Metrics for Electronic-Nursing-Record-Based Narratives: cross-sectional analysis

Kidong Kim[1]; Suyeon Jeong[2]; Kyogu Lee[3]; Hyeoun-Ae Park[4]; Yul Ha Min[5]; Joo Yun Lee[4]; Yekyung Kim[3]; Sooyoung Yoo[6]; Gippeum Doh[2]; Soyeon Ahn[7]

[1]Department of Obstetrics and Gynecology, Seoul National University Bundang Hospital, Seongnam, Gyeonggi-do, Korea;
[2]Medical Device Research and Development Center, Seoul National University Bundang Hospital, Seongnam, Gyeonggi-do, Korea;
[3]Graduate School of Convergence Science and Technology, Seoul National University, Seoul, Korea;
[4]College of Nursing and Systems Biomedical Informatics Research Center, Seoul National University, Seoul, Korea;
[5]College of Nursing, Gachon University, Incheon, Korea;
[6]Office of eHealth Research and Businesses, Seoul National University Bundang Hospital, Seongnam, Gyeonggi-do, Korea;
[7]Division of Statistics, Medical Research Collaborating Center, Seoul National University Bundang Hospital, Seongnam, Gyeonggi-do, Korea

Keywords

Electronic health records; nursing informatics; nursing records; narrative evaluation; narrative analysis

Summary

Objectives: We aimed to determine the characteristics of quantitative metrics for nursing narratives documented in electronic nursing records and their association with hospital admission traits and diagnoses in a large data set not limited to specific patient events or hypotheses.
Methods: We collected 135,406,873 electronic, structured coded nursing narratives from 231,494 hospital admissions of patients discharged between 2008 and 2012 at a tertiary teaching institution that routinely uses an electronic health records system. The standardized number of nursing narratives (i.e., the total number of nursing narratives divided by the length of the hospital stay) was suggested to integrate the frequency and quantity of nursing documentation.
Results: The standardized number of nursing narratives was higher for patients aged ≥ 70 years (median = 30.2 narratives/day, interquartile range [IQR] = 24.0–39.4 narratives/day), long (≥ 8 days) hospital stays (median = 34.6 narratives/day, IQR = 27.2–43.5 narratives/day), and hospital deaths (median = 59.1 narratives/day, IQR = 47.0–74.8 narratives/day). The standardized number of narratives was higher in "pregnancy, childbirth, and puerperium" (median = 46.5, IQR = 39.0–54.7) and "diseases of the circulatory system" admissions (median = 35.7, IQR = 29.0–43.4).
Conclusions: Diverse hospital admissions can be consistently described with nursing-document-derived metrics for similar hospital admissions and diagnoses. Some areas of hospital admissions may have consistently increasing volumes of nursing documentation across years. Usability of electronic nursing document metrics for evaluating healthcare requires multiple aspects of hospital admissions to be considered.

Correspondence to
Soyeon Ahn, Ph.D.
Division of Statistics, Medical Research Collaborating Center,
Seoul National University Bundang Hospital,
Seongnam, Gyeonggi-do, Korea
Email: ahnsoyeon@snubh.org

Appl Clin Inform 2016; 7: 1107–1119
http://dx.doi.org/10.4338/ACI-2016-07-RA-0119
received: 20. July 20, 2016
accepted: October 4, 2016
published: November 30, 2016
Citation: Kim K, Jeong S, Lee K, Park H-A, Min YH, Lee JY, Kim Y, Yoo S, Doh G, Ahn S. Metrics for electronic-nursing-record-based narratives: cross-sectional analysis. Appl Clin Inform 2016; 7: 1107–1119
http://dx.doi.org/10.4338/ACI-2016-07-RA-0119
Funding
Financial support for this study was provided by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning (NRF-2013R1A1A3012306); no financial relationships with any organizations that might have an interest in the submitted work in the previous three years, no other relationships or activities that could appear to have influenced the submitted work.

1. Background and Significance

The increasing volume of electronic nursing documentation has challenged researchers on how to utilize nursing records for to improve research efforts and patient care [1]. Some research focused on facilitating electronic capture of nursing records to detect physiological deterioration of patients [2]. Model-based attempts have been made to predict common hospitalized patient events such as mortality, readmission, and length of stay [3, 4] or the 5-year life expectancy index [5] on the basis of electronic health records (EHRs). Models relying on known risk factors readily extracted from EHRs have been developed to predict fall risk, which is regarded as one of the nurse-sensitive outcomes, among nursing home residents [6] or patients admitted to academic medical centers [7]. Previous analyses utilizing nursing records showed that higher numbers of optional comments were associated with increased mortality in randomly selected acute-care patients [8]. However, to the best of our knowledge, methodologies for quantifying ENR data considering nursing documentation patterns and adjusting for accumulating volume owing to different lengths of stay have not been established and only few studies have addressed deriving quantitative metrics from nursing documentation in ENRs without a priori nursing record selection and exploring their association with diverse inpatient hospital parameters in general hospital settings. We aimed to explore quantitative characteristics of ENRs without any restriction on specific patient events or hypothesis-driven retrospective review of data, and thereby to provide a basis for describing and comparing diverse hospital admissions.

