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Noncoding RNAs and machine learning for COVID-19 patients

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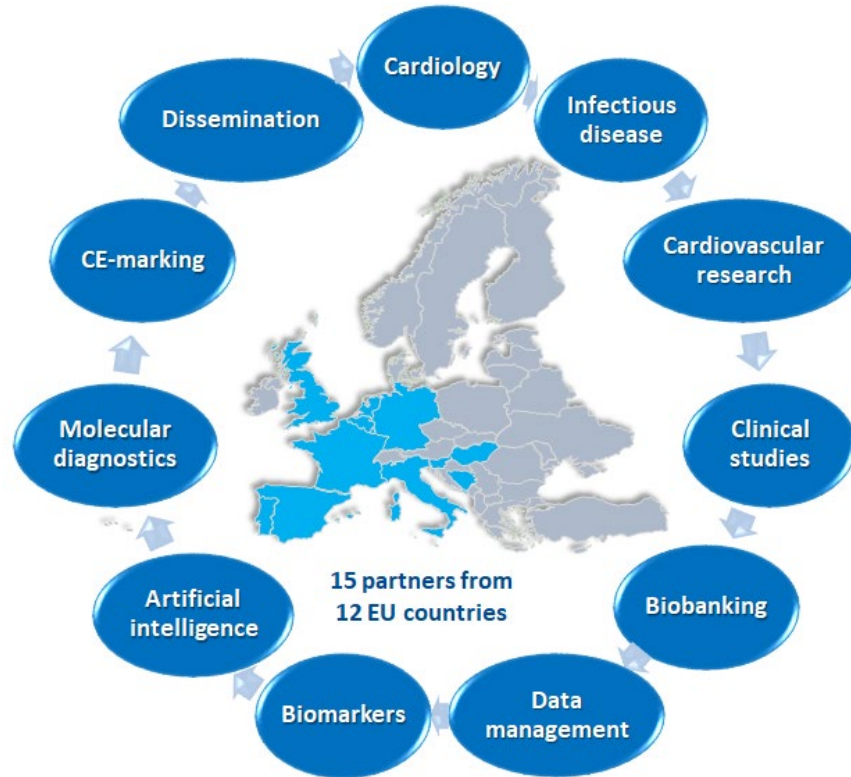
A diagnostic test to improve surveillance and care of COVID-19 patients

(H2020 SC1-PHE-CORONAVIRUS-2B projects)



Horizon 2020
European Union funding
for Research & Innovation

COVIRNA multidisciplinary team





COVIRNA concept

➤ **Biomedical issue**

COVID-19 pandemic

Predicting clinical outcome of COVID-19 patients is a challenge

➤ **Unmet clinical need**

Early predictors of outcome in COVID-19 patients

➤ **Solution/goal of the COVIRNA project**

A molecular diagnostic kit to predict outcome of COVID-19 patients

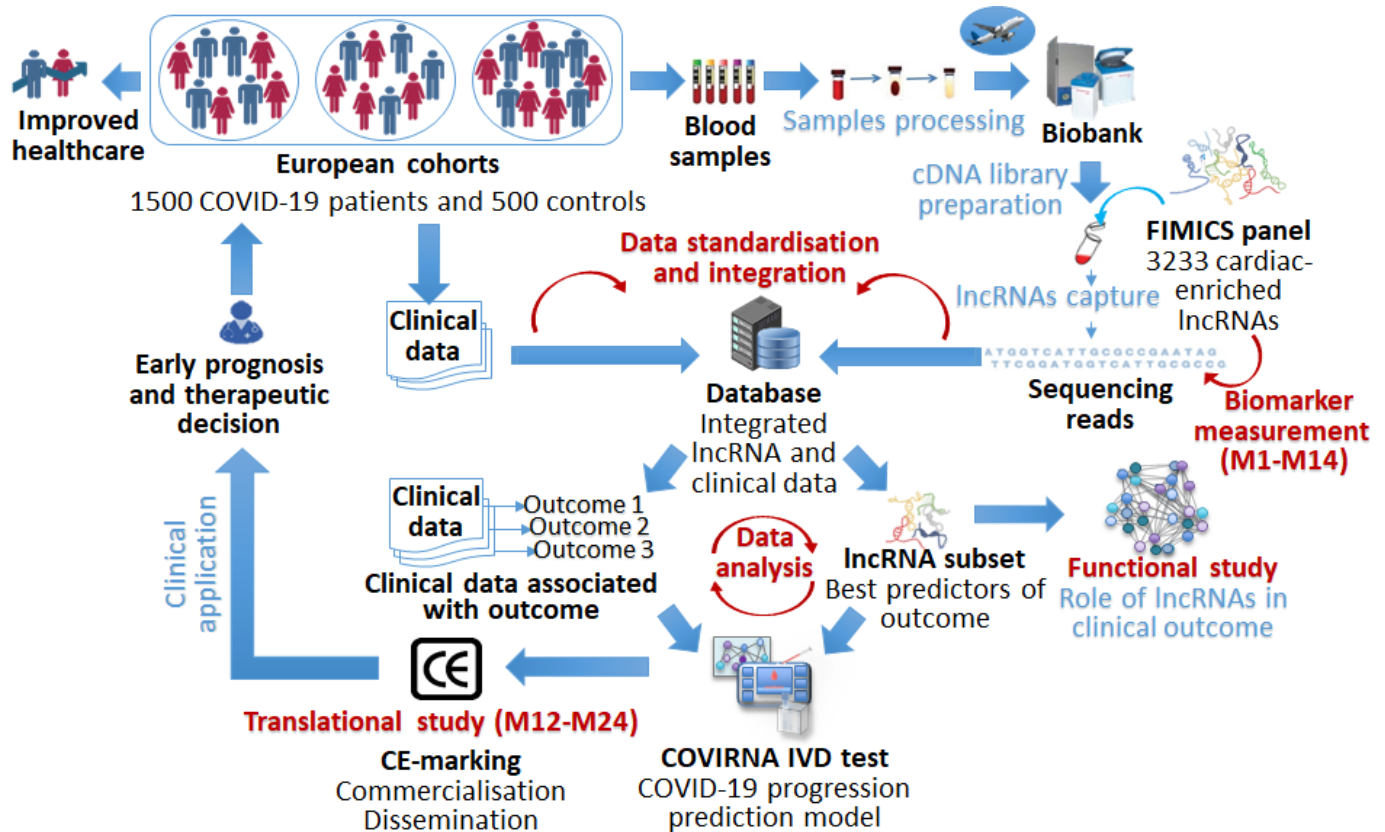
→ Simple, minimally invasive and rapid blood test

