BIO TUESDAYS

LE RDV BIMESTRIEL
SCIENCES DE LA VIE – SANTÉ

previa MEDICAL

2020
Fondée à
Lyon, France

15 ans
d'expérience
numérique en santé

previa MEDICAL

2022
Lauréat Grand Défi
Etude bénéfices

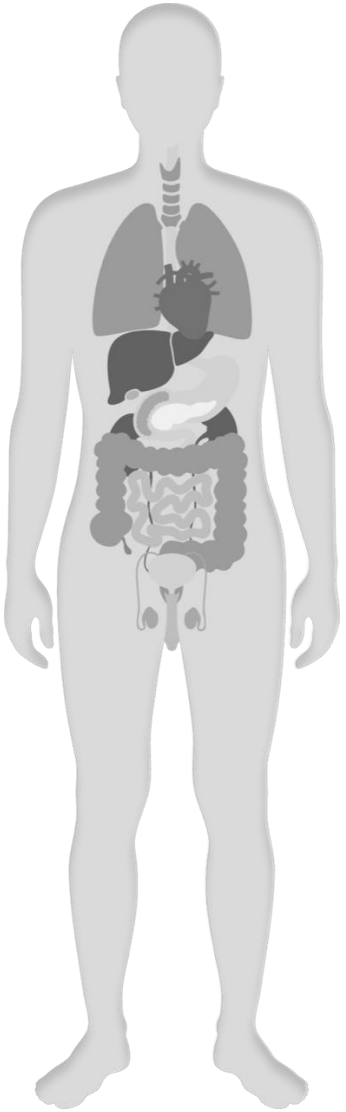
2023
Levée de fonds

prevOIR & prevENIR

LES URGENCES VITALES

previa MEDICAL

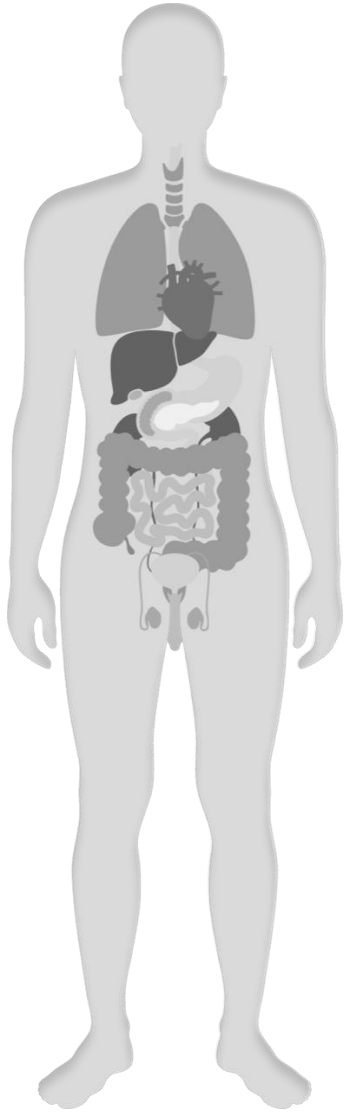
prevOIR & prevENIR



LES URGENCES VITALES

previa MEDICAL

prevOIR & prevENIR



LES SEPSIS

180 000 cas par an
50 000 décès **(27%)**

LES INSUFFISANCES RÉNALES AIGUËS (AKI)

200 000 cas par an
20 000 décès **(10%)**

LES SYNDROMES DE DÉTRESSE RESPIRATOIRE AIGUË (ARDS)

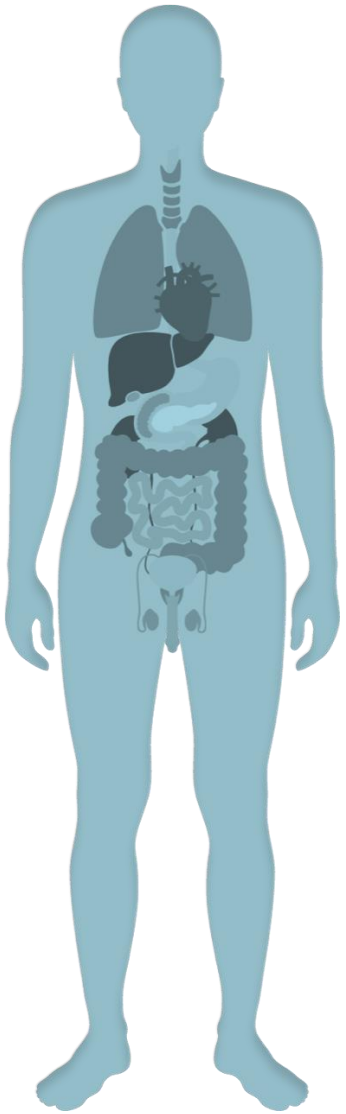
20 000 cas par an
10 000 décès **(50%)**

LES ARRÊTS CARDIAQUES (ACR)

30 000 cas par an

previa MEDICAL

prevOIR & prevENIR



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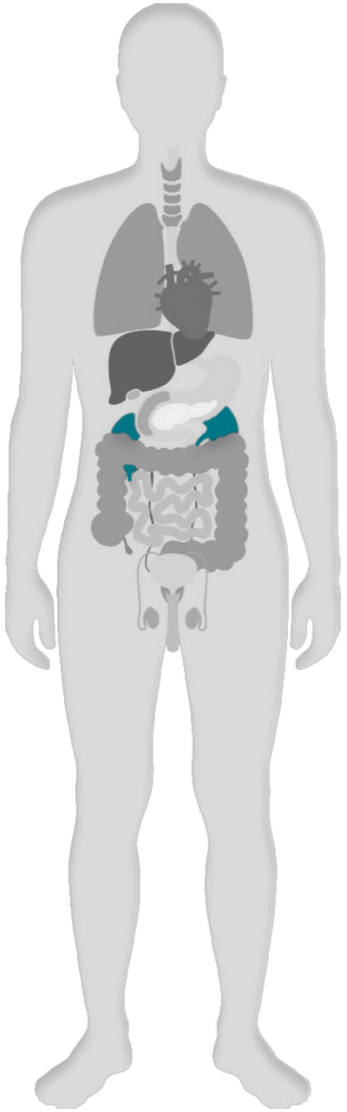

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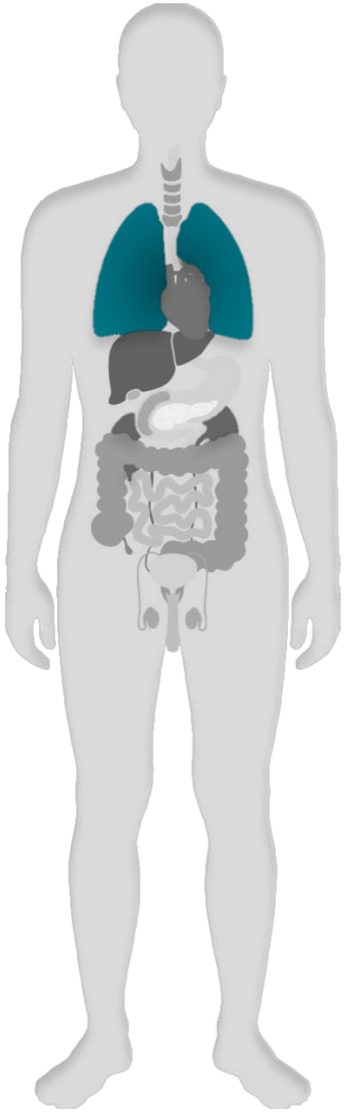
prevOIR & prevENIR



