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Original Study

# One Month Prediction of Pressure Ulcers in Nursing Home Residents with Bayesian Networks

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A B S T R A C T

*Objectives:* Pressure ulcers (PUs) are a common and avoidable condition among residents of nursing homes, and their consequences are severe. Reliable and simple identification of high-risk residents is a major challenge for prevention. Available tools like the Braden and Norton scale have imperfect predictive performance. The objective is to predict the occurrence of PUs in nursing home residents from electronic health record (EHR) data.
*Design:* Longitudinal retrospective nested case-control study.
*Setting and Participants:* EHR database of French nursing homes from 2013 to 2022.
*Methods:* Residents who suffered from PUs were cases and those who did not were controls. For cases, we analyzed the data available in their EHR 1 month before the occurrence of the first PU. For controls, we used available data 1 month before an index date adjusted on the delays of PU onset. We conducted a Bayesian network (BN) analysis, an explainable machine learning method, using 136 input variables of potential medical interest determined with experts. To validate the model, we used scores, features selection, and explainability tools such as Shapley values.
*Results:* Among 58,368 residents analyzed, 29% suffered from PUs during their stay. The obtained BN model predicts the occurrence of a PU at a 1-month horizon with a sensitivity of 0.94 ($\pm$0.01), a precision of 0.32 ($\pm$0.01) and an area under the curve of 0.69 ($\pm$0.02). It selects 3 variables: length of stay, delay since last hospitalization, and dependence for transfer. This BN model is suitable and simpler than models provided by other machine learning methods.
*Conclusions and Implications:* One-month prediction for incident PU is possible in nursing home residents from their EHR data. The study paves the way for the development of a predictive tool fueled by routinely collected data that do not require additional work from health care professionals, thereby opening a new preventive strategy for PUs.


Life expectancy is increasing worldwide, and the number of older adults is rising sharply. This population is heavily affected by disability, dependency, and multiple chronic illnesses, including neurocognitive disorders. Although assistance and care at home are making progress in developed countries, a significant proportion of the over-80s live in geriatric institutions. In the countries of the Organization for Economic Co-operation and Development, in 2021, more than 7.6 million older adults were living in long-term care facilities, and around 1 in 10 people aged 80 or older were living in an institution.[1] In these settings, providing assistance and medical care to residents is a considerable challenge, due to, on the one hand, the frailty and chronic illnesses of the residents, and on the other hand, to limited resources, characterized by a limited number of staff with a high turnover rate.

The prevalence of pressure ulcers (PUs) in nursing homes is high, and around 1 in 10 residents will develop 1 or more pressure sores during a year.[2] This condition is defined as a lesion of the skin caused

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by prolonged compression between a bone and the support on which the patient is resting. PUs are painful, restrict mobility, are a source of infection, and reduce quality of life.[3] Local care of PUs is time-consuming and difficult, can lead to pain associated with care, and takes up a significant amount of staff time.[4] The cost of treatment is significant and increases with the stage of the disease.[5] However, PUs are highly preventable with a specific, multidisciplinary approach based on resident mobilization and frequent repositioning protocols, the use of adapted mattresses and supports, and nutritional and general care. Prevention is effective, but it requires a great amount of time and energy on the part of health care professionals, and it is not possible to apply it to all residents of the nursing home. Identifying residents at risk of developing PUs is therefore crucial to implementing a prevention strategy that is both effective and feasible. Currently, nursing home staff can use clinical tools to identify residents at risk of developing PUs, such as the Norton and Braden scales, but they overlook important risk factors, like malnutrition or age.[2,6] The performance of the Braden scale has indeed been criticized a number of times.[7-9] Their use is also time-consuming in a context where many facilities are short of staff with high workloads.[10]

Machine learning methods are increasingly used for prediction of medical outcomes to promote precision medicine and personalized care. These methods were already investigated to predict PU and have provided promising results, particularly in intensive care settings.[6,11,12] A few studies conducted in nursing homes had several limitations like small dataset, low sensitivity, or a prediction window too short to set up an effective preventive treatment.[13-15]

The aim of this study was to develop, from electronic health records (EHRs), a 1-month prediction of pressure sores in nursing home residents, using Bayesian networks (BNs). We chose a 1-month horizon because this timeframe allows for preventive intervention, and BN models for their explainability and ability to explore new risk factors and their relationships.