→ Based on the FIMICS panel of cardiac-enriched long noncoding RNAs (lncRNAs) for which the consortium has the intellectual property and exclusive licenses

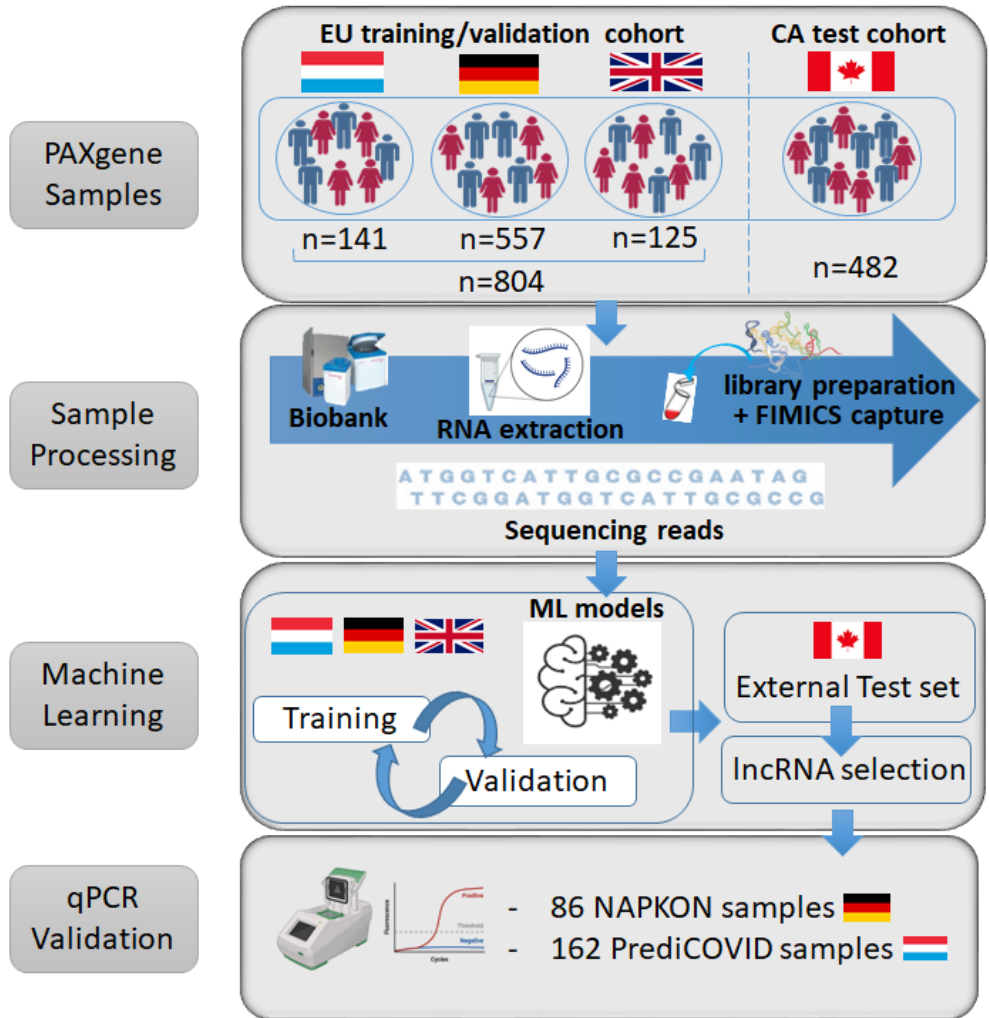
→ Suitable for PCR diagnostic platforms and cost-effective.