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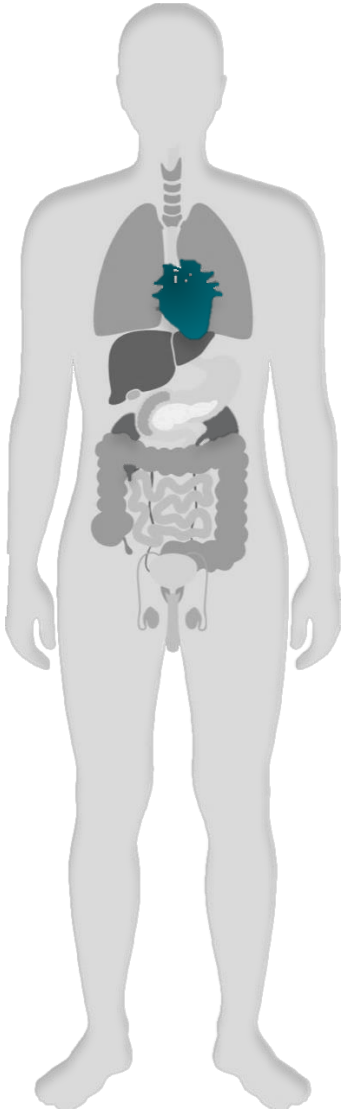

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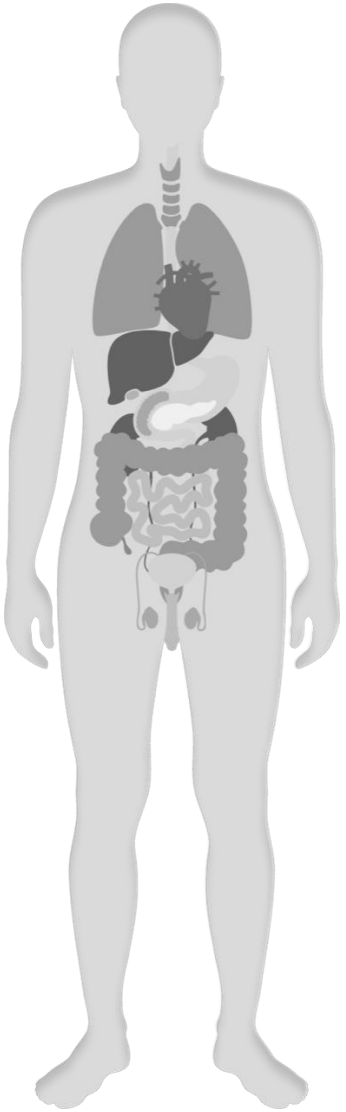
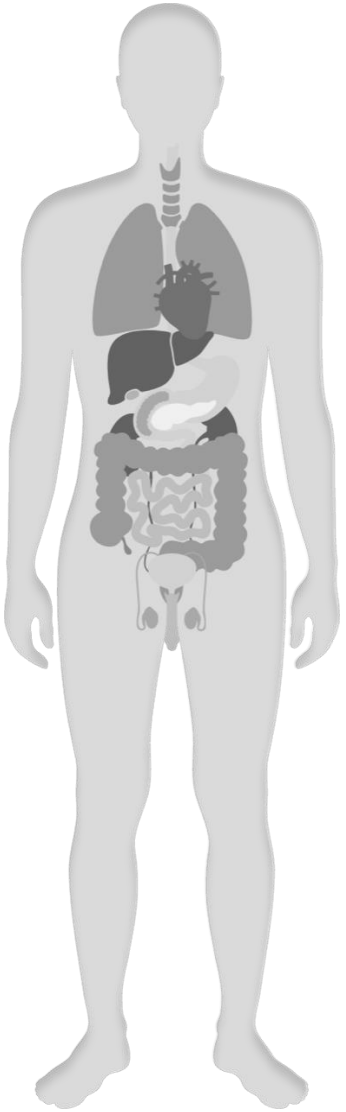


LES URGENCES VITALES

previa MEDICAL

DOSSIER MEDICAL



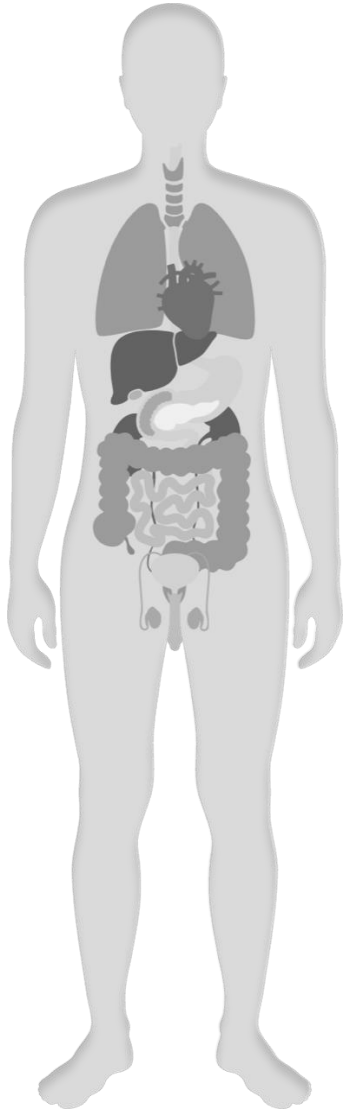
SIGNES VITAUX

Saturation pulsée en oxygène
Pression artérielle
Fréquence cardiaque
Température
Fréquence respiratoire

MÉDICAMENTS

Prescription
Administration
Dose

DOSSIER MEDICAL



ANTÉCÉDENTS

Age
Genre
Diabète
Hypertension

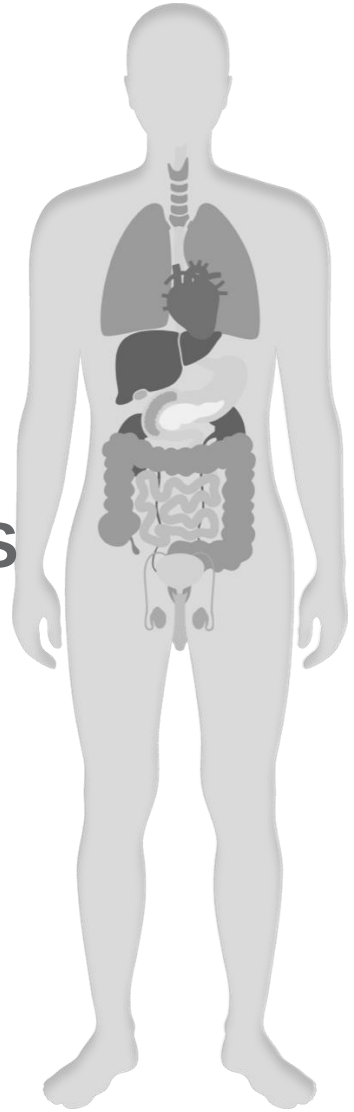
LABORATOIRES

Créatinine
Bilirubine
Leucocytes
Lactate

SIGNES VITAUX
Saturation pulsée en oxygène
Pression artérielle
Fréquence cardiaque
Température
Fréquence respiratoire

