
Review

Secondary use of standardized nursing care data for advancing nursing science and practice: a systematic review

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ABSTRACT

Objective: The study sought to present the findings of a systematic review of studies involving secondary analyses of data coded with standardized nursing terminologies (SNTs) retrieved from electronic health records (EHRs).

Materials and Methods: We identified studies that performed secondary analysis of SNT-coded nursing EHR data from PubMed, CINAHL, and Google Scholar. We screened 2570 unique records and identified 44 articles of interest. We extracted research questions, nursing terminologies, sample characteristics, variables, and statistical techniques used from these articles. An adapted STROBE (Strengthening The Reporting of OBServational Studies in Epidemiology) Statement checklist for observational studies was used for reproducibility assessment.

Results: Forty-four articles were identified. Their study foci were grouped into 3 categories: (1) potential uses of SNT-coded nursing data or challenges associated with this type of data (feasibility of standardizing nursing data), (2) analysis of SNT-coded nursing data to describe the characteristics of nursing care (characterization of nursing care), and (3) analysis of SNT-coded nursing data to understand the impact or effectiveness of nursing care (impact of nursing care). The analytical techniques varied including bivariate analysis, data mining, and predictive modeling.

Discussion: SNT-coded nursing data extracted from EHRs is useful in characterizing nursing practice and offers the potential for demonstrating its impact on patient outcomes.

Conclusions: Our study provides evidence of the value of SNT-coded nursing data in EHRs. Future studies are needed to identify additional useful methods of analyzing SNT-coded nursing data and to combine nursing data with other data elements in EHRs to fully characterize the patient's health care experience.

Key words: nursing informatics, electronic health records, standardized nursing terminology

INTRODUCTION

In the hospital setting, nurses are typically the main frontline providers of care. In their role, nurses continuously identify patients' issues and subsequently plan and implement care to achieve desired patient outcomes. In 2016, there were 3 million registered nurses working in the United States, of whom 61% worked in hospitals,¹ compared with only 25% of 312 500 pharmacists and 12% of 854 698 physicians who practiced full-time in hospitals.²⁻⁴ Despite these statistics, it has been difficult to effectively evaluate the impact of nursing care on patient outcomes. The rapid adoption of electronic health record (EHR) systems provides a growing opportunity to expand our knowledge about nursing practices using nursing data in EHRs. The documentation of nursing care in EHRs with standardized terms provides a means for producing consistent data about nursing needed to share, compare, and merge with other data across systems.⁵⁻⁷ In this article, we present a systematic review of studies characterizing nursing care through the analysis of standardized nursing data retrieved from EHRs. The review also provides a foundation for future paths of inquiries using nursing and other data retrievable from EHRs.

Nursing data include elements of nursing services (eg, personnel, equipment), patient demographics, progress notes, assessment data, and care plans.^{8,9} In particular, care plan data are a rich source of information that can improve our understanding of the nursing care provided to patients. Care plan information represents nurses' clinical reasoning and includes patient problems, target outcomes, and the planned and implemented nursing interventions.¹⁰

In the mid-1970s, nursing researchers began developing standardized nursing terminologies (SNTs) to help bedside nurses document diagnoses, as well as the care they provided to patients and families, which is different from medical diagnoses.¹¹ SNTs are controlled vocabularies that contain standardized terms to represent nursing diagnoses, interventions, and outcomes.⁷ Over time, SNTs evolved from alphabetical lists to conceptual systems that guide the decision-making process of nursing care at the individual, caregiver, group, family, and community levels.¹² The American Nurses Association recognizes the following 7 SNTs^{12,13}:

- Clinical Care Classification (CCC)¹⁴
- International Classification for Nursing Practice (ICNP)¹⁵
- Omaha System¹⁶
- Perioperative Nursing Data Set (PNDS)¹⁷
- NANDA-International (NANDA-I) (diagnoses)¹⁸
- Nursing Outcomes Classification (NOC) (outcomes)¹⁹
- Nursing Interventions Classification (NIC) (interventions)²⁰

The first 4 SNTs (ie, CCC, ICNP, Omaha System, PNDS) contain terms for nursing diagnoses, interventions, and outcomes. The NANDA-I, NIC, and NOC, each representing 1 element (diagnoses, interventions, and outcomes, respectively), are often used together and referred to as a set (NNN).

To date, there are few reviews of secondary analyses of nursing data coded in SNTs. Tasthan et al²¹ focused on determining how SNT usage has evolved over the years, mainly describing the study focus and frequency of SNTs in publications. More recently, Kim et al²² evaluated the coverage of the bioCADDIE (biomedical and healthCAre Data Discovery Index Ecosystem) metadata specification in representing nursing data from published studies. Our systematic review fills an important knowledge gap: we explored the analysis of SNT-coded nursing data in research studies and the potential of using these data to show the impact of nursing care.

The objective of this review was to understand how SNT-coded nursing data, retrieved from EHRs, have been utilized in research studies to answer important questions about nursing practice.

MATERIALS AND METHODS

We performed a systematic review of studies that conducted secondary data analysis on SNT-coded nursing data extracted from EHRs. Our protocol²³ was registered on PROSPERO (available at https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=99830), and developed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Statement.²⁴ The different phases of our systematic review are illustrated in Figure 1.

Data sources and search strategy

We built on previous systematic review on SNT usage in studies from the 1960s to 2011,²¹ which reported 19 studies focusing on secondary uses of SNT-coded nursing documentation. We then proceeded to search on PubMed and CINAHL for studies published from 2011 to May 27, 2018, in the English language, and with abstracts available. The search of the databases included the following themes: nursing, electronic health records, and the American Nurses Association-recognized SNTs. The database EMBASE was not included because we did not have access to it through our institution's library at the time of our search.

With the help of the sponsoring institution's nursing librarian, along with the authors of this review, a search strategy was developed including a comprehensive set of text words and MeSH (Medical Subject Headings) terms for electronic health records and SNTs. Details on the search strategies are presented in Table 1.

We downloaded potential publications into a reference management program (EndNote X7 V.17.8.0.13453, Thompson Reuters, Philadelphia, PA/USA), in which we identified and removed duplicates.

Abstract and full-text screening

We retained 2551 articles after duplicates were removed. Three reviewers (T.M., N.D., T.C.)—specifically, 2 doctoral students in nursing informatics (T.M. and N.D.) and 1 faculty member (T.C.) with expertise in nursing terminologies—participated in screening abstracts from all articles. At least 2 of these reviewers independently screened each abstract. To ensure consistency, a guide was created to assist in a systematic process for abstracts screening. The guide directed reviewers to include a record if its abstract described (1) any of the SNTs noted previously or words such as *nursing diagnoses* or *nursing interventions*, (2) if the analyzed SNT-coded nursing data were retrieved from EHRs or electronic medical records, and (3) if the nursing data were documented at the point of care, as part of their care routine. A record was excluded if it was clear in the abstract that nursing data were collected in a research setting, not part of patient's standard of care. All discrepancies were discussed until consensus was reached.