Approach



COVIRNA study workflow





PAXgene samples handling

The German National Pandemic Cohort Network (NAPKON):

- 583 COVID 19 positive PAXgene samples
- MTA signed June 2021
- Samples were sent to Firalis SA (France) for extraction and sequencing





PAXgene samples extraction and sequencing

- Batches of 64 samples were randomized for RNA extraction at Firalis
- RNA extraction using the KingFisher Apex instrument (fully automatized)
- RNA quantification with a Qubit Fluorometer
- Library preparation and capture using the FIMICS panel containing more than 55000 probes of 120 nucleotides each covering specific regions of 3233 lncRNAs, cardiac-enriched or associated with heart failure (Heliyon 2023; Noncoding RNA Res 2023)





Datasets available for analysis

- A technical issue in one run during targeted sequencing led to a loss of 26 samples, resulting in **557 RNAseq datasets available for analysis**
- RNAseq datasets were combined with clinical data and data analysis was performed



Study on in-hospital mortality

nature communications



Article

<https://doi.org/10.1038/s41467-024-47557-1>

Development of a long noncoding RNA-based machine learning model to predict COVID-19 in-hospital mortality

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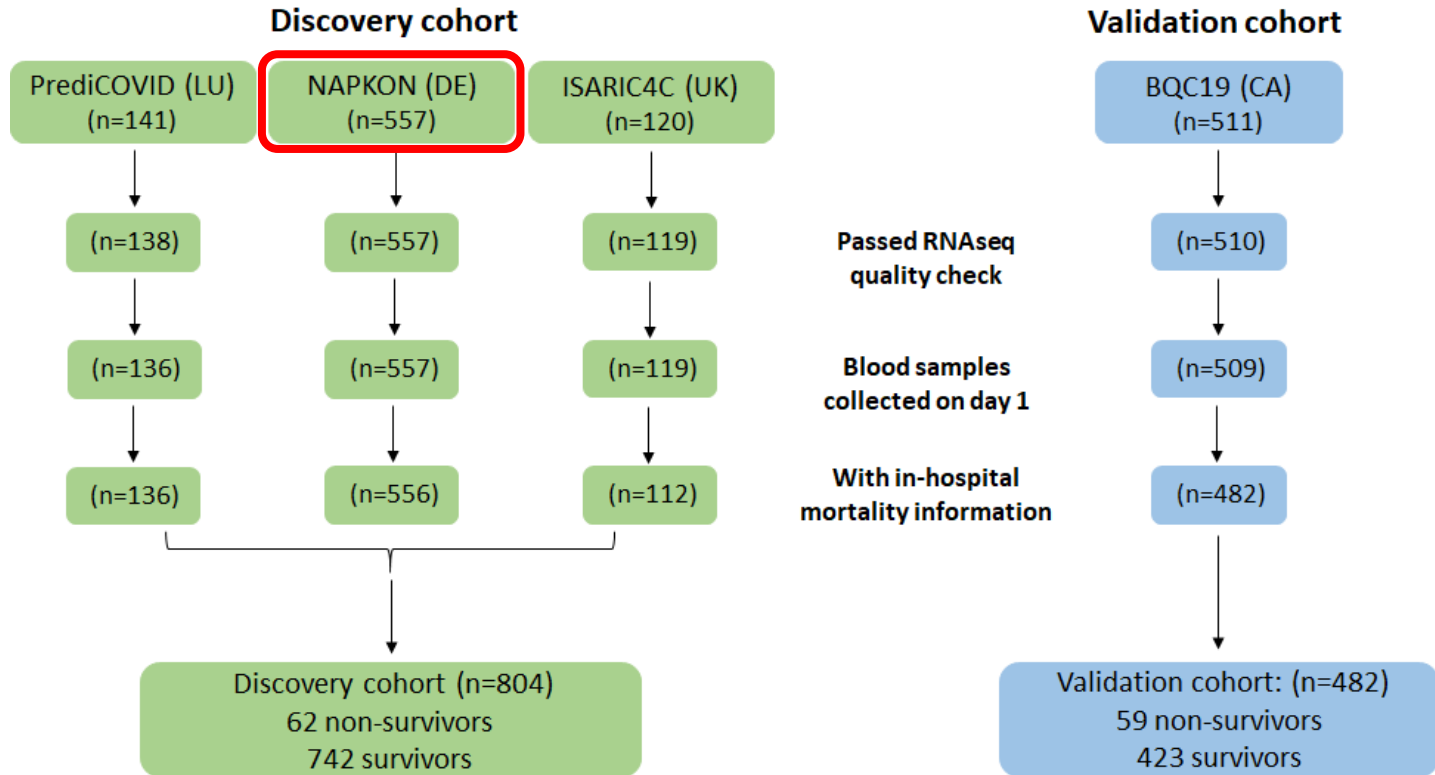
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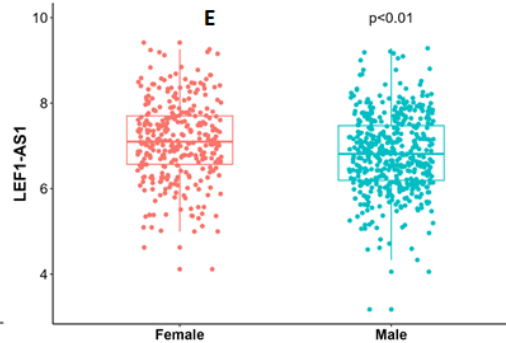
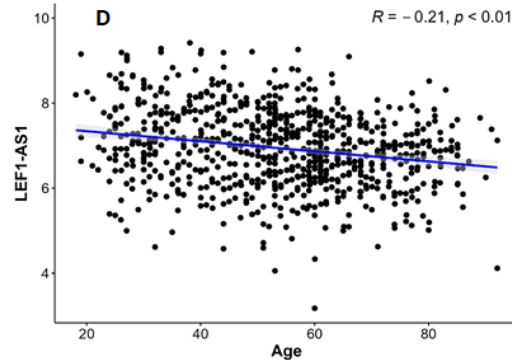
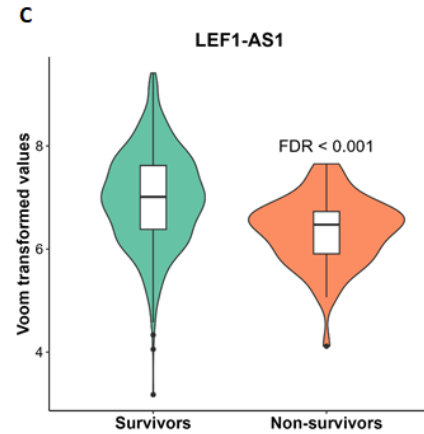
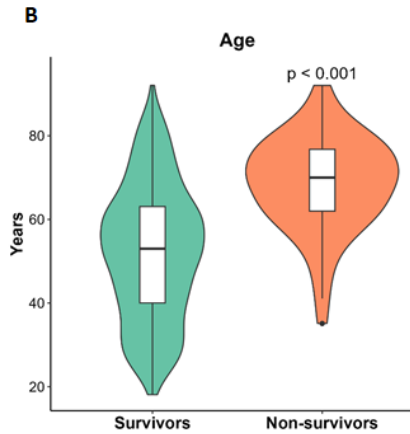
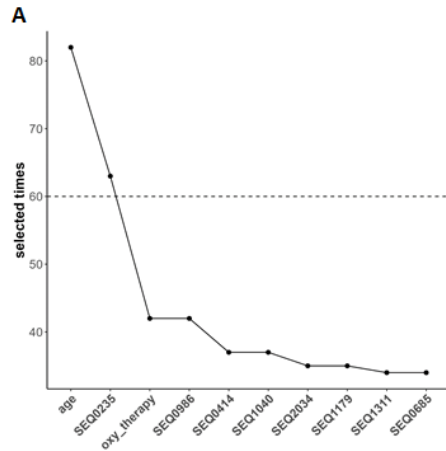
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Study design