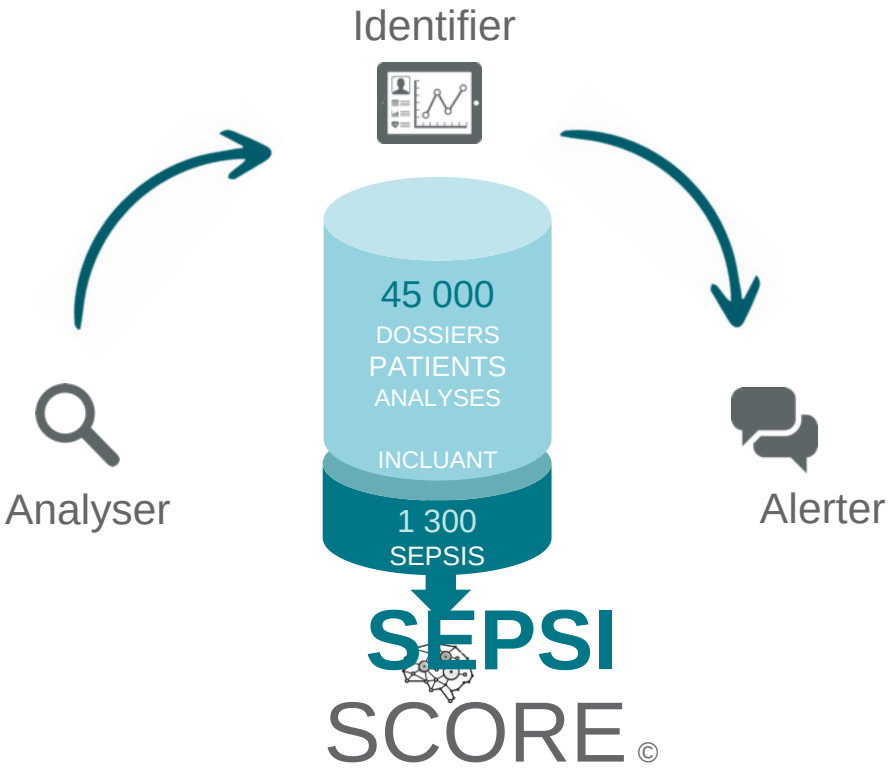
MÉDICAMENTS
Prescription
Administration
Dose

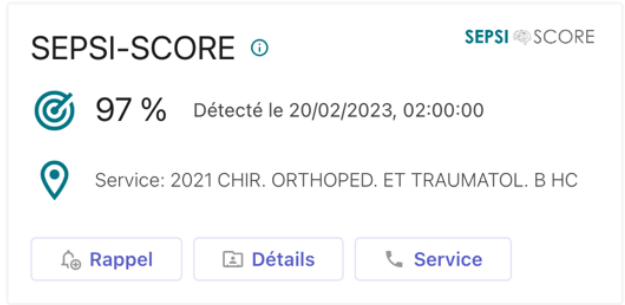
BIOMARQUEURS NUMÉRIQUES



ANTÉCÉDENTS
Age
Genre
Diabète
Hypertension

LABORATOIRES
Créatinine
Bilirubine
Leucocytes
Lactate





Etude rétrospective

Development and validation of a machine learning model to forecast early onset of sepsis in hospital inpatients: a retrospective study on a medically validated sepsis dataset

INTRODUCTION

Sepsis is defined as a life-threatening organ dysfunction caused by a dysregulated host response to infection, also called nosocomial infection when occurring after an invasive procedure. Subsets of sepsis are referred to as sepsis, severe sepsis and septic shock (Sepsis-3) (1). Tools for sepsis prognosis assessment include the scoring system, Sepsis-related Organ Failure Assessment (SOFA), based on six sub-scores (from 0-normal to 4-most abnormal) evaluating the respiratory, neurological, cardiovascular, hepatic, renal and coagulation systems (2). Sepsis onset is declared when global SOFA score reaches 2 or more, or is increased by at least 2 points.
Sepsis is a leading cause of morbidity and mortality globally, with an incidence of 30,000 deaths per year in France (3). Responsible for 1 in 5 deaths worldwide (3), future projections foresee a doubling of sepsis cases within the next 50 years due to aging of the population (3). Development of tools for sepsis prognosis, and more specifically early sepsis onset recognition, is of importance as one hour of delay in sepsis diagnosis causes a 7% reduction in survival (4).
Several sepsis predictive models have already emerged from machine learning (ML) algorithms (5, 6). Both retrospective and prospective studies demonstrated that implementation of the algorithm *InSight* (Dascena, USA) (7-9) for sepsis management, reduced sepsis-related hospital length of stay by 10% (8) or by 2.3 days (7). More recently, authors even claimed a 32% reduction in hospital length of stay in a multisite prospective real-world data study (9). However, sepsis detection by ML algorithms remains a work in progress as they can miss up to 67% of sepsis cases (10). Of note, the main limitation of prediction models is the lack of external validation to ensure reproducibility and generalizability (11).
Development and implementation of sepsis predictive models with whole hospital datasets in real-life settings is still limited. Moreover, more efficient prediction tools are still warranted to significantly impact sepsis patient survival. This study aims to develop and validate the ML model *Sepsi-Score* to forecast early sepsis onset in hospital inpatients. We developed a ML sepsis prediction model (prognostic setting) by training the algorithm on a dataset extracted from the database of a single French hospital (all medical services included), containing observations generally available shortly after patient admission at the hospital (medical history, vital signs and laboratory results). We then validated our model by the retrospective examination of a second dataset, for which sepsis cases were retrospectively confirmed by a medical expert, who also stated an estimated time of sepsis onset. Prediction capabilities of the algorithm, sepsis cases detection and sepsis onset prediction, were evaluated on this medically validated dataset. *Sepsi-Score* predictive performance was also compared to competitor sepsis scoring systems.

METHODS

Data source

We collected data at the Academic Hospital of Valenciennes (CHV, France) for both the training and the study datasets, originating from hospital inpatients of all medical services (including ICU, emergency, surgery and every medical services where spepsis cases occurred). We extracted data using an hospital hosted FHIR (Fast Healthcare Interoperability Resources) server, implemented and connected to the hospital EHR (Electronic Health Record) and ICD-10 (International Classification of Diseases) coding solution.

Eligibility criteria

In this study, we defined an encounter as a single inpatient hospital stay, associated with comorbidities and various observations (vitals signs and laboratory results) available from the patient medical record. We selected eligible patients based on the following inclusion criteria: adult patient (18 or older); at least one SOFA-related observation had to be recorded during the hospital stay; at least five out of six vital signs (heart rate, body temperature, diastolic blood pressure, systolic blood pressure, oxygen saturation SpO_2, respiratory rate) had to be documented; length of hospital stay comprised between 2 and 100 days (included); for septic patients only, sepsis onset had to be detected by a 2-point increase in SOFA score and > start +3h and sepsis onset < end -0h. Patients' encounters were excluded from the datasets based on the following criteria: no data available on the patient medical history regarding comorbidites; unknown gender (male/female); no observation recorded for vital signs and laboratory results (creatinine, lactate, leukocyte, platelets, bilirubin, diuresis, partial pressure of oxygen PaO_2, fraction of inspired oxygen FiO_2).

Preprocessing of the datasets

Before the datasets can be fed to the ML algorithm for development and validation, preprocessing of the extracted raw data is required. Preprocessing steps consisted of: (*i*) in case of multiple encounters for a patient, each encounter was considered separately; (*ii*) timestamped data were binned to round hours, using the last observation value available; (*iii*) missing values were imputed using simple fill-forward strategy (the last known value is propagated until a new value is available); (*iv*) predictor variables originated from a single 3-hour period, spanning 2 hours before and up to sepsis onset, or from a randomly chosen timepoint in the course of the hospital stay for non-septic patients; (*v*) metrics were computed over the previously designated 3-hour period (mean with standard deviation, median, minimum and maximum, last value).