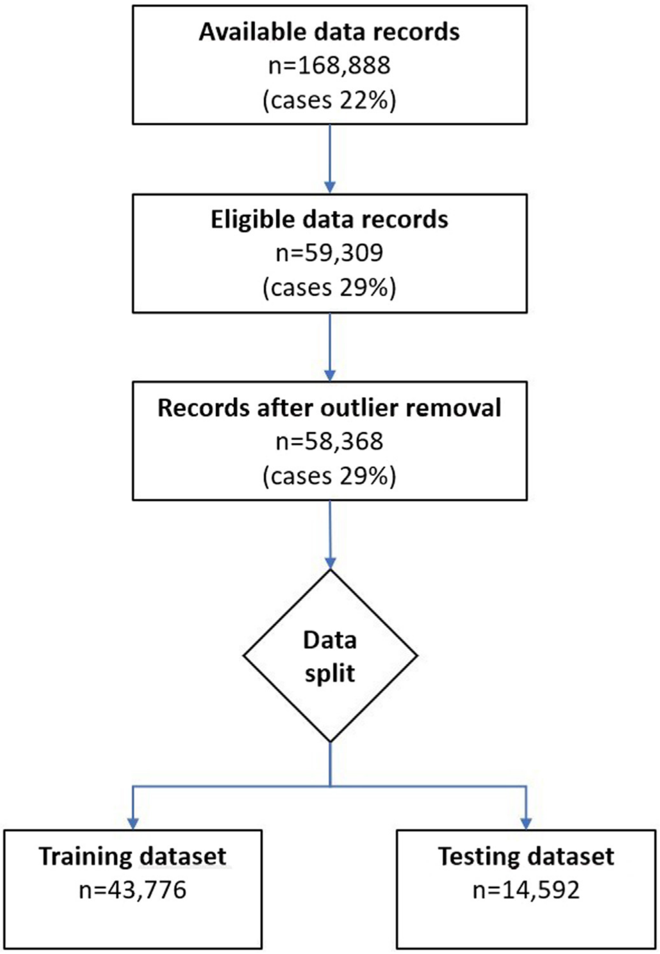


**Fig. 1.** Diagram representing the process of creating training and validation datasets.

## Methods

### *Study Design and Participants*

This longitudinal retrospective nested case-control study has been conducted on data from the EHR of nursing home residents recorded in a specialized software used by more than 3000 French long-term care facilities, representing approximately half of all French nursing homes (NETSoins, Teranga Software). Facilities and individuals who had opted out of inclusion of EHRs in research were excluded. A protocol for minimizing risk of identification has been carried out and is available on request. From more than 100,000 de-identified data records, only residents free of PUs at admission in the facility between 2013 and 2022 were eligible. Residents' records with missing values for sex, age, or weight were excluded. The modeling process is described in Figure 1. Cases were residents who suffered from PUs that occurred during their stay in the nursing home. PU was defined as an explicit diagnosis or use of PU dressings declared at any time during the nursing home stay, except those that occurred in the first month of the nursing home stay due to lack of information for the prediction task. Controls were the residents free from PUs during their stay.

### *Aim of the Predictive Model and Data Preprocessing*

We developed a binary classification model whose target was to identify residents at risk of developing a first PU within a month.

We determined, with expert geriatricians (J.B., C.H.T.), variables with potential interest for PU prediction and available in the EHR. These were kept in the analysis based on the completion rate. Finally, we retained 136 variables to fuel the models (see Supplementary Table 1). Furthermore, we paid particular attention to residents' level of dependency. We used the overall level of dependence provided by the AGGIR scale, a French national tool that assigns residents to 1 of 6 GIR groups (GIR1 being the most severe dependence and GIR6 being independence). We also included the ratings for each of the 24 variables in the AGGIR scale.

In case residents, feature values were the last observation value available 1 month before the occurrence of the first pressure ulcer. In control residents, feature values were the last observation value available 1 month before the index date. This index date was randomly determined to ensure a comparable distribution of delays between admission and the occurrence of the PU or index date. In a practical manner, we calculated in the case dataset the deciles of the delay for a PU to occur since admission to the facility, which defined 10 groups. Residents in the control group were randomly selected with respect to 1 of the 10 groups, and their index date was determined based on the allocated timeframe.

Information in the EHR is filled by the personnel of the facility on the basis of usual care: the nursing assistants, nurses, and physicians but also occupational therapists, pharmacists, and administrative and paramedical staff. The data entry concerning a nursing home resident is thus done by different people at different times, more or less periodically. We used different techniques to exploit the variables depending on the type. For dependency variables, we used values recorded at admission and the last observation value for the index date. For weight and blood pressure that are usually measured on several occasions, we have calculated, when possible, means, trends, or percentage changes with the first and last measure available over

**Table 1**
Characteristics of Nursing Home Residents Analyzed in the Study

| Variable | Cases (n = 16,942) | Controls (n = 41,435) | Standardized Mean Difference |
|---|---|---|---|
| Age at admission, y, mean (SD) | 84.5 (8.1) | 84.4 (8.7) | 0.01 |
| Women, % | 75.26 | 71.86 | 0.08 |
| Level of dependency at admission, % | | | |
| GIR1 (very severe) | 11.46 | 5.27 | 0.22 |
| GIR2 (severe) | 38.03 | 29.47 | 0.18 |
| GIR3 (moderate-severe) | 19.57 | 20.58 | 0.03 |
| GIR4 (moderate) | 23.28 | 32.08 | 0.20 |
| GIR5 (mild) | 4.6 | 7.6 | 0.13 |
| GIR6 (none) | 3.06 | 5.01 | 0.01 |
| Length of stay, mo, median (IQR) | 20.9 (4.1−48.8) | 14.9 (3.0−40.4) | 0.13 |
| Time to first pressure ulcer since admission in months (median and IQR) | 25.7 (6.9−52.9) | — | — |

several specified time periods (1, 3, and 6 months). For one-off events such as falls, we used the number of falls since the resident entered the facility and the time elapsed since the last event. An important issue was to take into account the transformation of an event database into tabular data that can be used by statistical learning, while keeping a medical meaning. We formulated these methods in agreement with an expert in geriatrics.