Feature selection (discovery cohort)



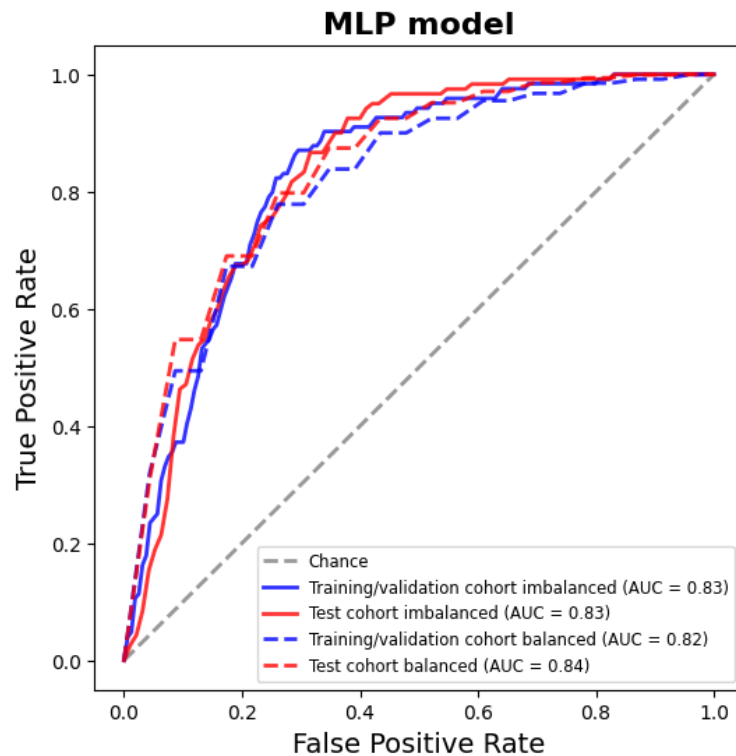
Machine learning models for in-hospital mortality

