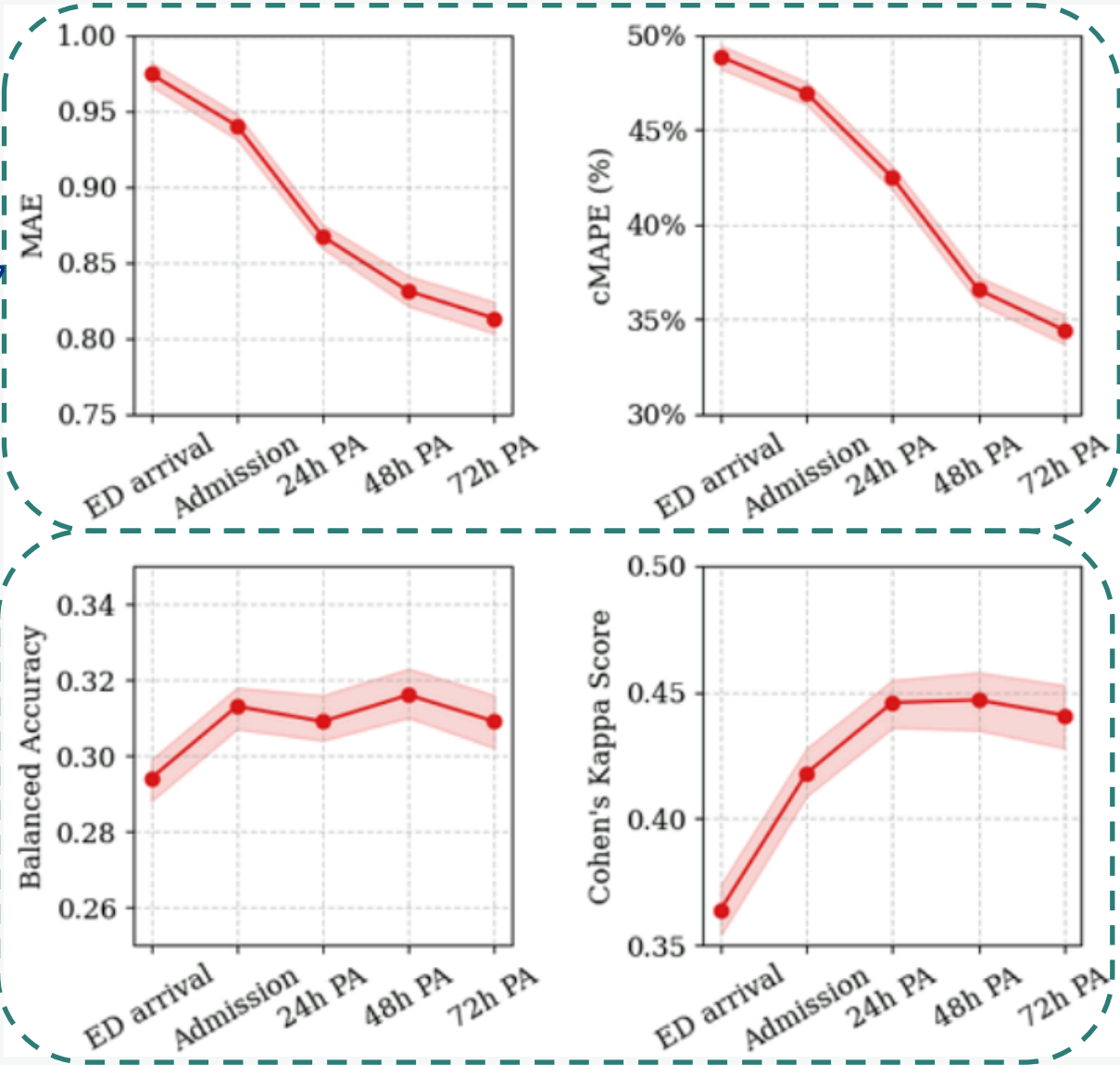


	All (n=98,242)	Level of healthcare need					p
		Very Low (n=9,687)	Low (n=26,994)	Medium (n=21,841)	Medium-High (n=19,981)	High (n=19,739)	
Age (mean, SD)	72±12	68±12	69±12	71±12	73±12	71±11	<0.001
Women (n, %)	50,214 (51%)	4,863 (50%)	13,246 (49%)	10,695 (49%)	10,423 (52%)	10,987 (56%)	<0.001
Health questionnaire results							
Delirium: 4AT Score (≥4, at risk)	6,540 (7%)	132 (1%)	675 (3%)	1,084 (5%)	1,797 (9%)	2,852 (14%)	<0.001
Malnutrition: MUST Score (≥2, at high risk)	5,911 (6%)	119 (1%)	650 (2%)	842 (4%)	1,377 (7%)	2,923 (15%)	<0.001
Pressure ulcer: Waterlow score (≥10, at risk)	17,023 (17%)	801 (8%)	2,660 (10%)	3,181 (15%)	4,323 (22%)	6,058 (31%)	<0.001
Fall event within 6 months of admission	16,043 (16%)	350 (4%)	2,149 (8%)	2,721 (13%)	4,052 (20%)	6,771 (34%)	<0.001
Walking dependence	17,074 (21%)	1,412 (15%)	6,341 (24%)	5,434 (25%)	4,338 (22%)	3,105 (16%)	<0.001
Bathing dependence	20,160 (21%)	1,473 (15%)	6,816 (25%)	5,727 (26%)	4,401 (22%)	2,428 (12%)	<0.001
Swallowing difficulties	1,719 (2%)	26 (<1%)	136 (1%)	175 (1%)	333 (2%)	1,049 (5%)	<0.001

Nursing risk indicators
can be linked to high
healthcare needs

Performance: Inpatient Care Intensity

Measure	Description	Interpretation
MAE (Mean Absolute Error)	Measure of average error size	lower=better (off by ~1 contact per patient)
cMAPE (Conditional Mean Absolute Percentage Error)	Average magnitude of error deviation	lower=better (50% = random chance, 35% = moderate)
BACC (Balanced accuracy)	Weighted average accuracy over 5 intensity quintiles	higher=better (0.25 = random chance)
CKS (Cohen's Kappa Score)⁵	Qualitative measure of reliability over 5 intensity quintiles	Higher=better (<0.2 = poor agreement, 0.4-0.6 = moderate)



⁵McHugh ML. Interrater reliability: the kappa statistic. Biochem Med (Zagreb). 2012;22(3):276-282. (<https://pubmed.ncbi.nlm.nih.gov/23092060/>)