We removed outliers with extreme responses in terms of age or delay after entry. Residents with missing values for more than 10 variables were also excluded. To complete the few remaining missing data, the "k nearest neighbors" method was used. Each of the missing values in the sample is imputed using the average value of the k number of nearest neighbors in the dataset. Two samples are close if their non-missing variables are close.[16] Discretization is necessary to implement a Bayesian network (BN) classifier. Expert discretization was made for weight, tensions, and number of falls. Finally, we discretized the last continuous variables according to their quantiles into a maximum of 18 categories, except for the delay after entry, which is discretized into deciles to avoid biases.

### *Learning*

In this study, we used BNs, which are probabilistic graphical models that represent a set of variables and their conditional dependencies via a directed acyclic graph.[17] More than a simple classifier, a BN builds a graph from data that represent the probabilistic relations between variables (including the class variable itself). To elaborate a BN classifier, the structure of the network is learned from estimates on the training base. To classify an individual, the probability of belonging to a class knowing the observations of each variable of the individual is computed and compared with the specific threshold. To train the classifier, 75% of the sample was used. The remaining 25% was used for validation. The size of the dataset was large enough to do a simple random split and not cross validation. We used the pyAGrum library, enabling the construction of models and algorithms for probabilistic graphical models in Python.[18] The learning method was optimized, by choosing the Multivariate Information-based Inductive Causation algorithm based on constraints,[19] as it maximized our results.

### *Validation*

Because we wished to obtain a model with a high negative predictive value (NPV), we chose a score that gives more weight to false negatives than to false positives.

Then, for the evaluation of the predictive models, we used as primary judgment criteria an F-β score where $\beta = 2$[20]:

$$F_\beta = \left(1+\beta^2\right) \times \frac{precision \times recall}{(\beta^2 \times precision) + recall}$$

F-β score is the weighted harmonic mean of the precision and sensitivity scores and when β is superior of 1, recall outweighs precision.[21] To classify individuals, we have chosen the probability threshold that maximizes the F2-score. We compared F2-score, F1-score, precision, recall, accuracy, PPV, negative predictive value (NPV), and specificity with other classical machine learning models from scikit-learn[22] and XGBoost.[23] Indeed, we implemented simple supervised learning methods easy to interpret: naive Bayes, which is the simplest form of BN where all the variables are independent knowing the class, decision tree, logistic regression, and quadratic discriminant analysis (QDA). We also tried ensemble methods that combine the predictions of several base estimators built to improve results but lose their interpretation capacity in the process, such as random forest, AdaBoost, and XGBoost. Finally, we also compared with a multilayer perceptron (MLP), a neural network that is a highly complex model often efficient but not explainable.[24]

The use of a graphical model allows us another type of evaluation. Here, the interpretability of the model can be confronted by studying the BN obtained and questioning expert geriatricians, who must be able to find a medical meaning in it. Finally, this model provides a way to select relevant features: indeed, the so-called Markov boundary of the class node is the substructure that is sufficient to perform the classification. In BN, it contains the parents of the class node, its children, and the other parents of its children and

**Table 2**
F2 Scores and Other Measurements Assessing the Performances of the Different Machine Learning Models for 1-Month Prediction of PUs Among Nursing Home Residents

| | F2-Score | F1-Score | Precision/PPV | Recall/Sensitivity | Accuracy | Specificity | NPV |
|---|---|---|---|---|---|---|---|
| BN classifier | **0.67** (0.01) | 0.47 (0.01) | 0.32 (0.01) | **0.94** (0.04) | 0.40 (0.03) | 0.18 (0.05) | **0.88** (0.02) |
| QDA* | 0.50 (0.08) | 0.45 (0.03) | 0.39 (0.03) | 0.56 (0.14) | 0.60 (0.08) | 0.62 (0.17) | 0.78 (0.02) |
| Naive Bayes | 0.47 (0.01) | **0.55** (0.01) | 0.38 (0.01) | 0.63 (0.01) | 0.60 (0.00) | 0.58 (0.01) | 0.79 (0.00) |
| Decision Tree | 0.39 (0.01) | 0.38 (0.01) | 0.37 (0.01) | 0.39 (0.01) | 0.63 (0.00) | 0.73 (0.00) | 0.75 (0.00) |
| MLP† | 0.37 (0.04) | 0.39 (0.03) | 0.44 (0.01) | 0.36 (0.05) | 0.68 (0.01) | 0.81 (0.04) | 0.76 (0.01) |
| XgBoost | 0.33 (0.01) | 0.39 (0.01) | 0.56 (0.01) | 0.30 (0.01) | **0.73** (0.00) | 0.91 (0.00) | 0.76 (0.00) |
| AdaBoost | 0.24 (0.01) | 0.30 (0.01) | 0.56 (0.01) | 0.21 (0.01) | 0.72 (0.00) | 0.93 (0.00) | 0.74 (0.00) |
| Logistic Regression | 0.21 (0.01) | 0.27 (0.01) | 0.56 (0.01) | 0.18 (0.01) | 0.72 (0.00) | 0.94 (0.00) | 0.74 (0.00) |
| Random Forest | 0.14 (0.01) | 0.20 (0.01) | **0.65** (0.02) | 0.12 (0.01) | 0.72 (0.00) | **0.97** (0.00) | 0.73 (0.00) |

Each model was tested on 25 random validation sets and results are expressed as mean (SD). The models are listed in descending order of F2-score values. For each column, bold value indicates the best (maximum) score.
*Quadratic discriminant analysis.
†Multilayer perceptron.