Classifier	AUC (95% CI)	Accuracy (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)	Brier score (95% CI)
RF	0.78 (0.76–0.80)	0.73 (0.71–0.75)	0.76 (0.73–0.78)	0.71 (0.68–0.74)	0.19 (0.18–0.20)
kNN	0.81 (0.79–0.83)	0.75 (0.73–0.77)	0.85 (0.83–0.87)	0.65 (0.62–0.68)	0.18 (0.17–0.19)
Logit	0.81 (0.79–0.83)	0.76 (0.74–0.77)	0.81 (0.78–0.84)	0.70 (0.67–0.73)	0.18 (0.17–0.19)
MLP	0.82 (0.80–0.84)	0.77 (0.75–0.79)	0.82 (0.80–0.84)	0.72 (0.69–0.75)	0.18 (0.17–0.18)
SVM	0.67 (0.62–0.72)	0.74 (0.72–0.76)	0.82 (0.80–0.84)	0.67 (0.63–0.70)	0.21 (0.20–0.22)
XGB	0.74 (0.72–0.76)	0.68 (0.66–0.70)	0.69 (0.66–0.71)	0.67 (0.64–0.70)	0.25 (0.24–0.26)

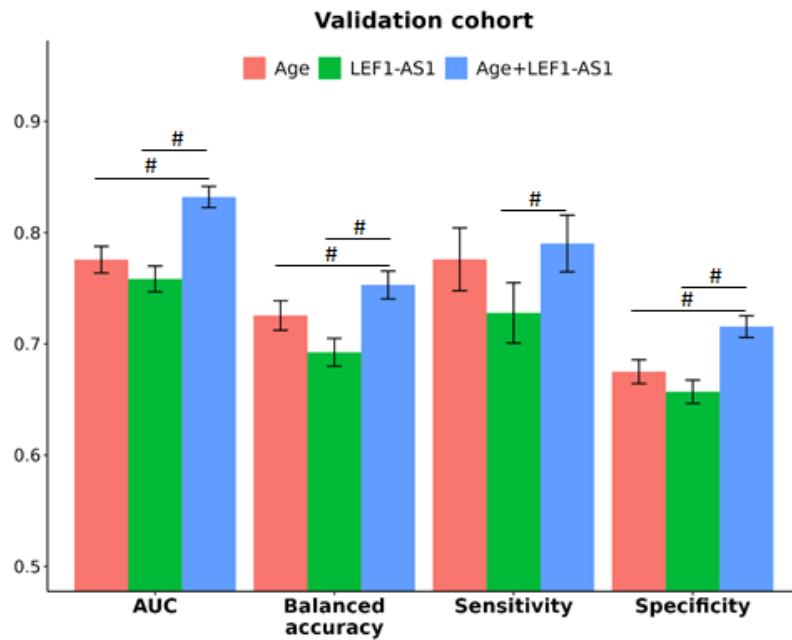
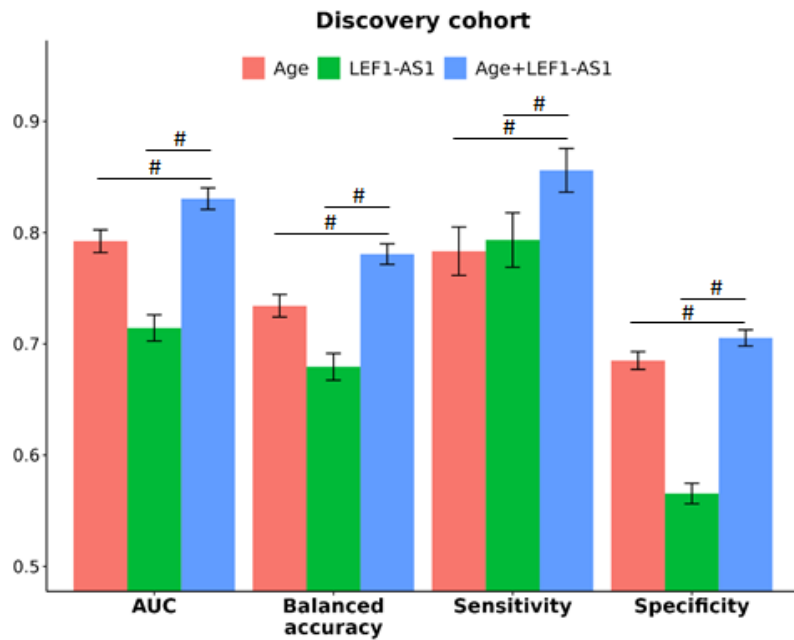


Performance of different classifiers to predict in-hospital mortality in the discovery cohort using two selected features (age and LEF1-AS1)

