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Diplôme d'État

par

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Trajectoire de soins précédant l'hospitalisation et survie en réanimation jusqu'à un an après des patients âgés de 80 ans ou plus ayant eu une infection respiratoire aigüe.

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En présence des Maîtres de cette Faculté, de
mes chers condisciples
et selon la tradition d'Hippocrate,
je promets et je jure d'être fidèle aux lois de l'honneur et de
la probité dans l'exercice de la Médecine.

Je donnerai mes soins gratuits à l'indigent, et n'exigerai
jamais un salaire au-dessus de mon travail.

Admis dans l'intérieur des maisons, mes yeux ne
verront pas ce qui s'y passe, ma langue taira
les secrets qui me seront confiés et mon état ne servira pas à
corrompre les mœurs ni à favoriser le crime.

Respectueux et reconnaissant envers mes Maîtres, je
rendrai à leurs enfants
l'instruction que j'ai reçue de leurs pères.

Que les hommes m'accordent leur estime si
je suis fidèle à mes promesses.
Que je sois couvert
d'opprobre et méprisé de
mes confrères si j'y manque.

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RESUME

Introduction : Le nombre d'hospitalisations pour infection respiratoire aigüe (IRA) en réanimation des personnes âgées a augmenté. Ces hospitalisations sont associées à une mortalité importante durant le séjour hospitalier et dans l'année suivant la sortie avec le doute pour de nombreux médecins sur l'utilité de l'admission en réanimation des personnes âgées. Notre hypothèse est que la trajectoire de soin avant l'hospitalisation peut être utilisée comme substitut à la fragilité clinique pour une aide à la décision d'admission en réanimation. L'objectif de cette étude était d'évaluer si la trajectoire de soins dans les 3 mois précédant l'admission en réanimation était prédictive de la survie à 1 an des patients âgés atteints d'IRA.

Matériel & méthodes : Une étude de cohorte nationale a été réalisée à partir des données d'hospitalisation (2013-2017) incluant les patients de 80 ans ou plus ayant eu une IRA hospitalisés en réanimation en France. Les caractéristiques des patients, les actes de réanimation ont été recueillis. Les trajectoires de soins ont été reconstituées, comprenant le nombre de passages aux urgences et le nombre de jours cumulés d'hospitalisation 3 mois avant l'admission réanimation. La mortalité fait référence à la mortalité pendant le séjour ou un an après la sortie. *Extreme Gradient Boosting* (XGboost), un outil de *machine learning* a été utilisé pour construire un modèle de prédiction. La performance du modèle a été estimée par différentes mesures : l'exactitude, la précision, le rappel, le score F1 et l'aire sous la courbe (AUC) du modèle. Un graphique de calibration a été réalisé. Le poids des variables du modèle a été analysée à l'échelle globale et de façon agnostique et localement (LIME). Résultats en médiane et interquartiles [*interquartile ranges,* IQR].

Résultats : Pendant la période étudiée, 40 327 patients âgés de 80 ans ou plus ont été hospitalisés en réanimation pour IRA. Parmi eux, 35 666 (88 %) avaient un statut vital connu à 1 an avec 19 379 (54 %) décès pendant le séjour en réanimation ou durant l'année suivante. Les caractéristiques des patients étaient : âge 84 ans [82-87], le sexe-ratio hommes/femmes était de 1,23 ; SAPS II : 30 [20-44], 9 241 (26%) sous ventilation mécanique invasive. L'algorithme issu de XGboost était capable de discriminer le statut vital à un an avec un AUC de 0,70. Et montrait que le score de fragilité, l'hospitalisation 3 mois avant l'admission en soins intensifs et le sexe masculin étaient associés à la mortalité.

Conclusion : La trajectoire de soins 3 mois avant l'admission en réanimation était associée à la mortalité à un an chez les patients âgés hospitalisés pour une IRA. Il s'agit d'une information simple, objective et facile à obtenir pouvant être utilisée pour la prise de décision concernant l'admission en réanimation des personnes âgées ayant une IRA.

Mots clés : Personnes âgées, infection respiratoire aiguë, trajectoire de soins, réanimation, machine Learning.

Prediction of 1-year survival among elderly patients hospitalized in ICU for acute respiratory infection using healthcare trajectories before critical illness.

To predict the future, you need to know the past

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Declarations:

List of abbreviations: ATIH: *Agence Technique de l'Information sur l'Hospitalisation ;* AECOPD : *Acute Exacerbation of Chronic Obstructive Pulmonary Disease* ; ARI : *Acute Respiratory Infection* ; AUC : *Area Under Curve* ; CNIL : *Commission Nationale de l'Informatique et des Libertés* ; CAP : *Community-Acquired Pneumonia* ; ECMO: *Extracorporal membrane oxygenation* ;ICD-10 : *International Classification id the Diseases, tenth revision* ; HDD: *hospital discharge database* ; ICU: *Intensive Care Unit* ; IQR : *Interquartile* ; LIME : *Local Interpretable Model Agnostic Explanations* ; LoS: *length of stay*, ML : *Machine Learning* ; PMSI: *Programme de Médicalisation des Systèmes d'Information ;* RRT*: Renal replacement therapy* ,SAE : *Statistique Annuelle des Etablissements*; SAPS II : *Simplified Acute Physiology Score II*; SD : S*tandard Deviation.*

Ethics approval and consent to participate: No nominative, sensitive or personal data of patients have been collected. Our study involved the reuse of already recorded and anonymized data. The study falls within the scope of the French Reference Methodology MR-005 (declaration 2205437 v 0, august 22nd, 2018, subscripted by the Teaching Hospital of Tours), which require neither information nor consent of the included individuals. This study was consequently registered with the French Data Protection Board (*CNIL* MR-005 number #2018160620).

Consent for publication: Not applicable.

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Authors' contributions: LTW, LGG and AG conceived and designed the study and were involved in drafting the manuscript. LTW and CG performed the data retrieval. AKS, GI and LTW performed the statistical analysis. All the authors were involved in the interpretation of the data, in drafting the manuscript and made critical revisions to the discussion section. All authors read and approved the final version to be published.