2. Objectives

The objective of the study was to develop practical and quantitative metrics for structured coded nursing narratives documented in ENRs and to explore the potentials of the metrics in ENR-based studies. We investigated the distribution patterns and usability of the suggested ENR-based metrics across different hospital admission characteristics and diagnoses.

3. Methods

3.1 Study setting and study design

Seoul National University Bundang Hospital is a tertiary teaching institution that had 879 beds and 817 registered nurses in 2012, and its EHR system and subordinate ENR system has been fully implemented since the institution was founded in 2003. All nursing documentation is computerized and stored with corresponding nursing document code. The nursing narratives used in documenting nursing records were mapped to standardized nursing terminology including International Classification for Nursing Practice (ICNP), ensuring that each nursing narrative have unique predefined code. We defined the study population as patients discharged between 2008 and 2012 and having nursing records. We extracted both ENRs and prespecified admission characteristics from the study population, and performed a cross-sectional study to examine the relationship between them. Nursing records that were documented in free text were excluded. All data were anonymized, and the confidentiality of the study population data was ensured throughout the study.

3.2 Structured coded narratives in ENRs

The ENR refers to the comprehensive system that integrate the nurse's assessment, care planned and provided for the patient, the patient's condition, nursing care provided in response to the patient's needs, and the patient's response to the nursing care. Nursing data are captured by the nursing documentation system in the ENR based on structured sets of nursing narratives. Structured sets of nursing narratives were developed by analyzing previous nursing documentation and clinical practice guidelines [9]. These nursing narrative sets were generated by the nursing data model. We herein refer to a structured coded nursing narrative as a pre-defined nursing narrative designed as a structured form with an identification code that a nurse enters during documentation episode. Typically,

a nurse sees a patient several times a day to check the status (vital signs, drainage amount, etc.) and to administer medications. During the visit, the nurse observes the patient and evaluates any problems. After the visit, the nurse documents the patient's status in the nursing documentation system by selecting structured coded nursing narratives and specifying the narratives by adding numerical values or free text for attributes assigned to the structured narratives. For example, to document a patient complaining of abdominal pain, the nurse selects a structured narrative ("Abdominal pain") with a predefined identification code and adds a value ("5") for a predefined attribute ("Numeric rating scale"), or adds a value ("Mild") for another attribute ("State"). Each narrative has predefined attributes, which are extracted from a standardized nursing terminology system such as ICNP. In this example, attributes such as ("State") can be mapped to ("Relative Judged State") in ICNP. For each patient admission, nursing documentation involves multiple nursing narratives across several documentation activities. Examples of this information for two real nursing-narrative sets of two-day long admission events are shown in ▶Table A.1 and ▶Table A.2 (see online supplementary material). The first patient was admitted to the department of Ophthalmology with "diseases of the eye and adnexa" (chapter VII), whereas the second patient was diagnosed with "neoplasms" (chapter II) and died in the hospital. More detailed information about the ENR system used in the study institute can be found elsewhere [9, 10].

3.3 Definitions

The frequency and quantity of nursing documentation were newly adopted as metrics in this study. The frequency of nursing documentation was measured as the mean documentation activity within the ENR system per day. Documentation activity was defined as a document prepared and signed by a nurse. The quantity of nursing documents was calculated as the mean number of nursing narratives per documentation activity. As an overall documentation summary, the standardized number of nursing narratives was defined as the total number of narratives divided by the length of the hospital stay, which accounts for the documentation volume during the hospital stay. Additionally, the percentage of unique relative to total nursing narratives was determined to address the uniqueness of the narratives. For the first admission example shown in ▶Table A.1, nurses visited the patient twice the first day and four times the second day, resulting in a mean documentation frequency of three documents per day. The mean number of narratives per documentation activity was 2.7. The total number of nursing narrative was 16 and the standardized number of nursing narratives was eight. The number of unique narratives was 13 and the percentage of unique narratives was 81.3%. In contrast, in the second admission in Table A.2, the mean frequency was 57.0 documents a day, which implied that nurses visited much more often than in the first admission. The mean number of narratives per documentation activity was 2.9 narratives, which was similar to that of the first case. The total number of narratives was 334, and 35.3% were unique narratives.

3.4 Characteristics and diagnoses of study population

The characteristics of the study population included age, gender, insurance type, routes of admission and discharge, length of stay, and surgery. Diagnoses were determined from the ICD-10 codes (International Classification of Diseases, Tenth Revision) documented in EHRs [11]. ICD-10 diagnosis codes are organized into 22 anatomical or functional chapters. Age was grouped into 10 categories, and the length of the hospital stay was grouped into 4 ordinal categories based on the quartile values.

3.5 Statistical analysis

Descriptive statistics were computed as median and interquartile range (IQR) values. A subgroup analysis of nursing document metrics was conducted on admissions stratified by the year of discharge. For standardized numbers of nursing narratives, t-tests or analysis of variance (ANOVA) tests were performed. Pearson's coefficients were calculated for the correlations between the percentage of unique narratives and the length of hospital stays, or the standardized number of narratives. All of the analyses were conducted using the R program (version 3.2.0, R Foundation for Statistical Computing, Vienna, Austria).