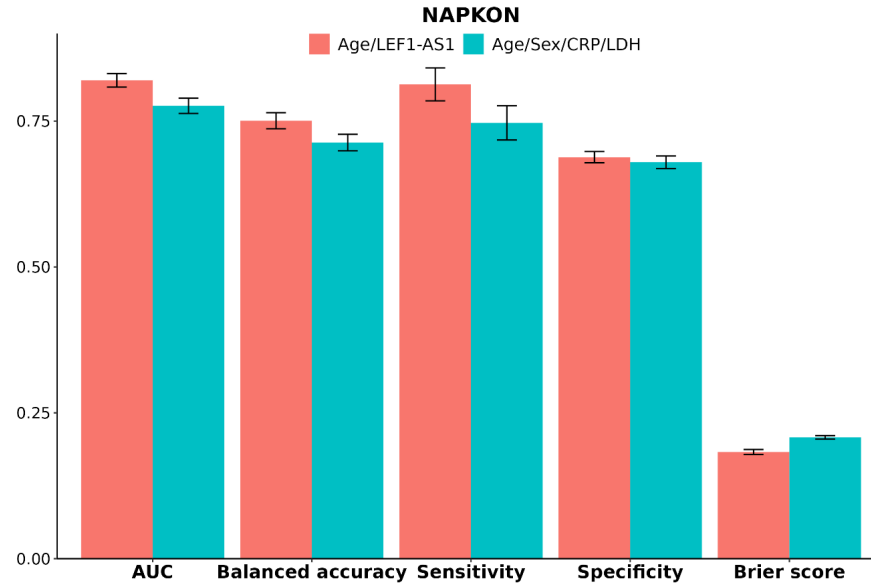
MLP model performance



MLP model performance

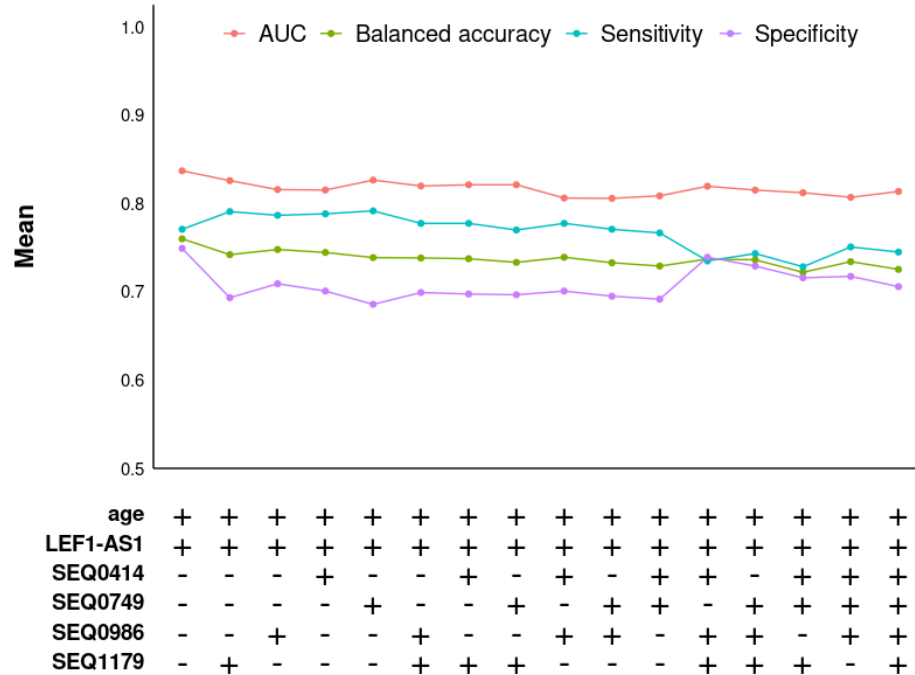


MLP model performance



Comparison of our model with age and LEF1-AS1 with a previously published model with age, sex, CRP and LDH