Datasets

Initially, we extracted 45,127 patient encounters, from February 6th, 2020, to July 31st, 2021, to build the training dataset, used for the ML model development (Supplementary Figure S1). We further filtered extracted data using eligibility criteria and applied pre-processing procedure. Finally, the training dataset spanned 26,652 patient encounters, with a 4.9% prevalence of sepsis (1,308 sepsis encounters and 25,344 non-sepsis encounters).
To build the study dataset, we first extracted 9,310 patient encounters, from August 1st, 2021, to November 30th, 2021 (Figure 1). After verifying patients compliance to eligibility criteria, the 139 sepsis cases identified in the

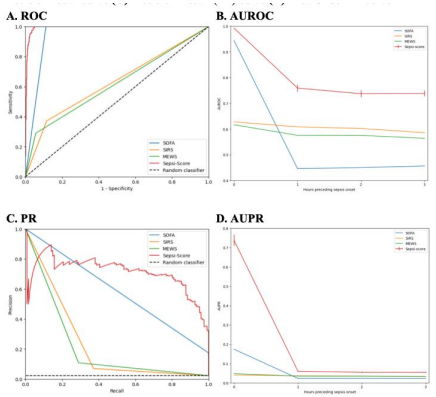
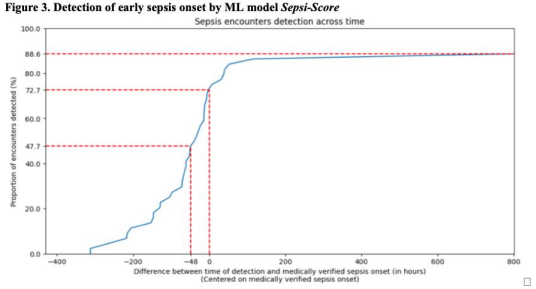


Figure 3. Detection of early sepsis onset by ML model *Sepsi-Score*



Entrainement

Centre	**CH de Valenciennes**
Lits	**> 1000 lits**
Type	**Etude rétrospective**
Durée	**22 mois**
Début	**02/2020**
Fin	**12/2021**

entrainement

2
Milliards
De
données

45 127
séjours

1,308
sepsis

2,9 %

CIM-10 sepsis code +
SOFA score augmente
de **2 points**

validation

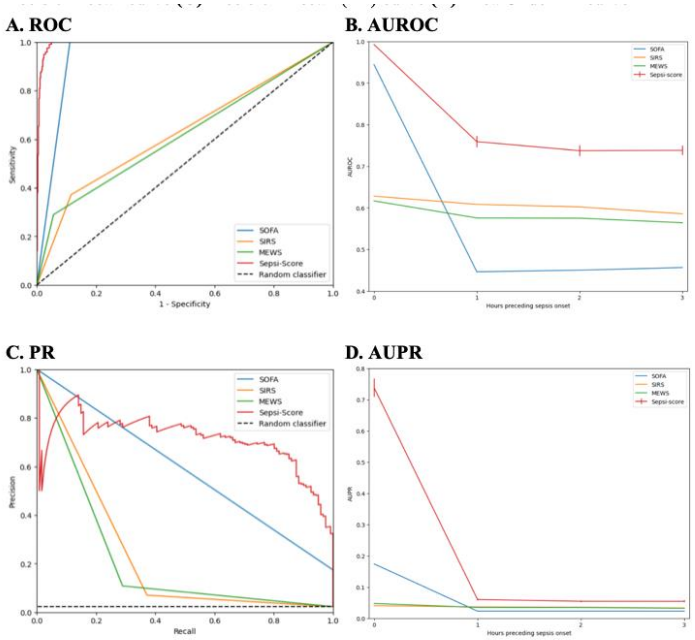
5 270
séjours

139
sepsis

2,6%

CIM-10 sepsis code +
SOFA score augmente de
2 points
+
Validation par un
infectiologue

Performances



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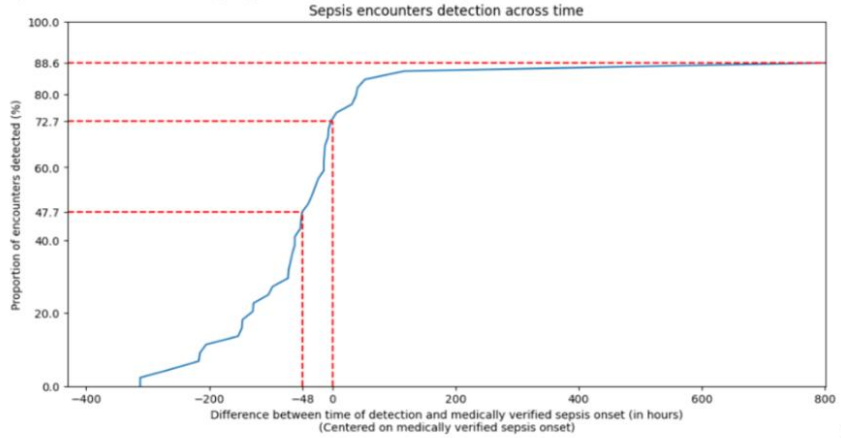
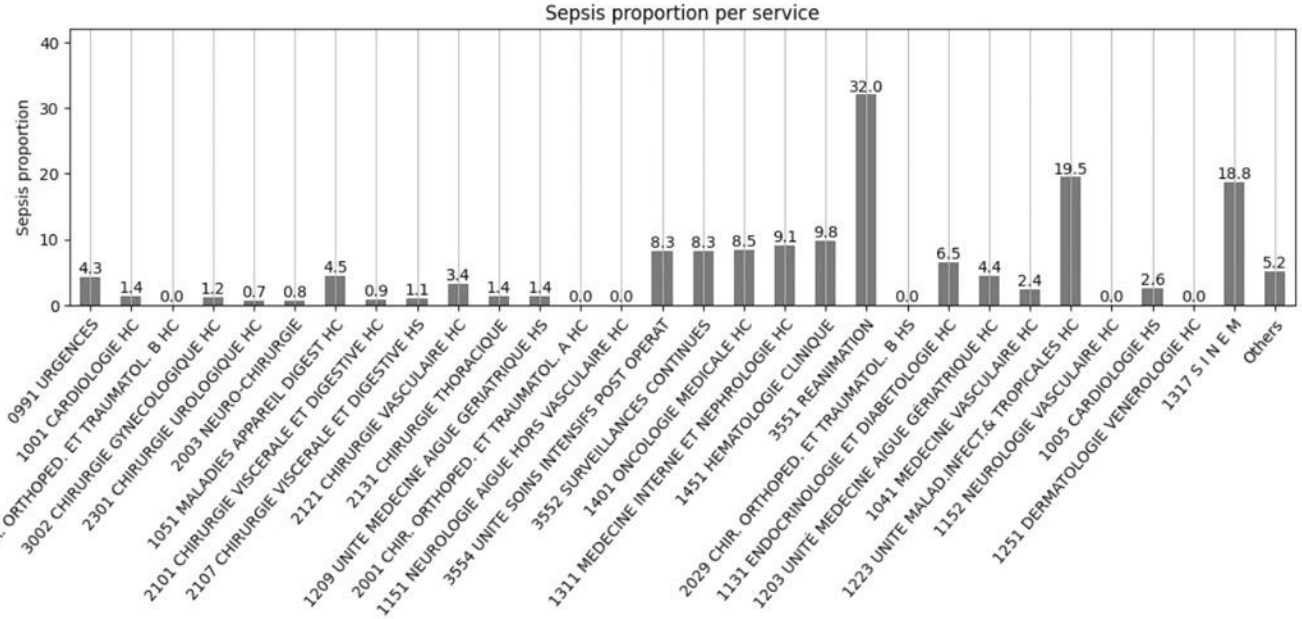
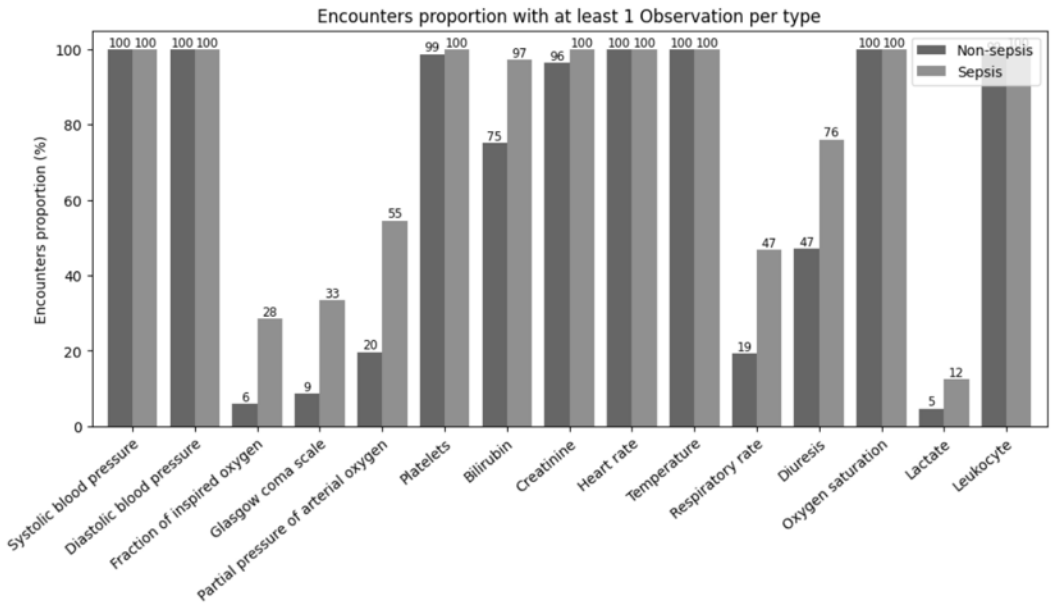


