Enhancing the performance of predictive models for Hospital mortality by adding nursing data

Gianfranco Sanson[a], John Welton[b], Ercole Vellone[c], Antonello Cocchieri[d], Massimo Maurici[c], Maurizio Zega[d], Rosaria Alvaro[c], Fabio D'Agostino[e,*]

[a] *Clinical Department of Medical, Surgical and Health Sciences, University of Trieste, Piazzale Valmaura, 9, 34100, Trieste, Italy*
[b] *University of Colorado, College of Nursing, 13120 E. 19th Ave., Aurora, CO, 80045, USA*
[c] *Department of Biomedicine and Prevention, University of Rome Tor Vergata, Via Montpellier, 1, 00133, Rome, Italy*
[d] *University Hospital Agostino Gemelli, IRCCS, Largo Agostino Gemelli, 8, 00168, Rome, Italy*
[e] *Saint Camillus International University of Health Sciences, Via di Sant'Alessandro, 8, 00131 Rome, Italy*

ARTICLE INFO

Keywords:
Diagnosis-related groups
Hospital mortality
Nursing dependency index
Nursing diagnosis
Predictive models
Risk adjustment

ABSTRACT

Background: Mortality is the most considered outcome for assessing the quality of hospital care. However, hospital mortality depends on diverse patient characteristics; thus, complete risk stratification is crucial to correctly estimate a patient's prognosis. Electronic health records include standard medical data; however, standard nursing data, such as nursing diagnoses (which were considered essential for a complete picture of the patient condition) are seldom included.
Objective: To explore the independent predictive power of nursing diagnoses on patient hospital mortality and to investigate whether the inclusion of this variable in addition to medical diagnostic data can enhance the performance of risk adjustment tools.
Methods: Prospective observational study in one Italian university hospital. Data were collected for six months from a clinical nursing information system and the hospital discharge register. The number of nursing diagnoses identified by nurses within 24 h after admission was used to express the nursing dependency index (NDI). Eight logistic regression models were tested to predict patient mortality, by adding to a first basic model considering patient's age, sex, and modality of hospital admission, the level of comorbidity (CCI), and the nursing and medical condition as expressed by the NDI and the All Patient Refined-Diagnosis Related Group weight (APR-DRGw), respectively.
Results: Overall, 2301 patients were included. The addition of the NDI to the model increased the explained variance by 20%. The explained variance increased by 56% when the APR-DRGw, CCI, and NDI were included. Thus, the latter model was nearly highly accurate ($c = 0.89$, 95% confidence interval: 0.87–0.92).
Conclusion: Nursing diagnoses have an independent power in predicting hospital mortality. The explained variance in the predictive models improved when nursing data were included in addition to medical data. These findings strengthen the need to include standardized nursing data in electronic health records.

1. Introduction

The opportunities and challenges created by digitization have led to a new vision for healthcare organizations, whose actions and decisions are based on the availability of data and the ability to analyze them [1]. Large amounts of data are generated to maintain patient records and to fulfill a wide range of functions to improve the quality of healthcare delivery while reducing related costs [2]. This growing need for quality of care measurement and cost control has forced researchers to deal with a large variety of outcome measures [3–7]. According to Donabedian [8], who conceptualized structure, process, and outcome as three dimensions of a framework that evaluates the quality of care, hospital mortality is the most frequently used and most appealing outcome measure to consider in clinical practice for assessing the quality of care [9,10].

Predictive models based on variables such as age, sex, type of admission, medical diagnosis, and comorbidity factors have been proved to explain variation in hospital mortality rates [11]. However, more complete risk stratification is crucial to correctly estimate a patient's prognosis and fully interpret and understand outcome data, as hospital

* Corresponding author at: Saint Camillus International University of Health Sciences, Via di Sant'Alessandro, 8, 00131, Rome, Italy.
E-mail address: fabio.dagostino@unicamillus.org (F. D'Agostino).

Accepted 25 February 2019

mortality can depend on diverse patient characteristics [12]. For this reason, mortality should be adjusted for differences in the case-mix by taking into account data at the patient level, such as urgency of admission, disease severity, and socioeconomic factors [13,14], as well as aspects of patient complexity related to functional and psychosocial problems [15]. The functional and psychosocial problems constitute some of the main fields of interest for nursing [16,17].

1.1. Background

Electronic information systems should collect all relevant standardized data generated by healthcare professionals, such as nurses and physicians, to improve the quality and efficiency of services provided to patients [18]. Unfortunately, today electronic health records include standard medical data through hospital discharge abstracts, while standard nursing data are seldom considered and, thus, cannot be used to investigate the independent contribution of nursing to healthcare outcomes [19]. Moreover, physicians and nurses use very different languages, so that both information are needed to differentiate the independent professional contributions to patient outcomes [19]. Standardized nursing data able to provide a valid representation of nursing care and suitable for efficient processing and analysis, such as nursing diagnoses, are considered essential for a complete picture of the patient condition [20,21].