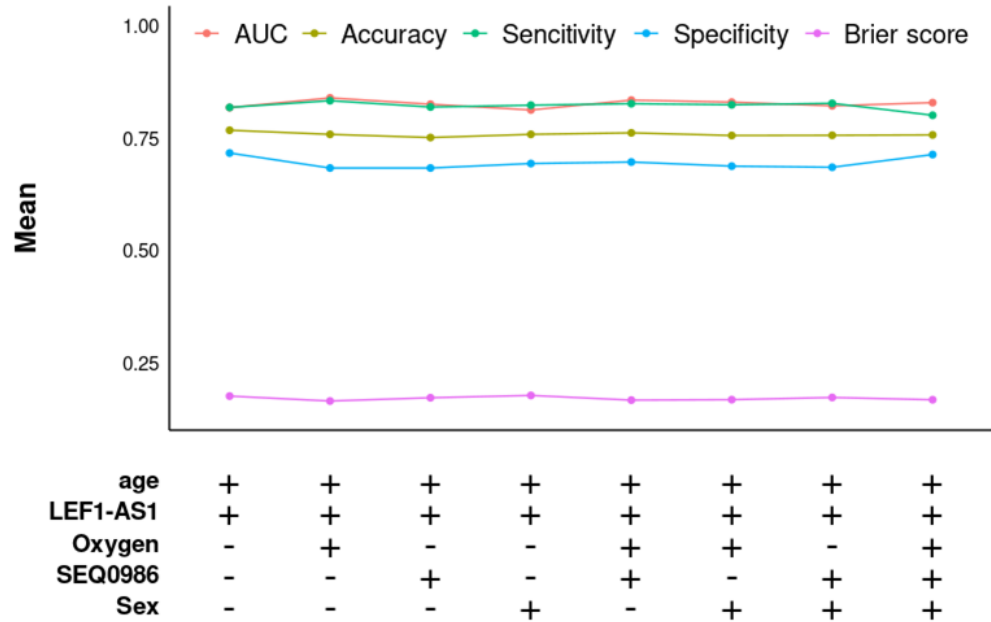
MLP model performance



Lack of added value of other lncRNAs to the model with age and LEF1-AS1



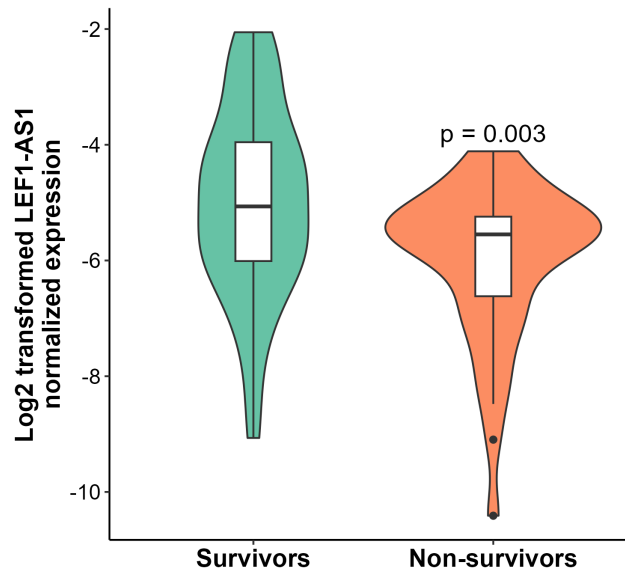
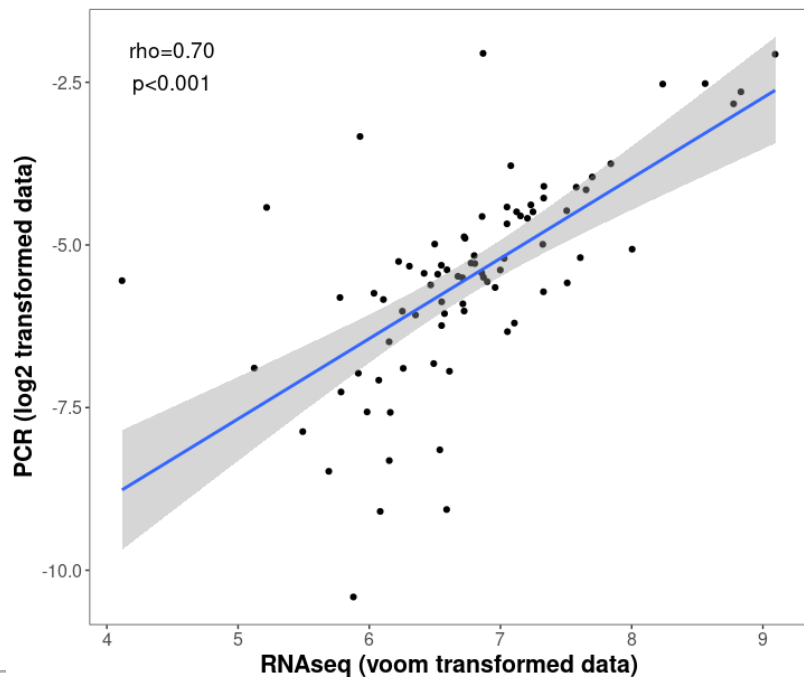
MLP model performance



Lack of added value of other data to the model with age and LEF1-AS1



PCR validation



LEF1-AS1 expression in 84 PAXgene samples from the NAPKON cohort. LEF1-AS1 expression assessed by PCR was correlated with RNAseq data and was higher in survivors (n= 41) vs. non-survivors (n=43).



Study on long COVID

No imputation

582 NAPKON participants

535 with LEF1-AS1 data

514 with severity at baseline

347 with BMI

288 with data about neuro comorbidity
(yes or no) and smoking status



Males and females

number participants	288			347			514			535		
male	178 (61%)			209 (60%)			308 (60%)			320 (60%)		
female	110			138			206			215		
CVD complication	142 (49%)			166 (48%)			252 (49%)			264 (49%)		
Univariate analysis for CVD	AUC	OR	p-value	AUC	OR	p-value	AUC	OR	p-value	AUC	OR	p-value
Gender	0.526	0.801	0.361	0.523	0.825	0.382	0.516	0.878	0.471	0.515	0.886	0.491
Age	0.583	1.331	0.019	0.58	1.309	0.015	0.569	1.247	0.014	0.574	1.265	0.008
BMI	0.556	1.189	0.146	0.539	1.126	0.274						
Comorb_neuro	0.526	1.636	0.18									
Current_smoker	0.501	1.031	0.941									
Former_smoker	0.501	1.011	0.965									
severity_no_compl	0.523	0.825	0.429	0.519	0.849	0.46	0.53	0.766	0.152			
severity_compl	0.502	0.978	0.93	0.503	0.97	0.894	0.515	1.161	0.442			
severity_severe_compl	0.525	2.981	0.067	0.523	2.478	0.073	0.515	1.823	0.142			
LEF1_AS1	0.567	0.763	0.027	0.545	0.826	0.08	0.557	0.786	0.008	0.556	0.785	0.006

