# Nursing Diagnoses as Predictors of Hospital Length of Stay: A Prospective Observational Study

Fabio D'Agostino, PhD, RN[1], Ercole Vellone, PhD, RN, FESC[2], Antonello Cocchieri, PhD, RN[3], John Welton, PhD, RN, FAAN[4], Massimo Maurici, MD[5], Barbara Polistena, PhD[6], Federico Spandonaro, MA Econ[7], Maurizio Zega, PhD, RN[8], Rosaria Alvaro, MSN, RN, FESC[9], & Gianfranco Sanson, PhD, RN[10]

1 *Mu Upsilon*, Research Fellow, Department of Biomedicine and Prevention, University of Rome Tor Vergata, Rome, Italy
2 Assistant Professor, Department of Biomedicine and Prevention, University of Rome Tor Vergata, Rome, Italy
3 Nurse Director, Catholic University of the Sacred Heart, Rome, Italy
4 Professor & Senior Scientist Health Systems Research, University of Colorado College of Nursing, Aurora, CO, USA
5 Assistant Professor, Department of Biomedicine and Prevention, University of Rome Tor Vergata, Rome, Italy
6 Research Fellow, Department of Economics and Finance, University of Rome Tor Vergata, C.R.E.A. Sanità, Rome, Italy
7 Aggregate Professor, Department of Economics and Finance, University of Rome Tor Vergata, Chair C.R.E.A. Sanità, Rome, Italy
8 Director of Health Professions, University Hospital Agostino Gemelli, Rome, Italy
9 Associate Professor, Department of Biomedicine and Prevention, University of Rome Tor Vergata, Rome, Italy
10 Adjunct Professor, School of Nursing, Department of Medicine, Surgery and Health Sciences, University of Trieste, Trieste, Italy

**Key words**
Diagnosis-related groups, hospital length of stay, nursing diagnosis, observational study, outcome, regression analysis

**Correspondence**
Dr. Fabio D'Agostino, Department of Biomedicine and Prevention, University of Rome Tor Vergata, Via Montpellier, 1, 00133 Rome, Italy.
E-mail: fabio.d.agostino@uniroma2.it

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## Abstract

**Purpose:** To investigate whether the number of nursing diagnoses on hospital admission is an independent predictor of the hospital length of stay.
**Design:** A prospective observational study was carried out. A sample of 2,190 patients consecutively admitted (from July to December 2014) in four inpatient units (two medical, two surgical) of a 1,547-bed university hospital were enrolled for the study.
**Methods:** Data were collected from a clinical nursing information system and the hospital discharge register. Two regression analyses were performed to investigate if the number of nursing diagnoses on hospital admission was an independent predictor of length of stay and length of stay deviation after controlling for patients' sociodemographic characteristics (age, gender), clinical variables (disease groupers, disease severity morbidity indexes), and organizational hospital variables (admitting inpatient unit, modality of admission).
**Findings:** The number of nursing diagnoses was shown to be an independent predictor of both the length of stay ($\beta = .15$; $p < .001$) and the length of stay deviation ($\beta = .19$; $p < .001$).
**Conclusions:** The number of nursing diagnoses is a strong independent predictor of an effective hospital length of stay and of a length of stay longer than expected.
**Clinical Relevance**: The systematic inclusion of standard nursing care data in electronic health records can improve the predictive ability on hospital outcomes and describe the patient complexity more comprehensively, improving hospital management efficiency.

Length of stay is a classical variable used to assess the quality of care and the performance of a hospital (Carter & Potts, 2014). Consequently, several studies have tested different models in order to identify the variables more likely to be predictive of hospital length of stay. A systematic literature review exploring risk adjustors and models adopted to explain length of stay showed that all the highest performing models included routinely collected variables, such as disease groupers (e.g., all patient refined diagnosis-related groups [APR-DRGs] or diagnosis-related groups [DRGs]), disease severity morbidity indexes (e.g., Charlson comorbidity index), and patients' sociodemographic characteristics (e.g., age, sex; Lu, Sajobi, Lucyk, Lorenzetti, & Quan, 2015). Nevertheless, the authors suggested that other variables, such as hospital organization and patient complexity measures, should be included to improve the performance of these models (Lu et al., 2015).

Patient complexity is a result of different patient needs that are related not only and exclusively to medical conditions, but also to other aspects, such as functional and psychosocial problems (Schaink et al., 2012), that can affect hospital length of stay (Welton & Halloran, 2005). Functional and psychosocial problems can be identified by nurses through the use of nursing diagnoses, and these data are complementary to the medical diagnosis. The nursing diagnosis represents the nurses' conceptual knowledge, being the nurses' clinical judgment regarding human responses to health conditions or life processes (Herdman, 2014). The NANDA-International Taxonomy is the worldwide standard terminology for nursing diagnosis (Herdman, 2014), and it is able to capture nursing complexity in different phases of hospitalization (Sanson, Vellone, Kangasniemi, Alvaro, & D'Agostino, 2017; Tastan et al., 2014).

Nursing diagnosis is useful for gathering uniform nursing information of clinical practice across various settings and patient groups (Bakken et al., 2005; Spigolon & Moro, 2012). Moreover, nursing diagnosis is included in the essential nursing care elements of the nursing minimum data set. The nursing minimum data set identifies and operationalizes a powerful, but limited, set of data representing the core components of nursing practice (Goossen, 2002). Also, it meets the information needs of multiple data users in the healthcare system by making nursing visible in the fields of research, healthcare effectiveness, and policy analysis (Werley, Devine, Zorn, Ryan, & Westra, 1991; Werley & Lang, 1988). These data are collected contemporaneously throughout the course of hospitalization and reflect changes in a patient's condition.