Four reviewers (T.M., T.C., M.S., and K.D.L.) then participated in full-text reviews of 87 articles using the same guide described previously. We further excluded articles that are letters, commentaries, news reports, and literature reviews. At least 2 of the reviewers independently reviewed each full-text article. Discrepancies were resolved by discussion and consultation with 2 other faculty members, a specialist in nursing informatics (G.K.) and a statistician (Y.Y.). Figure 1 lists reasons for exclusions after full-text review.

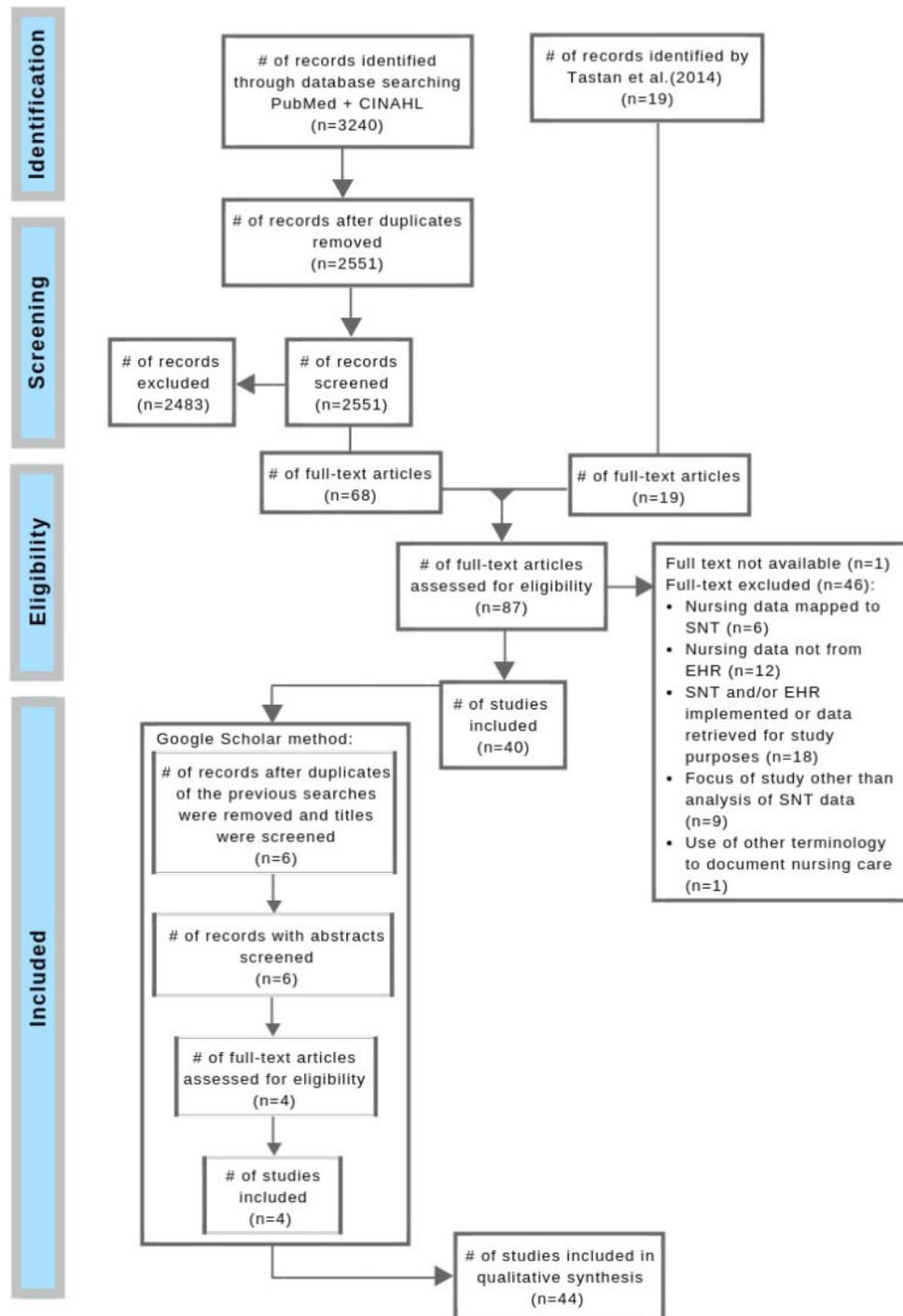


Figure 1. Flow diagram illustrating the different phases of the study selection process. EHR: electronic health record; SNT: standardized nursing terminology.

Google Scholar search for additional articles

Secondary analysis of nursing data is often an interdisciplinary effort. Nursing researchers often collaborate with experts outside of biomedical domain. Thus, relevant studies may be reported in journals of other fields (eg, computer science journals) and may not be indexed in PubMed or CINAHL. We searched on Google Scholar for authors ($n = 134$) whose articles were included in our study after full-text review. The same screening process described above was used to locate and include additional relevant articles.

Data extraction and synthesis

Data were extracted into individual tables for each study included in the qualitative synthesis process. The following items were extracted:

- Research questions answered by the analysis of SNT-coded nursing data
- Specific SNTs used to code the data
- Sample characteristics (setting, number of records, type of patient)
- Variables (descriptive, predictor, outcome, covariate)
- Statistical techniques applied

Table 1. Search strategies for PubMed and CINAHL databases

Database	Search	Restrictions
PubMed	("Nursing Intervention Classification"[Text Word] OR "Nursing Interventions Classification"[Text Word] OR "Nursing Outcome Classification"[Text Word] OR "Nursing Outcomes Classification"[Text Word] OR "North American Nursing Diagnosis"[Text Word] OR "Omaha System"[Text Word] OR "International Classification for Nursing Practice"[Text Word] OR "Clinical Care Classification"[Text Word] OR "Perioperative Nursing Data Set"[Text Word] OR "Home Health Care Classification"[Text Word] OR Standardized Nursing[tw]) OR ((("nursing"[Subheading] OR "nursing"[All Fields] OR "nursing"[MeSH Terms] OR "nursing"[All Fields] OR "breast feeding"[MeSH Terms] OR ("breast"[All Fields] AND "feeding"[All Fields]) OR "breast feeding"[All Fields]) AND (NIC[Text Word] OR NOC[Text Word] OR NANDA[Text Word] OR ICNP[Text Word] OR HHCC[Text Word] OR ccc[tw] OR PNDS[Text Word] OR electronic health records[tw] OR electronic health record[tw] OR ehr[tw] OR hrs[tw]))	Abstract Available English Language
CINAHL	(TX "Nursing Intervention Classification") OR (TX "Nursing Interventions Classification") OR (TX "Nursing Outcome Classification") OR (TX "Nursing Outcomes Classification") OR (TX "North American Nursing Diagnosis") OR (TX "Omaha System") OR (TX "International Classification for Nursing Practice") OR (TX "Clinical Care Classification") OR (TX "Perioperative Nursing Data Set") OR (TX "Home Health Care Classification") OR (TX "Standardized Nursing") OR ((TX Nursing) AND ((TX NIC) OR (TX NOC) OR (TX NANDA) OR (TX ICNP) OR (TX HHCC) OR (TX ccc) OR (TX PNDS) OR (TX "electronic health records") OR (TX "electronic health record") OR (TX ehr) OR (TX hrs)))	Abstract Available English Language Source Types: Academic Journals

Three reviewers (T.M., T.C., and M.S.) extracted the data for included articles. For each article, 2 reviewers independently extracted the data. T.M. and M.S. reached an agreement of 93% for the data extracted. The interrater reliability for the second pair of reviewers (T.M. and T.C.) was 84%.