Age and LEF1-AS are significantly associated with development of long CVD symptoms (12 months),
but AUC is <0.60



Males only

number MALE participants	178			209			308			320		
CVD complication	84 (47%)			96 (46%)			147 (48%)			154 (48%)		
Univariate analysis for CVD	AUC	OR	p-value	AUC	OR	p-value	AUC	OR	p-value	AUC	OR	p-value
Age	0.555	1.177	0.286	0.573	1.241	0.130	0.561	1.202	0.113	0.563	1.211	0.093
BMI	0.559	1.191	0.251	0.531	1.096	0.511						
Comorb_neuro	0.521	1.874	0.288									
Current_smoker	0.500	0.994	0.991									
Former_smoker	0.514	1.129	0.701									
severity_no_compl	0.510	1.089	0.779	0.505	1.041	0.887	0.527	0.795	0.329			
severity_compl	0.542	0.691	0.242	0.539	0.705	0.235	0.505	1.046	0.855			
severity_severe_compl	0.532	3.193	0.095	0.534	3.169	0.058	0.522	2.296	0.106			
LEF1_AS1	0.552	0.869	0.356	0.512	0.977	0.870	0.520	0.921	0.475	0.520	0.916	0.437

No significant predictor for long CVD symptoms in males (neither age nor LEF1-AS1)



Females only

number FEMALE participants	110			138			206			215		
CVD complication	58 (53%)			70 (51%)			105 (51%)			110 (51%)		
Univariate analysis for CVD	AUC	OR	p-value	AUC	OR	p-value	AUC	OR	p-value	AUC	OR	p-value
Age	0.626	1.615	0.021	0.586	1.404	0.057	0.580	1.311	0.059	0.588	1.344	0.036
BMI	0.515	1.111	0.586	0.522	1.107	0.553						
Comorb_neuro	0.526	1.380	0.505									
Current_smoker	0.505	1.132	0.859									
Former_smoker	0.518	0.850	0.690									
severity_no_compl	0.583	0.457	0.065	0.561	0.573	0.131	0.538	0.693	0.234			
severity_compl	0.567	1.962	0.124	0.554	1.696	0.166	0.534	1.436	0.263			
severity_severe_compl	0.516	2.782	0.382	0.507	1.478	0.674	0.504	1.212	0.779			
LEF1_AS1	0.594	0.618	0.023	0.598	0.638	0.016	0.613	0.615	0.002	0.612	0.618	0.001

Age and LEF1-AS1 are predictors of CVD complications in females



Multivariable analysis

n=288 – Females only (n=110)

variables	AIC	wald_p	AUC
LEF1_AS1 + Age	146.836	0.010	0.659
LEF1_AS1 + Age + severity_severe_compl	148.054	0.020	0.671
LEF1_AS1 + Age + severity_compl	148.149	0.022	0.663
Age	150.370	0.023	0.626
LEF1_AS1 + Age + BMI	148.493	0.023	0.664
LEF1_AS1	150.497	0.025	0.594
LEF1_AS1 + Age + Comorb_neuro	148.681	0.025	0.660
LEF1_AS1 + Age + Former_smoker	148.713	0.026	0.664
LEF1_AS1 + Age + Current_smoker	148.814	0.026	0.660
LEF1_AS1 + Age + severity_compl + severity_severe_compl	149.134	0.034	0.675
LEF1_AS1 + Age + BMI + severity_severe_compl	149.587	0.036	0.679
LEF1_AS1 + Age + BMI + severity_compl	149.893	0.041	0.671
LEF1_AS1 + Age + Current_smoker + severity_severe_compl	149.990	0.042	0.669
LEF1_AS1 + Age + Comorb_neuro + severity_severe_compl	149.992	0.042	0.669
LEF1_AS1 + Age + Former_smoker + severity_severe_compl	149.936	0.043	0.674
LEF1_AS1 + Age + Comorb_neuro + severity_compl	149.900	0.043	0.666
LEF1_AS1 + severity_compl	150.898	0.043	0.627
Age + severity_compl	151.137	0.044	0.635
LEF1_AS1 + Age + Current_smoker + severity_compl	150.060	0.045	0.666
LEF1_AS1 + Age + Former_smoker + severity_compl	150.049	0.045	0.661
LEF1_AS1 + Age + BMI + Former_smoker	150.304	0.047	0.677
LEF1_AS1 + Age + BMI + Comorb_neuro	150.378	0.047	0.664
LEF1_AS1 + Age + BMI + Current_smoker	150.449	0.048	0.664
LEF1_AS1 + severity_severe_compl	151.167	0.048	0.609



Age + LEF1-AS1 is the best model to predict CVD in females, but AUC is low (0.66)





Conclusions

- NAPKON study helped to identify LEF1-AS1 as a predictor of in-hospital mortality
- In NAPKON, the capacity of baseline levels of LEF1-AS1 to predict the development of cardiovascular symptoms at 12 months is low (AUC < 0.60)





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Thank you

