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Applying Text Classification Techniques for NANDA-Oriented Nursing Diagnoses Based on Assessment Findings

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Abstract. Nurses play a crucial role in healthcare, directly influencing the quality of patient care. Facing a global nursing shortage, there is an urgent need for strategies to enhance nursing efficiency and care quality. This foundational study explores an NLP-based approach to determine NANDA nursing diagnoses, leveraging both subjective and objective patient data recorded by nurses. Employing text data similarity analysis and a prototype predictive model, our research aims to refine the nursing assessment process and pave the way for the potential automation of nursing diagnoses. This work highlights the potential of AI to support nursing practices and sets a platform for future research to fully realize AI's benefits in addressing the challenges posed by the nursing shortage.

Keywords. Nursing diagnosis, prediction, degree of similarity

1. Introduction

Nurses constitute one of the largest human resources in the healthcare sector, playing a pivotal role in determining the quality of patient care. According to the World Health Organization's (WHO) 2020 report, the global shortage of nurses is estimated to be 5.9 million [1], and in Japan, a potential shortage of up to 250,000 nurses is projected by 2025 [2]. This presents a significant challenge for Japan's healthcare industry, which faces urgent needs for cost reduction and operational efficiency amidst an aging society and limited human resources. Against this backdrop, researchers believe that the application of Artificial Intelligence (AI) in the nursing field has the potential not only to streamline operations but also to enhance the quality of nursing care.

Nurses constantly use "information" to make various decisions to provide the best possible care for patients. The quality of this "information" influences the quality of nursing care, suggesting that understanding how nurses process data and generate information directly contributes to improving nursing quality. However, the thought

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processes of nurses often involve tacit and practice-based knowledge, making it challenging to effectively utilize such knowledge due to its difficulty in being articulated.

Nursing records, documented daily by nurses, are vital documents recording observations and judgments acquired through daily care. Mitha et al. conducted a review study on the potential of applying Natural Language Processing (NLP) to nursing records for predicting nursing diagnoses and supporting clinical decision-making. However, insights into the applicability of NLP in nursing remained limited[3]. This indicates a current state where nursing records are underutilized for enhancing nursing practice.

This study proposes a method utilizing subjective and objective data collected by nurses to predict Nursing Diagnoses (NANDA). Through this research, we aim to demonstrate the potential of NLP and AI technologies in supporting decision-making in nursing practice, ultimately contributing to the improvement of patient care quality.

The structure of this paper is as follows: Section 2 organizes the thought processes for nursing practice and explains the framework used in this study. Section 3 reviews research on the thought processes of nurses using data science technologies. Section 4 describes the overview of the proposed method. Section 5 discusses the constructed algorithm and future perspectives. Finally, Section 6 concludes the paper.

2. Thought Process of Nurses in Nursing Assessment

In Japan, nursing involves licensed nursing professionals (midwives, public health nurses, registered nurses, and licensed practical nurses) practicing across various settings in health, medical, and welfare sectors, targeting individuals, families, groups, and community societies of all ages [4]. For this study, the focus is on registered nurses working in hospital wards, where significant nursing activities occur.

The nursing process, regarded as a systematic method for providing optimal and individualized care based on the body of nursing knowledge and experience, is critical for assessing health issues and delivering appropriate nursing interventions. It typically encompasses five steps: assessment, nursing diagnosis, planning, implementation, and evaluation. These steps are interrelated and dynamically progress in a spiraling manner, where evaluation informs the subsequent assessment [5] (Fig. 1).

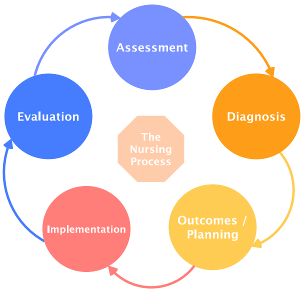


Figure 1. Five steps of The Nursing Process

The commencement of the nursing process is with the assessment. This phase involves collecting and organizing data about the patient, including health-related and social background information, to capture a holistic view of the patient. Several frameworks exist for capturing patient data; this study employs Gordon's functional health patterns, widely used by nurses in Japanese hospitals for data collection.