The nursing diagnosis synthesizes the nurses' clinical judgment regarding human responses to health conditions or life processes, representing nurses' conceptual knowledge [22]. Nursing diagnoses can describe the patient condition as a series of clinical situations according to which the nurse provides interventions mostly on his or her own direct prescription [23]. The nursing diagnosis can be used to represent overall nursing care [16], as the diagnosis gathers uniform information about clinical practice across various settings and patient groups [24] and captures nursing complexity in different phases of hospitalization (e.g., upon hospital admission) [25–27]. Moreover, nursing diagnoses have great potential to predict hospital mortality independent of medical care. However, only a few methods of risk adjustment that consider nursing diagnoses have been reported and, furthermore, these studies were quite dated and conducted only in the United States [26].

The objective of this study was to explore the independent predictive power (that is, the ability to anticipate an outcome) of nursing diagnoses on hospital mortality controlling for patients' age and sex, modality of admission, and comorbidity factors, and to investigate whether the inclusion of nursing diagnoses in addition to medical diagnostic data can enhance the performance of risk adjustment tools.

2. Materials and methods

2.1. Design and setting

This was a prospective observational study carried out in a 1,547-bed university hospital in Rome, Italy. The study was approved by the hospital's ethics committee.

2.2. Data sources

Data were collected from the hospital clinical nursing information system (Professional Assessment Instrument [PAI]) and the hospital discharge register, which were matched through a probabilistic matching process [28] in a single dataset study by using the patient's health code and the medical record number as the link variables.

In the PAI, nursing care is recorded according to the structure of the nursing process (e.g., nursing assessment, nursing diagnoses, and interventions) [29]. A clinical decision support system (the Nursing Assessment Form) [30] is embedded in the system to help nurses correctly identify the 44 NANDA-I [22] nursing diagnoses present in the PAI by using algorithmic methods based on patient assessment data.

The hospital discharge register was the source for medical data (e.g., medical diagnosis, comorbidities, and severity of disease), socio-demographic and organizational data (patient's age and sex, modality of hospital admission), and outcome data (mortality).

2.3. Sample and participants

All patients admitted from July until December 2014 in the medical (Internal Medicine and Oncology) and surgical (General Surgery and Thoracic Surgery) wards, where the PAI was implemented, were included in the study. The exclusion criteria were: (a) patient transferred to any other ward during hospitalization, due to the interruption of nursing data collection (i.e. nursing data were not collected by the PAI); (b) nursing assessment not filled out; (c) patient with a V64.x International Classification of Diseases, Ninth Revision-Clinical Modification (ICD-9-CM) coding at discharge, meaning that the specific procedure or treatment for which the patient was admitted to the hospital was not carried out because of unexpected circumstances [31]; (d) patient's age < 18 years.

2.4. Collected variables

The number of nursing diagnoses identified for each patient within 24 h after admission was used to express the nursing dependency index (NDI), a measure of nursing dependency for an individual patient. The higher the number of nursing diagnoses on admission, the higher the score and thus, the level of nursing dependency [32].

The patient's medical condition was expressed by the All Patient Refined DRG (APR-DRG), which expresses the severity of illness and the risk of mortality as a measure of the complexity of care for a given medical condition across a diagnosis group. For each APR-DRG, patients are classified in four subclasses (ranging from 1 to 4) to indicate minor, moderate, major, or extreme severity of illness (degree of physiologic decompensation or organ system loss of function) and risk of mortality (the likelihood of dying), respectively. Starting from the APR-DRG, the APR-DRG weight (APR-DRGw) was calculated with the APR grouping program from 3 M Health Information Systems [33]. The higher the score, the higher the patient's severity of illness and the amount of hospital resources required to care for patients with the same disease or operation.

The Charlson comorbidity index (CCI) was calculated using the ICD-9-CM according to the method proposed by Quan and colleagues [34] for administrative databases. The CCI considers the potential influence on mortality and resource use of 19 comorbid conditions, weighted with an inclusive score ranging from 0 to 24.

2.5. Data analysis

The continuous variables (e.g., age, the CCI, the NDI, and the APR-DRGw) were described as the mean, standard deviation (SD), and range. The difference between the means was analyzed using the unpaired Student *t*-test, after determining whether equal variance could be attributed to the subgroups according to Levene's test. The nominal variables (e.g., sex, modality of hospital admission) were described as a number and percentage, and analyzed with contingency tables and the chi-square (χ^2) test.

Eight logistic regression models were tested to predict patient mortality. The first basic model (Model 1) was built by using age, gender, and the modality of hospital admission as independent variables. Subsequently, seven models were tested by adding to the predictors above: the NDI (Model 2), the CCI (Model 3), the APR-DRGw (Model 4), the CCI and the NDI (Model 5), the NDI and the APR-DRGw (Model 6), the CCI and the APR-DRGw (Model 7), and the CCI, the NDI, and the APR-DRGw (Model 8).

The bivariate correlation among the independent variables entered into the models was investigated with Pearson's correlation coefficient

(r). Only little or no correlation was found among the independent variables (Age *vs* CCI: $r = 0.034$, $p = 0.103$; Age *vs* APR-DRGw: $r = 0.057$, $p = 0.006$; Age *vs* NDI: $r = 0.116$, $p < 0.001$; CCI *vs* APR-DRGw: $r = 0.183$, $p < 0.002$; CCI *vs* NDI: $r = 0.166$; $p < 0.003$; APR-DRGw *vs* NDI: $r = 0.155$, $p < 0.004$). Moreover, multicollinearity among the independent variables was assessed with the variance inflation factor (VIF) and tolerance. A VIF > 4 and a tolerance < 0.20 indicate multicollinearity [35]. The VIF and tolerance values for all tested models were ≤ 1.085 and ≥ 0.922, respectively, indicating no multicollinearity among the independent variables. To obtain a more normal distribution for data that showed excessive skewness or kurtosis, a square-root transformation was performed on the CCI, NDI, and APR-DRGw. Gender (0 = male; 1 = female) and modality of admission (0 = elective; 1 = from emergency department) were converted into dummy variables.