Reproducibility assessment

We used an adapted version of the STROBE (Strengthening The Reporting of Observational Studies in Epidemiology) Statement checklist for observational studies²⁵ to assess the reproducibility of studies included in our review. Pairs of reviewers (T.M. and M.S.; T.M. and T.C.) independently evaluated the reproducibility of these studies, given their descriptions of (1) setting, (2) participants, (3) variables, (4) data sources or measurement, and (5) statistical methods. The reviewers also evaluated if the variables were described with sufficient clarity to be collected in future studies, scoring them as 1 (not defined), 2 (partially defined), and 3 (well defined). Interrater reliability scores were an agreement of 83% for T.M. and M.S. and agreement of 89% for T.M. and T.C..

RESULTS

The initial and updated searches on the 2 databases resulted in 3240 records. A total of 2551 records remained after duplicates were deleted and were submitted to abstract screening. 2483 records were further removed because they were not related to nursing or to SNTs. Reasons for the initial high volume of publications matching our search keywords but outside the scope of nursing or SNTs could be attributed to our use of the acronyms for each SNT as a text word (eg, CCC). Many of these acronyms have meanings other than those for nursing terminologies. We also used the Boolean term *OR* to combine either nursing or SNTs to EHRs (and its variations), which resulted in a more thorough search but also more false hits.

Sixty-eight records from PubMed and CINAHL and 19 records from Tastan et al²¹ were included in full-text review, of which 40 met our inclusion criteria. Four additional records were identified through search on Google Scholar. After qualitative synthesis, 44 articles were included. In 1 article, 2 studies were reported. Thus, the findings below refer to a sample of 45 studies.

SNTs used

Amongst the 45 studies, we found that only 5 of the 7 SNTs were used. There was no study that analyzed nursing data coded with CCC or PNDS. Twenty-six (58%) studies analyzed nursing data coded with NANDA-I,^{26–28} NOC,^{29,30} NIC,^{31–33} a combination of these terminologies (eg, NIC and NOC),^{34–36} or the NNN set.^{37–51} Fourteen (31%) studies used Omaha System,^{52–65} while 4 (9%) used ICNP.^{66–68} One (2%) study compared nursing data coded with NANDA-I and ICNP from different EHRs.⁶⁹

Study foci and variables

The specific study foci varied widely across studies. They can be grouped into the following areas: (1) feasibility of standardizing nursing data, (2) characterization of nursing care, and (3) impact of nursing care. Table 2 includes a description of the different research questions answered by SNT-coded nursing data in our sample of studies.

Descriptive studies analyzed nursing diagnoses, interventions, and outcomes relevant to SNTs. For studies that explored associations, the majority of independent variables were these same 3 nursing care plan elements, along with other factors related to delivery of care. Dependent variables in those studies varied significantly. The following sections summarize the variables analyzed across studies to help contextualize their main focus.

Feasibility of standardizing nursing data

Nine of 45 (20%) studies focused on potential uses of SNT-coded nursing data or challenges associated with this type of data. Keenan et al⁴² reported benefits of using SNTs in EHRs to increase availability, validity, and reliability of data for research purposes and statistical data analyses. Johnson et al⁵³ demonstrated differences between *t* test and Cohen's *d* in describing changes in nursing outcomes ratings. Park et al⁶⁷ analyzed nursing interventions provided to hospitalized patients compared with standard nursing care from guidelines. Farri et al⁵² and Melton et al⁵⁸ analyzed nursing free-text entries to standardized terms to describe potential flaws in a terminology's content coverage. Rivas et al⁴⁵ compared standardized and nonstandardized nursing care plans for delivery of health promotion and prevention services. Park and Lee⁵⁰ and Westra et al⁶¹

Table 2. Summary of study focus and statistical methods of included studies grouped by publications on 1 dataset

First author	Year	Dataset ^a	Sample ^b	Study Focus	Area ^c	Statistical analyses
Frauenfelder ²⁶	2018	A	424	To describe nursing diagnoses in the psychiatric setting	2	Chi-square
Horning ⁶³	2018	B	558	To measure nutrition-related nursing care	2	Chi-square, general linear models
Monsen ⁶⁴	2017	B	208	To measure the impact of nursing care on maternal risk index	3	Visualization methods, ANCOVA
Monsen ⁵⁴	2015	B	141	To explore association between nursing care and health literacy	3	Mixed-effects logistic regression
Johnson ⁵³	2013	B	1016	To test the feasibility of 2 statistical methods in describing changes in outcomes scores	1	<i>t</i> test, effect sizes (Cohen's <i>d</i>)
Monsen ⁵⁵	2011	B	486	To compare nursing care between groups of low and high risk	2	Descriptive statistics
Rodríguez-Álvarez ²⁸	2018	C	9063	To describe grieving-related nursing diagnoses	2	Chi-square, <i>t</i> test, Mann-Whitney U
Rodríguez-Álvarez ³⁶	2018	C	6091	To describe nursing care for patients with and without complications of grieving	2	Chi-square
Olsen ⁶⁵	2018	D	419	To measure the association between nursing care and physical activity-related outcomes	3	Chi-square, <i>t</i> test, multiple regression
Gao ⁶²	2017	E	1618	To examine associations between frailty and social and behavioral determinants of health for older adults	3	Visualization methods, <i>t</i> test, ANOVA
González-Rodríguez ²⁷	2017	F	9928	To describe nursing diagnoses	2	Descriptive statistics
Lodhi ³⁸	2017	G	2300	To predict readmission for patients with pain problem	3	Data mining
Lodhi ⁴¹	2015	G	438	To predict comfortable death outcome in end-of-life patients	3	Data mining, chi-square, logistic regression
Lodhi ⁴³	2015	G	160	To predict current pain outcome ratings for hospitalized patients	3	Data mining, logistic regression, Pearson correlation
Stifter ⁴⁷	2015	G	840	To measure the association between nurse continuity and occurrence of pressure ulcers	3	Logistic regression
Yao ⁴⁴	2015	G	901	To describe marks of shift from standard care to palliative care among patients who died during hospitalization	3	ANOVA, Tukey post hoc test
Lodhi ³⁷	2014	G	432	To measure the impact of nursing care on death anxiety for end-of-life patients	3	Data mining, chi-square
Almasalha ⁴⁰	2013	G	569	To predict whether or not an end-of-life patient would meet the expected pain-related outcomes	3	Data mining, chi-square, <i>t</i> test
Yao ³⁹	2013	G	596	To report pain care from admission to discharge or death for end-of-life patients	3	Chi-square, Wald test
Keenan ⁴²	2012	G	40 747	To describe the availability of plans-of-care data	1	Descriptive statistics
Rabelo-Silva ⁶⁹	2017	H	138	To describe nursing diagnoses for patients with heart failure	2	<i>t</i> test
Yang ⁵¹	2017	I	220	To describe nursing care for obstetric patients	2	Descriptive statistics
Rivas ⁴⁵	2016	J	379 601	To compare standardized and nonstandardized nursing data	1	Chi-square, <i>t</i> test
Escalada-Hernandez ⁴⁶	2015	K	690	To establish associations between national outcome mental illness scores and nursing care	3	Multiple regression, Pearson correlation
Park ⁵⁰	2015	L	180	To describe the nursing care of an SNT-based EHR	1	Descriptive statistics
Jenkins ³⁰	2014	M	3111	To determine nursing cost per acute care episode	3	Least squares regression
García ⁵⁹	2013	N	680	To compare outcome ratings for Latina adolescent and adult mothers with mental problems	3	General linear mixed-methods models
Kim ⁶⁸	2012	O	759 ^c	To test different computerized search strategies to analyze the incidence of contrast media hypersensitivity	1	Descriptive statistics
Park ⁶⁷	2012	O	s1: 427 s2: 355	s1: To compare pressure-ulcers nursing interventions against measures from 2 published guidelines s2: To describe narrative nursing statements of cancer patients treated with cisplatin-based chemotherapy	s1: 1 s2: 2	s1: ANOVA s2: Descriptive statistics