Since length of stay also depends on factors related to nursing conditions, it seems obvious that not considering nursing care would be inappropriate and inefficient in representing the quality of the healthcare system. However, massive data sets are needed to validate the association between nursing data and hospital outcomes. In only a few studies were nursing diagnoses found to predict hospital length of stay (Castellan, Sluga, Spina, & Sanson, 2016; Paans, Muller-Staub, & Krijnen, 2016; Sanson et al., 2017). The aim of this study was to investigate if the number of nursing diagnoses on hospital admission was an independent predictor of length of stay, controlling for patients' sociodemographic characteristics (age, gender), clinical variables (disease groupers and disease severity morbidity indexes), and organizational hospital variables (admitting inpatient unit and modality of admission).

# Methods

## Study Design and Setting

This was a prospective observational study carried out in a 1,547-bed university hospital in Rome, Italy. The university hospital has eight departments and 55 inpatient units.

## Data Sources

Data sources were two databases: the hospital discharge register for medical and organizational data (e.g., disease groupers, severity morbidity indexes, modality of admission) and the Professional Assessment Instrument for sociodemographic and nursing data (D'Agostino, Vellone, Tontini, Zega, & Alvaro, 2012). The Professional Assessment Instrument is a clinical nursing information system used to electronically document nursing care according to the structure of the nursing process. This information system includes data on patient demographics (e.g., personal identification, age, gender), admitting inpatient unit, hospital length of stay (measured as the number of days from hospitalization to hospital discharge), and nursing care (nursing assessment, nursing diagnoses, nursing interventions, evaluation scales).

Patient assessments were carried out on admission (within 24 hr of admission) through interviews and clinical examinations by nurses according to the Gordon's Functional Health Patterns (Gordon, 1994). The patient needs identified by nurses were described using up to 44 nursing diagnosis labels based on NANDA-International taxonomy (Herdman, 2014) and recorded in the Professional Assessment Instrument. The choice of these 44 nursing diagnoses in the Professional Assessment Instrument was based on a literature review examining the prevalence of certain nursing diagnoses in different settings of hospital care and on the analysis of nursing diagnoses recorded in nursing documentation of Italian hospitals (D'Agostino et al., 2012). These 44 nursing diagnoses were included in the Professional Assessment Instrument because they were the ones most used by Italian nurses. However, if nurses identified other nursing diagnoses not present in the set of 44, they also had the option to insert these diagnoses as free-text entries.

Nurses were supported in their diagnostic reasoning by a specifically validated Nursing Assessment Form (Zega et al., 2014), which is an automated, interactive clinical decision support system included in the Professional Assessment Instrument based on specific standard items (signs or symptoms and risk factors according to NANDA-International) to suggest the possible nursing diagnoses. Therefore, the input of standard data (signs or symptoms and risk factors) in the Nursing Assessment Form allowed the Professional Assessment Instrument to prompt nurses with some possible diagnoses. Then, these suggested diagnoses were accepted or rejected by nurses who lastly validated the diagnoses. Moreover, nurses could describe each diagnosis according to the PES (problem, etiology, and signs or symptoms) format, providing evidence of the nursing diagnosis accuracy.

To improve the correct use of nursing diagnoses in practice, before Professional Assessment Instrument implementation at the university hospital, all nurses were trained with a specific course on diagnostic reasoning and NANDA-International taxonomy. Moreover, during the use of the Professional Assessment Instrument as a trial (for 3 months before its implementation), clinical audits were performed to further improve the use of nursing diagnoses.

After obtaining approval from the Institutional Review Board, data from the two databases (Professional Assessment Instrument, hospital discharge register) were linked through two key variables, namely, the patient's health code number and medical record number. Then, the two databases were matched to create a single study database by the Hospital Management Control Department through a probabilistic matching process (Bradley, Penberthy, Devers, & Holden, 2010).

## Eligibility Criteria for Participants

Overall, 3,191 patients consecutively admitted for 6 months (July to December 2014) in four inpatient units (Internal Medicine and Gastroenterology, General and Hepatobiliary Surgery, Thoracic Surgery and Pneumology, and Oncology) were considered eligible for the study. These inpatient units were selected because they were the first inpatient units in which the Professional Assessment Instrument was implemented in February 2013.

A total of 1,001 subjects (31.4%) were excluded from the study after applying the following exclusion criteria (Figure 1): (a) patients transferred to a different hospital inpatient unit; (b) patients with the nursing assessment not filled out; (c) patients admitted to the hospital for a specific procedure or treatment not carried out because of unexpected circumstances (coded as V64.x in the International Classification of Diseases, 9th revision, Clinical Modification; Centers for Disease Control and Prevention, 2007); (d) patients with a hospital length of stay of only 1 day, since this is considered a "day-hospital admission"; and (e) patients who died during their hospital stay. A total of 2,190 patients constituted the final study sample.