The coefficient of the determination of each model was calculated based on the Nagelkerke R^2. The performance of the logistic models was measured through the c statistic (equivalent to the area under the receiver operating characteristic [ROC] curve), a standard measure of the predictive accuracy of a logistic regression model when the outcome is binary [36]. Through the c statistic, we measured how well each model predicted mortality, by interpreting the probability that a randomly selected patient who died had a score greater than a similarly selected one who survived [11]. Results of the c statistic were interpreted according to the following criteria [37]: $c \leq 0.5$: non-informative; $0.5 < c \leq 0.7$: less accurate; $0.7 < c \leq 0.9$: moderately accurate; $0.9 < c < 1$: highly accurate; and $c = 1.0$: perfect test. A p value of < 0.01 was considered statistically significant for independent variables that have a strong association with patient mortality in the regression models. To assess possible 'over-optimism' in the model performance, the internal validity of the final model (Model 8) was tested by bootstrapping technique, as this analysis was recommended for estimating internal validity of predictive logistic regression models [38]. One-thousand replications of random sampling with replacement by drawing same size samples (i.e., 2301 subjects) from the original data set were performed. The 95% CI of each covariate was compared to that obtained by the bootstrapping re-sampling method. The difference between the bootstrap and the original c-statistics represented the optimism for the study data set.

Statistical analyses were performed using the software SPSS Statistics for Windows, version 23.0 (IBM Corp., Armonk, NY, US), excepted for the bootstrapping procedure that was performed by using of a web-based software [39].

3. Results

During the study period, 3178 patients were admitted in the wards studied. After the exclusion criteria were applied, 877 (27.6%) patients were excluded from the study (Fig. 1). Table 1 shows the main characteristics of the 2301 patients who constituted the study population. In bivariate analyses, the mortality rate was statistically significantly associated with older age (deceased: 72.3, SD 16.7; discharged: 62.1, SD 16.1; $t = -5.976$; $p < 0.001$), higher CCI (deceased: 2.9, SD 2.6; discharged: 1.5, SD 2.2; $t = -5.296$; $p < 0.001$), modality of admission (from emergency department: 9.8%; elective: 0.6%; $\chi^2 = 116.081$; $p < 0.001$), higher APR-DRGw (deceased: 1.5, SD 1.0; discharged: 1.0, SD 0.6; $t = -4.664$; $p < 0.001$) and higher NDI (deceased: 8.5, SD 7.4; discharged: 4.3, SD 4.2; $t = -5.432$; $p < 0.001$). No association with patient's sex was shown (female: 4.3%; male: 3.8%; $\chi^2 = 0.442$; $p = 0.506$).

Table 2 shows the results of the multivariate analysis. In the eight models, all considered variables but patient's sex were statistically significant predictors ($p < 0.01$) of hospital mortality. Compared to Model 1, the addition of the NDI increased the explained variance by 19.9%, whereas the explained variance increased by 36.8%, 46.8%, and 56.2% in Models 5, 6, and 8, respectively. The addition of the NDI to the otherwise most complete predictive model (Model 7) increased the explained variance by 6.4% (Table 3). Overall, all explored models were shown to be moderately accurate, with a progressive increase in predictive accuracy with the transition from Model 1 to Model 8. The last model (including the APR-DRGw, CCI, and NDI) was nearly highly accurate ($c = 0.89$). Fig. 2 shows the ROCs for the eight logistic models.

For Model 8, the 95% CIs of the covariates in the bootstrap samples (age: 1.008–1.056; admission from ED: 6.801–53.045; CCI: 1.224–2.065; APR-DRGw: 3.451–16.273; NDI: 1.169–1.785) were very similar to those in the original data set, particularly for age, CCI and NDI (Table 2). The bootstrap optimism estimate was 0.002, thus the c-

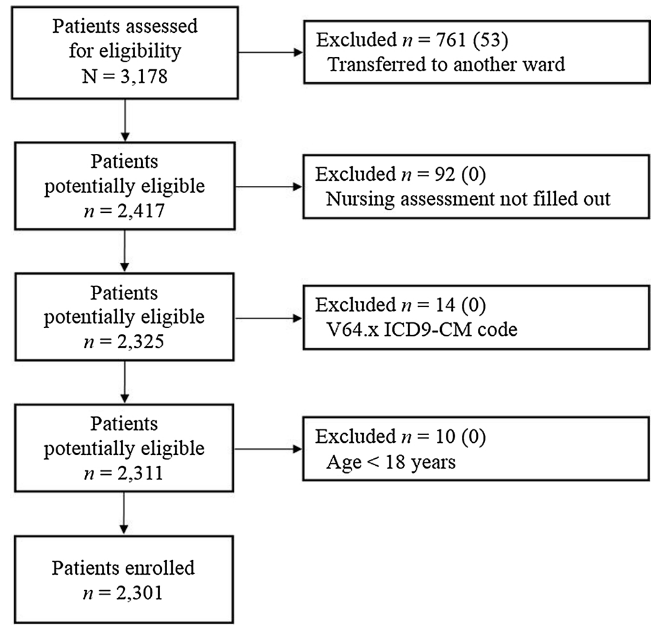

Fig. 1. Flow diagram of the participants' selection process (in brackets: number of dead).
Note. V64.x ICD9-CM code: patients admitted in hospital for a specific procedure or treatment not carried out because of unexpected circumstances.