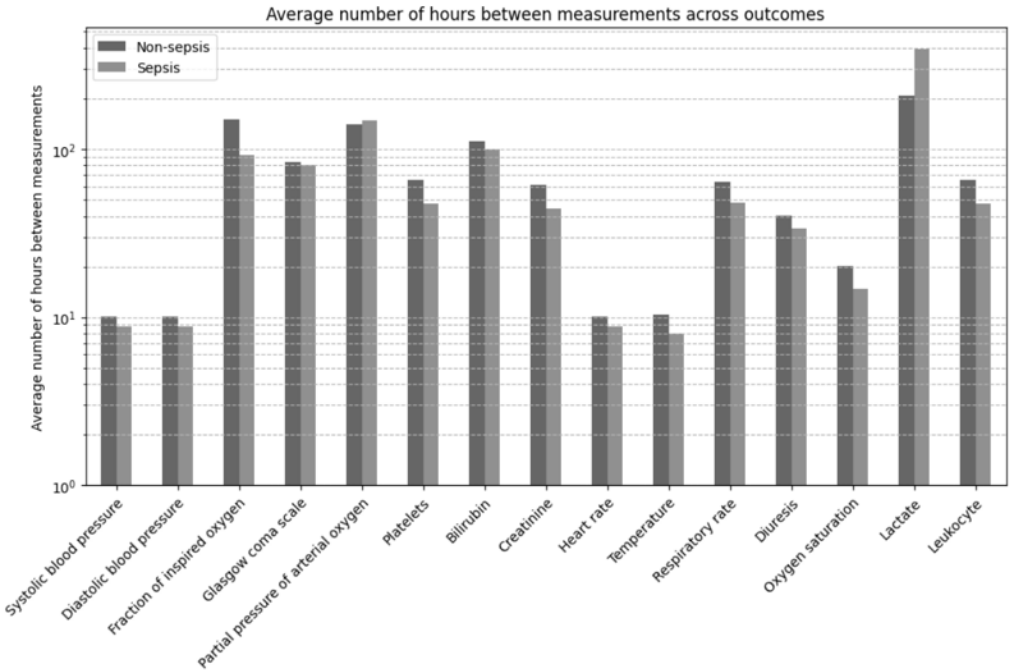
		Study dataset N=5,270 121 sepis / 5,149 non-sepsis			
		ML model	SOFA	SIRS	MEWS
AUROC	Mean ± SD	0.992 ± 0.001	0.944	0.628	0.617
	Median	0.992	-	-	-
	Min; Max	0.992; 0.993	-	-	-
AUPR	Mean ± SD	0.738 ± 0.029	0.174	0.041	0.048
	Median	0.728	-	-	-
	Min; Max	0.711; 0.775	-	-	-
Precision (Positive Predictive Value)	Mean ± SD	0.610 ± 0.018	0.174	0.070	0.108
	Median	0.606	-	-	-
	Min; Max	0.593; 0.640	-	-	-
Recall (Sensitivity)	Mean ± SD	0.845 ± 0.018	1.000	0.372	0.289
	Median	0.851	-	-	-
	Min; Max	0.826; 0.868	-	-	-
Specificity	Mean ± SD	0.987 ± 0.001	0.889	0.884	0.944
	Median	0.987	-	-	-
	Min; Max	0.986; 0.989	-	-	-
F1 score	Mean ± SD	0.708 ± 0.013	0.297	0.118	0.158
	Median	0.705	-	-	-
	Min; Max	0.699; 0.730	-	-	-

Sensibilité	**84%**
Spécificité	**98%**
Valeur prédictive positive	**61%**

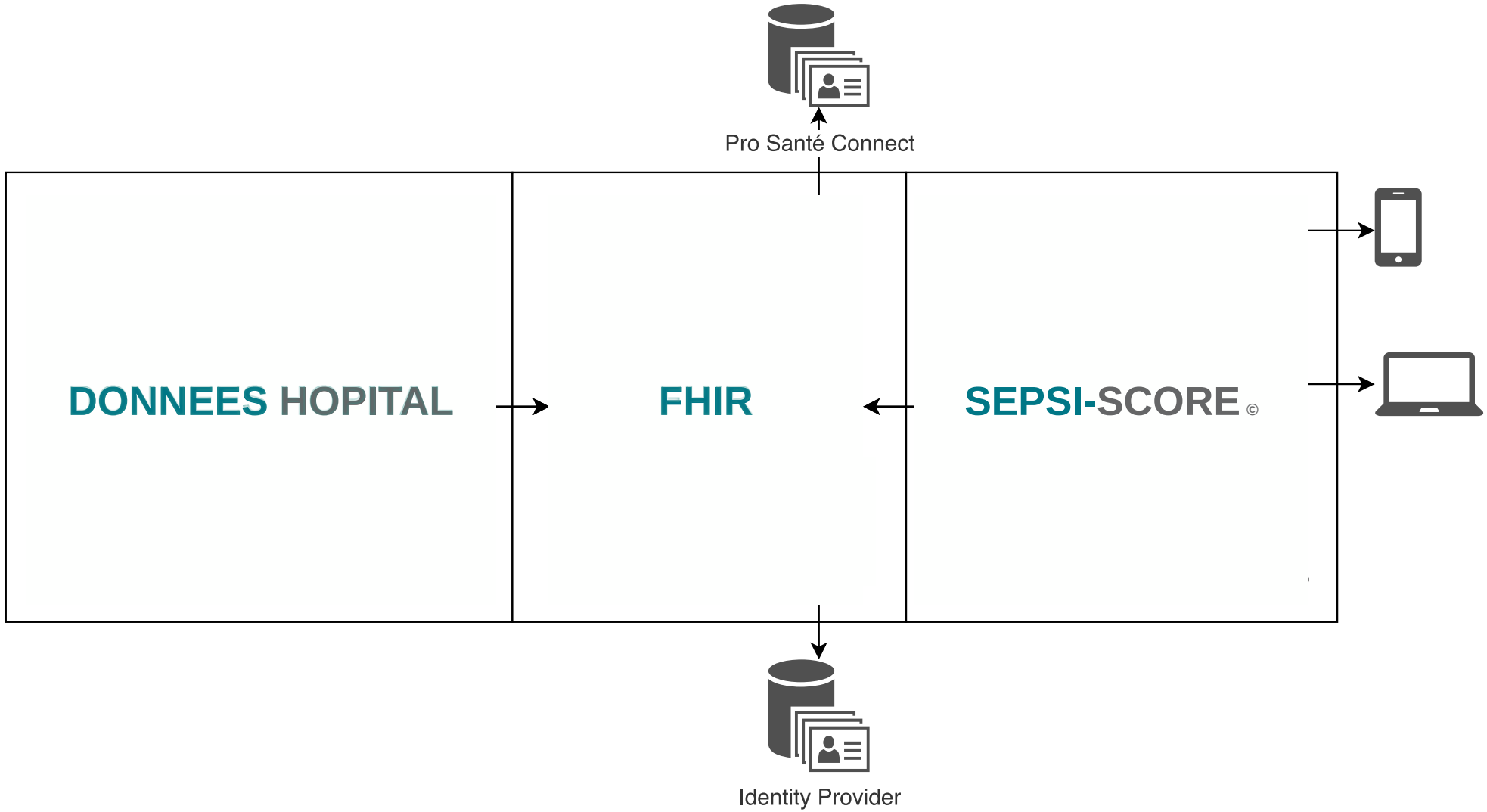
84 % des patients qui ont un sepsis
sont détectés en moyenne 48h avant les premiers symptômes