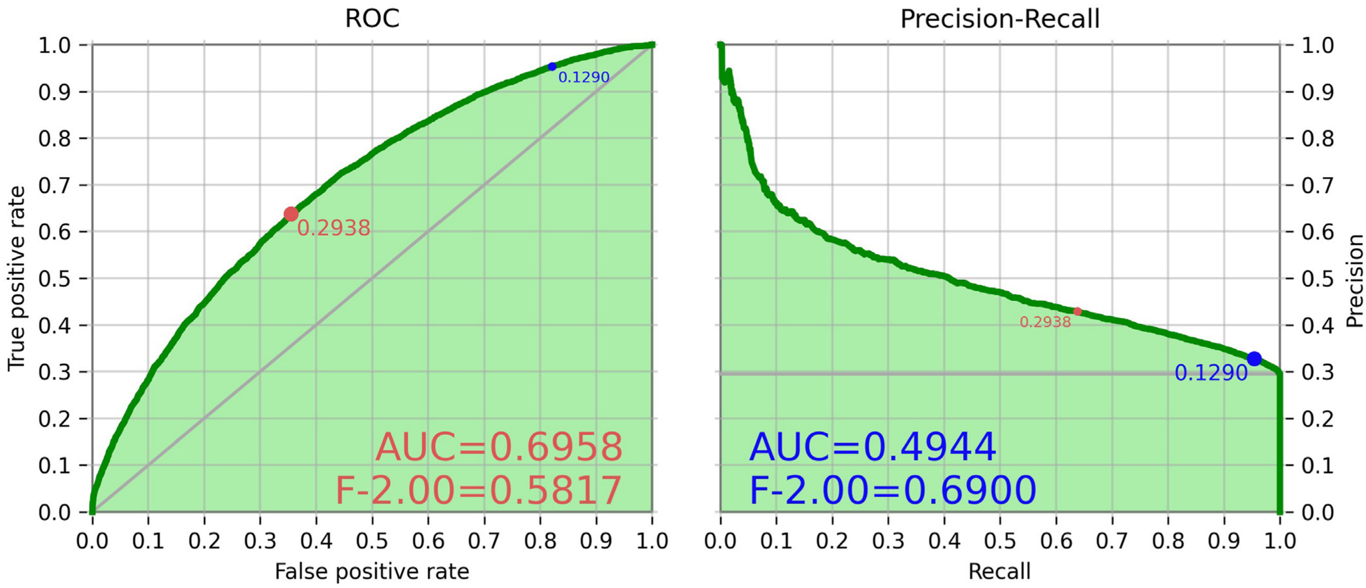


**Fig. 2.** ROC and precision-recall curve of the BN classifier (the red dot corresponds to the threshold maximizing the true positive rate and false positive rate, and the blue dot the F2-score).

provides all the information required for the inference of the class.[25]

## Results

We used the data of 58,368 residents (age 84.0 ± 8.6 years, 73% women) and we found that 16,942 of them experienced PUs, which corresponds to 29% prevalence.

The characteristics of the nursing home residents analyzed in the study are shown in Table 1. By comparing case and control characteristics, we found no large differences for age, sex, and length of stay; however, severe dependency was more frequent among cases with a large standardized mean difference.

The performance of the BN classifier was evaluated using a comprehensive set of metrics to assess its effectiveness in differentiating between classes. Various comparisons with other classical classifiers were made, and the results obtained are shown in Table 2. Considering the F2-score as our primary evaluation metric, the BN classifier outperformed all other methods in predicting PU. However, when examining overall accuracy, our method exhibited comparatively lower performance. It is important to note that accuracy measures the classifier's ability to correctly classify instances across all classes without accounting for class imbalances. In our dataset, pressure ulcer cases accounted for approximately 29% of the samples, meaning that a classifier that predicts only negative classes would achieve an accuracy of approximately 71%, similar to the random forest result here. These results highlight that the BN classifier