(continued)

Table 2. continued

First author	Year	Dataset ^a	Sample ^b	Study Focus	Area ^c	Statistical analyses
Park ⁶⁶	2011	O	41 891	To describe nursing care to prevent and treat pressure ulcers	2	Descriptive statistics
Farri ⁵²	2011	P	61 701 ^d	To compare free-text entries with existing standard terms	1	Descriptive statistics
Melton ⁵⁸	2010	P	3388	To compare free-text entries with existing standard terms	1	Descriptive statistics
Head ⁴⁹	2011	Q	451	To describe nursing care for hospitalized older patients with a primary discharge diagnosis related to pneumonia	2	Descriptive statistics
Scherb ⁴⁸	2011	Q	302	To describe nursing care for hospitalized older patients with a primary discharge diagnosis of heart failure	2	Descriptive statistics
Scherb ²⁹	2002	Q	669	To describe changes in nursing outcomes ratings	2	<i>t</i> test
Monsen ⁵⁶	2011	R	1750	To predict hospitalization for frail and nonfrail elders	3	Data mining, logistic regression
Westra ⁵⁷	2011	R	2072	To measure the association between nursing care and improvement in urinary and bowel incontinence	3	Data mining, logistic regression, chi-square
Westra ⁶¹	2010	R	2900	To describe nursing care across 2 different EHR vendors	1	Descriptive statistics
Shever ³³	2011	S	10 004	To measure the impact of nursing care on failure to rescue	3	Propensity scores, logistic regression
Titler ³¹	2011	S	7851	To measure the association between nursing, medical and pharmacy care, and falls for older adults	3	Generalized estimating equations
Shever ³²	2008	S	7851	To measure the cost of delivering high surveillance for hospitalized elders at risk for falling	3	Propensity scores, generalized estimating equations regression
Orlygsdottir ⁶⁰	2007	T	75	To describe nursing care for patients in an LBW program	2	Descriptive statistics
Scherb ³⁵	2007	U	29	To determine changes in outcomes scores for pediatric patients with dehydration	2	<i>t</i> test
Tseng ³⁴	2007	V	29	To describe nursing care for patients with cancer	2	<i>t</i> test

Groups based on study's description of the dataset and authorship.

ANCOVA: analysis of covariance; ANOVA: analysis of variance; EHR: electronic health record; LBW: low birth weight; SNT: standardized nursing terminology; s1: study 1; s2: study 2.

^aData from (A) 1 university hospital, (B) 1 family home visiting services, (C) 105 primary healthcare centers, (D) 1 county health department, (E) 8 homecare agencies, (F) 1 hospital and 2 primary healthcare centers, (G) 1 university hospital and 3 community hospitals, (H) 2 hospitals, (I) 1 hospital, (J) 34 primary healthcare centers, (K) 5 psychiatric clinics, (L) 1 hospital, (M) 1 academic medical center, (N) 1 public health agency, (O) 1 university hospital, (P) 1 home care/hospice facility and 1 maternal home visiting program, (Q) 3 community hospitals, (R) 15 home care agencies, (S) 1 academic medical center, (T) 1 LBW program, (U) 1 community hospital, (V) 1 hospital.

^bUnique patients, unless specified otherwise.

^c(1) Feasibility of standardized nursing data, (2) characterization of nursing care, and (3) impact of nursing care.

^dDaily or shift entries of documentation of care.

compared SNT-coded nursing data from different EHR vendors. Kim et al⁶⁸ tested different nursing intervention terms as search strategy to identify and analyze the incidence of contrast-media hypersensitivity.

Characterization of nursing care

Sixteen (36%) studies of 45 described characteristics of nursing care. Ten of 16 (63%) studies described the most common nursing diagnoses, interventions, and outcomes for patients with heart failure^{48,67}; older patients with pneumonia⁴⁹; younger patients with dehydration³⁵; obstetric patients⁵¹; low- and high-risk groups⁵⁵; infants with low birth weight⁶⁰; patients with cancer⁶⁹; patients with pressure ulcers⁶⁶; and patients with pneumonia, total hip or knee replacement, or heart failure.²⁹ In 6 of 16 (37%) studies, researchers explored interactions between nursing diagnoses, interventions, or outcomes with patient's age and sex^{27,28,36}; patient's

age and length of stay³⁴; medical diagnoses and hospital characteristics²⁶; and number of home-visits performed by nurses, patient's age, and race.⁶³

Impact of nursing care

Twenty of 45 (44%) studies measured the impact or effectiveness of nursing care. Table 3 lists patient outcomes and key predictors for the 20 studies.

Garcia et al⁵⁹ compared nursing outcome ratings given at admission and discharge to measure effectiveness of nursing care. Yao et al³⁹ compared pain-related nursing diagnoses and outcome ratings across different hospitals to investigate the quality of current pain management practices. Shever et al³² associated number of times a day the intervention "surveillance" was documented with total hospital costs for older patients at risk of falling to measure the cost of delivering this nursing intervention. On the other hand,

Table 3. Summary of predictors and outcomes for included studies that measured impact of nursing care