4. Results

4.1 Nursing documentation statistics

In total, 231,494 hospital admissions were included, involving 152,889 patients with a median age of 51 years, 49.3% females, and a median length of hospital stay of 4 days with an IQR of 3–8 days, and 135,406,873 narratives were analyzed. ►Table 1 lists the characteristics of nursing document metrics at admission summarized as medians and IQRs across the admission years included in the study. The nurses documented a median of 6.0 documents per day (IQR = 5.0–8.0), with a median of 4.4 (IQR = 3.6–5.5) narratives per document, aggregating a median of 28.0 (IQR = 22.7–35.7) nursing narratives daily as a standardized metric. The median of total nursing narratives was 123.0 (IQR = 61.0–255.0), and 42.9% (IQR =29.7–62.0%) of the nursing narratives were uniquely documented through different documentation activities. No trend was identified in the summary statistics during the study period.

4.2 Association between nursing record metrics and hospital admissions

►Table A.3 presents the summary statistics of nursing document metrics according to the characteristics of the hospital admissions (see online supplementary material). Nursing narratives were most frequently documented in the oldest age group (median frequency = 7.0 and 4.8 documents/day in those aged ≥ 70 years and < 1 year, respectively), short or long hospital stays (median = 7.0, 6.8, 5.3, and 5.6 documents/day for stays of 1 or 2, ≥ 8, 3, and 4–7 days, respectively), surgery (median = 6.4 and 5.7 documents/day for surgery and no surgery, respectively), and hospital deaths (median = 140 documents/day for hospital deaths). The amount of nursing narratives per documentation activity was the highest in the youngest age group (median = 6.3 and 4.2 narratives/activity in those aged < 1 year and ≥ 70 years, respectively) and for intermediate hospital stay duration (median = 4.9 and 3.5 narratives/activity for stays of 4–7 days and 1 or 2 days, respectively). The standardized number of nursing narratives was highest in the oldest age group (≥ 70 years; median = 30.2 [IQR = 24.0–39.4] narratives/day), short (1–2 days) or long (≥ 8 days) hospital stays (median = 24.0, 34.6 [IQR = 21.0–27.0, 27.2–43.5] narratives/day for stays of 1-2, ≥ 8, respectively), surgery (median = 28.3 [IQR = 24.0–35.5] narratives/day), and hospital deaths (median = 59.1 [IQR = 47.0–74.8] narratives/day) (►Figure 1 and ►Figure A.1 in online supplementary material).

4.3 Association between nursing record metrics and diagnoses

The associations between nursing documents and diagnoses are presented in ►Table 2. Nurses documented nursing narratives more frequently among "pregnancy, childbirth, and puerperium" (chapter XV) admission (median = 9.2 [IQR = 7.1–12.0] documents/day) and "diseases of the circulatory system" (chapter IX) admissions (median = 8.8 [IQR = 6.6–11.8] documents/day) and less frequently among "certain conditions originating in the perinatal period" (chapter XVI) admissions (median = 4.7 [IQR = 4.0–5.4] documents/day) and "diseases of the respiratory system" (chapter X) admissions (median = 5.2, [IQR = 4.6–6.4] documents/day). The number of nursing narratives per documentation activity was high among "certain conditions originating in the perinatal period" (chapter XVI) admissions (median = 6.8 [IQR = 5.7–9.6] narratives/activity) and "diseases of the respiratory system" (chapter X) admissions (median = 5.6, [IQR = 4.7–6.4] narratives/activity) and low among "diseases of the eye and adnexa " (chapter VII) admissions (median = 3.7 [IQR = 3.2–4.1] narratives/activity) and "diseases of the circulatory system" (chapter IX) admissions (median = 3.9 [IQR = 3.3–4.9] narratives/activity). The standardized number of narratives was high among "pregnancy, childbirth, and puerperium" (chapter XV) admissions (median = 46.5 [IQR = 39.0–54.7] narratives/day) and "diseases of the circulatory system" (chapter IX) admissions (median = 35.7 [IQR = 29.0–43.4] narratives/day), as illustrated in ►Figure A.2 (see online supplementary material). Although the yearly volume of nursing documents tended to increase over time, the overall standardized numbers of narratives were consistent across the diagnosis groups, indicating that

the overall nursing record patterns persisted across different diagnoses (►Table A.5 in online supplementary material)

4.4 Uniqueness of nursing narratives

►Figure 2 illustrates the patterns of the uniqueness of nursing narratives in relation to length of hospital stays. The uniqueness of narratives gradually decreased over the course of hospital stays (Pearson's correlation coefficient = –0.43; ►Figure 2A). Admissions with hospital stay lengths of 1 or 2 days were linked with the highest frequency of unique nursing narratives (median = 88.9%, [IQR = 76.9–92.6%] unique narratives). Longer hospital stays led to more redundancy in the nursing narratives (median = 54.3%, 39.6%, and 23.8% [IQR = 47.7–61.8%, 33.3–46.3%, and 17.9–29.4%] unique narratives for stays of 3, 4–7, and ≥ 8 days, respectively.) (►Table A.3 in online supplementary material).