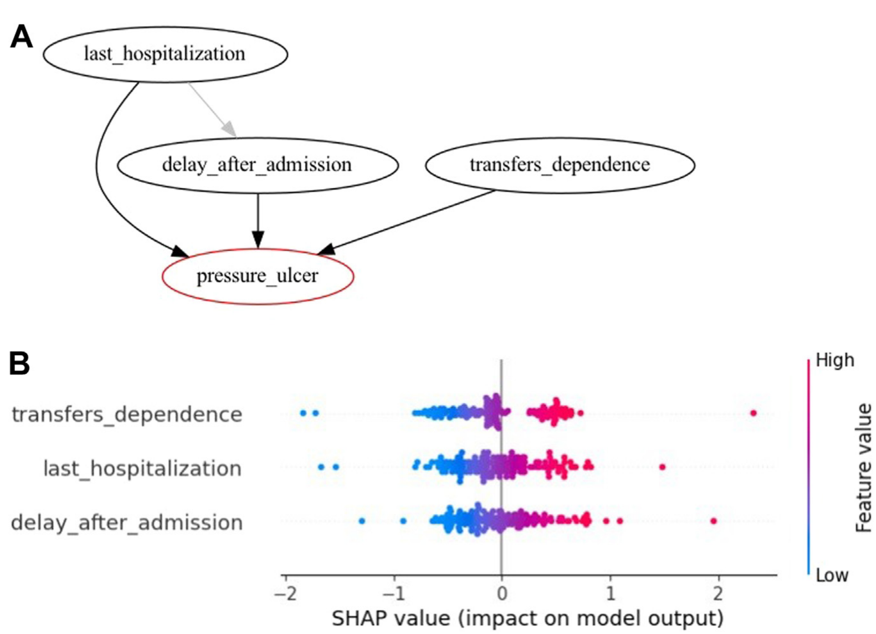


**Fig. 3.** Markov boundary of the BN classifier and Shap values of its features.

**Table 3**
Variables in the Markov Boundary of Level 2 of the Target PU

| Features | Variables |
|---|---|
| Demographic | sex |
| Weight | 6mo_body_weight_slope |
| | 6mo_body_weight_difference |
| | 3mo_body_weight_difference |
| | last_body_weight |
| Features of dependency | difference_levels_dependency |
| | level_dependency |
| | admission_level_dependency |
| | admission_lower_body_dressing |
| | admission_table_ustensils_use |
| | admission_transfers_dependence |
| | coherent_speech |
| | coherent_behavior |
| | oriented_in_time |
| | lower_body_grooming |
| | upper_body_dressing |
| | lower_body_dressing |
| | table_ustensils_use |
| | eating_dependence |
| | urinary_hygiene_elimination |
| | indoor_mobility |
| | outdoor_mobility |
| Occupational activity | number_attendance_leisure |
| | last_attendance_leisure |
| Disease | aggravated_disease |
| | infection |
| | diabetes |
| Hospitalization | 1mo_hospitalization_slope |
| | hospitalization_number |
| | hospitalization_history |
| Fall and fractures | 3mo_falls_slope |
| | 1mo_falls_slope |
| | fall_number |
| | last_fall |
| | femoral_fracture_history |
| | hip_fracture_history |
| Drugs | psychostimulants |
| | bronchodilatators |

excelled in correctly classifying positive instances with high precision, but at the cost of more false positives. We also observed that BN classifier results are quite stable across the different validation set (cf the standard deviations indicated in Table 2).

The receiver operating characteristic (ROC) curve and precision-recall curve offer a comprehensive assessment of the classifier's performance at varying classification thresholds, as seen in Figure 2. Opting for a conventional threshold, such as the optimal point on the ROC curve, may yield a slightly higher precision at the expense of a notable reduction in recall. In this context, selecting a threshold that maximizes the F2-score emerged as a more appropriate choice.

The BN model obtained has also been confronted with expert knowledge. In particular, the features of the Markov boundary and their Shap values (Figure 3) were studied by geriatricians, which considered them coherent with clinical knowledge and literature. Indeed, the features selected by the model included dependency for transfers, which is strongly related to impaired mobility, a classic risk factor for PU.[2] They also comprised recent hospitalization, which is often associated with factors favoring PU, like acute illness, worsening immobility, poor nutrition, and systemic inflammation.[26] A third feature selected by the model was the total duration of nursing home stay. Indeed, longer stay in nursing homes is associated with advancing age, decline of independence, and longer duration of chronic diseases, factors that might favor the onset of PU. Notably, among the 136 available features, the BN identified only 3 features that were sufficient for predicting PU occurrence. We wondered which of these 3 features summarized the information, so we computed the Markov boundary of level 2 (Table 3) that includes 39 features that are related to dependency, hospitalization, falls and femoral fractures, infectious diseases and diabetes, loss of weight, and lack of participation in leisure activities, which have also been considered as relevant by the experts.

## Discussion

This study found that a machine learning algorithm can predict the onset of PUs in nursing home residents from the data of their EHR obtained as part of usual care. This algorithm was set to provide a 1-month prediction horizon of a time appropriate to implement personalized care for PU prevention. We obtained a model with a few variables related to dependency for transfers, delay from last hospitalization, and length of stay in the nursing home. With this model, 1 resident of 3 classified at risk will develop PUs within a month.

Our findings are original, as no machine learning algorithm has yet been designed to predict the occurrence of PUs in nursing home residents.[27] In Korea, Lee et al investigated machine learning methods to predict the prevalence of PUs in 60 nursing homes from characteristics of the nursing homes and from the aggregated profiles of the residents, but they did not explore individual prediction of PUs.[13] Few studies have been yet published and designed algorithms capable of predicting incident PUs in the context of intensive care, surgery, or hospitalization.[11,12,14,15,28-32] All found predictive models with relevant performances, but it is difficult to compare them with those of our study because they apply to a younger population than ours, hospitalized and with a short stay at the facility.