Following assessment is the nursing diagnosis, where multiple necessary nursing diagnoses are derived based on the assessed data and information, and the necessary nursing diagnosis for the patient is determined. Nursing diagnoses may be identified by the nurses themselves or through frameworks such as the North American Nursing Diagnosis Association (NANDA). Once a nursing diagnosis is established, a nursing plan based on the diagnosis is formulated, leading to nursing practice and evaluation. The Nursing Interventions Classification (NIC) and Nursing Outcomes Classification (NOC) systems classify nursing practices and outcomes. These systems are designed to ensure consistent care quality throughout the nursing process [6]. The thought process leading to nursing practice is organized by the nursing process, where nurses interpret and analyze the assessed data and information to identify nursing problems unique to each patient. In Japan, most of this process is carried out by the nurses themselves, and inappropriate nursing diagnoses can lead to failure to provide appropriate care, to the detriment of the patient.

Therefore, this study proposes the development of a system to support the process from assessment to planning. By basing nursing diagnoses on NANDA-I (2021-2023), a foundation for predicting nursing diagnoses from assessed data is established. The construction of this system will enable a consistent connection to NIC and NOC from collected data. It is anticipated that even nurses with less experience or those working in new areas will be able to formulate appropriate nursing diagnoses.

3. Efforts of Applying NLP and ML in Nursing Diagnostic Process

A search of the Medical Journal Web for previous studies in Japan utilizing natural language processing in the field of nursing revealed the following studies: a study on the extraction of pain expressions from medical records using BERT [7], a study that attempted to extract time-series knowledge about the course of medical conditions and treatment effects by text mining from discharge summaries, which are medical documents, a study that used Studio [8], and a study that used Studio® to text-mine the content of interviews with nurses to verify the effectiveness of a nursing delivery method [9].

Internationally, 43 review studies using natural language processing for nursing records highlighted the relatively small but growing number of publications on natural language processing in nursing and the potential for NLP to expand the methods and findings in the future through the use of appropriate performance measures and existing standard nursing terminology [10]. Other studies used NLP to identify communication failures between home care nurses and physicians and to evaluate communication [11], and a study on creating an NLP algorithm to extract wound infection-related information from nursing records [12].

While the performance of computers has dramatically improved, coupled with the promotion of research methods based on Artificial Intelligence (AI), and the number of studies incorporating data science techniques in the field of nursing is increasing internationally, the number of such studies in Japan is extremely small [13–15]. In addition, as far as we could find, there were no studies on the nursing diagnostic process conducted by nurses.

These considerations highlight the transformative potential of NLP and ML in the nursing field, ranging from the extraction of critical patient information from unstructured data sources. We believe that the integration of these technologies into the nursing field represents a major step forward in the pursuit of improved healthcare outcomes and operational efficiency. The uniqueness of this paper lies in the application of natural language processing (NLP) techniques in nursing diagnosis. While previous research has focused on the analysis of general medical documents, the use of NLP in the specific domain of nursing diagnosis has not yet been fully explored. Our approach is to explore the potential value of textual data routinely recorded by nurses and to directly link the results to improved accuracy in nursing diagnosis and quality of patient care.

4. Data Preparation and Experiments

4.1. Datasets

A literature search was conducted through the National Diet Library (NDL) ONLINE, focusing on publications between 2018 and 2023 that included "nursing process" in their titles. Works pertaining to "psychiatric," "maternal," "pediatric," or "home care" nursing were systematically excluded to refine the scope of the selection towards digital format publications, facilitating ease of access and dataset compilation.

Within the defined period, 61 publications were identified that met the initial search criteria for "nursing process." Of these, exclusions were made based on predefined criteria: 22 titles for containing excluded keywords, 17 for lack of digital availability, and 18 for the absence of case-based Subjective and Objective data. Consequently, the dataset was compiled from 4 books, each encompassing case studies conducive to extracting data and information for nursing diagnosis derivation (Table1).

Table 1. Target Books

No	Title	Publication year	Author	Publisher	Number of cases
1	Disease-Specific Nursing Process Seminar - Volume 1 [疾患別看護過程セミナー上巻]	2021	Yukihiro Yamada (Author)	Scio Publishing	11
2	Disease-Specific Nursing Process Seminar - Volume 2 [疾患別看護過程セミナー下巻]	2021	Yukihiro Yamada (Author)	Scio Publishing	7
3	Guide to the Development of the Nursing Process: How to Write a Practice Record, Volume 2 [実習記録のかきかたがわかる　看護過程展開ガイド 第２版]	2022	Kazuko Ren (Editor)	Shorin-company	8
4	Nursing Process Development Guide by Area [領域別 看護過程 展開ガイド]	2022	Kazuko Ren (Editor)	Shorin-company	3

From these four selected publications, 29 cases were extracted (Table2).