Performance: Hospital Outcomes

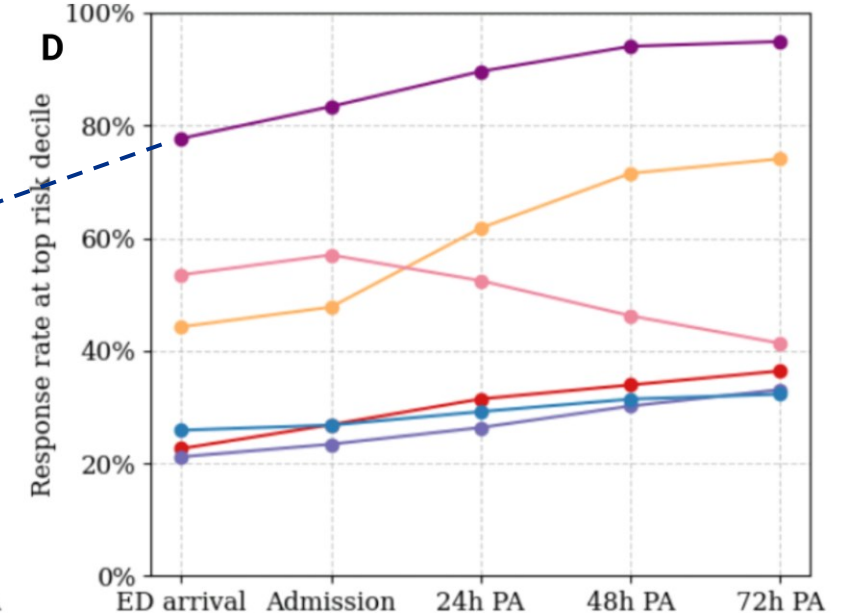
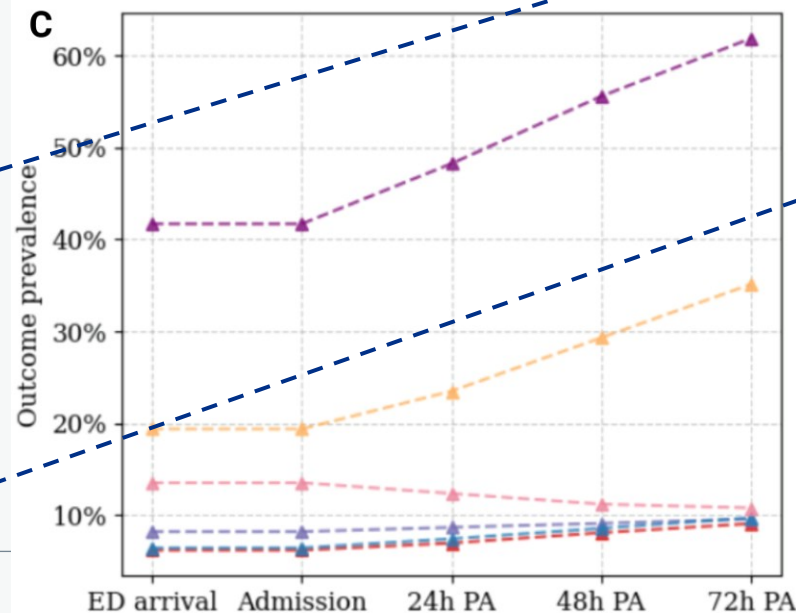
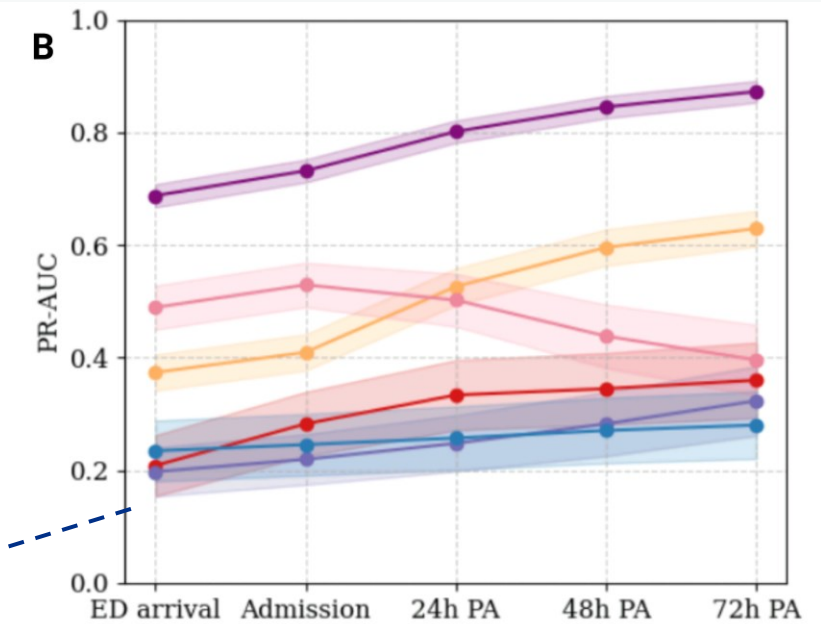
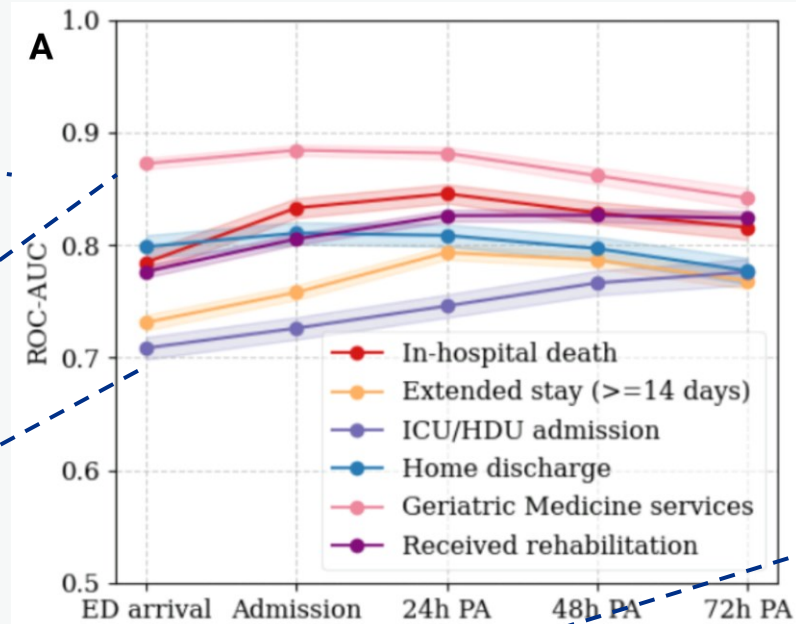
Moderate to great discrimination (ROC-AUC between 0.71-0.89)

Excellent detection for GM-related admissions (ROC-AUC=0.89 at hospitalisation)

More limited for ICU admissions (ROC-AUC=0.71-0.78)

Improved detection rate over time (PR-AUC), excl. GM admission

Captured 9 out of 10 patients within top 10% of risk that required any future rehabilitation