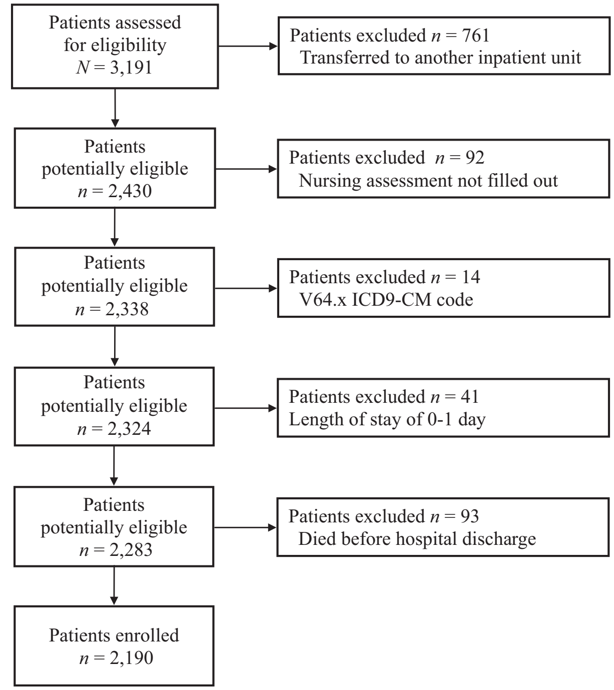


**Figure 1.** Flow diagram of the participants' selection process. *Note.* V64.x ICD9-CM code, 2007 version = patients admitted in hospital for a specific procedure or treatment not carried out because of unexpected circumstances; ICD9-CM = International Classification of Diseases, 9th Revision, Clinical Modification.

## Collected Variables

For each included patient, the following variables were collected:

- The major diagnostic categories, which are 25 mutually exclusive diagnosis areas of diseases or disorders corresponding to a single organ system or etiology. The major diagnostic categories were obtained by all possible principal diagnoses from the International Classification of Diseases, 9th revision (Centers for Disease Control and Prevention, 2007).
- The APR-DRG, which is a measure of complexity of care for given medical conditions expressing the severity of illness and the risk for mortality across a diagnosis group. For each APR-DRG, patients are classified into 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 for mortality (the likelihood of dying), respectively.

- The APR-DRG weight, which is a continuous score based on the above-defined severity of illness subclasses; 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 severity of illness and risk for mortality subclasses and the APR-DRG weight were obtained by the APR grouper program from 3M Health Information Systems (2003).
- The Charlson comorbidity index, which is the most widely used measure of clinically important concomitant diseases. It considers 19 comorbid conditions weighted with a score of 1, 2, 3, or 6 according to their potential influence on mortality and resource use. The scores are summed up to provide the final index score (ranging from 0 to 24); the higher the index, the higher the presence of clinically important comorbidities. The Charlson comorbidity index was calculated using the International Classification of Diseases, 9th revision (Centers for Disease Control and Prevention, 2007) according to the method of Quan et al. (2011) for administrative databases.
- The number of nursing diagnoses identified by nurses on patient admission. This variable was used to establish a measure of nursing complexity; the higher the number of nursing diagnoses, the higher the nursing complexity (Halloran & Kiley, 1987; O'Brien-Palla s, Li, Wang, Meyer, & Thomson, 2010).
- The hospital length of stay, which was measured as the difference (in days) between the dates of hospital admission and discharge.
- The hospital length of stay deviation (LOS deviation), which is a variable calculated to measure the difference between the effective patients' hospital stay and the DRG-specific national expected (average) hospital length of stay (General Direction for Health Planning, 2015).

The collected data also included patients' gender, age, modality of admission (scheduled [elective admission] or from the Emergency Department), and discharge (home or transferred to other healthcare facilities) and inpatient unit groups (surgical or medical).

## Ethical Considerations

The local ethics committee of the hospital approved the study. Data of the patient records were anonymized and assigned to a progressive numerical code before being entered into the study database. Once the data were stored in the database, the researchers could not identify individual patients.

## Data Analysis

Statistical analysis was performed using the IBM SPSS Statistics for Windows, version 22.0 software (IBM Corp., Armonk, NY, USA). Descriptive statistics, frequencies, means, standard deviations, and ranges were used to describe the variables of the study. No case had missing data.

A first ordinary least squares multiple linear regression model was used to investigate the independent association between the number of nursing diagnoses and the patients' hospital length of stay, after controlling for sociodemographic (age, gender), clinical (APR-DRG weight and Charlson comorbidity index), and hospital organizational variables (modality of admission, inpatient unit groups). The same predictors were tested via a second ordinary least squares multiple linear regression in which the LOS deviation was adopted as a dependent variable in order to test which variables were predictors of the nonstandard length of stay, since, for each DRG, a length of stay threshold is defined ("trim point") beyond which the hospital stay is considered nonstandard (General Direction for Health Planning, 2015).

The presence of excessive skewness or kurtosis in data distribution can be a risk for the assumptions of the linearity of the relationships among variables, normality, and homoscedasticity of residuals (Tabachnick, 2013); therefore, normality tests were used for all considered continuous variables to establish if data were modeled by a normal distribution. Since all variables, except for age, were non-normally distributed, square root transformations were done on the Charlson comorbidity index, number of nursing diagnoses, and LOS deviation, while logarithmic transformations were done on APR-DRG weight and hospital length of stay in order to obtain a more normal data distribution. The categorical variables were transformed to dummy variables as follows: gender coded as 0 = male and 1 = female; modality of admission coded as 0 = scheduled and 1 = from the Emergency Department; and inpatient unit groups coded as 0 = surgical and 1 = medical. With the use of a $p < .001$ criterion for Mahalanobis distance, five outliers among the cases were found in the first regression model (hospital length of stay as a dependent variable) and 15 cases were found as outliers in the second regression model (LOS deviation as a dependent variable). To test whether the outlier cases influenced the model parameters, we performed multiple regression analyses including or not including the outliers. Since there was no difference between parameters when estimated using all cases and when outliers were excluded, that is, all standardized DFBeta were far less than the cut-off value |1| (Field, 2013), we included the outlier cases in the analysis.