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ABSTRACT

Background: Intensive care unit (ICU) hospitalizations of elderly patients with acute respiratory infection (ARI) are increasing; however, we observed an important mortality during the ICU stay and the following year after discharge, giving doubts to many physicians whether elderly patients benefit from ICU admission. Our hypothesis is that healthcare trajectories before critical illness might be used as a surrogate of frailty and can be useful for decision-making. The aim of this study was to assess whether the healthcare trajectories in the 3 months preceding the ICU admission could help to predict the 1-year survival in elderly ARI patients.

Methods. A national population-based cohort study was performed from French hospital discharge databases (2013-2017) and included ICU patients ≥80 y.o. with an ARI. Patient's characteristics were collected as well as ICU procedures and their healthcare trajectories before and after discharge from ICU. Healthcare trajectories before critical illness were estimated by the number of emergency room visits and the cumulative number of hospitalization day 3 months before ICU admission. Mortality refers to mortality at hospital until one year after discharge, during the follow-up period. Extreme Gradient Boosting (XGboost), a machine learning (ML) method was trained to build a predictive model of patient's outcome. A sample of 66% of the cohort was used for the training set and the remaining 34% was applied for testing the model. The accuracy, precision, recall, f1 score and the area under the receiver operator characteristic curve (AUC) of the model were measured. A calibration plot was drawn to compare the probability predicted by the model to their empirical probability. Feature importance was analyzed and the Local Interpretable Model Agnostic Explanations (LIME) was performed to identify the contribution of the top 10 key features on prediction.

Results. During the study period, 40,327 patients aged 80 years or older were hospitalized in ICU for ARI. Among them, 35,666 (88%) had a vital status known at 1 year, of which 19,379 (54%) died during ICU stay or over the first year after discharge. Patients ‘characteristics were: age 84 y.o. [82-87], sex ratio male/female 1.23, SAPS II 30 [20; 44], invasive mechanical ventilation 9,241 (26%). XGboost model provided a discrimination of the vital status at one year with an AUC of 0.7. Feature importance and LIME showed that the most predictive factors of poor survival were frailty score, cumulative numbers of days of hospitalization in the 3 months prior ICU and male gender

Conclusions. Healthcare consumption 3 months prior to ICU was associated with 1-year mortality among elderly patients hospitalized for ARI. Healthcare consumption is a simple, objective, and easy-to-obtain information that may be used to help the decision-making for ICU admission of elderly with ARI.

Key words: Elderly, acute respiratory infection, heath care consumption, intensive care unit, machine learning.

INRODUCTION

Current predictions indicate that by 2050, the percentage of the population that will be 80 years old or older will double, representing nearly 10% of the European and 8% of the North American population [1]. An important consequence of longer life expectancies is that this growth of the ageing population may result in increasing demand for critical care and affect the composition of the patient population cared for in ICUs [1,2].

Before the COVID-19 pandemic, we demonstrated that there was a substantial increase in acute respiratory infection (ARI) hospitalizations over a decade, with a growing demand for critical care services. Both the absolute number and the percentage of ICU admissions that were elderly increased, driving an overall 2.7-fold increase in the number of ICU stays for ARI [1,2]. However, this increase in ICU hospitalization rate of elderly was not associated with a significant change in ICU mortality. The mortality rate during the hospitalization cannot be consider as the unique criterion to assess the benefit of the ICU care because the long-term effects of ICU admission for elderly patients are complicated to assess and can lead to a postponed excess of mortality. For example, elderly patients hospitalized for ARI in ICU and discharged alive from hospital had eventually a 10-fold higher risk of death at 6 months and still a 4-fold higher risk of death at 2 years, compared with age-matched population [2]. During the first wave of the pandemic (2020, March to June), critically ill COVID-19 patients $\geq$ 80 y.o. had a 6-month mortality of 72% [3]. These findings highlight the need for more informed goals-of-care discussions for critically ill elderly patients.

Predicting the outcome of ICU patients after a hospital stay is difficult. Available predictive scores are mainly based on acute physiologic measurements during the first 24 hours in the ICU. Yet, the genuine challenge is to predict the long-term outcome with information available before ICU admission [4]. It has been shown that aggregation of previous disease history and acute physiology measures yielded a more accurate prediction of in-hospital mortality than acute physiology alone [5]. However, previous patient’s medical condition history at the time of admission is often scarce. Medicoadministrative databases in France can provide objective information that can be consulted before patient admission and included: age, sex, comorbidities (that can be computed in scores) and previous hospital visits or admissions. Healthcare consumption seems to be a relevant indicator of patient’s comorbidity [2]. Our hypothesis is that healthcare trajectories before critical illness might be used as a surrogate of frailty and should be included in the decision-making process for ICU hospitalization of elderly. The aim of this study was to assess whether a machine-learning integrative approach using information from medicoadministrative databases that are available before ICU admission, and that included previous healthcare trajectories, could predict 1-year survival among elderly patients hospitalized in ICU for ARI.

METHODS

Data source and Study population

A population-based cohort study of patients over 80 years old with an ARI admitted in the ICU was performed from January 1st, 2013, to December 31st, 2017, in France Information were gathered from the French PMSI (*Programme de Médicalisation des systèmes d'information*) database. This national database is implemented for every hospital stay in French private or public hospitals by coding diagnoses and procedures performed in a standardized resume, using the international classification id the Diseases, tenth revision (ICD-10). Each patient stay is linked to a unique identification number , allowing the same individual to be followed over time [4].

Case definition

We defined cases of « ARI » using a computerized ICD-10 algorithm based on the French ICD-10 codes, previously validated and largely used for epidemiological purposes [1,2,6]. ARI was defined by ICD-10 diagnosis codes for community-acquired pneumonia (CAP) and acute exacerbation of chronic obstructive pulmonary disease (AECOPD). Thus, hospitalized patients who received at least one of these ICD-10 diagnosis codes as (1) the primary diagnosis in their discharge summary or (2) the secondary diagnosis with a primary diagnosis of respiratory failure were defined as having been hospitalized with ARI. Hospital-acquired pneumonia, defined as pneumonia that occurs after 48 hours or more after hospital admission were excluded.