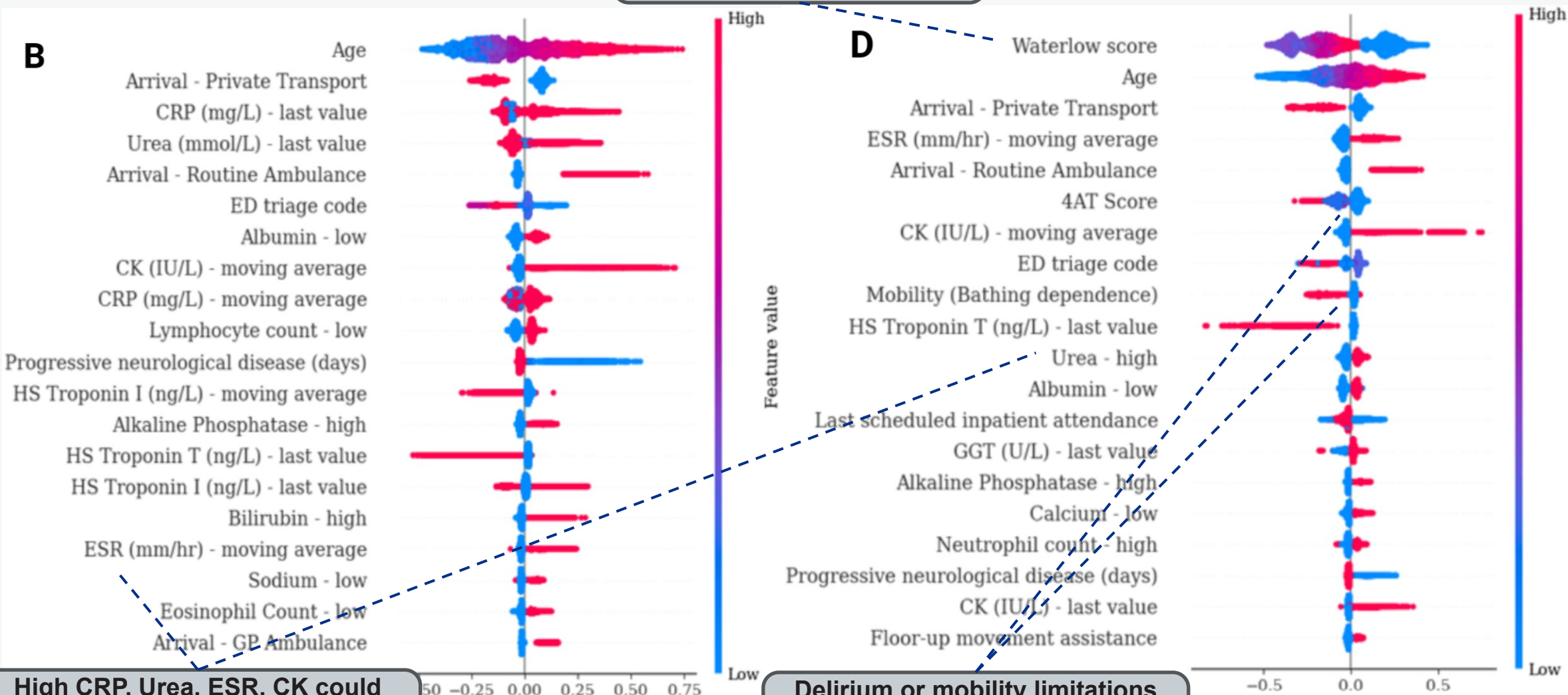


Important Predictors of Care Intensity

Point of hospital admission

Pressure Ulcer risk could limit contact frequency

48-hours post-admission



High CRP, Urea, ESR, CK could increase healthcare needs due to multisystem decline

Delirium or mobility limitations could also explain fewer health contacts



Summary

- ML-driven approaches can predict in-hospital healthcare needs and requirements for specialist services in urgent care with **moderate to excellent** quality.
- Markers of geriatric health and frailty in routine data can be used to explain intensity of inpatient care.
- Some predictions are likely confounded by **serious acute events** (e.g. myocardial infarction) or **death**.
- Need to capture a greater array of providers for a **holistic** representation of delivered healthcare (e.g. medical doctors, pharmacists, pain management team).
- In the future, forecasting models for **healthcare intensity** could feed insights to other risk assessment tools to support precise '**front-door**' approaches and **resource allocation** NHS Lothian.

Acknowledgments

UoE PhD supervision team:

- Dr Atul Anand
- Prof Susan D Shenkin
- Prof Joanne McPeake
- Prof Jacques Fleuriot

Data collaborators:

- DataLoch (Data-Driven Innovation Initiative)



Funding body:

- Sir Jules Thorn Charitable Trust (PhD award, 21/01PhD)



Lothian
R&D conference

Thank you!

Contact:

K.S.Georgiev@sms.ed.ac.uk

University of Edinburgh

BHF Centre for Cardiovascular Science