Sepsis proportion per service
Sepsis proportion
0991 URGENCES
1001 CARDIOLOGIE HC
2021 CHIR. ORTHOPED. ET TRAUMATOL. B HC
3002 CHIRURGIE GYNECOLOGIQUE HC
2301 CHIRURGIE UROLOGIQUE HC
2003 NEURO-CHIRURGIE
1051 MALADIES APPAREIL DIGEST HC
2101 CHIRURGIE VISCERALE ET DIGESTIVE HC
2107 CHIRURGIE VISCERALE ET DIGESTIVE HS
2121 CHIRURGIE VASCULAIRE HC
2131 CHIRURGIE THORACIQUE
1209 UNITE MEDECINE AIGUE GERIATRIQUE HS
2001 CHIR. ORTHOPED. ET TRAUMATOL. A HC
1151 NEUROLOGIE AIGUE HORS VASCULAIRE HC
3554 UNITE SOINS INTENSIFS POST OPERAT
3552 SURVEILLANCES CONTINUES
1401 ONCOLOGIE MEDICALE HC
1311 MEDECINE INTERNE ET NEPHROLOGIE HC
1451 HEMATOLOGIE CLINIQUE
3551 REANIMATION
2029 CHIR. ORTHOPED. ET TRAUMATOL. B HS
1131 ENDOCRINOLOGIE ET DIABETOLOGIE HC
1203 UNITE MEDECINE AIGUE GERIATRIQUE HC
1041 MEDECINE VASCULAIRE HC
1223 UNITE MALAD.INFECT.& TROPICALES HC
1152 NEUROLOGIE VASCULAIRE HC
1005 CARDIOLOGIE HS
1251 DERMATOLOGIE VENEROLOGIE HC
1317 S I N E M
Others
4.3
1.4
0.0
1.2
0.7
0.8
4.5
0.9
1.1
3.4
1.4
1.4
0.0
0.0
8.3
8.3
8.5
9.1
9.8
32.0
0.0
6.5
4.4
2.4
19.5
0.0
2.6
0.0
18.8
5.2

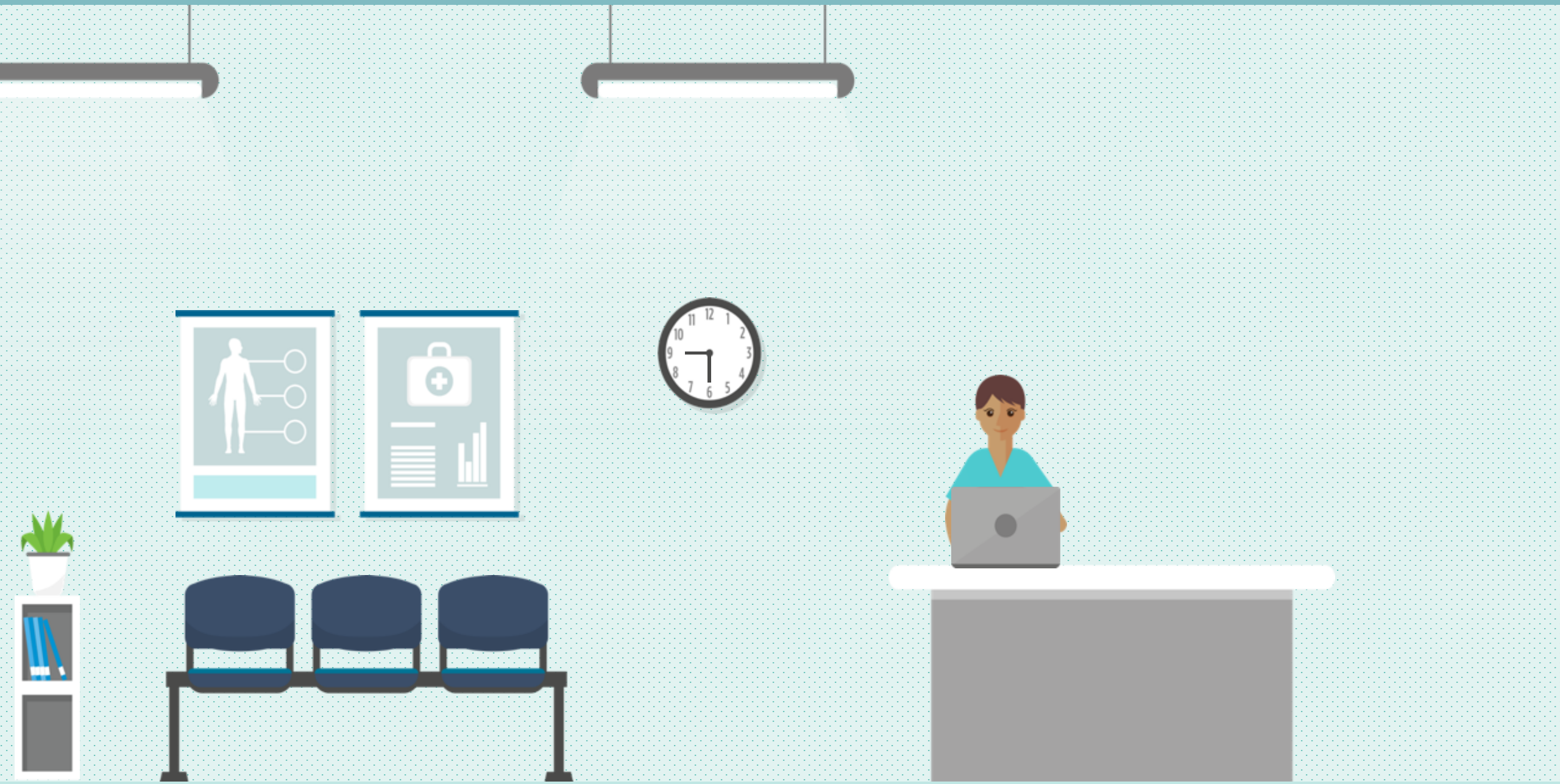

Encounters proportion with at least 1 Observation per type
Encounters proportion (%)
Non-sepsis
Sepsis
Systolic blood pressure
Diastolic blood pressure
Fraction of inspired oxygen
Glasgow coma scale
Partial pressure of arterial oxygen
Platelets
Bilirubin
Creatinine
Heart rate
Temperature
Respiratory rate
Diuresis
Oxygen saturation
Lactate
Leukocyte
100 100
100 100
6
28
9
33
20
55
99 100
75
97
96
100
100 100
100 100
19
47
47
76
100 100
5
12