Data collection

For each patient, the following data were extracted: age, sex, primary diagnosis, comorbidities (Additional file for ICD-10 diagnosis codes used according to the ICD-10 codes from the two previous years of hospital discharge summaries) and hospital frailty risk score at admission (measured as a continuous quantitative score from 0 to 99 [7]). Moreover, procedures performed during the ICU stay and the hospitalization characteristics were recorded. The care pathway before and after ICU discharge (hospitalization, follow-up care and rehabilitation home, nursing home, or home) were extracted. Healthcare consumption has been assessed by the number of emergency admissions and the number of days of hospitalization (in medicine and rehabilitation care homes) during the 3 months prior to admission to intensive care (Supplementary Figure 1).

Data pre-processing

Patients without information on their 1-year outcome were excluded. After exclusion of the resuscitation procedures, 51 variables were retained out of the initial 84 for the construction of the machine learning (ML) model, including data on healthcare consumption (number of emergency room visits, cumulative number of hospitalizations days) prior to ICU stay; patient comorbidities; and socio-demographic characteristics (age, sex). Univariate analyses were performed, then we selected the most clinically relevant variables for the construction of the model through techniques such as Random Forest to extract the 25 top features, variance threshold to remove features whose variances were low and SelectKbest method to extract the k top features based on the dependency score of the target variable and the specific variable. After normalization, a sample of 66% of the population was randomly created for the training set and the remaining 34% for the testing set in other to compare the performances.

Definition of the vital status

Mortality refers to death during a one-year period after ICU-admission (death during the initial hospital stay or subsequently during the follow-up period). To accurately achieve this aim, the ICD-10 algorithm examined the 3-year period (2017–2020) to capture more information on the living or dead status (i.e., being alive in 2020 indicated an individual was alive at the end of 2018) (Supplementary Figure 1).

Statistical analyses

Continuous variables were expressed as median and interquartiles unless otherwise specified and compared using Student *t* tests or Pearson's correlation coefficients. Qualitative variables were expressed as number and percentage (N %) and compared using parametric or nonparametric methods, as appropriate (X^2 tests or Fisher tests). *P* values were 2-tailed, and values less than .05 were considered significant. Kaplan-Meier curves were used to visualize the evolution of the survival from ICU stay to the year after discharge from the ICU.

Mortality predictions were performed using XGBoost, a scalable ML system for tree boosting [8]. The performance of the ML model was assessed by the accuracy, precision, recall, f1 score and AUC [9]. The calibration of the ML model was assessed by the calibration plot. The model parameters 'significance was identified and the top ten of them were plot using the Shapley additive explanation (SHAP) methodology which explain individual predictions by assigning each feature an importance value for a particular prediction [10]. Because MLs produce complex results that are difficult to read at the individual scale, explanation techniques have been developed to facilitate the interpretation [11]. Local interpretable model-agnostic explanations (LIME) is design to clarify the predictions of machine learning models in an interpretable and faithful manner, by learning an interpretable model locally around the prediction [11,12]. Thus, we explained the black-box of model in an agnostic way by the LIME model [11,13]. For each patient, the LIME model selected the top 10 variables from the ML that had a great impact on the outcome and their critical values in order to explain the result found at a patient scale.

Statistical analyses were carried out using R software. (RStudio Team, 2015, v1.0.153) and Python (version 3.7.1).

Ethical approval

No nominative, sensitive or personal data on patients have been collected. Our study involves the reuse of already recorded and anonymized data. The study falls within the scope of the French Reference Methodology MR-005 according to 2016–41 law dated 26 January 2016 on the modernization of the French health system, which require neither information nor non-opposition of the included individuals. Access to linked anonymous file in the PMSI databases was approved by the French National Commission for Data Protection and Liberties (CNIL MR-005 number 4116221019).

RESULTS

Hospitalizations for ARI from 2013 to 2017

We identified 40,327 elderly hospital stays attributed to ARI in the ICU among 3,856,785 total ICU stays in France from 2013 to 2017. Among them, 4,661(12%) patients had no information on vital status at 1 year, thus 35,666 (88%) patients were analyzed. Among them, 19,379 (54%) died in the one-year period after ICU-admission (Figure 1). Patients hospitalized for ARI had 84 [82-85] years old, a median Frailty Score of 2.60 [0-9.7]; 47% of them had 3 comorbidities or more; 26% were mechanically ventilated via an endotracheal tube. The median hospital time before ICU admission was 0 [0-4] days and 24.9% of patients had visited the emergency room at least once before the ICU stay over the 3 previous months. The median length of stay in hospital was 16 [9-26] days (Table I).