Table 1
Descriptive characteristics of the study population (N = 2301).

Age (years)[§]	62.5 (16.2)
Sex (male)[¥]	1,191 (51.8)
Charlson Comorbidity Index[§]	1.5 (2.3)
Modality of hospital admission[¥]	
Elective	1,441 (62.6)
From Emergency Department	860 (37.4)
Admission wards[¥]	
Internal Medicine	944 (41.0)
Thoracic Surgery	559 (24.3)
Oncology	436 (18.9)
General Surgery	362 (15.7)
APR-DRG severity of illness[¥]	
Minor	1,091 (47.4)
Moderate	855 (37.2)
Major	327 (14.2)
Extreme	28 (1.2)
APR-DRG risk of mortality[¥]	
Minor	1,442 (62.7)
Moderate	608 (26.4)
Major	220 (9.6)
Extreme	31 (1.3)
APR-DRG weight[§]	1.1 (0.6)
Nursing Dependency Index[§]	4.5 (4.5)
Mortality[¥]	93 (4.0)

APR-DRG = All Patient Refined Diagnostic Related Group.
[¥] : number (percentage).
[§] : mean (standard deviation).

Table 2
Logistic regression models to predict patient mortality (N = 2301).

Model	Variables	B (SE)	Wald χ^2	OR (95% CI)	*p*-value
# 1	Age	0.030 (0.008)	14.861	1.030 (1.015–1.046)	< 0.001
	Adm. from ED	2.666 (0.357)	55.714	14.387 (7.143–28.976)	< 0.001
# 2	Age	0.027 (0.008)	11.796	1.027 (1.012–1.043)	0.001
	Adm. from ED	2.507 (0.359)	48.702	12.268 (6.067–24.806)	< 0.001
	NDI	0.508 (0.096)	27.907	1.662 (1.377–2.007)	< 0.001
# 3	Age	0.031 (0.008)	13.982	1.031 (1.015–1.048)	< 0.001
	Adm. from ED	2.638 (0.360)	53.808	13.983 (6.911–28.295)	< 0.001
	CCI	0.671 (0.119)	31.768	1.956 (1.549–2.470)	< 0.001
# 4	Age	0.030 (0.008)	13.587	1.030 (1.014–1.047)	< 0.001
	Adm. from ED	2.481 (0.370)	58.802	17.126 (8.286–35.398)	< 0.001
	APR-DRGw	2.432 (0.339)	51.420	11.379 (5.854–22.119)	< 0.001
# 5	Age	0.028 (0.008)	11.664	1.029 (1.012–1.046)	0.001
	Adm. from ED	2.518 (0.362)	48.487	12.400 (6.105–25.188)	< 0.001
	CCI	0.567 (0.122)	24.018	1.817 (1.431–2.307)	< 0.001
	NDI	0.438 (0.099)	19.601	1.549 (1.276–1.881)	< 0.001
# 6	Age	0.027 (0.008)	11.295	1.028 (1.011–1.044)	0.001
	Adm. from ED	2.718 (0.375)	51.517	15.153 (7.265–31.605)	< 0.001
	APR-DRGw	2.204 (0.346)	40.632	9.059 (4.601–17.839)	< 0.001
	NDI	0.413 (0.099)	17.518	1.511 (1.245–1.833)	< 0.001
# 7	Age	0.031 (0.008)	13.630	1.032 (1.015–1.049)	< 0.001
	Adm. from ED	2.772 (0.371)	55.784	15.994 (7.727–33.105)	< 0.001
	CCI	0.512 (0.122)	17.671	1.669 (1.315–2.120)	< 0.001
	APR-DRGw	2.136 (0.356)	35.987	8.465 (4.213–17.009)	< 0.001
# 8	Age	0.029 (0.008)	11.641	1.029 (1.012–1.046)	0.001
	Adm. from ED	2.672 (0.375)	50.865	14.469 (6.943–30.153)	< 0.001
	CCI	0.461 (0.124)	13.775	1.585 (1.243–2.022)	< 0.001
	APR-DRGw	1.963 (0.362)	29.457	7.118 (3.504–14.459)	< 0.001
	NDI	0.369 (0.101)	13.448	1.446 (1.187–1.760)	< 0.001

Sex: not significant in all models.
Adm. from ED = Admission from Emergency Department. NDI = Nursing dependency index. CCI = Charlson comorbidity index. APR-DRGw = All Patient Refined Diagnostic Related Group weight.

Table 3
Summary of R2 and c-statistics for the explored logistic regression models.