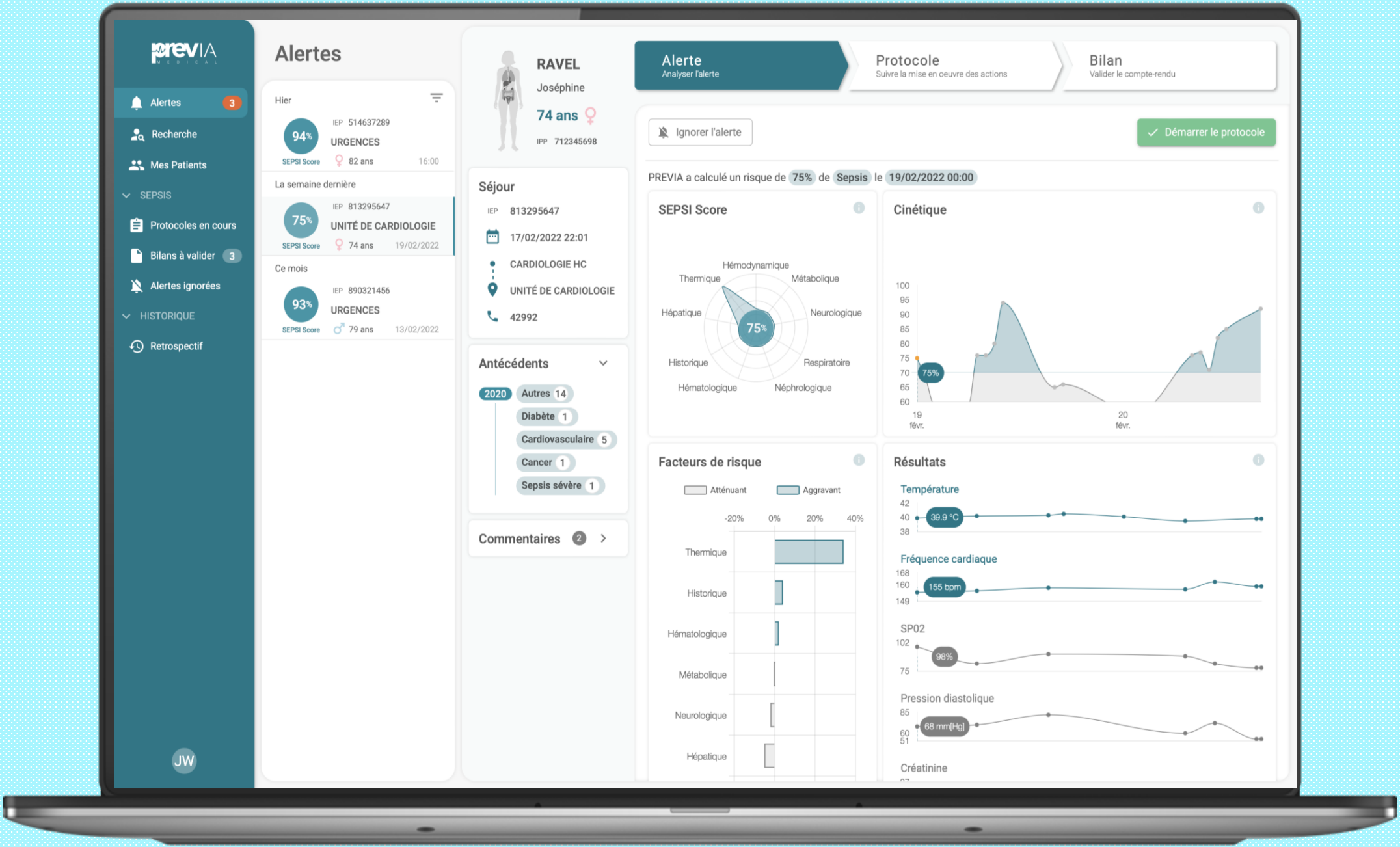

Average number of hours between measurements across outcomes
Average number of hours between measurements
Non-sepsis
Sepsis
Systolic blood pressure
Diastolic blood pressure
Fraction of inspired oxygen
Glasgow coma scale
Partial pressure of arterial oxygen
Platelets
Bilirubin
Creatinine
Heart rate
Temperature
Respiratory rate
Diuresis
Oxygen saturation
Lactate
Leukocyte