5. Discussion

The study included 135,406,873 electronic nursing narratives from 231,494 hospital admissions. Since it is mandatory for nurses to enter nursing notes at least once per shift, three times per day at our institute, nursing documents covered a comprehensive group of hospital admissions. We examined the trends in defined quantitative metrics for nursing records across hospital admissions with diverse characteristics and diagnoses. Several nursing document metrics were needed to capture the diverse nature of hospital admissions in terms of frequency, quantity and uniqueness of nursing narratives documented.

The standardized number of narratives was useful as a unified metric since it adjusts the accumulated document volumes for the length of the stay. Using this metric, we observed that the volume of nursing narratives tended to be associated with certain types of admissions. For example, large numbers of narratives were observed among patients who died in the hospital (median = 59.1 [IQR = 47.0–74.8] narratives/day), patients diagnosed with circulatory diseases (median = 35.7 [IQR = 29.0–43.4] narratives/day), and pregnancy-related admissions (median = 46.5 [IQR = 39.0–54.7] narratives/day).

In terms of redundancy of narratives, longer hospital stays were associated with a lower frequency of unique narratives, which is consistent with previous findings [12, 13].

This study was subject to some limitations. First, the time sequence of entries was not evaluated in the present study. Second, caution is needed when generalizing the findings, as they are based on single-center data obtained from an institution that has fully implemented the EHR and ENR system since its foundation (2003). Third, we did not adjust various clinical settings that may be attributed to large variation in metrics. Furthermore, it did not take into account different nursing protocols assigned across diverse clinical units. Finally, this research was based on structured coded nursing narrative sets implemented in the study institute. Every nursing narrative was generated from entity-attribute-value triplets of each component was mapped to ICNP 2.0. This structurally coded nursing narrative allows nurses to enter nursing notes in a uniform manner. In addition, the study institute is a tertiary hospital and nurses are responsible for keeping records in routine practice as well as any unexpected clinical event. Since there are multiple documentation parameters that determines the size and quality of documents such as proportion of structured EHR documentation or use of problem-oriented templates [14, 15], these parameters may limit the generalizability of the study results. However, this research expanded the coping system mapped to ICNP and showed the effectiveness of standardized coding for quantifying the narratives.

Our study has three strengths. First, the frequency and quantity of nursing document metrics were adopted anew in this study and they can be expanded to other EHR-based narratives. There are some empirical barriers to extensive adoption of EHRs including time delays and the cost of implementation [16]. However, implementing EHRs is inevitable, and their meaningful use is warranted for ensuring patient safety [15, 17], while their clinical benefits have been demonstrated [18–21]. We have provided a basis for methodical mining of EHRs through structured nursing narratives. Second, the results were based on almost all admissions of a paperless hospital spanning a period of five

years. In such a large-scale data set, the lack of noticeable yearly variation in summary statistics implies the stable temporal behavior of nursing documentation. Third, variations in the size of nursing metrics may indicate different patients acuity as the examples in ►Table A.1 and ►Table A.2 showed that nurses tended to document more frequently for a severe patient.

Our proposed nursing document metrics may serve as a measure of patient acuity and the metric seems to hold potential as an adjuster that would complement measures of patient severity in studies of patient outcomes. Our current analysis was based on the quantity of nursing narratives, and future research should look at the content and quality of nursing records. Quantifying the workload of nurses itself is a challenging task since nurses are exposed to simultaneous demands and diverse clinical settings [22, 23]. When analyzing the nursing narratives, one should examine the quality of nursing records in terms of appropriateness and redundancy. It is possible for nurses to enter inappropriate nursing narratives when they are overloaded with work. Moreover, it is also entirely possible for nurses to enter redundant entries by copying and pasting [12, 13, 24]. Future studies using both retrospective and prospective data analyses are required to validate the new metrics in differentiating clinically meaningful events, and to prove the usefulness of EHRs in patient care by incorporating values, free text information, and temporal patterns across diverse clinical settings. For example, one may examine whether the nursing narratives documented during the early hospital admission phase can predict a longer length-of-stay or severe complications. The ease of analyzing the free-text records could also be improved in the near future with further advances in natural language processing and machine learning by computers [23–25]. As our structured coded nursing narrative can be further mapped to ICNP and be associated with various patient diagnoses, our experience can be extended to studies elucidating how nursing information affects patient care.

6. Conclusions

This study has shown that diverse hospital admissions can be quantitatively described by nursing-document-derived metrics. The study addressed methods that quantify large, semi-structured data sets and thus, can be classified as study that investigates methods for big data research [25]. The frequency of nursing documentation per day and the quantity of nursing narratives per documentation activity are suggested as two distinct metrics for nursing documentation behavior, while the standardized number of nursing narratives is an aggregate metric that could be used to characterize hospital admissions. To utilize ENRs in research, multiple metrics for nursing documents should be considered in order to adequately capture patient characteristics.