Model	R^2	*p*-value	*c*-statistic (95% CI)	*p*-value
# 1	0.201	< 0.001	0.823 (0.782–0.863)	< 0.001
# 2	0.241	< 0.001	0.855 (0.825–0.885)	< 0.001
# 3	0.248	< 0.001	0.860 (0.830–0.891)	< 0.001
# 4	0.270	< 0.001	0.868 (0.833–0.903)	< 0.001
# 5	0.275	< 0.001	0.877 (0.850–0.903)	< 0.001
# 6	0.295	< 0.001	0.880 (0.851–0.910)	< 0.001
# 7	0.295	< 0.001	0.882 (0.852–0.912)	< 0.001
# 8	0.314	< 0.001	0.891 (0.865–0.918)	< 0.001

CI = confidence interval.

statistic of Model 8 corrected for optimism was 0.889, showing a good internal validity of the model.

4. Discussion

In this study, we demonstrated the independent power of nursing diagnoses in predicting hospital mortality, after adjusting for patient's age, sex, modality of hospital admission, level of comorbidity, and medical condition as expressed by the APR-DRGw. Each additional point on the NDI (i.e., each additional nursing diagnosis on admission identified by nurses) determined a 1.45 times increase in the odds of hospital mortality (i.e., the odds for hospital mortality are increased by 45%). Moreover, the explained variance of the multivariate models improved when nursing data were considered in addition to medical data, with the performance of the logistic model becoming almost highly accurate in predicting mortality. For this latter model, bootstrapping showed only a minimal overfitting, confirming the internal validity of the model and indicating that this model can have similar performance when applied to population similar to the study sample.

Similarly to previous studies conducted in the United States [40,41], the number of nursing diagnoses on hospital admission, controlled for medical and sociodemographic data, was an independent predictor of mortality in a population of medical and surgical patients. Moreover, in both studies the joint use of medical and nursing data was more accurate in predicting mortality than the use of either type of data alone. Finally, very similar results were achieved in the *c* statistic in the present study and in the previously cited studies.

The predictive power of nursing diagnoses on mortality was shown in another previous larger study by Welton and Halloran that considered nursing dependency according to daily collected nursing diagnoses [16]. However, the explained variance reported in that study for models including nursing diagnoses was higher than that in the present study. The first possible explanation could be that Welton and Halloran considered a higher number of identifiable standard nursing diagnoses (up to 61, compared to 44 on the PAI). The possibility of identifying more diagnoses may have led nurses to more effectively describe the level of dependency of the patients. Moreover, in the same study the presence of each nursing diagnosis was measured daily for the whole hospital stay. This method, probably, better described the overall characteristics of patient conditions, because nursing diagnoses are not stable during hospitalization. Nursing diagnoses not present at admission may present in the following days, and some nursing diagnoses identified upon admission may resolve faster than others [42].

However, the nursing diagnoses collected upon admission can serve as prognostic factor, contributing to identify patients at higher dependency and at higher risk for death. In particular, the strength of the NDI is that the index identifies mortality risk before death in models without medical data. Conversely, routinely collected medical data, the APR-DRG and the CCI are scored after patient death and thus, have no value as an early prognostic factor.

Most importantly, the present findings underscore that nursing care cannot be considered implicitly embedded in the medical condition [6,19]. Nursing and medical diagnoses pursue different goals and involve different application methodologies. Thus, what it means to diagnose is different for a nurse from what it means for a physician. A

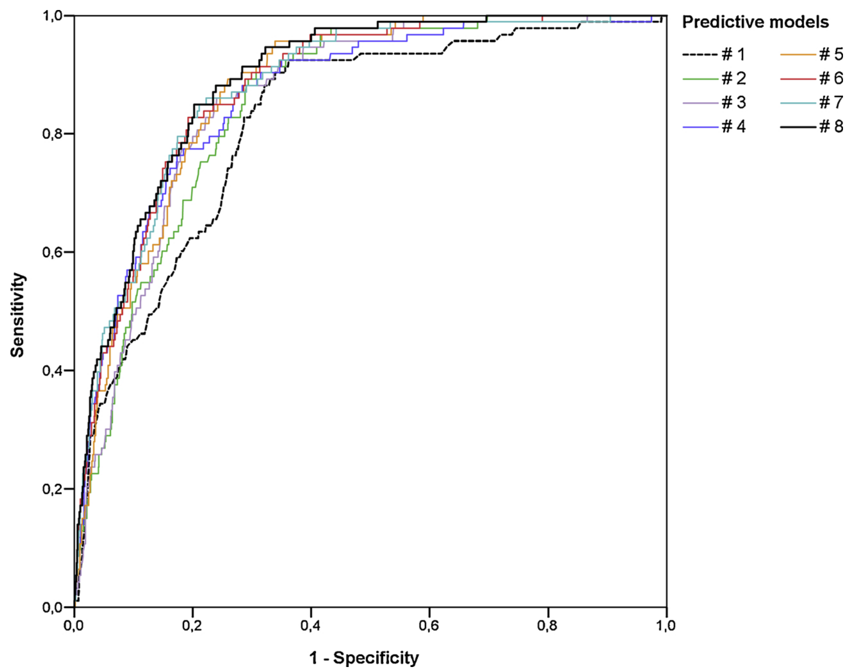

Fig. 2. Comparison of ROC curves for the explored logistic regression models (see Material and Methods for details).