Architecture

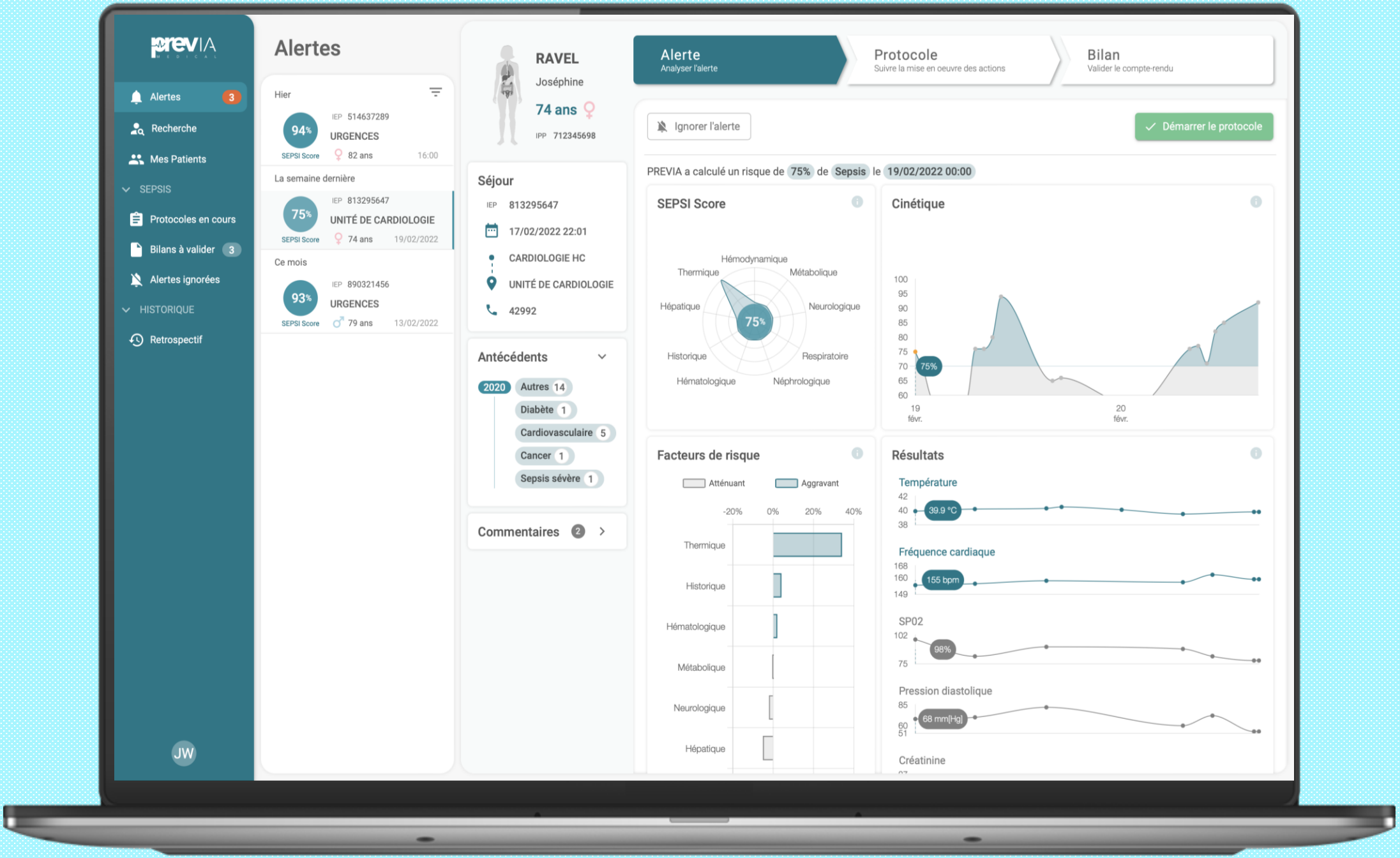



HOPITAL




previa MEDICAL
Alertes 3
Recherche
Mes Patients
SEPSIS
Protocoles en cours
Bilans à valider 3
Alertes ignorées
HISTORIQUE
Retrospectif
JW
Alertes
Hier
94% SEPSI Score
IEP 514637289
URGENCES
82 ans
16:00
La semaine dernière
75% SEPSI Score
IEP 813295647
UNITÉ DE CARDIOLOGIE
74 ans
19/02/2022
Ce mois
93% SEPSI Score
IEP 890321456
URGENCES
79 ans
13/02/2022
RAVEL
Joséphine
74 ans
IPP 712345698
Séjour
IEP 813295647
17/02/2022 22:01
CARDIOLOGIE HC
UNITÉ DE CARDIOLOGIE
42992
Antécédents
2020
Autres 14
Diabète 1
Cardiovasculaire 5
Cancer 1
Sepsis sévère 1
Commentaires 2
Alerte
Analyser l'alerte
Protocole
Suivre la mise en oeuvre des actions
Bilan
Valider le compte-rendu
Ignorer l'alerte
Démarrer le protocole
PREVIA a calculé un risque de 75% de Sepsis le 19/02/2022 00:00
SEPSI Score
Hémodynamique
Métabolique
Neurologique
Respiratoire
Néphrologique
Hématologique
Historique
Hépatique
Thermique
75%
Cinétique
100
95
90
85
80
75
70
65
60
75%
19 févr.
20 févr.
Facteurs de risque
Atténuant
Aggravant
-20%
0%
20%
40%
Thermique
Historique
Hématologique
Métabolique
Neurologique
Hépatique
Résultats
Température
42
40
38
39.9 °C
Fréquence cardiaque
168
160
149
155 bpm
SP02
102
75
98%
Pression diastolique
85
60
51
68 mm[Hg]
Créatinine


Retour à la liste
L••••••
P•••
79 ans
IPP a••••••••••
Séjour
IEP b••••••••••••••••
11/02/2022 10:18
URGENCES
URGENCES
46758
Antécédents
32
Commentaires
2
Alerte
Protocole
Bilan
Ignorer l'alerte
Démarrer le protocole


previa MEDICAL
Alertes 3
Recherche
Mes Patients
SEPSIS
Protocoles en cours
Bilans à valider 3
Alertes ignorées
HISTORIQUE
Retrospectif
JW
Alertes
Hier
94% SEPSI Score
IEP 514637289
URGENCES
82 ans 16:00
La semaine dernière
75% SEPSI Score
IEP 813295647
UNITÉ DE CARDIOLOGIE
74 ans 19/02/2022
Ce mois
93% SEPSI Score
IEP 890321456
URGENCES
79 ans 13/02/2022
RAVEL
Joséphine
74 ans
IPP 712345698
Séjour
IEP 813295647
17/02/2022 22:01
CARDIOLOGIE HC
UNITÉ DE CARDIOLOGIE
42992
Antécédents
2020
Autres 14
Diabète 1
Cardiovasculaire 5
Cancer 1
Sepsis sévère 1
Commentaires 2
Alerte
Analyser l'alerte
Protocole
Suivre la mise en oeuvre des actions
Bilan
Valider le compte-rendu
Ignorer l'alerte
Démarrer le protocole
PREVIA a calculé un risque de 75% de Sepsis le 19/02/2022 00:00
SEPSI Score
Hémodynamique
Métabolique
Neurologique
Respiratoire
Néphrologique
Hématologique
Historique
Hépatique
Thermique
75%
Cinétique
100
95
90
85
80
75
70
65
60
75%
19 févr.
20 févr.
Facteurs de risque
Atténuant
Aggravant
-20%
0%
20%
40%
Thermique
Historique
Hématologique
Métabolique
Neurologique
Hépatique
Résultats
Température
42
40
38
39.9 °C
Fréquence cardiaque
168
160
149
155 bpm
SP02
102
75
98%
Pression diastolique
85
60
51
68 mm[Hg]
Créatinine

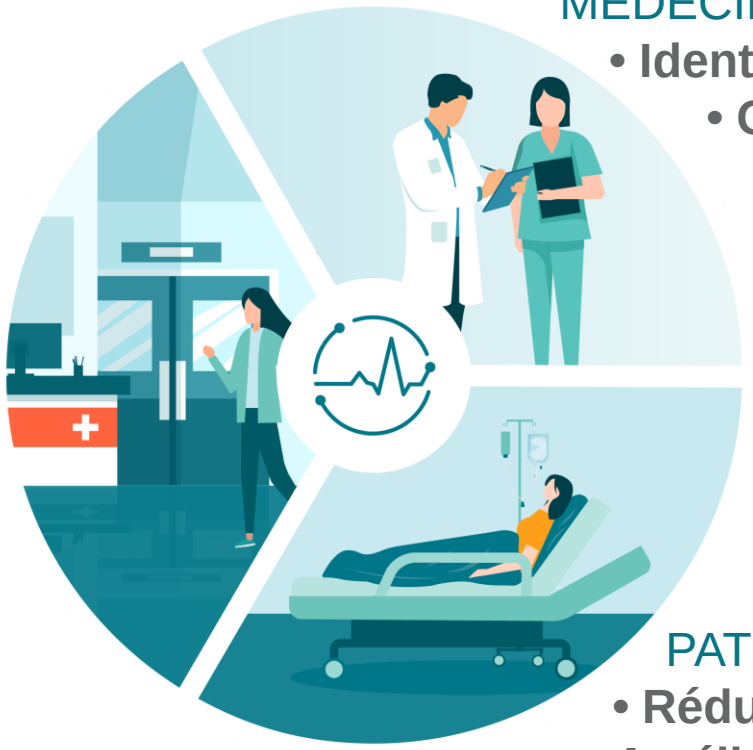
Bénéfices

MEDECINS

- Identification précoce des patients à risque
- Optimisation du parcours de soins

HÔPITAUX

- Réduction des coûts
- Amélioration de la performance des soins



PATIENTS

- Réduction du taux de mortalité
- Amélioration de la qualité de vie

KPIs des bénéfices médico-économiques

Etude clinique prospective en cours afin de démontrer les **bénéfices médicaux économique** de la solution. Nous prévoyons une **réduction de 15% du taux de mortalité** et **15% de la durée de séjour.**

Abaque SEPSI Score 2024 ©

	Cas de Sepsis/an		Coût Sepsis/an		**Estimation Réduction des coûts/an**		Décès Sepsis/an		**Réduction mortalité/an**	
Lits MCO surveillés	Min	Max	Min	Max	Min 10%	Max 20%	Min	Max	Min 10%	Max 20%
500	450	900	4,5 M€	18 M€	**450 K€**	**3,6 M€**	90	225	**9**	**45**
1 000	900	1 800	9 M€	36 M€	**900 K€**	**7,2 M€**	180	450	**18**	**90**
1 500	1350	2700	13,5 M€	54 M€	**1,35 M€**	**10,8 M€**	270	675	**27**	**135**

Audit interne pris en charge par PREVIA MEDICAL:

- Évaluation de la faisabilité technique
- Etude des performances sur un mois pour affiner le potentiel ROI de votre établissement.
- Analyse du codage PMSI des sepsis sur un mois

Livrable : rapport d'audit avec évaluation détaillée, potentiel ROI en : optimisation de codage, réduction de durée de séjour et de mortalité

Merci pour votre attention...

previa MEDICAL & LYONBIOPOLE AUVERGNE-RHÔNE-ALPES LE RÉSEAU INNOVATION SANTÉ · CENTRE HOSPITALIER DE VALENCIENNES · C.A.I.H. Centrale d'Achat de l'Informatique Hospitalière · PULSALYS SATT LYON ST ETIENNE · bpifrance · génération DEEPTECH · Accelera Health · LAURÉAT Réseau Entreprendre RHÔNE

previa MEDICAL