Clinical relevance statement

As adoption of EHRs is accelerated, the meaningful use of EHRs is encouraged. Nurses perform surveillance to keep patients safe and improve quality. Using the large-scale structured nursing narratives from a tertiary hospital, we quantified nursing narratives and associated quantified measures with hospital admission characteristic. This study provides the relationship of nursing-narratives-based measures to patient-outcome.

Conflict of interest

The authors declare that they have no competing interests.

Protection of Human and Animal Subjects

The study was performed in compliance with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects, and was reviewed by the Seoul National University Bundang Hospital Institutional Review Board (IRB no.: B-1402/238–104).

Acknowledgements

The authors are indebted to J. Patrick Barron, Professor Emeritus, Tokyo Medical University, and Adjunct Professor, Seoul National University Bundang Hospital, for his pro bono editing of this manuscript.

Abbreviations

- ENR: electronic nursing record
- EHR: electronic health record
- ICNP: International Classification for Nursing Practice

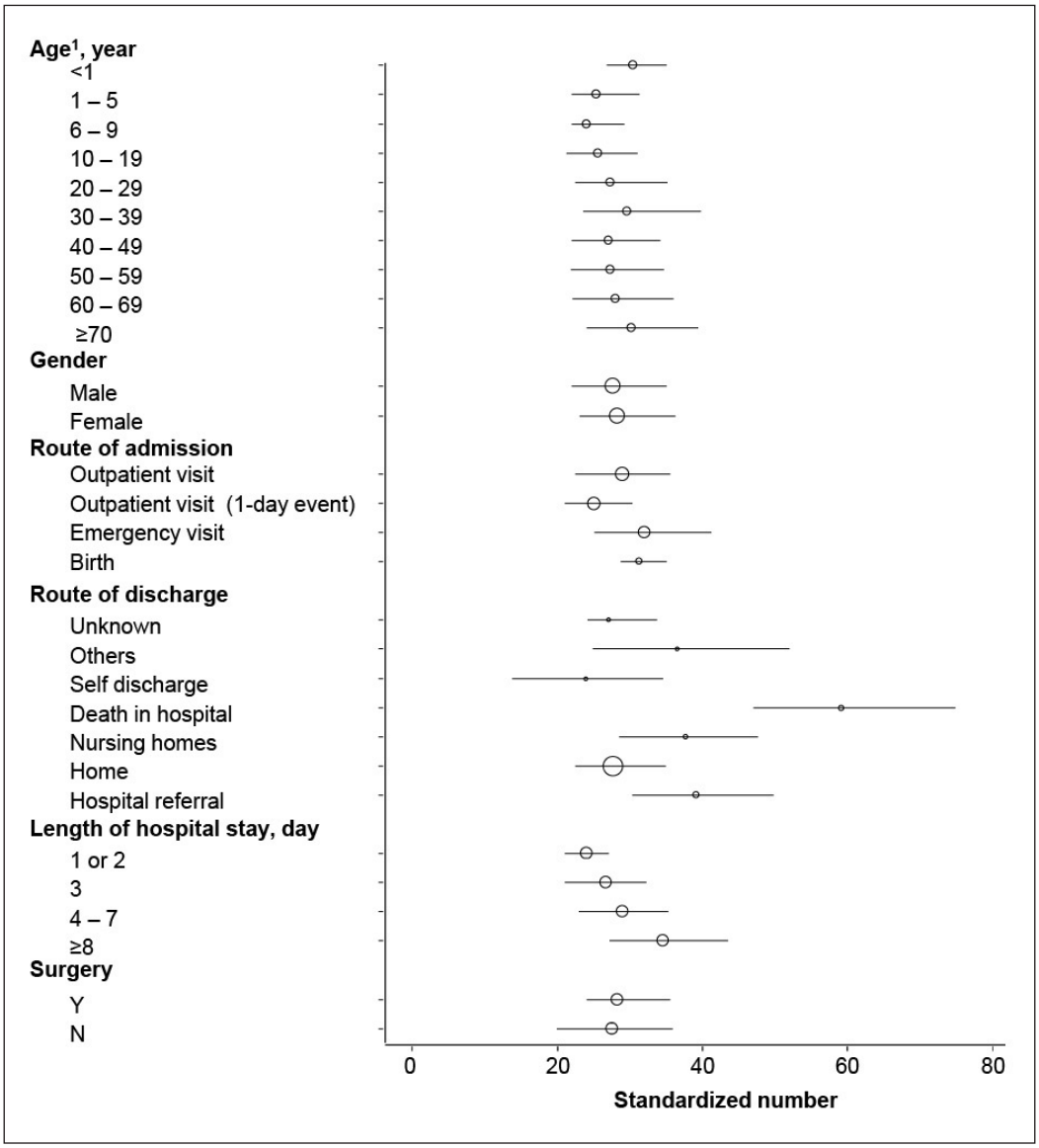

Fig. 1 Standardized number of nursing records across various hospital admission characteristics ([1]The dots in the figure represent the proportions of each group except Age groups). Median and interquartile range were displayed.