Prior to running the multiple linear regression models, due to the clustered structure of our data set (i.e., several inpatient units), we checked to determine if multilevel techniques were needed. The intraclass correlation coefficient was 0.003, which did not justify the adoption of a multilevel analysis (Twisk, 2006). For all tests, an alpha level of $p$ = .05 was set for statistical significance.

## Results

Overall, the mean age of the study sample was 61.9 years (*SD* 16.4; range 6–98), and 1,133 subjects (51.7%) were male. The majority of the admissions were scheduled ($n$ = 1,408; 64.3%), whilst the remaining patients ($n$ = 782; 35.7%) came via the Emergency Department. Most patients ($n$ = 890; 40.6%) were admitted to Internal Medicine and Gastroenterology, followed by Thoracic Surgery and Pneumology ($n$ = 531; 24.2%), Oncology ($n$ = 409; 18.7%), and General and Hepatobiliary Surgery ($n$ = 360; 16.4%). As shown in Table 1, a large majority of the diseases and disorders belonged to medical categories (70.7%). The most prevalent major diagnostic categories belonged to the diseases and disorders of the hepatobiliary system and pancreas (26.8%), digestive system (22.0%), and respiratory system (18.2%). According to the APR-DRG subclasses, the overwhelming percentage of patients presented with minor or moderate levels of severity of illness and risk for mortality (86.4% and 91.3%, respectively).

Risk for infection was the most prevalent nursing diagnosis (64%), followed by Risk for impaired skin integrity (24.8%) and Imbalanced nutrition: less than body requirements (24.6%). The mean Charlson comorbidity index value was 1.5 (*SD* 2.2; range 0–10), the mean APR-DRG weight 1.1 (*SD* 0.6; range 0.3–9.9), and the mean number of nursing diagnoses 4.3 (*SD* 4.2; range 0–32). Nearly all patients were discharged to home ($n$ = 2165; 98.9%), and only 1.1% were transferred to other healthcare facilities. The mean length of stay was 7.4 days (*SD* 5.9; range 2–68), whereas the mean LOS deviation was -1.3 days (*SD* 5.4; range -15.2 to 51.1).

The first multiple regression analysis was run to predict the hospital length of stay from age, gender, APR-DRG weight, Charlson comorbidity index, number of nursing diagnoses, modality of admission and inpatient unit groups. The regression model predicted the hospital length of stay ($F$ = 149.1, $p$ < .001) and explained 33% of logarithmic hospital length of stay variance. All but one of the variables (Charlson comorbidity index, $p$ = .6) were significant determinants ($p$ < .01) of length of stay (Table 2).

The second regression analysis was performed using the LOS deviation as a dependent variable with the same independent variables. The regression model was statistically significant ($F$ = 35.6; $p$ < .001) and explained 10% of the square root LOS deviation. Only the modality of admission, number of nursing diagnoses,

**Table 1.** Descriptive Statistics of Patients' Clinical Characteristics ($N$ = 2,190)

| Variables | $n$ (%) |
|---|---|
| Patients group | |
| Medical | 1,549 (70.7) |
| Surgical | 641 (29.3) |
| Major diagnostic categories | |
| Hepatobiliary system and pancreas DDs | 587 (26.8) |
| Digestive system DDs | 481 (22.0) |
| Respiratory system DDs | 398 (18.2) |
| Myeloproliferative DDs | 202 (9.2) |
| Nervous system DDs | 158 (7.2) |
| Endocrine, nutritional, and metabolic system DDs | 53 (2.4) |
| Skin, subcutaneous tissue, and breast DDs | 47 (2.1) |
| Circulatory system DDs | 47 (2.1) |
| Infectious and parasitic DDs | 45 (2.1) |
| Kidney and urinary tract DDs | 45 (2.1) |
| Other | 127 (5.8) |
| Ten most prevalent nursing diagnoses | |
| Risk for infection | 1,401 (64) |
| Risk for impaired skin integrity | 543 (24.8) |
| Imbalanced nutrition: less than body requirements | 539 (24.6) |
| Acute pain | 532 (24.3) |
| Risk for constipation | 509 (23.2) |
| Disturbed sleep pattern | 502 (22.9) |
| Anxiety | 466 (21.3) |
| Impaired physical mobility | 428 (19.5) |
| Risk for falls | 380 (17.4) |
| Risk for activity intolerance | 298 (13.6) |
| APR-DRG severity of illness | |
| Minor | 1,069 (48.8) |
| Moderate | 824 (37.6) |
| Major | 282 (12.9) |
| Extreme | 15 (0.7) |
| APR-DRG risk for mortality | |
| Minor | 1,427 (65.2) |
| Moderate | 571 (26.1) |
| Major | 176 (8.0) |
| Extreme | 16 (0.7) |

*Note.* APR-DRG = all patient refined diagnostic-related group; DDs = diseases and disorders.