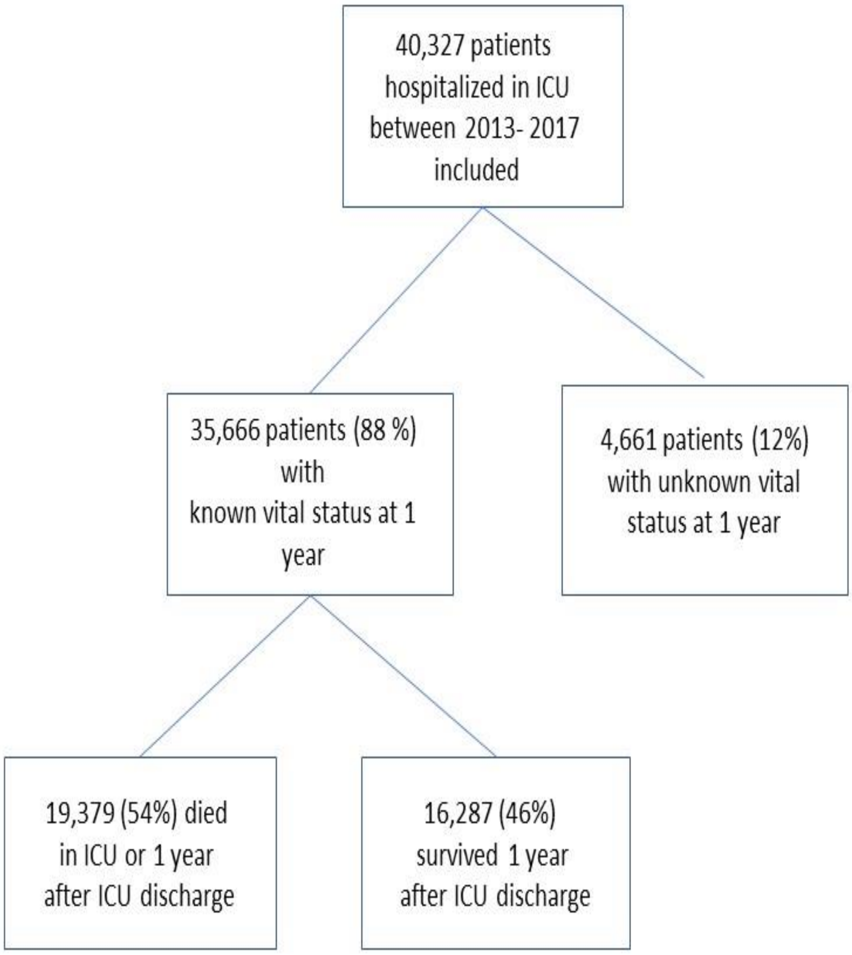


Figure 1: Flow chart of population

Tableau 1 : Characteristics of elderly patients aged 80 years old or more hospitalized in French ICUs for ARI from 2013 to 2017. Quantitative values are expressed as median and interquartiles.

Variables	All	Survivors	Non survivors	p value
	35,666	16,287	19,379	
Age	84 [82-85]	84 [82-87]	85 [82-88]	<0.001
Sex ratio (M/F)	1.23	1.06	1.4	<0.001
Frailty score	2.6 [0-9.7]	3.5 [0-11]	1.8 [0-8]	<0.001
IGS II	48 [38-62]	57 [41-69]	42 [34-53]	<0.001
LoS in hospital	16 [9-26]	17 [11-26]	14 [7-25]	<0.001
Comorbidities (n,%)				
0	9,331(26%)	4,712(28.9%)	4,619(23.8%)	<0.001
1	3,978(11%)	1,985(12.2%)	1,993(10.3%)	<0.001
2	5,669(16 %)	2,685(16.5%)	2,984(15.4%)	0.005
≥ 3	16,688(47%)	6,905(42.4%)	9,783(50.5%)	<0.001
Hospitalization (3-month period before, cumulative days)	0 [0-4]	0 [0-7]	0 [0-0]	<0.001
Emergency room visit (3-month period before, number of visit) (n,%)				
0	26,788(75.1%)	12,817(78.7%)	13,971(72.1%)	<0.001
1	6,798(19.1%)	2,724(16.7%)	4,074(21%)	<0.001
2	1,640(4.6%)	583(3.6%)	1,057(5.5%)	<0.001
> 2	440(1.2%)	163(1%)	277(1.4%)	<0.001
Care supports				
Non invasive ventilation (n,%)	11,279(31.6%)	5,073(31.2%)	6,206(32%)	0.07
Invasive ventilation (n,%)	9,241(26%)	3,009(18.5%)	6,232(32.2%)	<0.001
Vassopressors (n,%)	8,610(24.1%)	2,631(16.2%)	5,974(30.8%)	<0.001
RRT (n,%)	1,198(3.4%)	261(1.6%)	937(4.8%)	<0.001
ECMO (n,%)	10(0.03%)	6(0.04%)	4(0.02%)	0.553

LoS: length of stay, RRT: Renal replacement therapy, ECMO: Extracorporal membrane oxygenation

Patient global survival

The Kaplan Meir curve showed two phases for the survival rate with a fast decrease during the first 3 months and more regular decrease thereafter. Nearly half of the patients were dead at the end of the first year (median survival: 11.4 months [10.8-12]). Four years after the initial ICU admission, 4,247 (10.5%) patients were alive. The ultimate survivors were observed during the 8th year after admission (174 patients, 0.43%) (Figure 2).

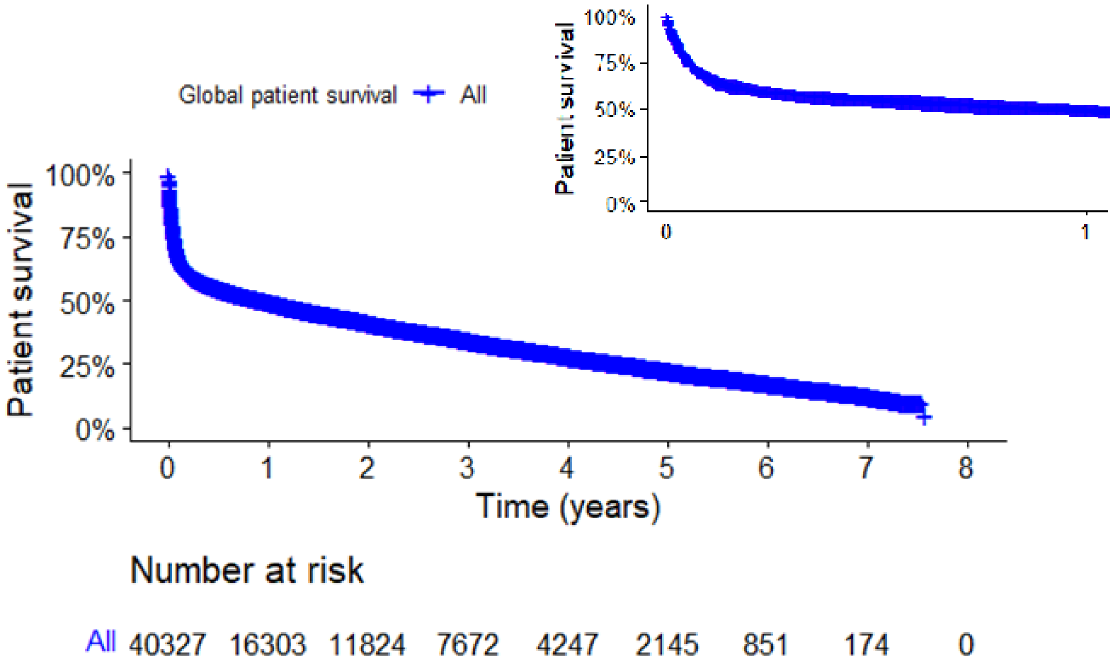


Figure 2: Kaplan-Meier curves showing the cumulative probabilities of survival at 8 years for elderly patients from ICU hospitalization after acute respiratory infection.