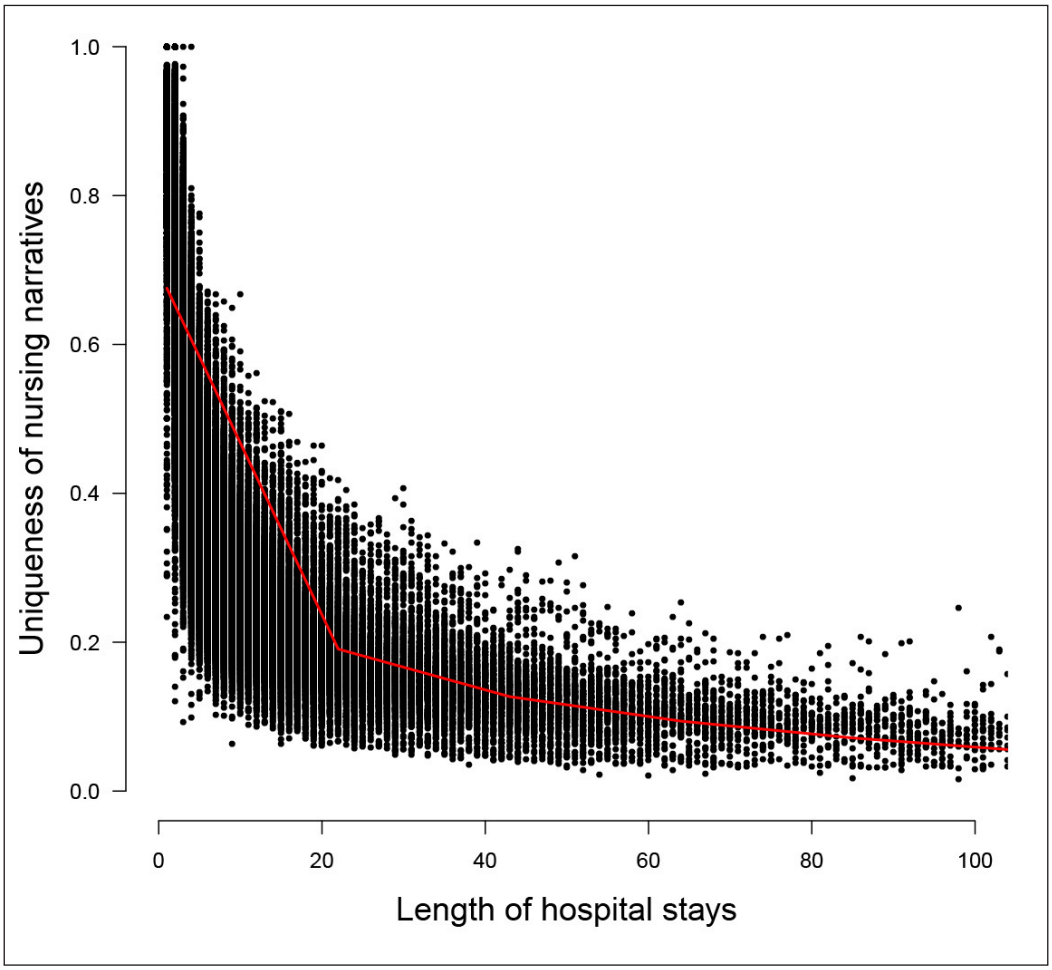

Fig. 2 Uniqueness of nursing narratives according to length of stay

Table 1 Characteristics of nursing records over time[1]

	2008	2009	2010	2011	2012	Pooled
Nursing documentation behavior						
Frequency (mean no. of documentations per day)	5.7 (4.7–7.5)	6 (4.8–7.5)	6 (5–7.8)	6.3 (5–8)	6.3 (5–8)	6.0 (5–8)
Quantity (mean no. of narratives per documentation activity)	4.5 (3.6–5.5)	4.4 (3.6–5.5)	4.5 (3.6–5.6)	4.4 (3.6–5.5)	4.4 (3.6–5.5)	4.4 (3.6–5.5)
Overall nursing records						
Total no. of narratives	122 (64–251)	121 (64–247)	126 (64–261)	124 (57–262)	121 (55–256)	123 (61–255)
Standardized no. of narratives (narratives per day)	26.5 (21.8–33.5)	27 (22–34.2)	28.3 (22.6–36.5)	29 (23–36.8)	29 (24–36.5)	28.0 (22.7–35.7)
Percentage of free-text narratives (%)	1.3 (0.7–2.5)	1.3 (0.7–2.5)	1.3 (0.7–2.4)	1.2 (0.7–2.6)	1.3 (0.7–2.6)	1.3 (0.7–2.5)
Percentage of unique narratives (%)	42.5 (29.9–59.4)	42.4 (29.8–59.7)	42.3 (29.2–61.1)	43 (29.6–64.1)	43.8 (30.1–66.3)	42.9 (29.7–62.0)

[1]Data are median (interquartile range) values

Table 2 Association between nursing records and diagnosis groups[1]