**Table 2.** Standard Multiple Regression of Sociodemographic, Clinical, Organizational, and Nursing Variables on Length of Hospital Stay (adjusted $R^2 = 0.33$; $p < .001$; $N = 2{,}190$)

| Variables | *B* | 95% CI | *SE* | β | p value |
|---|---|---|---|---|---|
| Intercept | 0.53 | 0.49–0.58 | 0.02 | / | <.001 |
| Gender[a] | 0.03 | 0.01–0.05 | 0.01 | .05 | .002 |
| Age | 0.00 | 0.00–0.00 | 0.00 | .07 | <.001 |
| Charlson comorbidity index | 0.00 | -0.01–0.01 | 0.01 | -.01 | .583 |
| APR-DRG weight | 0.53 | 0.48–0.58 | 0.03 | .39 | <.001 |
| Modality of admission[b] | 0.20 | 0.18–0.22 | 0.01 | .35 | <.001 |
| Inpatient unit groups[c] | 0.03 | 0.01–0.05 | 0.01 | .05 | .008 |
| Number of nursing diagnoses | 0.04 | 0.03–0.05 | 0.00 | .15 | <.001 |

*Note.* Charlson comorbidity index and number of nursing diagnoses: square root transformation. APR-DRG weight and length of hospital stay: logarithmic transformation. APR-DRG = all patient refined diagnostic related group; CI = confidence interval; *SE* = standard error.
[a]1= female.
[b]1 = Emergency Department.
[c]1 = medical.

**Table 3.** Standard Multiple Regression of Sociodemographic, Clinical, Organizational, and Nursing Variables on Difference Between the Sample Hospital Stay and the DRG-Specific National Average Length of Hospital Stay (LOS deviation; adjusted $R^2 = 0.10$; $p < .001$; $N = 2{,}190$)

| Variables | *B* | 95% CI | *SE* | β | p value |
|---|---|---|---|---|---|
| Intercept | 3.35 | 3.23–3.47 | 0.06 | / | <.001 |
| Gender[a] | 0.16 | 0.1–0.21 | 0.03 | .12 | <.001 |
| Age | 0.00 | 0.00–0.00 | 0.00 | .01 | .618 |
| Charlson comorbidity index | -0.02 | -0.05–0.01 | 0.01 | -.03 | .145 |
| APR-DRG weight | 0.11 | -0.02–0.25 | 0.07 | .04 | .097 |
| Modality of admission[b] | 0.28 | 0.22–0.34 | 0.03 | .21 | <.001 |
| Inpatient unit groups[c] | 0.04 | -0.02–0.10 | 0.03 | .03 | .160 |
| Number of nursing diagnoses | 0.12 | 0.09–0.14 | 0.01 | .19 | <.001 |

*Note.* Charlson comorbidity index, number of nursing diagnoses, and length of stay deviation: square root transformation. APR-DRG weight: logarithmic transformation. APR-DRG = all patient refined diagnostic related group; CI = confidence interval; *SE* = standard error.
[a]1 = female.
[b]1 = Emergency Department.
[c]1 = medical.

and gender were significant determinants of LOS deviation ($p < .001$; see Table 3).

## Discussion

The main finding of this study was that the number of nursing diagnoses was an independent predictor of hospital length of stay controlled for patients' sociodemographic and clinical variables and hospital organizational variables. Moreover, the number of nursing diagnoses was an independent predictor of the difference between the effective patients' hospital stay and the DRG-specific expected hospital length of stay in Italy.

The results of the regression analysis in which the hospital length of stay was a dependent variable showed that the full model explained about one third of the hospital length of stay variance. Even if a comparison with other studies is not easy because of different populations or variables included, our results in explaining the length of stay variance were similar to studies on general hospital populations in which the same statistical approach (i.e., ordinary least squares) was used (Lu et al., 2015). Moreover, to our knowledge, our study was one of the few investigations conducted in Europe (Paans et al., 2016) and the first conducted in Italy in general hospital populations.

The main significant predictors of length of stay were the APR-DRG weight, modality of hospital admission, and number of nursing diagnoses. The number of nursing diagnoses was shown to be an important independent predictor of the hospital length of stay. This result is consistent with previous studies conducted in different hospital populations in North America (Sanson et al., 2017) and in Europe (Castellan et al., 2016; Paans et al., 2016). Interestingly, in these previous studies the number of nursing diagnoses was also controlled for medical conditions and was found to predict the hospital length of stay. Moreover, as discussed later, in our study we showed, for the first time, that nursing diagnoses were also predictors of a length of stay longer than expected according to the DRG. This finding confirms that, although data produced by healthcare systems mostly describe patients' complexity and outcome or establish the payment criteria based only on medical diagnosis and procedures (Pirson et al., 2013), the patient complexity is explained by many other factors independent of medical problems, such as nursing diagnoses. Indeed, nursing diagnoses describe patients' health responses and experiences, and this "nursing perspective" adds substantially to predicting hospital length of stay and therefore also hospital costs.

Another independent predictor was APR-DRG weight, showing that patients' severity is one of the factors that most affect hospital length of stay. This result is not surprising considering that the APR-DRG algorithm is well developed and the use of the DRG-based system is the current method used worldwide to evaluate and reimburse health care (Mihailovic, Kocic, & Jakovljevic, 2016). However, based on the results of this study, further variables should be added to models of care funding, such as nursing diagnoses and modality of hospital admission.

Indeed, we showed that the admission through the Emergency Department was a further independent predictor of length of stay. This could mean that, compared to those admitted with a scheduled hospitalization, patients hospitalized with an unplanned admission were presumably in more serious clinical condition; furthermore, an unplanned hospitalization may have increased the hospital length of stay as a result of organizational reasons, given to less planned clinical pathways (e.g., surgery or procedures) or managerial difficulties (e.g., patients admitted to an inpatient unit different from the one most suited to her or his clinical needs; Morse, 2013; Pietrantonio, Piasini, & Spandonaro, 2016). It is interesting to note that this variable related to hospital organizational factors strongly affects the length of stay.