In our study, we have taken several methodological directions that are important for future applicability. First, we focused on the BN, an artificial intelligence method often considered as a good compromise between accuracy and explainability. It is capable of exploring new risk factors and being validated by experts, unlike other classification methods. Second, we paid attention to defining a time horizon for the prediction of PUs, a point that is relevant given the long length of stay of residents in nursing homes. To this purpose, we used only the information available at the time of the prediction window (1 month before the PU date or index date). Third, we configured the classifier to have a high NPV to ensure that a resident classified as low risk would have a low probability of developing a PU in the following month.

Based on our data, we were unable to compare the performances of our algorithm with conventional clinical scales, in particular the Braden scale recommended by the European/North American Pressure Ulcer Advisory Panel to assess risk factors for PUs.[33] In the residents' records we studied, these scales were used very little and probably on the basis of clinical awareness. The meta-analysis by Chen et al found only 8 studies evaluating the Braden scale in nursing home residents.[34] In 6 of these, the scale's performance was studied cross-sectionally, which produced concurrent validity results that were unsuitable to assess PU prediction. The 2 prospective studies were small ($n = 335$) and their sensitivities (0.73 and 0.79) and specificities (0.74 and 0.76) for predicting PU had fairly wide confidence intervals.[35,36] In both studies, the incidence of PU was extremely high (21% in 90 days in De Souza et al and 27% in 4 weeks in Braden and Bergstrom),[35,36] which raises the question of the applicability of their results to standard nursing homes.

Our study has some limitations. The quality of the data from the EHR is imperfect, with missing values and possibly errors and, for variables that change over time, the frequency of acquisition varied from one resident to another. In addition, the stage of PU was not available in most of the records, and it is likely that stage 1 PUs were largely underdiagnosed or underreported in the EHR. Similarly, we were unable to find in the EHR any specific care measures for the prevention of PUs, even though they could have had an impact on the occurrence of PUs.

## Conclusions and Implications

This study demonstrated that a machine learning algorithm can predict PU onset in nursing home residents using their EHR data. It opens up interesting perspectives for designing innovative approaches to preventing PUs in the future. It reveals few and simple features that help predict PUs in nursing homes and that can be used in the clinical setting. In addition, we are now working to elaborate a decision support system for nursing homes, based on alerts generated by our predictive algorithm, to focus attention of health care professionals on residents at high risk of developing PUs in the next month. This decision support system will be linked to the EHR resident and will operate without any additional work for nursing staff, as it will use the data generated in the EHR as part of routine care. If staff trust it and implement active preventive care for high-risk residents, this could help reduce the incidence of PUs and PU-related pain and help promote quality of life in nursing homes.

## Discloure

The authors declare no conflicts of interest.