Diagnosis group	ICD-10 code	Frequency (mean no. of documentations per day)	Quantity (mean no. of narratives per documentation activity)	Total no. of narratives	Standardized no. of narratives (narratives per day)	Percentage of unique narratives (%)
Certain infectious and parasitic diseases (I)	A00–B99	5.2 (4.4–6.5)	5.1 (4.2–6.1)	141 (90–260)	27.3 (22.5–33.7)	36.7 (27.1–47.3)
Neoplasms (II)	C00–D48	5.8 (4.8–7.2)	4.4 (3.7–5.3)	144 (74–316)	27 (20.3–34.6)	38.1 (27.8–50.9)
Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism (III)	D50–D89	5.9 (4.8–7.7)	4.8 (4–5.8)	172 (101–322.2)	29.2 (24–36)	34.5 (25.7–45.4)
Endocrine, nutritional, and metabolic diseases (IV)	E00–E90	6.2 (5–8.1)	4.1 (3.2–5.5)	155 (111–248)	27.6 (21.8–34.6)	34.2 (26–44.8)
Mental, behavioral, and neurodevelopmental disorders (V)[2]	F00–F99	3.9 (3.4–4.7)	2 (1.7–2.8)	129 (72–225)	7.6 (6.1–11.3)	34 (25.5–44.6)
Diseases of the nervous system (VI)	G00–G99	5.4 (4.2–7)	4.8 (3.8–5.8)	134 (57–287)	26.2 (19.3–35.2)	36.5 (25.1–55.7)
Diseases of the eye and adnexa (VII)	H00–H59	7 (6–8)	3.7 (3.2–4.1)	26 (24–30)	25 (22–27)	91.7 (86.4–95)
Diseases of the ear and mastoid process (VIII)	H60–H95	4.8 (4.2–6)	5.7 (4.1–6.6)	108 (55–156)	27 (22.4–30.8)	39.7 (31.2–56.1)
Diseases of the circulatory system (IX)	I00–I99	8.8 (6.6–11.8)	3.9 (3.3–4.9)	149 (86–350)	35.7 (29–43.4)	43.9 (27.6–60)
Diseases of the respiratory system (X)	J00–J99	5.2 (4.6–6.4)	5.6 (4.7–6.4)	114 (84–212)	29.7 (25.5–35)	41.7 (29.2–50.7)

Table 2 Continued

Diagnosis group	ICD-10 code	Frequency (mean no. of documentations per day)	Quantity (mean no. of narratives per documentation activity)	Total no. of narratives	Standardized no. of narratives (narratives per day)	Percentage of unique narratives (%)
Diseases of the digestive system (XI)	K00–K93	6 (5–7.3)	4.1 (3.5–5)	112 (68–226)	25.2 (21.2–31.7)	47 (32.5–62.2)
Diseases of the skin and subcutaneous tissue (XII)	L00–L99	6 (4.8–7.9)	4 (3.3–5.3)	79.5 (25–229)	25 (22.6–28.3)	50.6 (26–91.3)
Diseases of the musculoskeletal system and connective tissue (XIII)	M00–M99	6.5 (5.4–8)	4.9 (4.1–5.7)	251 (115–422)	32.5 (25.1–39)	33.4 (25.8–47.1)
Diseases of the genitourinary system (XIV)	N00–N99	6 (4.8–7.8)	4.2 (3.5–5.1)	86 (35–159)	26 (21–32.1)	57.1 (39.3–78)
Pregnancy, childbirth, and puerperium (XV)	O00–O99	9.2 (7.1–12)	4.8 (4.2–5.8)	215 (139–297)	46.5 (39–54.7)	41.7 (35.6–49.5)
Certain conditions originating in the perinatal period (XVI)	P00–P96	4.7 (4–5.4)	6.8 (5.7–9.6)	154 (95–351)	32.2 (28.2–47.9)	29.4 (20.4–42.4)
Congenital malformations, deformations, and chromosomal abnormalities (XVII)	Q00–Q99	6 (5–7.7)	4 (3.4–5.1)	70 (24–137)	25 (22.3–31.4)	62.3 (42.1–90.5)
Symptoms, signs, and abnormal clinical and laboratory findings, not classified elsewhere (XVIII)	R00–R99	5.9 (4.7–7.6)	4.3 (3.6–5.3)	95 (51–176)	26 (21–33)	48.4 (33.3–65.6)
Injury, poisoning, and certain other consequences of external causes (XIX)	S00–T98	6.2 (5.2–7.8)	4.9 (4–5.7)	152 (76–304)	30 (24.9–36.8)	41.3 (27.9–59.7)
External causes of morbidity and mortality (XX)	V01–Y98	5.7 (5–8.1)	4.4 (3.9–5.3)	193.5 (148.8–246.8)	28.8 (20.1–39.7)	30.1 (25.2–35.3)
Factors influencing health status and contact with health services (XXI)	Z00–Z99	5.4 (4.3–7)	5.4 (4.1–6.5)	93 (67–150)	29.2 (26–32.3)	43.8 (31.5–58.4)
Codes for special purposes (XXII)	U00–U99	6 (5.8–8.8)	4.4 (4.1–4.9)	364 (173–1111)	30.8 (24.4–42.4)	24.3 (19.3–34.4)

[1]Data are median (interquartile range) values
[2]Free-text nursing documents are the most common form of documentation in patients with chapter V diagnoses