Sociodemographic and inpatient unit groups variables were less strong, but still significant, predictors: older, female, and medical patients were associated with a longer length of stay; this result is similar to the findings of other studies (Lu et al., 2015; Maiorano, Bodini, Cavaiani, Pelosi, & Sansone, 2017; Peltola et al., 2015). Interestingly, age independently explained part of the variability of the average hospital stay, probably due to difficulties in discharging some older patients to home (e.g., post-hospitalization functional decline in previously independently functioning patients or the unavailability of one or more caregivers at home, as well as adequate resources to support the patient at the community level; Tanwir, Montgomery, Chari, & Nesathurai, 2014; Zisberg et al., 2016). The finding that women had a longer length of stay than men could be explained by the different perception of their informal caregiver roles; most men could be discharged earlier than women because they are often cared for by their wives, who desire to care for their husbands at home, thus reducing their length of stay (Carter & Potts, 2014; Ono et al., 2010). The Charlson comorbidity index was not a significant predictor of length of stay; this could be explained by the low rate and variability of patients affected by comorbidities, and it also confirmed that this index is a valid score for predicting mortality but not hospital length of stay (Toson, Harvey, & Close, 2015).

In our population, the mean LOS deviation was -1.3 days, which means that—on average—our patients stayed in hospital about a day less than the nationally DRG-specific expected length of stay. However, interestingly, the number of nursing diagnoses, as well as admission from the Emergency Department, were the main independent predictors of a positive LOS deviation. This means that, although the severity of the patient's clinical conditions, as summarized by the APR-DRG weight, is able to predict the standard hospital length of stay, a significant increase in expected length of stay is independently predicted by a higher number of nursing diagnoses or an unplanned hospital admission. This finding is very important, because a length of stay longer than expected can cause an increase in the use of resources and costs. For example, in daily clinical practice, if nursing resources are not adequate (e.g., nurse staffing, workload), there is a risk that the priorities in patient care are given to medical-related acute needs and procedures, thus reducing the provision of nursing care. This choice, already described as "implicit nursing care rationing," contributes to a functional and cognitive decline in complex and vulnerable older patients, as well as to higher rates of hospital-acquired complications and increased length of stay (Bail & Grealish, 2016, p. 149). If nursing data were collected in a routine and systematic way to complement medical data, it would be possible to know the patient's condition at hospital admission (e.g., functional status as described by nursing diagnosis), the provision of appropriate prevention or support nursing interventions throughout the hospital stay, and the patient's condition at discharge. This strategy would make it possible to correctly understand the respective responsibilities of any factor for any deviation from the expected DRG-related length of hospital stay.

The results of our study strengthen the importance of systematically collecting data related to nursing care for each patient admitted to the hospital. The use of standard nursing data, such as nursing diagnoses, can contribute to explaining the patient's complexity (Welton & Halloran, 2005), which highlights the nursing aspect of care provided and is complementary to medical diagnosis and treatment. Not considering such important elements as nursing care can lead to failure in the goal of having an overall description of patient complexity. We found that length of stay can be longer for patients affected by the same disease, but with a higher nursing complexity. Thus, the complementary use of medical and nursing data can be very useful in developing predictive tools for hospital outcomes. As stated by the Committee on Data Standards for Patient Safety of the Institute of Medicine, a defined data set, including medical and nursing diagnoses, can ensure ready availability of the needed information for healthcare providers (Tang, 2003). The collection of these data, routinely and continuously in electronic health records, does not require additional efforts by nurses to identify the complexity of care through different and often more complicated systems.

As Thompson (1984), the co-inventor of the DRG system, highlighted more than 30 years ago, the nursing diagnosis is a way to identify patient conditions from a nursing point of view that is not included in the DRG system, so that nursing care is considered just as a routine cost in the DRG system. Most healthcare financial models do not take into account the contribution of nurses, so that the value of nursing care is difficult to assess (Welton & Harper, 2016). Consequently, when evaluating healthcare systems, nursing care remains invisible at the policy and payment levels (Welton, Zone-Smith, & Fischer, 2006). The results of the present study show that the level of nursing complexity contributes to explaining an important outcome variable related to the quality of hospital care such as the length of stay. Nursing diagnoses could be integrated into DRG systems as a measure of nursing complexity. This would bring new resources to nursing and be extremely important from the perspective of missed nursing care that is associated with lower nurse staffing due to financial constrictions in hospital nursing (Ball et al., 2018; Sasso et al., 2017).

Some limitations of this study must be considered. First, this study was conducted in a single hospital; therefore, the results cannot be generalized. Second, the adopted models considered only the patients' sociodemographic, clinical, and organizational hospital variables. Other factors that can influence the length of stay, such as the characteristics of community services, patient's caregiver, and family environment, should be investigated in multivariate models (Lu et al., 2015).

## Conclusions

The classification of patients based solely on clinical severity as measured through the APR-DRG weight does not comprehensively explain the hospital length of stay. The modality of hospital admission, the number of nursing diagnoses and the patient's age and gender should be taken into account to improve the variance explained in the hospital length of stay. Moreover, the number of nursing diagnoses is a strong independent predictor of a length of stay longer than expected, and that is not taken into account by the APR-DRG weight.