Selection of variables

After univariate analyses, there were 31 variables retained. The ones allowing a good discrimination of the patients' one-year status were represented by random forest method (supplementary Figure 2): hospital frailty score, age, health care consumption, sex, and various comorbidities (vascular disease, hypertension, respiratory insufficiency, etc.).

Prediction by machine leaning models

The model had an AUC of 0.7 (Figure 3). Accuracy, recall, f1 score, Matthew correlation coefficient (MCC) are reported in Table II. Furthermore, the model seemed correctly calibrated, as shown in Figure 4.

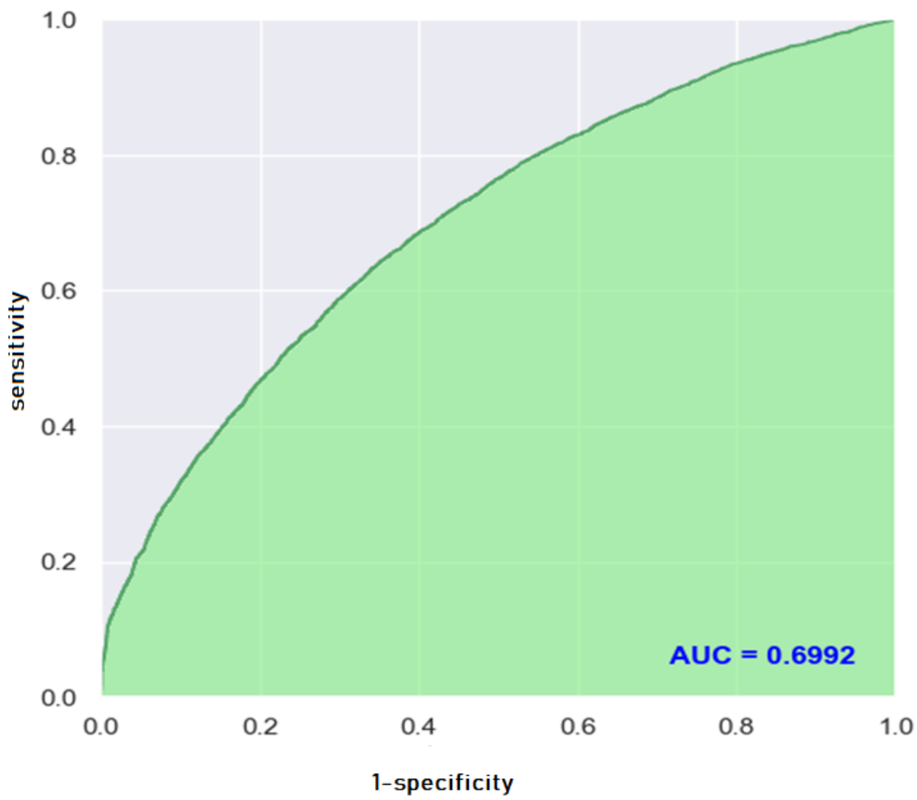


Figure 3: Receiver operating characteristic curve (ROC) of the XGboost model

Tableau 2: XGboost model predictors on mortality on test sets.

Parameters	AUC	Accuracy	Precision	Recall	F1	MCC
XGboost	0.70	0.65	0.67	0.68	0.68	0.28

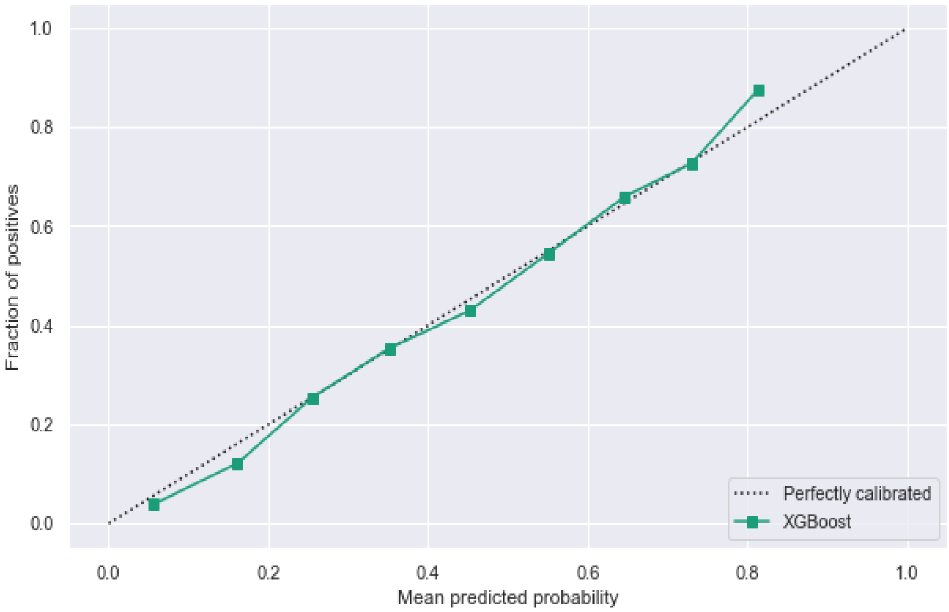


Figure 4: Calibration plot of the XGboost

The significance of the predictors in the XGBoost model is presented in Figure 5. In the SHAP methodology, the top ten predictors were: frailty score, age, arterial hypertension, male sex, number of cumulative days at hospital 3 months prior ICU, undernutrition, chronic cardiac failure, neurological disorders and obesity.