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## Supplementary Material

**Supplementary Table 1**
Feature Characteristics of Input Dataset

| Feature name | Distribution | Modalities | Completion (%) |
|---|---|---|---|
| 1mo_attendance_leisure_slope | | [(0 1], (1, 2], (2, 3], (3, 4], (4, 5], (5, 6], (6, 8], (8, 11], (11, 15], (15, 23], (23, 93]] | 100.0 |
| 1mo_body_weight_change | | [<=-15%-, -15%,-10%, -10%-0, 0-10%, 10%-15%, >=15] | 99.1 |
| 1mo_body_weight_difference (kilos) | | [(-10, -2], (-2, -1], (-1, 0], (0, 1], (1, 6]] | 99.1 |
| 1mo_mean_systolic_blood_pressure (mmHg) | | [<80, 80-100, 100-120, 120-140, >140] | 52.1 |
| 3mo_attendance_leisure_slope | | [(0, 1], (1, 2], (2, 3], (3, 4], (4, 5], (5, 7], (7, 10], (10, 14], (14, 21], (21, 97]] | 100.0 |
| 3mo_body_weight_change | | [<=-15%-, -15%, -10%, -10%-0, 0-10%, 10%-15%, >=15] | 99.1 |
| 3mo_body_weight_difference (kilos) | | [(-10, -5], (-5, -3], (-3, -2], (-2, -1], (-1, 0], (0, 1], (1, 2], (2, 3], (3, 14]] | 99.1 |
| 3mo_body_weight_slope | | [(-33, -1], (-1, 0], (0, 1], (1, 38]] | 99.1 |
| 3mo_falls_slope | | [(0, 1], (1, 2], (2, 31]] | 100.0 |
| 3mo_hospitalizations_ slope | | [0, 1, 2, 3, 4, 6, 7, 9] | 100.0 |
| 3mo_mean_systolic_blood_pressure (mmHg) | | [<80, 80-100, 100-120, 120-140, >140] | 70.5 |
| 6mo_attendance_leisure_slope | | [(0, 1], (1, 2], (2, 3], (3, 5], (5, 6], (6, 9], (9, 13], (13, 20], (20, 89]] | 100.0 |
| 6mo_body_weight_change | | [<=-15%-, -15%,-10%, -10%-0, 0-10%, 10%-15%, >=15] | 99.1 |
| 6mo_body_weight_difference (kilos) | | [(-11, -7], (-7, -5], (-5, -3], (-3, -2], (-2, -1], (-1, 0], (0, 1], (1, 2], (2, 3], (3, 4], (4, 13]] | 99.1 |
| 6mo_bod_weight_slope | | [(-18, -1], (-1, 0], (0, 22]] | 99.1 |
| 6mo_fall_slope | | [(0, 1], (1, 30]] | 100.0 |
| 6mo_hospitalizations_slope | | [0, 1, 2, 3, 4, 5, 6] | 100.0 |
| 6mo_mean_systolic_blood_pressure (mmHg) | | [<80, 80-100, 100-120, 120-140, >140] | 77.7 |
| adherence_to_treatment | | [independent, partially dependent, dependent] | 99.4 |
| admission_adherence_to_treatment | | [independent, partially dependent, dependent] | 99.8 |
| admission_coherent_behavior | | [independent, partially dependent, dependent] | 99.8 |
| admission_coherent_speech | | [independent, partially dependent, dependent] | 99.8 |
| admission_distance_purchasing | | [independent, partially dependent, dependent] | 99.8 |
| admission_do_all_houseworks | | [independent, partially dependent, dependent] | 99.8 |
| admission_eating_autonmy | | [independent, partially dependent, dependent] | 99.8 |
| admission_fecal_hygiene_elimination | | [independent, partially dependent, dependent] | 99.8 |
| admission_indoor_mobility | | [independent, partially dependent, dependent] | 99.8 |
| admission_level_dependency | | [independent, partially dependent, dependent] | 99.8 |
| admission_lower_body_dressing | | [independent, partially dependent, dependent] | 99.8 |
| admission_lower_body_grooming | | [independent, partially dependent, dependent] | 99.8 |
| admission_meal_preparation | | [independent, partially dependent, dependent] | 99.8 |
| admission_middle_body_dressing | | [independent, partially dependent, dependent] | 99.8 |
| admission_oriented_in_places | | [independent, partially dependent, dependent] | 99.8 |
| admission_oriented_in_time | | [independent, partially dependent, dependent] | 99.8 |
| admission_outdoor_mobility | | [independent, partially dependent, dependent] | 99.8 |
| admission_participate_in_leisure | | [independent, partially dependent, dependent] | 99.8 |
| admission_personnal_management | | [independent, partially dependent, dependent] | 99.8 |
| admission_public_transportation_use | | [independent, partially dependent, dependent] | 99.8 |
| admission_remote_communication | | [independent, partially dependent, dependent] | 99.8 |
| admission_table_ustensils_use | | [independent, partially dependent, dependent] | 99.8 |
| admission_transfers_dependence | | [independent, partially dependent, dependent] | 99.8 |
| admission_upper_body_dressing | | [independent, partially dependent, dependent] | 99.8 |
| admission_upper_body_grooming | | [independent, partially dependent, dependent] | 99.8 |
| admission_urinary_hygiene_elimination | | [independent, partially dependent, dependent] | 99.8 |

| | | | |
|---|---|---|---|
| age (years) | | [(44, 72], (72, 78], (78, 81], (81, 83], (83, 85], (85, 86], (86, 87], (87, 88], (88, 89], (89, 90], (90, 91], (91, 92], (92, 93], (93, 94], (94, 95], (95, 96], (96, 98], (98, 113]] | 100.0 |
| aggravated disease | | [absence, presence] | 100.0 |
| aid_for_mobility | | [absence, presence] | 100.0 |
| antibiotics | | [absence, presence] | 100.0 |
| antidementia_drugs | | [absence, presence] | 100.0 |
| antidepressants | | [absence, presence] | 100.0 |
| antidiabetics | | [absence, presence] | 100.0 |
| antiepileptics | | [absence, presence] | 100.0 |
| antiosteoporotic_drugs | | [absence, presence] | 100.0 |
| antiparkinson_drugs | | [absence, presence] | 100.0 |
| antipsychotics | | [absence, presence] | 100.0 |
| arthritis | | [absence, presence] | 100.0 |
| asthma | | [absence, presence] | 100.0 |
| BMI (kg/m²) | | [(6,0, 17], (17, 18], (18, 20], (20, 21], (21, 22], (22, 23], (23, 24], (24, 25], (25, 26], (26, 27], (27, 28], (28, 30], (30, 32], (32, 89]] | 69.4 |
| bpco | | [absence, presence] | 100.0 |
| bronchodilators | | [absence, presence] | 100.0 |
| cancer | | [absence, presence] | 100.0 |
| cardiovascular_disease | | [absence, presence] | 100.0 |
| cholesterol_lowering_ drugs | | [absence, presence] | 100.0 |
| chronic_renal_failure | | [absence, presence] | 100.0 |
| coherent_behavior | | [independent, partially dependent, dependent] | 99.4 |
| coherent_speech | | [independent, partially dependent, dependent] | 99.4 |
| coronary_heart_disease | | [absence, presence] | 100.0 |
| corticosteroids | | [absence, presence] | 100.0 |
| delay_after_admission (month) | | [(0, 7], (7,13], (13, 18], (18, 24], (24,31], (31, 41], (41,53], (53,68], (64, 84], (84,120]] | 100.0 |
| denutrition | | [absence, presence] | 100.0 |
| depression | | [absence, presence] | 100.0 |
| diabetes_type_1 | | [absence, presence] | 100.0 |
| diabetes_type_2 | | [absence, presence] | 100.0 |
| diabetes | | [absence, presence] | 100.0 |
| difference_levels_dependency | | [-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5] | 99.4 |
| distance_purchasing | | [independent, partially dependent, dependent] | 99.4 |
| do_all_houseworks | | [independent, partially dependent, dependent] | 99.4 |
| eating_autonmy | | [independent, partially dependent, dependent] | 99.4 |
| fall_number | | [0, 1, 2, 3+] | 100.0 |
| fecal_hygiene_elimination | | [independent, partially dependent, dependent] | 99.4 |
| femoral_fracture_history | | [absence, presence] | 100.0 |
| femoral_neck_fracture_history | | [absence, presence] | 100.0 |
| hearing_impaired | | [absence, presence] | 100.0 |
| heart_failure | | [absence, presence] | 100.0 |
| height (cm) | | [(100, 148], (148, 150], (150, 153], (153, 154], (154, 155], (155, 156], (156, 157], (157, 158], (158, 160], (160, 161], (161, 162], (162, 163], (163, 165], (165, 167], (167, 169], (169, 173], (173, 200]] | 69.9 |
| hip_fracture_history | | [absence, presence] | 100.0 |
| hospitalization_history | | [absence, presence] | 100.0 |
| hospitalization_number | | [0, 1, 2, 3, 4+] | 100.0 |
| hypertension | | [absence, presence] | 100.0 |
| hyperthyroid | | [absence, presence] | 100.0 |
| incontinence | | [absence, presence] | 100.0 |
| indoor_mobility | | [independent, partially dependent, dependent] | 99.4 |