The number of nursing diagnoses seems to be a good proxy of the patient's nursing complexity. The number of nursing diagnoses collected through the electronic health records can contribute to more efficient hospital management, allowing a more objective determination of nursing workload and, thus, a tailored allocation of nursing resources in terms of the number of nurses and the nursing skill mix. Moreover, nursing diagnoses have been shown to be related to hospital outcomes, providing a tool to be used routinely in electronic health records to overcome the policy barrier of non-reimbursement of nursing practice in hospitals.

In light of these results, the integration of nursing data, such as nursing diagnoses, into the revised version of the Italian DRG system (IT.DRG project) seems to be appropriate, since this revision is aimed at providing new classifications for diagnoses, procedures, and DRG in order to make them more responsive to the specific characteristics and information needs of Italian hospitals (Italian Ministry of Health, 2015).

Finally, two essential aspects should be considered in projecting further and larger studies. First, a wider and shared list of standardized nursing diagnoses should be selectable by nurses in electronic health records in daily clinical practice. Second, further analyses should be performed to weight each single nursing diagnosis according to its specific impact on the hospital length of stay, as well as on other key outcomes.

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## Clinical Resource

- NANDA International. http://www.nanda.org/

### References

3M Health Information Systems. (2003). *All patient refined diagnosis related groups (APR-DRGs). Methodology overview*. Salt Lake City, UT: Author.

Bail, K., & Grealish, L. (2016). "Failure to maintain": A theoretical proposition for a new quality indicator of nurse care rationing for complex older people in hospital. *International Journal of Nursing Studies, 63*, 146–161.

Bakken, S., Holzemer, W. L., Portillo, C. J., Grimes, R., Welch, J., & Wantland, D. (2005). Utility of a standardized nursing terminology to evaluate dosage and tailoring of an HIV/AIDS adherence intervention. *Journal of Nursing Scholarship*, *37*(3), 251–257.

Ball, J. E., Bruyneel, L., Aiken, L. H., Sermeus, W., Sloane, D. M., & Rafferty, A. M.,… RN4Cast Consortium. (2018). Post-operative mortality, missed care and nurse staffing in nine countries: A cross-sectional study. *International Journal of Nursing Studies*, *78*, 10–15.

Bradley, C. J., Penberthy, L., Devers, K. J., & Holden, D. J. (2010). Health services research and data linkages: Issues, methods, and directions for the future. *Health Services Research*, *45*(5 Part 2), 1468–1488.

Carter, E. M., & Potts, H. W. (2014). Predicting length of stay from an electronic patient record system: A primary total knee replacement example. *BMC Medical Informatics and Decision Making*, 14, 26.

Castellan, C., Sluga, S., Spina, E., & Sanson, G. (2016). Nursing diagnoses, outcomes and interventions as measures of patient complexity and nursing care requirement in intensive care unit. *Journal of Advanced Nursing*, *72*(6), 1273–1286.

Centers for Disease Control and Prevention. (2007). *International classification of diseases, 9th revision, clinical modification*. Retrieved from ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/ICD9-CM/2007/

D'Agostino, F., Vellone, E., Tontini, F., Zega, M., & Alvaro, R. (2012). Development of a computerized system using standard nursing language for creation of a nursing minimum data set. *Professioni Infermieristiche*, *65*(2), 103–109.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. London, UK: Sage.

General Direction for Health Planning. (2015). *Rapporto annuale sull'attività di ricovero ospedaliero, Dati SDO 2014* [*Annual report on hospitalization, hospital discharge register data (year 2014)*]. Retrieved from http://www.salute.gov.it/imgs/C_17_pubblicazioni_2396_allegato.pdf

Goossen, W. T. (2002). Statistical analysis of the nursing minimum data set for The Netherlands. *International Journal of Medical Informatics*, *68*(1–3), 205–218.

Gordon, M. (1994). *Nursing diagnosis: Process and application* (3rd ed.). St. Louis, MO: Mosby.

Halloran, E. J., & Kiley, M. (1987). Nursing dependency, diagnosis-related groups, and length of hospital stay. *Health Care Financing Review*, *8*(3), 27–36.

Herdman, H. (2014). *Nursing diagnoses: Definitions and classification. 2015–2017*. Oxford, UK: Wiley-Blackwell.

Italian Ministry of Health. (2015). *Progetto it.DRG* [it.DRG project]. Retrieved from http://www.salute.gov.it/portale/temi/p2_6.jsp?lingua=italiano&id=4294&area=ricoveriOspedalieri&menu=vuoto

Lu, M., Sajobi, T., Lucyk, K., Lorenzetti, D., & Quan, H. (2015). Systematic review of risk adjustment models of hospital length of stay (LOS). *Medical Care*, *53*(4), 355–365.

Maiorano, E., Bodini, B. D., Cavaiani, F., Pelosi, C., & Sansone, V. (2017). Length of stay and short-term functional outcomes after total knee arthroplasty: Can we predict them? *Knee*, *24*(1), 116–120.

Mihailovic, N., Kocic, S., & Jakovljevic, M. (2016). Review of diagnosis-related group-based financing of hospital care. *Health Services Research and Managerial Epidemiology*, *12*(3). doi: 10.1177/2333392816647892

Morse, A. (2013). *Emergency admissions to hospital: Managing the demand*. London, UK: The Stationery Office.

O'Brien-Pallas, L., Li, X. M., Wang, S., Meyer, R. M., & Thomson, D. (2010). Evaluation of a patient care delivery model: System outcomes in acute cardiac care. *Canadian Journal of Nursing Research*, *42*(4), 98–120.