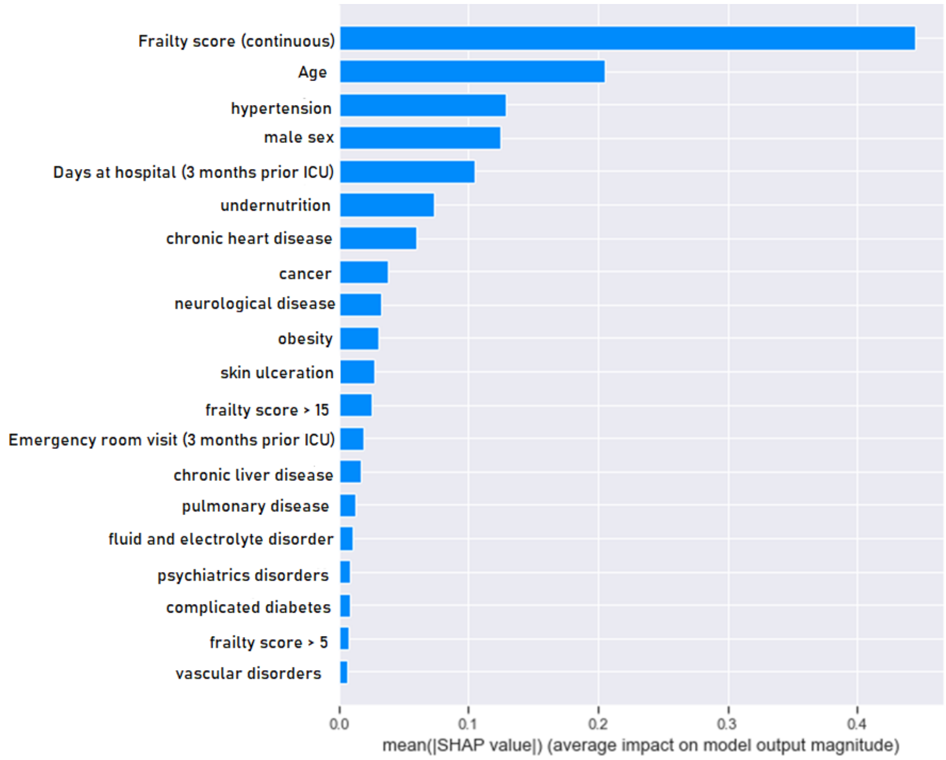


Figure 5: Feature importance derived from XGboost model

Next, we used LIME algorithm for interpretation and model-agnostic explanations at a patient scale and to figure out what parts of the interpretable input are contributing to the prediction.

As shown in figure 6, for a randomly chosen patient, on the left are represented the variables contributing to the survival or death of the patient with for each variable its own contribution in percentage. Thus, this specific patient had a 17% probability of survival and a probability 83% of death. On the right is represented the ten critical values of the different variables that drove the prediction. The results were quite like those of the feature importance with the following variables associated with death: frailty score (53 as critical value), hospitalization 3 months prior ICU (39 days as critical value), male sex, hypertension, and undernutrition. The variables associated with survival were: absence of hepatic failure, heart failure and skin ulceration.

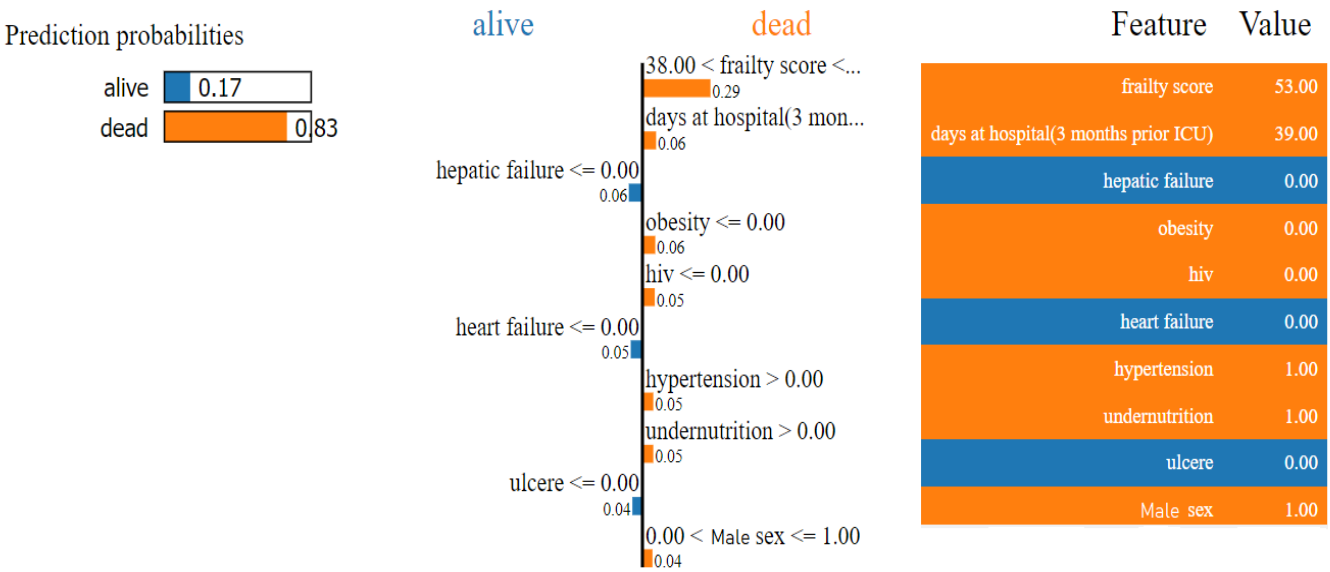


Figure 6: LIME results of XGboost model.

DISCUSSION

The present research studied elderly hospitalized in ICU for ARI and developed a mortality predictive model using patient's previous disease history and healthcare consumption available before admission in medicoadministrative databases. The Artificial intelligence programm (XGboost model) provided a good discrimination of the vital status at one year with an AUC of 0.7. Frailty score, age, hypertension, male gender, cumulative days of hospitalization 3 months prior ICU, undernutrition, cardiac failure, obesity were the top eight predictors that considerably contribute to the survival patient's prediction one year after discharge.