| | | | |
|---|---|---|---|
| infection | | [absence, presence] | 100.0 |
| IV_fluid_infusion | | [absence, presence] | 100.0 |
| last_attendance_leisure | | [never, +6mo, 3mo-6mo, 1mo-3mo, 1mo] | 100.0 |
| last_body_weight (kilos) | | [(20, 41], (41, 45], (45, 47], (47, 50], (50, 52], (52, 54], (54, 56], (56, 58], (58, 60], (60, 63], (63, 65], (65, 67], (67, 70], (70, 73], (73, 76], (76, 81], (81, 89], (89, 200]] | 99.1 |
| last_fall | | [never, +6mo, 3mo-6mo, 1mo-3mo, 1mo] | 100.0 |
| last_hospitalization | | [never, +6mo, 3mo-6mo, 1mo-3mo, 1mo] | 100.0 |
| level_dependency | | [independent, partially dependent, dependent] | 99.4 |
| liver_disease | | [absence, presence] | 100.0 |
| lower_body_dressing | | [independent, partially dependent, dependent] | 99.4 |
| lower_body_grooming | | [independent, partially dependent, dependent] | 99.4 |
| malnutrition | | [absence, presence] | 100.0 |
| meal_preparation | | [independent, partially dependent, dependent] | 99.4 |
| med_hypotension | | [absence, presence] | 100.0 |
| med_steroide | | [absence, presence] | 100.0 |
| middle_body_dressing | | [independent, partially dependent, dependent] | 99.4 |
| neurologic_disease | | [absence, presence] | 100.0 |
| non_steroidal_ antiinflammatory_drugs | | [absence, presence] | 100.0 |
| number_attendance_leisure | | [(0, 2], (2, 4], (4, 8], (8, 14], (14, 22], (22, 33], (33, 47], (47, 66], (66, 90], (90, 124], (124, 172], (172, 248], (248, 368], (368, 606], (606, 1000]] | 100.0 |
| opioids | | [absence, presence] | 100.0 |
| oriented_in_places | | [independent, partially dependent, dependent] | 99.4 |
| oriented_in_time | | [independent, partially dependent, dependent] | 99.4 |
| osteoporosis | | [absence, presence] | 100.0 |
| outdoor_mobility | | [independent, partially dependent, dependent] | 99.4 |
| participate_in_cultural/sports_activities | | [independent, partially dependent, dependent] | 99.4 |
| personnal_management | | [independent, partially dependent, dependent] | 99.4 |
| polyarthritis | | [absence, presence] | 100.0 |
| pressure_ulcer | | [absence, presence] | 100.0 |
| psychostimulants | | [absence, presence] | 100.0 |
| psychotropics | | [absence, presence] | 100.0 |
| public_transportation_use | | [independent, partially dependent, dependent] | 99.4 |
| remote_communication | | [independent, partially dependent, dependent] | 99.4 |
| rhythm_disorder | | [absence, presence] | 100.0 |
| sex | | [absence, presence] | 100.0 |
| shoulder_fracture_history | | [absence, presence] | 100.0 |
| smoker | | [absence, presence] | 100.0 |
| spine_fracture_history | | [absence, presence] | 100.0 |
| table_ustensils_use | | [independent, partially dependent, dependent] | 99.4 |
| thyroid_disease | | [absence, presence] | 100.0 |
| transfers_dependence | | [independent, partially dependent, dependent] | 99.4 |
| upper_body_dressing | | [independent, partially dependent, dependent] | 99.4 |
| upper_body_grooming | | [independent, partially dependent, dependent] | 99.4 |
| urinary_hygiene_elimination | | [independent, partially dependent, dependent] | 99.4 |
| visually_impaired | | [absence, presence] | 100.0 |
| wrist_fracture_history | | [absence, presence] | 100.0 |