medical diagnosis deals with disease, providing information about the patient's pathology, while a nursing diagnosis describes the comprehensive impact of illness on each individual, by considering health from a different and wider perspective. For example, nursing diagnoses intercept pathophysiologic conditions (e.g., acute or chronic pain, mental confusion, impaired skin integrity, impaired swallowing, ineffective airway clearance, or imbalanced nutrition), or a patient's functional status (e.g., urinary and bowel incontinence, impaired physical mobility, or self-care deficits), or conditions that could compromise a patient's ability to effectively cope with impaired health conditions (e.g., anxiety, fear, disturbed body image, or ineffective coping) not considered by medical classification. In addition, a nursing diagnosis considers the concrete threat that a certain unwanted situation may occur (risk diagnosis), toward which prevention strategies must be implemented. Furthermore, although the medical diagnosis (e.g., pneumonia) is a discrete condition established at a particular point in time, nursing diagnoses can show changes in a patient's state of health and/or dependence across time. Consequently, patients with the same medical diagnosis may receive very different nursing diagnoses over time [43]. The effect of a nursing diagnosis (i.e., a human response diagnosis) may influence patient outcomes differently from the effects of a disease-based diagnosis [6]. The study data showed that mortality is independently related to medical and nursing conditions.

The present findings strengthen the need to include standardized nursing data in electronic health records to improve predictive models for patient hospital outcome. As well as on the prognostic level, the availability of standardized nursing data can have important implications for issues such as funding nursing care, planning adequate nursing resources, and determining nursing's contribution to healthcare quality [44–46]. Accordingly, nurses should actively pursue the development of individual professional performance metrics, analysis, benchmarks, and practice standards before they are mandated by payers and policymakers [47].

4.1. Limitations

Results should be generalized with caution because the study was conducted in a single hospital by considering only patients admitted to four medical-surgical wards and having their entire hospital stay in a single ward. Thus, the external validity of this study should be confirmed by applying the predictive models to external data-set involving different settings and populations.

Only a limited number of nursing diagnoses available in the NANDA-I Taxonomy were included in the PAI system; although in hospital practice nurses might to employ a limited set of nursing diagnoses even when the entire Taxonomy is available [48], this fact may have prevented to record additional nursing diagnoses, thus underestimating the level of nursing dependency. As the NDI is dependent on the number of diagnoses registered, a potential concern exists that the method for identifying and recording nursing diagnoses could have been different among wards. Since all nurses identified the diagnoses using the same clinical decision support system (Nursing Assessment Form), a good uniformity in the identification of the diagnoses should have been ensured. Moreover, other standard nursing data such as nursing interventions that can have a relationship with the outcome [49] were not analyzed in this study; this fact must be taken into account when interpreting the results.

5. Conclusion

Nursing data complement medical data and have a significant independent prognostic impact on the prediction of hospital mortality. Including standard nursing data, such as nursing diagnoses, in electronic health records is essential to improve predictive models, as well as to summarize specific aspects of patients' complexity.

Future challenges for research should consider the standardization of a method for collecting data, making available wider lists of nursing diagnoses in electronic health records, and establishing the timing where nursing diagnoses are identified (e.g., upon admission and/or during the entire hospital stay). Moreover, based on the number or the pattern of nursing diagnoses identified on admission, different care strategies could be tested to assess the possibility of preventing patient risk of mortality as predicted by the level of nursing dependency.

Funding

This work was funded by the Italian Center of Excellence for Nursing Scholarship, Rome, Italy.

Conflict of interest

No conflict of interest has been declared by the authors.

Author statement

G.S., J.W., E.V., A.C., M.M., M.Z., R.A., and F.D. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Summary points

What was already known on the topic

- Mortality is frequently considered as an outcome measure for assessing the quality of hospital care, but a risk stratification comprising different patient characteristics is crucial to correctly interpret outcome data.
- Risk stratification is normally adjusted according to standard medical data, while standard nursing data are seldom included.
- The nursing diagnosis can be used to represent overall nursing care and captures nursing dependency in different phases of hospitalization.

What this study added to our knowledge

- Nursing diagnoses have an independent power in predicting hospital mortality, after adjusting for patient's age, sex, modality of hospital admission, level of comorbidity, and medical condition.
- The explained variance and the accuracy of the predictive models improved when nursing data were included in addition to medical data.
- Including standard nursing data in electronic health records is essential to improve predictive models, and to summarize specific aspects of patients' dependency.