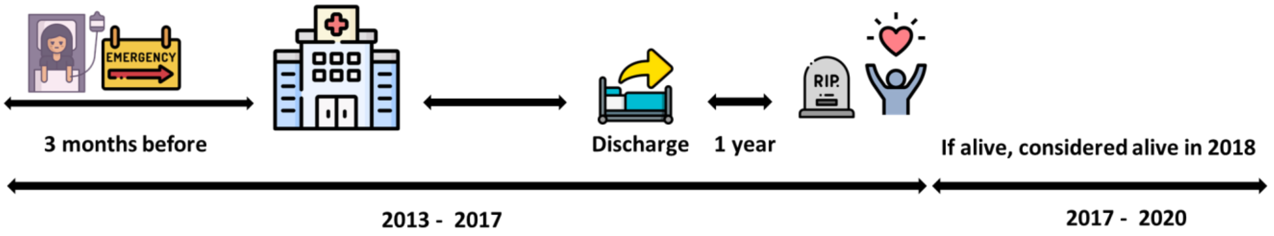
We found that health consumption (hospitalization day in medicine and emergency room visit 3 months prior to ICU) to be predictive of patient's outcome from ICU hospitalization to one year after discharge. Recent data of patients aged of 75 years or more including 42.5% of patients with ARI found that a stay in a care facility before ICU admission was an independent factor associated with mortality in ICU and one year after discharge from ICU [14]. In a previous study, we had observed that elderly patients hospitalized in ICU for ARI had twice more healthcare consumption two years after their discharge compared to a control population [2]. Thus, consumption of care appears to be an important surrogate of health conditions of elderly patients before and after ICU admission. Regarding the consumption of care, we chose to focus on a 3-month period because we observed that longer periods did not increase the discriminative performances of the algorithm (data not showed). Furthermore, a shorter period has a better clinical relevance as this information is easier to obtain. Hospital frailty score was the most important predictor of elderly outcome from ICU hospitalization to one year after discharge. Our result are consistent with the VIP 2 trial [15], where clinical frailty scale alone was an independent prognostic factor for 1-month survival after ICU admission among 80 years or older patients. Frailty affects several important body functions like the endocrine system and brain, muscular, and immune functions which add to acute vital organ dysfunctions explaining increased short-term but also long-term mortality found in frail ICU patients [16]. Comorbidities (hypertension, undernutrition, cardiac failure, neurological disorders) were predictive factors of elderly outcome from ICU hospitalization to one year after discharge. In a recent study [5], machine learning was used to predict mortality for ICU patients based on datasets with disease history up to 23 years before ICU admission (using data from the Danish national disease registry including 230,000 ICU patients). It had observed that mortality predictions (at 30 and 90 days) with a model based only on disease history outperformed the Multimorbidity Index and performed similarly to SAPS II and APACHE II. Furthermore, the aggregation of previous disease history and acute physiology measures in a neural network yielded the most precise predictions of in-hospital mortality [5].

Our population is comparable to recent published data in terms of sex ratio and number of patients on mechanical ventilation [1]. Regarding one-year mortality, we had a lower value than a cohort of ICU patients 80 years or older, of whom 47% had respiratory failure [17]. These discrepancies may be explained by the younger age (65 and 75 years or older) and a more accurate screening of patients in recent studies. Nevertheless, recent cohorts [14,18] with 42-49% of patients admitted for acute respiratory failure had a one-year mortality similar to ours.

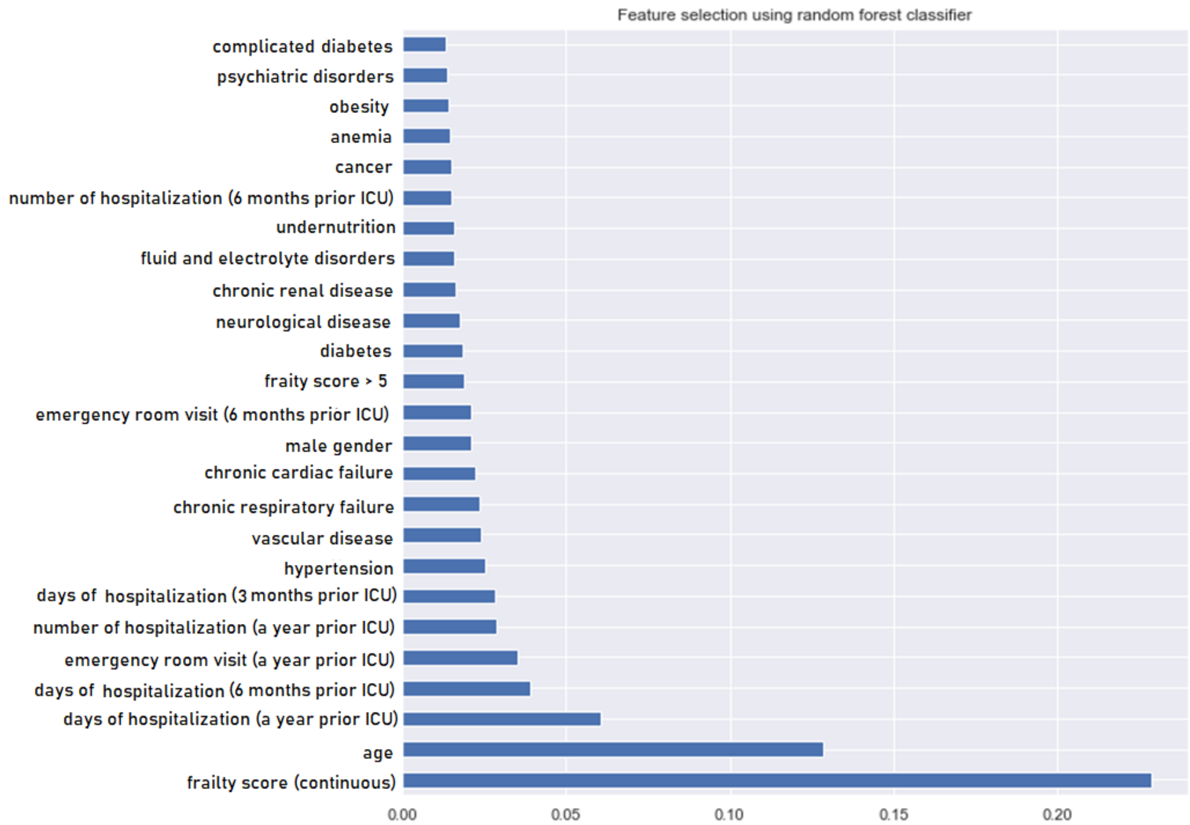
The findings of the present study must be viewed in the light of the following limitations. First, the use of administrative hospital databases introduced an inherent bias that should be taken into consideration. Strengths and limitations of using healthcare databases for epidemiological purposes have already been extensively discussed elsewhere [1,19–21]. Second, we had no data on the rehabilitative and social support of the patients at discharge from the ICU, which are confusing factors that can impact their outcome afterwards [22]. Likewise, we did not have information on patients who were not admitted to ICU, nor on the proportion of patients who died as a result of therapeutic limitations, thus making the interpretation of our results less accurate. Third, this study population is representative of only one country, so the results may not be globalize. Our study also had strengths. First it is a database of several ICUs in France over years with a large population of patients. Second, the definition of cases was done according to an algorithm that avoided variations in coding for various purposes [23]; third, we used a machine learning model which is more suitable for classification problems on large database compare to logistic regression due to its ability to limit overfitting by adding different regularizations in the loss function. Recent studies have shown that XGboost was the best performing classification model for large databases compared to other methods such as logistic regression, random forests, neural network, or bagging [24–27].