First author	Predictors	Outcomes
Monsen ⁶⁴	Nurses, nursing diagnoses (ie, problems), nursing interventions	Maternal risk index score
Monsen ⁵⁴	Patient's characteristics, nurses, nursing interventions	Health literacy score
Olsen ⁶⁵	Patient's age, gender and body mass index, nursing diagnoses, number of physical activity-related nursing interventions	Physical activity-related outcomes scores
Gao ⁶²	Nursing diagnoses used to determine social and behavioral determinants of health index, and frailty	Knowledge, behavior, and status outcomes scores
Lodhi ³⁸	Patient's age, nurse experience, length of stay, time of admission, time of discharge, outcome ratings	Hospital readmissions
Lodhi ⁴¹	Patient's age, nurse experience, length of stay, nursing diagnoses and interventions domains	Meeting or not expected comfortable death outcome score
Lodhi ⁴³	Patient's age, nurse experience, length of stay, nursing diagnoses and interventions domains, outcomes scores	Meeting or not expected pain-related outcome score
Stifter ⁴⁷	Nurse continuity, nurse-staffing variables	Pressure ulcer-related outcomes
Yao ⁴⁴	Patient's age, length of stay, pain-related outcomes, number of nursing diagnoses in a care plan	Nursing diagnoses, interventions, and outcomes related to palliative care
Lodhi ³⁷	Patient's age, nurse experience, length of stay, nursing diagnosis of death anxiety	Meeting or not expected comfortable death outcome score
Almasalha ⁴⁰	Nursing interventions, length of stay	Meeting or not expected pain-related outcome score
Yao ³⁹	Nursing diagnoses, pain-related outcome scores, length of stay	Meeting or not expected pain-related outcome score
Escalada-Hernandez ⁴⁶	Health of the Nation Outcome Scale scores	Number of nursing diagnoses
Jenkins ³⁰	Patient characteristics, nurse characteristics	Nursing cost
Garcia ⁵⁹	Patient's mental health conditions	Knowledge, behavior, and status outcomes scores
Monsen ⁵⁶	Nursing interventions	Patient's hospitalization
Westra ⁵⁷	Nursing interventions, assessment data	Improvement on urinary or bowel incontinence
Shever ³³	Number of times the nursing intervention "surveillance" is delivered per day (more or less than 12 times)	Failure to rescue
Titler ³¹	Patient characteristics, nursing unit characteristics, nursing interventions medical interventions, pharmacy interventions	Occurrence of falls
Shever ³²	Nursing staff variables, number of medical treatments, number of pharmacy treatments	Cost of the nursing intervention "surveillance"

Jenkins and Welton³⁰ multiplied the sum of nursing outcomes ratings per shift by actual nursing wages and patient's length of stay to estimate nursing care costs.

Olsen et al⁶⁵ explored association of nursing outcome ratings with patient's age, body mass index, nursing diagnoses, and nursing interventions. Monsen et al⁵⁴ investigated associations among nurses, nursing interventions, patient characteristics, and nursing outcomes ratings used to determine patients' health literacy. Meanwhile, Gao et al⁶² translated specific nursing diagnoses into social and behavioral determinants of health and frailty concepts and determined association between those and nursing outcomes ratings.

Monsen et al⁶⁴ used similar approach to assess the frequency of nursing diagnoses and used them as a measure of maternal risk index. Monsen et al⁵⁶ tested different data management approaches to identify nursing interventions groups associated with patient's hospitalization in homecare.

Of 20 studies, 7 (35%) focused on establishing associations among a broader number of nursing-related variables such as patient characteristics, support system factors, and nursing characteristics. For instance, Lodhi et al^{37,41,43} explored associations between patient's age, nurse's years of experience, length of stay, nursing diagnoses, and interventions, with outcomes for end-of-life patients. Almasalha et al⁴⁰ focused on analyzing length of stay and nursing interventions to predict whether or not a patient would meet pain-related outcomes. Yao et al⁴⁴ identified nursing diagnoses and interventions associated with changes in outcomes that could be used as an indicator of a shift from standard nursing care to palliative care. Lodhi et al³⁸ created predictive models for hospital readmission

using patient's age, length of stay, nurse years of experience, time of admission and discharge, and pain outcomes ratings. Last, Stifter et al⁴⁷ used nursing diagnoses, interventions, and outcomes to determine presence of pressure ulcers in hospitalized patients, and then examined their association with nurse staffing (eg, nurse years of experience, education, shift length, work pattern) and nurse continuity.

Other 5 (25%) studies of 20 merged nursing data to other parts of EHRs, namely unit characteristics, medical and pharmacy prescriptions,^{31,33} national outcome scales and psychiatric medical diagnoses,⁴⁶ and medical diagnoses or treatment conditions, nutritional therapies, and patient's service utilization.⁵⁷

Statistical analysis

Fifteen of 45 (33%) studies used descriptive statistics only. Eleven of 15 (73%) studies exclusively analyzed nursing care plans.^{48–50,52,55,58,60,61,66–68} Three of 15 (20%) studies provided descriptive analyses of care plans along with other nursing data (eg, patient's age and sex, nurse's years of experience)^{27,34,42} and 1 (7%)⁵¹ analyzed nursing care plans merged with other parts of EHR (eg, medical diagnoses).

The remaining studies (30 of 45, 67%) applied descriptive statistics and other statistical methods specified in Table 2. At least 9 (30%) of 30 studies used only chi-square or *t* tests^{26,28,29,34–36,39,45,69}; meanwhile, other studies from the 30 used a combination of these basic tests and more complex methods such as data mining,^{37,38,40,41,43,56,57} logistic regression,^{33,41,43,47,54,56,57} analysis of

covariance,⁶⁴ multiple regression,^{46,63,65} and generalized estimating equations.^{31,32}

Among 30 studies that conducted association analyses, 6 (20%) exclusively analyzed nursing care plans,^{29,35,53,56,62,69} Eight (27%) of 30 merged these data with other parts of EHRs.^{26,31–33,45,46,57,67} The majority (16 of 30, 53%) of studies analyzed care plans and other nursing data.^{28,30,36–41,43,44,47,54,59,63–65}

Table 2 shows 22 SNT-coded nursing datasets. Ten (45%) of 22 were retrieved from at least 2 different institutions/clinics. Some of the datasets were analyzed in more than 1 study (see Table 2). For example, the datasets referred as “B” (data from 1 family home visiting services) and “G” (data from 1 university hospital and 3 community hospitals) were analyzed in at least 5 different publications each since 2011. Earlier publications typically provided descriptive statistics on aspects of the broader dataset. Through the years, researchers began using more specific and complex statistical analysis (eg, generalized estimating equations, different types of regressions, and data mining procedures) to analyze smaller parts of the dataset.

It can also be noted in Table 2 that descriptive or basic statistics were used by the researchers that focused on exploring the feasibility of standardizing nursing data (study focus area 1) or characterizing nursing care (study focus area 2). For studies on the feasibility of standardizing nursing data (9 of 45, 20%), earlier publications (eg, the 2010s) employed descriptive analysis only and evolved to the use of chi-square and *t* tests across the years. Among studies that focused on the characterization of nursing care (16 of 45, 36%), publications from the early 2000s applied *t* tests and other basic statistics to smaller samples. From 2011 to 2017, the studies used descriptive statistics only, but to analyze larger amounts of readily available data.

More complex statistical analyses were employed by researchers interested in measuring the impact of nursing care (study focus area 3). Within this study focus area, publications from 2008 reported using generalized estimating equations and logistic regression and have evolved to the use of other advanced statistical methods, such as data mining (first study in 2011) and generalized linear mixed-effects models (since 2013), among others.