References

[1] J. Koster, E. Stewart, E. Kolker, Health care transformation: a strategy rooted in data and analytics, Acad. Med. 91 (2016) 165–167.
[2] W. Raghupathi, V. Raghupathi, Big data analytics in healthcare: promise and potential, Health Inf. Sci. Syst. 2 (2014).
[3] S. Burston, W. Chaboyer, B. Gillespie, Nurse-sensitive indicators suitable to reflect nursing care quality: a review and discussion of issues, J. Clin. Nurs. 23 (2014) 1785–1795.
[4] N. Hahtela, B. McCormack, E. Paavilainen, P. Slater, M. Helminen, T. Suominen, The relationship of workplace culture with nursing-sensitive organizational factors, J. Nurs. Adm. 45 (2015) 370–376.
[5] L. Kim, C.H. Lyder, D. McNeese-Smith, L.S. Leach, J. Needleman, Defining attributes of patient safety through a concept analysis, J. Adv. Nurs. 71 (2015) 2490–2503.
[6] W. Paans, M. Muller-Staub, W.P. Krijnen, Outcome calculations based on nursing documentation in the first generation of electronic health records in the Netherlands, Stud. Health Technol. Inform. 225 (2016) 457–460.
[7] F. D'Agostino, E. Vellone, A. Cocchieri, J. Welton, M. Maurici, B. Polistena, F. Spandonaro, M. Zega, R. Alvaro, G. Sanson, Nursing diagnoses as predictors of hospital length of stay: a prospective observational study, J. Nurs. Scholarsh. 51 (2019) 96–105.
[8] A. Donabedian, The quality of care. How can it be assessed? JAMA 260 (1988) 1743–1748.
[9] M. Capuzzo, R. Moreno, Clinical Outcome, Available: http://pact.esicm.org/media/Clinical%20outcome%20pdf%20update%202010.pdf , Last Access: 29/4/2017 (2010).
[10] Y.R. van Gestel, V.E. Lemmens, H.F. Lingsma, I.H. de Hingh, H.J. Rutten, J.W. Coebergh, The hospital standardized mortality ratio fallacy: a narrative review, Med. Care 50 (2012) 662–667.
[11] M.J. Campbell, R.M. Jacques, J. Fotheringham, R. Maheswaran, J. Nicholl, Developing a summary hospital mortality index: retrospective analysis in English hospitals over five years, BMJ 344 (2012) e1001.
[12] M. Sladojevic, M. Cankovic, S. Cemerlic, B. Mihajlovic, F. Adic, M. Jarakovic, Data mining approach for in-hospital treatment outcome in patients with acute coronary syndrome, Med. Pregl. 68 (2015) 157–161.
[13] B. Jarman, S. Gault, B. Alves, A. Hider, S. Dolan, A. Cook, B. Hurwitz, L.I. Iezzoni, Explaining differences in English hospital death rates using routinely collected data, BMJ 318 (1999) 1515–1520.
[14] M.E. Pouw, L.M. Peelen, H.F. Lingsma, D. Pieter, E. Steyerberg, C.J. Kalkman, K.G. Moons, Hospital standardized mortality ratio: consequences of adjusting hospital mortality with indirect standardization, PLoS One 8 (2013) e59160.
[15] A.K. Schaink, K. Kuluski, R.F. Lyons, M. Fortin, A.R. Jadad, R. Upshur, W.P. Wodchis, A scoping review and thematic classification of patient complexity: offering a unifying framework, J Comorb 2 (2012) 1–9.
[16] J.M. Welton, E.J. Halloran, Nursing diagnoses, diagnosis-related group, and hospital outcomes, J. Nurs. Adm. 35 (2005) 541–549.
[17] J.M. Welton, L. Zone-Smith, M.H. Fischer, Adjustment of inpatient care reimbursement for nursing intensity, Policy Polit. Nurs. Pract. 7 (2006) 270–280.
[18] E. Dufour, A. Duhoux, D. Contandriopoulos, Reliability of a Canadian database for primary care nursing services' clinical and administrative data, Int. J. Med. Inform. 117 (2018) 1–5.
[19] A.D. Boyd, K.D. Lopez, C. Lugaresi, T. Macieira, V. Sousa, S. Acharya, A. Balasubramanian, K. Roussi, G.M. Keenan, Y.A. Lussier, Physician nurse care: a new use of UMLS to measure professional contribution: are we talking about the same patient a new graph matching algorithm? Int. J. Med. Inform. 113 (2018) 63–71.
[20] T.G. Macieira, M.B. Smith, N. Davis, Y. Yao, D.J. Wilkie, K.D. Lopez, G. Keenan, Evidence of progress in making nursing practice visible using standardized nursing data: a systematic review, AMIA Annual Symposium Proceedings, American Medical Informatics Association, (2017), p. 1205.
[21] A. Khokhar, M.K. Lodhi, Y. Yao, R. Ansari, G. Keenan, D.J. Wilkie, Framework for mining and analysis of standardized nursing care plan data, West. J. Nurs. Res. 39 (2017) 20–41.
[22] H. Herdman, Nursing Diagnoses: Definitions and Classification. 2015-2017, Wiley-Blackwell, Oxford, 2014.
[23] G. Sanson, R. Alvaro, A. Cocchieri, E. Vellone, J. Welton, M. Maurici, M. Zega, F. D'Agostino, Nursing diagnoses, interventions, and activities as described by a nursing minimum data set: a prospective study in an oncology hospital setting, Cancer Nurs. (2018).
[24] D.N. Spigolon, C.M. Moro, Nursing minimum data set based on ehr archetypes approach, NI 2012: Proceedings of the 11th International Congress on Nursing Informatics (2012) 386.
[25] F. D'Agostino, G. Sanson, A. Cocchieri, E. Vellone, J. Welton, M. Maurici, R. Alvaro, M. Zega, Prevalence of nursing diagnoses as a measure of nursing complexity in a hospital setting, J. Adv. Nurs. 73 (2017) 2129–2142.
[26] G. Sanson, E. Vellone, M. Kangasniemi, R. Alvaro, F. D'Agostino, Impact of nursing diagnoses on patient and organisational outcomes: a systematic literature review, J. Clin. Nurs. 26 (2017) 3764–3783.
[27] S. Tastan, G.C. Linch, G.M. Keenan, J. Stifter, D. McKinney, L. Fahey, K.D. Lopez, Y. Yao, D.J. Wilkie, Evidence for the existing American Nurses Association-recognized standardized nursing terminologies: a systematic review, Int. J. Nurs. Stud. 51 (2014) 1160–1170.
[28] C.J. Bradley, L. Penberthy, K.J. Devers, D.J. Holden, Health services research and data linkages: issues, methods, and directions for the future, Health Serv. Res. 45 (2010) 1468–1488.
[29] F. D'Agostino, E. Vellone, F. Tontini, M. Zega, R. Alvaro, Development of a computerized system using standard nursing language for creation of a nursing minimum data set, Prof. Inferm. 65 (2012) 103–109.
[30] M. Zega, F. D'Agostino, K.H. Bowles, M.G. De Marinis, G. Rocco, E. Vellone, R. Alvaro, Development and validation of a computerized assessment form to support nursing diagnosis, Int. J. Nurs. Knowl. 25 (2014) 22–29.
[31] Centers for Disease Control and Prevention, International Classification of Diseases, 9th Revision - Italian Version, (2007).
[32] E.J. Halloran, M. Kiley, Nursing dependency, diagnosis-related groups, and length of hospital stay, Health Care Financ. Rev. 8 (1987) 27–36.
[33] 3M Health Information Systems, All Patient Refined Diagnosis Related Groups (APR-DRGs). Methodology Overview, 3M Health Information Systems, Utah, USA, 2003.
[34] H. Quan, B. Li, C.M. Couris, K. Fushimi, P. Graham, P. Hider, J.M. Januel, V. Sundararajan, Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries, Am. J. Epidemiol. 173 (2011) 676–682.
[35] J. Fox, Regression Diagnostics: an Introduction, Sage, Newbury Park, California, 1991.
[36] P.C. Austin, E.W. Steyerberg, Interpreting the concordance statistic of a logistic regression model: relation to the variance and odds ratio of a continuous explanatory variable, BMC Med. Res. Methodol. 12 (2012) 82.
[37] J.A. Swets, Measuring the accuracy of diagnostic systems, Science 240 (1988) 1285–1293.
[38] E.W. Steyerberg, F.E. Harrell Jr, G.J. Borsboom, M. Eijkemans, Y. Vergouwe, J.D.F. Habbema, Internal validation of predictive models: efficiency of some procedures for logistic regression analysis, J. Clin. Epidemiol. 54 (2001) 774–781.
[39] H. Skalská, V. Freylich, Web-bootstrap estimate of area under ROC curve, Austrian J. Stat. 35 (325–330) (2006) 325–330.
[40] G.E. Rosenthal, E.J. Halloran, M. Kiley, C.S. Landefeld, Predictive validity of the Nursing Severity Index in patients with musculoskeletal disease, J. Clin. Epidemiol. 48 (1995) 179–188.
[41] G.E. Rosenthal, E.J. Halloran, M. Kiley, C. Pinkley, C.S. Landefeld, Development and validation of the Nursing Severity Index. A new method for measuring severity of illness using nursing diagnoses, Med. Care 30 (1992) 1127–1141.