In conclusion, we provided one of the few studies that have assessed the long-term outcome of elderly ICU patients solely based on information available prior to their admission, including their healthcare trajectories. Healthcare consumption 3 months prior to ICU was critical to predict elderly patients' outcome 1-year after discharge. Healthcare consumption is an objective and easy-to-obtain information that could be reliably used to guide the clinician in the admission of elderly patients to the ICU for ARI.

SUPPLEMENTARY FIGURES



Supplementary Figure 1: Study design



Supplementary Figure 2: Random Forest selection

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ANNEXE.

Présentation orale au congrès de la Société de Réanimation de Langue Française, Paris 2022

réanimation 2022
PARIS 22-24 JUIN

Espace Flash Com 06

22/06 14:10 - 15:10

FLASH COM - La personne âgée en réanimation

Communications Flash-com

Médecin - Ethique

Modérateurs : Bertrand GUIDET (Paris), Caroline HAUW-BERLEMONT (Paris)

14:10 - 14:18

FC-044 - Association between healthcare trajectories before critical illness and 1-year survival among elderly patients hospitalized in ICU for acute respiratory infection - To predict the future, you need to know the past

Auteur présentateur : Lionel TCHATAT (Tours)

14:18 - 14:26

FC-045 - Evaluation of preoperative frailty in cardiac surgery patients using the Edmonton Frail Scale. "Frail heart" study, a preliminary analysis.

Auteur présentateur : Francis NTWALI (Bruxelles, BELGIQUE)

14:26 - 14:34

FC-046 - Community peritonitis in the elderly

Auteur présentateur : Ibtissam JARIR (Casablanca, MAROC) (A confirmer)

14:34 - 14:42

FC-047 - COVID 19 and elderly population

Auteur présentateur : Nour Zayneb JAAFAR (Zaghouan, TUNISIE) université de TOURS | Faculté de médecine

Vu, le Directeur de Thèse

Vu, le Doyen
De la Faculté de Médecine de Tours Tours, le

TCHATAT WANGUEU Lionel Legrand

43 pages – 2 tableaux – 8 figures.

Résumé :

Introduction : Le nombre d'hospitalisations pour infection respiratoire aigüe (IRA) en réanimation des personnes âgées a augmenté. Ces hospitalisations sont associées à une mortalité importante durant le séjour hospitalier et dans l'année suivant la sortie avec le doute pour de nombreux médecins sur l'utilité de l'admission en réanimation des personnes âgées. Notre hypothèse est que la trajectoire de soin avant l'hospitalisation peut être utilisée comme substitut à la fragilité clinique pour une aide à la décision d'admission en réanimation. L'objectif de cette étude était d'évaluer si la trajectoire de soins dans les 3 mois précédant l'admission en réanimation était prédictive de la survie à 1 an des patients âgés atteints d'IRA.

Matériel & méthodes : Pendant la période étudiée, 40 327 patients âgés de 80 ans ou plus ont été hospitalisés en réanimation pour IRA. Parmi eux, 35 666 (88 %) avaient un statut vital connu à 1 an avec 19 379 (54 %) décès pendant le séjour en réanimation ou durant l'année suivante. Les caractéristiques des patients étaient : âge 84 ans [82-87], le sexe-ratio hommes/femmes était de 1,23 ; SAPS II : 30 [20-44], 9 241 (26%) sous ventilation mécanique invasive. L'algorithme issu de XGboost était capable de discriminer le statut vital à un an avec un AUC de 0,70. Et montrait que le score de fragilité, l'hospitalisation 3 mois avant l'admission en soins intensifs et le sexe masculin étaient associés à la mortalité.

Résultats : Pendant la période étudiée, 40 327 patients âgés de 80 ans ou plus ont été hospitalisés en réanimation pour IRA. Parmi eux, 35 666 (88 %) avaient un statut vital connu à 1 an avec 19 379 (54 %) décès pendant le séjour en réanimation ou durant l'année suivante. Les caractéristiques des patients étaient : âge 84 [82-87] ans, le sex-ratio hommes/femmes était de 1,23 ; SAPS II : 30 [20 ; 44], 9 241 (26%) sous ventilation mécanique invasive. L'algorithme issu de XGboost était capable de discriminer le statut vital à un an avec un AUC de 0,70. Et montrait que le score de fragilité, l'hospitalisation 3 mois avant l'admission en soins intensifs et le sexe masculin étaient associés à la mortalité.

Conclusion : La trajectoire de soins 3 mois avant l'admission en réanimation était associée à la mortalité à un an chez les patients âgés hospitalisés pour une IRA. Il s'agit d'une information simple, objective et facile à obtenir pouvant être utilisée pour la prise de décision concernant l'admission en réanimation des personnes âgées ayant une IRA.

Mots clés : Personnes âgées, infection respiratoire aiguë, trajectoire de soins, réanimation, machine Learning

Jury :

Président du Jury :	Professeur Pierre-Francois DEQUIN
Directeur de thèse :	Professeur(e)s Antoine GUILLON et Leslie GUILLON-GRAMMATICO
Membres du Jury :	Docteur FLORENT BAVOZET, Docteur Thomas FLAMENT

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