Reproducibility of publications included

All studies described sample sizes and listed statistical methods applied. Thirty-three (73%) of 45 studies defined their variables well and scored a 3, while 11 (25%) studies partially defined variables and received a 2.^{30,34,42,45,51,52,54,57,67,68} Only 1 (2%) study⁵⁹ of 45 did not define variables clearly. Overall, our sample’s completeness in reporting information was rated “of good reproducibility.”

DISCUSSION

In this systematic review, we comprehensively identified and evaluated 45 studies to determine how SNT-coded nursing data retrieved from EHRs are being analyzed to answer important questions about nursing practice. We identified studies that analyzed nursing data documented with the terminologies NANDA-I, NOC, NIC, Omaha System, and ICNP. We observed that, although distinct, these terminologies structured the nursing care plans in the same manner across EHRs, which enabled easy retrieval and analyses of nursing diagnoses, interventions, and outcomes for different groups of patients. Additionally, the use of SNTs to code nursing care plans supported the analysis of data from multiple institutions (eg, 105 primary health-

care centers)^{28,36} and from distinct healthcare practices, such as 2 primary healthcare centers and a hospital.²⁷

We synthesized foci of included studies into the following categories: (1) feasibility of standardizing nursing data, (2) characterization of nursing care, and (3) impact of nursing care. Within each focus, studies addressed different questions and analyzed distinct variables. For example, some studies that measured the impact of nursing care examined associations between nursing interventions and patient outcomes, such as patient’s health literacy, readmission, and presence of pressure ulcers, while others focused on developing predictive models. In 2014, a systematic review by Topaz et al⁷⁰ on the use of the Omaha System described a shift from studies focusing on terminology development to the analysis of standardized nursing data to understand patient outcomes, through the years. Our findings support those of Topaz et al.⁷⁰

The potential and versatility of SNT terms to characterize patients’ social, financial, and behavioral status were evidenced by the use of nursing diagnoses and interventions to operationalize patients’ income, social contact, and physical activity level, among others.^{62,63} The range of research questions studied using SNT-coded data demonstrates the potential that SNTs have in helping generate new knowledge about care offered by nurses. These studies show that incorporation of SNTs in electronic nursing documentation allows nursing care data to be available in a consistent format amenable to feasible analyses.^{71,72} The use of SNTs in EHR offers an advantage over allowing nurses to document with free-text. Two studies in our review^{52,58} compared free-text documentation with standard terms and reported that the use of SNTs reduces errors, such as typos and duplicated information. Nonetheless, the use of methods such as natural language processing offers the potential to augment standardized data through analyses of free-text notes entered by nurses into EHRs, further enhancing our understanding of the impact of nursing care.

Most studies used descriptive statistical analysis or basic tests, such as *t* tests, correlations, and chi-square tests. Our results indicate that these statistical methods have been more often used by researchers studying the feasibility of standardizing nursing data and characterization of nursing care. These statistical methods provide crucial results to understand a dataset and the population under study.⁷³ We also noted that these basic statistical tests have been applied increasingly to larger datasets across the years. Our results suggest SNTs are more widely implemented to code point-of-care nursing documentation in EHRs within clinical settings than previously thought.^{74,75}

The vast majority of studies conducted association analyses, employing methods such as multiple regression analysis, data clustering, and association mining techniques to select clinically important features and reduce dimensions of the dataset. Some also used decision trees, *k*-nearest neighbors, and support vector machines to identify hidden patterns in nursing data or to construct predictive models for patient outcomes.

We observed a research trend toward using more sophisticated statistical methods when analyzing SNT-coded nursing data, mainly to measure the impact of nursing care. Monsen et al⁶⁴ showed how specific interventions delivered by public health nurses during home visits were associated with decreased risks for pregnant women and their families suffering from social disadvantages and poverty. Lodhi et al³⁸ showed that SNT-coded nursing care plans are valuable in predicting hospital readmissions, which may help practitioners develop strategies to identify at-risk patients and potentially reduce healthcare costs in the future.

We also observed efforts from research teams to ensure full and valid representation of SNTs in EHRs through the analysis of the same datasets across the years. Specifically, 2 research teams stood out with nine^{37–44,47} and five^{53–55,63,64} publications each in the past 8 years. The dedication of these teams generated evidence of the feasibility of SNT-coded nursing data to characterize nursing care and enable analysis on the impact of nursing care on patient outcomes. Studies, however, are needed to examine the impact of nursing as component of total health care and these can be done through merging standardized nursing data with other types of data captured within EHRs.

Finally, our review showed that SNT-coded nursing data enables aggregation and comparison of nursing care plans providing the context of the care delivered.⁷¹ In addition, our systematic review provides evidence that SNT-coded nursing data are a viable foundation for systematically building knowledge to demonstrate nursing's contribution to health care. Only 9 studies in our sample, however, included variables such as medical diagnoses, medical and pharmaceutical treatments. In future studies that utilize SNT-coded data, we recommend that other EHR data (eg, free text and non-nursing elements) be added to the analyses for the purpose of deepening our understanding of the impact of nursing on patient outcomes.

Limitations of this study

Our systematic review has a few limitations. Although some articles from other sources were identified through Google Scholar, our review ultimately included only 2 databases. Furthermore, the fact that our review focused on study methods rather than study results limits the overall conclusions on the impact of nursing care that we offer.

CONCLUSION

The need for controlled vocabularies in EHRs is well known. Our systematic review showed that SNTs are a foundation for creating sharable and comparable nursing data in larger datasets. This review also revealed the value of initially examining nursing variables separate from other sources. Research is needed, however, to expand and refine methods that will unleash the deep knowledge captured in standardized nursing data when it is merged with other data elements stored in EHRs. The adoption of SNTs in EHRs was shown to be stable, where future refinement may not be needed for a longer period of time to allow comparable findings. We, therefore, recommend wider adoption of SNTs in EHRs to document nursing care plans.

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AUTHOR CONTRIBUTIONS

TM and GK conceived of the main conceptual idea. TM, TC, MS, and KDL collected and performed the analysis of the data. YY and GK acted as experts throughout. TM wrote the article, with all authors contributing significant edits to all versions of the work. All authors approved the final version to be published.

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CONFLICT OF INTEREST STATEMENT

None declared.