References

1. Weng C, Appelbaum P, Hripcsak G, Kronish I, Busacca L, Davidson KW, Bigger JT. Using EHRs to integrate research with patient care: promises and challenges. J Am Med Inform Assoc 2012; 19(5): 684–687.
2. Capan M, Wu P, Campbell M, Mascioli S, Jackson VE. Using electronic health records and nursing assessment to redesign clinical early recognition systems. Health Systems 2015.
3. Cai X, Perez-Concha O, Coiera E, Martin-Sanchez F, Day R, Roffe D, Gallego B. Real-time prediction of mortality, readmission, and length of stay using electronic health record data. J Am Med Inform Assoc 2016; 23(3): 553–561.
4. McCoy TH, Castro VM, Cagan A, Roberson AM, Kohane IS, Perlis RH. Sentiment Measured in Hospital Discharge Notes Is Associated with Readmission and Mortality Risk: An Electronic Health Record Study. PLoS One 2015; 10(8): e0136341.
5. Mathias JS, Agrawal A, Feinglass J, Cooper AJ, Baker DW, Choudhary A. Development of a 5 year life expectancy index in older adults using predictive mining of electronic health record data. J Am Med Inform Assoc 2013; 20(e1): e118–124.
6. Marier A, Olsho LE, Rhodes W, Spector WD. Improving prediction of fall risk among nursing home residents using electronic medical records. J Am Med Inform Assoc 2016; 23(2): 276–282.
7. Castro VM, McCoy TH, Cagan A, Rosenfield HR, Murphy SN, Churchill SE, Kohane IS, Perlis RH. Stratification of risk for hospital admissions for injury related to fall: cohort study. Bmj 2014; 349: g5863.
8. Collins SA, Cato K, Albers D, Scott K, Stetson PD, Bakken S, Vawdrey DK. Relationship between nursing documentation and patients‘ mortality. Am J Crit Care 2013; 22(4): 306–313.
9. Min YH, Park HA, Chung E, Lee H. Implementation of a next-generation electronic nursing records system based on detailed clinical models and integration of clinical practice guidelines. Healthc Inform Res 2013; 19(4): 301–306.
10. Park HA, Cho I, Ahn HJ. Use of narrative nursing records for nursing research. Nurs Inform 2012; 2012: 316.
11. International Classification of Diseases (ICD). Geneva: World Health Organization [Internet]. Available from: http://www.who.int/classifications/icd/en.
12. Cohen R, Elhadad M, Elhadad N. Redundancy in electronic health record corpora: analysis, impact on text mining performance and mitigation strategies. BMC Bioinformatics 2013; 14: 10.
13. Wrenn JO, Stein DM, Bakken S, Stetson PD. Quantifying clinical narrative redundancy in an electronic health record. J Am Med Inform Assoc 2010; 17(1): 49–53.
14. Poissant L, Pereira J, Tamblyn R, Kawasumi Y. The impact of electronic health records on time efficiency of physicians and nurses: a systematic review. J Am Med Inform Assoc 2005; 12(5): 505–516.
15. Blumenthal D, Tavenner M. The „meaningful use“ regulation for electronic health records. N Engl J Med 2010; 363(6): 501–504.
16. Spellman Kennebeck S, Timm N, Farrell MK, Spooner SA. Impact of electronic health record implementation on patient flow metrics in a pediatric emergency department. J Am Med Inform Assoc 2012; 19(3): 443–447.
17. Sittig DF, Singh H. Electronic health records and national patient-safety goals. N Engl J Med 2012; 367(19): 1854–1860.
18. Poulin C, Shiner B, Thompson P, Vepstas L, Young-Xu Y, Goertzel B, Watts B, Flashman L, McAllister T. Predicting the risk of suicide by analyzing the text of clinical notes. PLoS One 2014; 9(1): e85733.
19. Reed M, Huang J, Brand R, Graetz I, Neugebauer R, Fireman B, Jaffe M, Ballard DW, Hsu J. Implementation of an outpatient electronic health record and emergency department visits, hospitalizations, and office visits among patients with diabetes. JAMA 2013; 310(10): 1060–1065.
20. Hanauer DA, Ramakrishnan N, Seyfried LS. Describing the Relationship between Cat Bites and Human Depression Using Data from an Electronic Health Record. PLoS One 2013; 8(8): e70585.
21. Makam AN, Nguyen OK, Moore B, Ma Y, Amarasingham R. Identifying patients with diabetes and the earliest date of diagnosis in real time: an electronic health record case-finding algorithm. BMC Med Inform Decis Mak 2013; 13: 81.
22. Association CN. Measuring nurses’ workload. Nursing Now: Issues and trends in Canadian Nurs 2003.
23. Morris R, MacNeela P, Scott A, Treacy P, Hyde A. Reconsidering the conceptualization of nursing workload: literature review. J Adv Nurs 2007; 57(5): 463–471.
24. Weis JM, Levy PC. Copy, paste, and cloned notes in electronic health records: prevalence, benefits, risks, and best practice recommendations. Chest 2014; 145(3): 632–638.
25. Murdoch TB, Detsky AS. The inevitable application of big data to health care. JAMA 2013; 309(13): 1351–1352.