Ono, T., Tamai, A., Takeuchi, D., Tamai, Y., Iseki, H., Fukushima, H., & Kasahara, S. (2010). Predictors of length of stay in a ward for demented elderly: Gender differences. *Psychogeriatrics*, *10*(3), 153–159.

Paans, W., Muller-Staub, M., & Krijnen, W. P. (2016). Outcome calculations based on nursing documentation in the first generation of electronic health records in the Netherlands. *Studies in Health Technology and Informatics*, *225*, 457–460.

Peltola, M., Seppala, T. T., Malmivaara, A., Belicza, E., Numerato, D., & Goude, F.,… EuroHOPE Study Group. (2015). Individual and regional-level factors contributing to variation in length of stay after cerebral infarction in six European countries. *Health Economics*, *24*(Suppl. 2), 38–52.

Pietrantonio, F., Piasini, L., & Spandonaro, F. (2016). Internal medicine and emergency admissions: From a national hospital discharge records (SDO) study to a regional analysis. *Italian Journal of Medicine*, *10*(2), 157–167.

Pirson, M., Delo, C., Di Pierdomenico, L., Laport, N., Biloque, V., & Leclercq, P. (2013). Variability of nursing care by APR-DRG and by severity of illness in a sample of nine Belgian hospitals. *BMC Nursing*, *12*, 26. doi: 10.1186/1472-6955-12-26

Quan, H., Li, B., Couris, C. M., Fushimi, K., Graham, P., Hider, P., … Sundararajan, V. (2011). Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. *American Journal of Epidemiology*, *173*(6), 676–682.

Sanson, G., Vellone, E., Kangasniemi, M., Alvaro, R., & D'Agostino, F. (2017). Impact of nursing diagnoses on patient and organisational outcomes: A systematic literature review. *Journal of Clinical Nursing*, *26*(23–24), 3764–3783.

Sasso, L., Bagnasco, A., Aleo, G., Catania, G., Dasso, N., Zanini, M. P., & Watson, R. (2017). Incorporating nursing complexity in reimbursement coding systems: The potential impact on missed care. *BMJ Quality & Safety*, *26*(11), 929–932.

Schaink, A. K., Kuluski, K., Lyons, R. F., Fortin, M., Jadad, A. R., Upshur, R., & Wodchis, W. P. (2012). A scoping review and thematic classification of patient complexity: Offering a unifying framework. *Journal of Comorbidity*, *2*, 1–9.

Spigolon, D. N., & Moro, C. M. (2012, June). *Nursing minimum data set based on EHR archetypes approach*. Paper presented at the 11th International Congress on Nursing Informatics, Montreal, Canada.

Tabachnick, B. G., & Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Boston, MA: Pearson.

Tang, P. (2003). *Key capabilities of an electronic health record system: Letter report*. Washington, DC: Institute of Medicine Committee on Data Standards for Patient Safety.

Tanwir, S., Montgomery, K., Chari, V., & Nesathurai, S. (2014). Stroke rehabilitation: Availability of a family member as caregiver and discharge destination. *European Journal of Physical and Rehabilitation Medicine*, *50*(3), 355–362.

Tastan, S., Linch, G. C., Keenan, G. M., Stifter, J., McKinney, D., Fahey, L., … Wilkie, D. J. (2014). Evidence for the existing American Nurses Association-recognized standardized nursing terminologies: A systematic review. *International Journal of Nursing Studies*, *51*(8), 1160–1170.

Thompson, J. D. (1984). The measurement of nursing intensity. *Health Care Financing Review, 1984* (Suppl.), 47–55.

Toson, B., Harvey, L. A., & Close, J. C. (2015). The ICD-10 Charlson comorbidity index predicted mortality but not resource utilization following hip fracture. *Journal of Clinical Epidemiology*, *68*(1), 44–51.

Twisk, J. W. R. (2006). *Applied multilevel analysis: A practical guide for medical researchers*. New York, NY: Cambridge University Press.

Welton, J. M., & Halloran, E. J. (2005). Nursing diagnoses, diagnosis-related group, and hospital outcomes. *Journal of Nursing Administration*, *35*(12), 541–549.

Welton, J. M., & Harper, E. M. (2016). Measuring nursing care value. *Nursing Economic$*, *34*(1), 7–15.

Welton, J. M., Zone-Smith, L., & Fischer, M. H. (2006). Adjustment of inpatient care reimbursement for nursing intensity. *Policy, Politics & Nursing Practice*, *7*(4), 270–280.

Werley, H. H., Devine, E. C., Zorn, C. R., Ryan, P., & Westra, B. L. (1991). The Nursing Minimum Data Set: Abstraction tool for standardized, comparable, essential data. *American Journal of Public Health*, *81*(4), 421–426.

Werley, H. H., & Lang, N. M. (Eds.). (1988). *Identification of the nursing minimum data set*. New York, NY: Springer.

Zega, M., D'Agostino, F., Bowles, K. H., De Marinis, M. G., Rocco, G., Vellone, E., & Alvaro, R. (2014). Development and validation of a computerized assessment form to support nursing diagnosis. *International Journal of Nursing Knowledge*, *25*(1), 22–29.

Zisberg, A., Sinoff, G., Agmon, M., Tonkikh, O., Gur-Yaish, N., & Shadmi, E. (2016). Even a small change can make a big difference: The case of in-hospital cognitive decline and new IADL dependency. *Age and Ageing*, *45*(4), 500–504.