[42] C. Castellan, S. Sluga, E. Spina, G. Sanson, Nursing diagnoses, outcomes and interventions as measures of patient complexity and nursing care requirement in Intensive Care Unit, J. Adv. Nurs. 72 (2016) 1273–1286.
[43] W. Paans, M. Müller-Staub, Standardized Nursing Language in Intelligent Electronic Healthcare Documentation, HIMMS, Europe, 2012.
[44] K.D. Lopez, A. Febretti, J. Stifter, A. Johnson, D.J. Wilkie, G. Keenan, Toward a more robust and efficient usability testing method of clinical decision support for nurses derived from nursing electronic health record data, Int. J. Nurs. Knowl. 28 (2017) 211–218.
[45] M. Muller-Staub, H. de Graaf-Waar, W. Paans, An internationally consented standard for nursing process-clinical decision support systems in electronic health records, Comput. Inform. Nurs. 34 (2016) 493–502.
[46] J. Stifter, V.E.C. Sousa, A. Febretti, K. Dunn Lopez, A. Johnson, Y. Yao, G.M. Keenan, D.J. Wilkie, Acceptability of clinical decision support interface prototypes for a nursing electronic health record to facilitate supportive care outcomes, Int. J. Nurs. Knowl. 29 (2018) 242–252.
[47] J.M. Welton, Nurses and the ethics of big data, Nurs. Econ. 34 (2016) 257–259.
[48] W. Paans, M. Müller-Staub, Patients' care needs: documentation analysis in general hospitals, Int. J. Nurs. Knowl. 26 (2015) 178–186.
[49] M. Muller-Staub, I. Needham, M. Odenbreit, M.A. Lavin, T. van Achterberg, Implementing nursing diagnostics effectively: cluster randomized trial, J. Adv. Nurs. 63 (2008) 291–301.