REFERENCES

1. Bureau of Labor Statistics, U.S. Department of Labor. Occupational Outlook Handbook, Registered Nurses. <https://www.bls.gov/ooh/healthcare/registered-nurses.htm#tab-3>. Accessed August 7, 2018.
2. Bureau of Labor Statistics, U.S. Department of Labor. Occupational Outlook Handbook, Pharmacists. <https://www.bls.gov/ooh/healthcare/pharmacists.htm#tab-3>. Accessed August 7, 2018.
3. U.S. Department of Health and Human Services, Health Resources and Services Administration, National Center for Health Workforce Analysis. *The U.S. Health Workforce Chartbook*. Rockville, MD; 2013. <https://bhwh.hrsa.gov/sites/default/files/bhwh/nchwa/chartbookpart1.pdf>. Accessed August 9, 2018.
4. Statista. Percentage of U.S. physicians by major professional activity (MPA) in 2015. <https://www.statista.com/statistics/797611/percentage-of-physicians-in-us-working-in-select-mpa/>. Accessed August 24, 2018.
5. Baro E, Degoul S, Beuscart R, et al. Toward a literature-driven definition of big data in healthcare. *Biomed Res Int* 2015; 2015: 639021.
6. Van Poucke S, Thomeer M, Hadzic A. 2015, big data in healthcare: for whom the bell tolls? *Crit Care* 2015; 19 (1): 171–2.
7. Bernhart-Just A, Lassen B, Schwendimann R. Representing the nursing process with nursing terminologies in electronic medical record systems: a swiss approach. *Comput Inform Nurs* 2010; 28 (6): 345–52.
8. Pruinelli L, Delaney CW, Garcia A, et al. Nursing management minimum data set: cost-effective tool to demonstrate the value of nurse staffing in the big data science era. *Nurs Econ* 2016; 34 (2): 66–71.
9. Werley HH, Devine CE, Zorn CR, et al. The nursing minimum data set: abstraction tool for standardized, comparable, essential data. *Am J Public Health* 1991; 81 (4): 421–6.
10. Gallagher-Lepak S. Nursing diagnosis basics In: Herdman TH, Kamitsuru S, eds. *NANDA International Nursing Diagnoses: Definitions & Classification, 2015–2017*. Oxford, UK: Wiley Blackwell; 2014: 21–30.
11. Boyd AD, Dunn Lopez K, Lugaesi C, et al. 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* 2018; 113: 63–71.
12. Lundberg C, Warren JJ, Brokel J, et al. Selecting a standardized terminology for the electronic health record that reveals the impact of nursing on patient care. *Online J Nurs Inform* 2008; 12 (2): 1–20.
13. The Office of the National Coordinator for Health Information Technology. Standard Nursing Terminologies: A Landscape Analysis. 2017. https://www.healthit.gov/sites/default/files/snt_final_05302017.pdf. Accessed August 3, 2018.
14. Saba V, ed. *Clinical Care Classification (CCC) System Version 2.5*. 2nd ed. New York, NY: Springer; 2012.
15. International Council of Nurses. About ICNP. <https://www.icn.ch/what-we-do/projects/ehealth-icnp/about-icnp>. Accessed November 25, 2017.
16. Martin KS. *The Omaha System: A Key to Practice, Documentation, and Information Management*. 2nd ed. Omaha, NE: Health Connections Press; 2005.
17. Beyea S, ed. *Perioperative Nursing Data Set*. 2nd ed. Denver, CO: Association of periOperative Registered Nurses; 2002.
18. Herdman TH, Kamitsuru S, eds. *NANDA International Nursing Diagnoses: Definitions & Classification, 2018–2020*. 11th ed. New York, NY: Thieme; 2018.

19. Moorhead S, Johnson M, Maas M, Swanson E, eds. *Nursing Outcomes Classification (NOC)*. 6th ed. St. Louis, MO: Elsevier; 2018.
20. Butcher H, Bulechek GM, Dochterman JMM, Wagner C, eds. *Nursing Interventions Classification (NIC)*. 7th ed. St. Louis, MO: Elsevier; 2018.
21. Tastan S, Linch GCF, Keenan GM, et al. Evidence for the existing American Nurses Association-recognized standardized nursing terminologies: a systematic review. *Int J Nurs Stud* 2014; 51 (8): 1160–70.
22. Kim H, Jang I, Quach J, et al. Explorative analyses of nursing research data. *West J Nurs Res* 2017; 39 (1): 5–19.
23. Macieira TGR, Chianca T, Smith M, et al. The impact of nursing care through the lens of data coded with standardized nursing terminologies: a systematic review. http://www.crd.york.ac.uk/PROSPERO/display_record.php?ID=CRD42018099830. Accessed August 15, 2018.
24. Moher D, Liberati A, Tetzlaff J, et al. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Ann Intern Med* 2009; 151 (4): 264–70.
25. von Elm E, Altman DG, Egger M, et al. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. *Int J Surg* 2014; 12 (12): 1495–9.
26. Frauenfelder F, van Achterberg T, Müller Staub M. Nursing diagnoses related to psychiatric adult inpatient care. *J Clin Nurs* 2018; 27 (3–4): e463–e475.
27. González-Rodríguez R, Martelo-Baro MA, Bas-Sarmiento P. Diagnostic labels of NANDA-I in Southern region of Spain. *Rev Lat Am Enfermagem* 2017; 8: e2911.
28. Rodríguez-Álvaro M, Brito-Brito PR, García-Hernández AM, et al. The grieving nursing diagnoses in the primary healthcare setting. *Int J Nurs Knowl* 2019; 30 (1): 34–42.
29. Scherb CA. Outcome research: making a difference in practice. *Outcomes Manag* 2002; 6 (1): 22–6.
30. Jenkins P, Welton J. Measuring direct nursing cost per patient in the acute care setting. *J Nurs Adm* 2014; 44 (5): 257–62.
31. Titler MG, Shever LL, Kanak MF, et al. Factors associated with falls during hospitalization in an older population. *Res Theory Nurs Pract* 2011; 25 (2): 127–52.
32. Shever LL, Titler MG, Kerr P, et al. The effect of high nursing surveillance on hospital cost. *J Nurs Scholarsh* 2008; 40 (2): 161–9.
33. Shever LL. The impact of nursing surveillance on failure to rescue. *Res Theory Nurs Pract* 2011; 25 (2): 107–26.
34. Tseng H, Moorhead S. The use of standardized terminology to represent nursing knowledge: nursing interventions relevant to safety for patients with cancer. *Stud Health Technol Inform* 2014; 201: 298–303.
35. Scherb CA, Stevens MS, Busman C. Outcomes related to dehydration in the pediatric population. *J Pediatr Nurs* 2007; 22 (5): 376–82.
36. Rodríguez-Álvaro M, García-Hernández AM, Brito-Brito PR, et al. Bereavement care interventions and outcome criteria planned by community nurses in the Canary Islands. *Enferm Clin* 2018; 28 (4): 217–78.
37. Lodhi MK, Cheema U, Stifter J, et al. Death anxiety in hospitalized end-of-life patients' as captured from a structured electronic record: difference by patient and nurse characteristics. *Res Gerontol Nurs* 2014; 7 (5): 224–34.
38. Lodhi MK, Ansari R, Yao Y, et al. Predicting hospital re-admissions from nursing care data of hospitalized patients. *Adv Data Min* 2017; 2017: 181–93.
39. Yao Y, Keenan G, Al-Masalha F, et al. Current state of pain care for hospitalized patients at end of life. *Am J Hosp Palliat Care* 2013; 30 (2): 128–36.
40. Almasalha F, Xu D, Keenan G, et al. Data mining nursing care plans of end-of-life patients: a study to improve healthcare decision making. *Int J Nurs Knowl* 2013; 24 (1): 15–24.
41. Lodhi MK, Ansari R, Yao Y, et al. Predictive modeling for comfortable death outcome using electronic health records. *Proc IEEE Int Congr Big Data* 2015; 2015: 409–15.
42. Keenan G, Yakel E, Yao Y, et al. Maintaining a consistent big picture: meaningful use of a web-based POC EHR system. *Int J Nurs Knowl* 2012; 23 (3): 119–33.
43. Lodhi MK, Stifter J, Yao Y, et al. Predictive modeling for end-of-life pain outcome using electronic health records. *Adv Data Min* 2015; 9165: 56–68.
44. Yao Y, Stifter J, Ezenwa MO, et al. Informarkers for transition to goals consistent with palliative care in dying patients. *Palliat Support Care* 2015; 13 (5): 1427–34.
45. Rivas PFJ, Martín-Iglesias S, del Cerro JLP, et al. Effectiveness of nursing process use in primary care. *Int J Nurs Knowl* 2016; 27 (1): 43–8.
46. Escalada-Hernandez P, Munoz-Hermoso P, Gonzalez-Fraile E, et al. A retrospective study of nursing diagnoses, outcomes, and interventions for patients with mental disorders. *Appl Nurs Res* 2015; 28 (2): 92–8.
47. Stifter J, Yao Y, Lodhi MK, et al. Nurse continuity and hospital-acquired pressure ulcers: a comparative analysis using an electronic health record “big data” set. *Nurs Res* 2015; 64 (5): 361–71.
48. Scherb CA, Head BJ, Maas ML, et al. Most frequent nursing diagnosis, nursing interventions and nursing sensitive patient outcomes of hospitalized older adults with heart failure: part 1. *Int J Nurs Terminol Classif* 2011; 22 (1): 13–22.
49. Head BJ, Scherb CA, Reed D, et al. Nursing diagnoses, interventions, and patient outcomes for hospitalized older adults with pneumonia. *Res Gerontol Nurs* 2011; 4 (2): 95–105.
50. Park H, Lee E. Incorporating standardized nursing languages into an electronic nursing documentation system in Korea: a pilot study. *Int J Nurs Terminol Knowledge* 2015; 26 (1): 35–42.
51. Yang MJ, Kim HY, Ko E, et al. Identification of nursing-outcome-intervention linkages for inpatients in the obstetrics department nursing unit in south Korea. *Int J Nurs Terminol Knowl* 2019; 30 (1): 12–20.
52. Farri O, Monsen K, Westra B, et al. Analysis of free text with Omaha system targets in community-based care to inform practice and terminology development. *Appl Clin Inform* 2011; 2 (3): 304–16.
53. Johnson K, McMorris B, Raynor L, et al. What big size you have! using effect sizes to determine the impact of public health nursing interventions. *Appl Clin Inform* 2013; 4 (3): 434–44.
54. Monsen KA, Chatterjee SB, Timm JE, et al. Factors explaining variability in health literacy outcomes of public health nursing clients. *Public Health Nurs* 2015; 32 (2): 94–100.
55. Monsen KA, Radosevich DM, Kerr MJ, et al. Public health nurses tailor interventions for families at risk. *Public Health Nurs* 2011; 28 (2): 119–28.
56. Monsen KA, Westra BL, Oancea SC, et al. Linking home care interventions and hospitalization outcomes for frail and non-frail elderly patients. *Res Nurs Health* 2011; 34 (2): 160–8.
57. Westra BL, Savik K, Oancea C, et al. Predicting improvement in urinary and bowel incontinence for home health patients using electronic health record data. *J Wound Ostomy Continence Nurs* 2011; 38 (1): 77–87.
58. Melton GB, Westra BL, Raman N, et al. Informing standard development and understanding user needs with Omaha system signs and symptoms text entries in community-based care settings. *AMIA Annu Symp Proc* 2010; 2010: 512–6.
59. Garcia C, McNaughton D, Radosevich DM, et al. Family home visiting outcomes for latina mothers with and without mental health problems. *Public Health Nurs* 2013; 30 (5): 429–38.
60. Orlygsdottir B. Use of NIDSEC-Compliant CIS in community-based nursing-directed prenatal care to determine support of nursing minimum data set of objectives. *Comput Inform Nurs* 2007; 25 (5): 283–93.
61. Westra BL, Oancea C, Savik K, et al. The feasibility of integrating the Omaha system data across home care agencies and vendors. *Comput Inform Nurs* 2010; 28 (3): 162–71.
62. Gao G, Maganti S, Ka M. Older adults, frailty, and the social behavioral determinants of health. *Big Data & Information Analytics* 2017; 2 (3–4): 191–202.
63. Horning ML, Olsen JM, Lell S, et al. Description of public health nursing nutrition assessment and interventions for home-visited women. *Public Health Nurs* 2018; 34 (4): 317–26.
64. Monsen KA, Peterson JJ, Mathiason MA, et al. Discovering public health nurse-specific family home visiting intervention patterns using visualization techniques. *West J Nurs Res* 2017; 39 (1): 127–46.
65. Olsen JM, Horning ML, Thorson D, Monsen KA. Relationships between public health nurse-delivered physical activity interventions and client physical activity behavior. *Appl Nurs Res* 2018; 40: 13–9.

66. Park H, Cho I, Chung E. Exploring use of a clinical data repository containing international classification for nursing practice-based nursing practice data. *Comput Inform Nurs* 2011; 29 (7): 419–26.
67. Park HA, Cho I, Ahn H. Use of narrative nursing records for nursing research. *NI 2012 (2012)* 2012; 2012: 316–21.
68. Kim M-H, Park C-H, Kim D-I, *et al.* Surveillance of contrast-media-induced hypersensitivity reactions using signals from an electronic medical recording system. *Ann Allergy Asthma Immunol* 2012; 108 (3): 167–71.
69. Rabelo-Silva ER, Cavalcanti ACD, Caldas M, *et al.* Advanced nursing process quality: comparing the international classification for nursing practice (ICNP) with the NANDA-international (NANDA-I) and nursing interventions classification (NIC). *J Clin Nurs* 2017; 26 (3–4): 379–87.
70. Topaz M, Golfenshtein N, Bowles KH. The Omaha System: a systematic review of the recent literature. *J Am Med Inform Assoc* 2014; 21 (1): 163–70.
71. Cimino JJ. Desiderata for controlled medical vocabularies in the twenty-first century. *Methods Inf Med* 1998; 37 (4–5): 394–403.
72. Westra BL, Latimer GE, Matney SA, *et al.* A national action plan for sharable and comparable nursing data to support practice and translational research for transforming health care. *J Am Med Inform Assoc* 2015; 22 (3): 600–7.
73. Khokhar A, Lodhi MK, Yao Y, *et al.* Framework for mining and analysis of standardized nursing care plan data. *West J Nurs Res* 2017; 39 (1): 20–41.
74. Strudwick G, Hardiker NR. Understanding the use of standardized nursing terminology and classification systems in published research: a case study using the international classification of nursing practice. *Int J Med Inform* 2016; 94: 214–21.
75. Törnvall E, Jansson I. Preliminary evidence for the usefulness of standardized nursing terminologies in different fields of application: a literature review. *Int J Nurs Knowl* 2017; 28 (2): 119.