Table 2. Case list

Case No	Book No	Disease	Case No	Book No	Disease
1	3	Retinal detachment	16	1	Cerebral infarction
2	4	Gastric cancer	17	2	Renal failure
3	4	COPD*1	18	2	Benign prostatic hyperplasia
4	4	Sequelae of cerebral hemorrhage	19	2	Femoral neck fracture
5	3	Cerebral infarction	20	2	Parkinson's disease
6	3	Acute myocardial infarction	21	2	Diabetes mellitus
7	3	Multiple sclerosis	22	2	Dementia
8	1	Lung cancer	23	2	Breast cancer
9	1	Heart failure	24	3	Gastric cancer
10	1	Angina pectoris	25	3	Lung cancer
11	1	Myocardial infarction	26	3	Breast cancer
12	1	Gastric cancer	27	3	Diabetes mellitus
13	1	Colorectal cancer	28	1	Pneumonia
14	1	Liver cirrhosis	29	1	COPD*1
15	1	Subarachnoid hemorrhage			

*1Chronic obstructive pulmonary disease

4.2. Data collection

In the analysis of 29 case studies derived from five selected texts, the following methodological steps were undertaken:

① Extraction of Subjective data, Objective data, and nursing diagnoses from each case study.

② The assessment framework employed for Subjective and Objective data categorization was based on Gordon's Functional Health Patterns. This framework includes patterns such as Health Perception-Health Management, Nutritional-Metabolic, Elimination, Activity-Exercise, Sleep-Rest, Cognitive-Perceptual, Self-Perception-Self-Concept, Role-Relationship, Sexuality-Reproductive, Coping-Stress Tolerance, and Value-Belief. Cases already aligned with Gordon's framework were directly classified accordingly, whereas cases utilizing alternate frameworks underwent manual classification by the researcher to fit Gordon's categories.

③ In instances where NANDA nursing diagnosis labels were not explicitly utilized, each case was meticulously reviewed to assign the most applicable NANDA label manually. A particular case was excluded from this study due to the absence of an applicable NANDA counterpart.

④ Subsequently, the study represented 57 utilized NANDA nursing diagnosis labels in binary form for each analyzed case.

4.3. Data Preprocessing

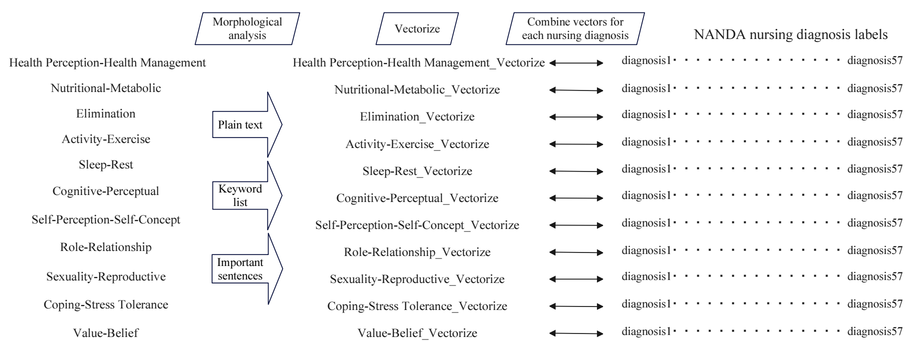
This study delves into the unstructured textual data of nursing records, systematically recorded in natural language by nurses on a daily basis. In text analysis, cosine similarity has emerged as a prevalent metric for gauging the degree of similarity between documents. Comelli et al. utilized ontology-based similarity computations for the comparative analysis of unstructured radiological reports, highlighting the utility of this metric [16]. Cosine similarity has been validated as an effective tool for analyzing short texts and domain-specific narratives [16,17], and was thus employed for our similarity assessments.

Nursing records are comprehensive, chronicling every aspect of a patient's hospitalization experience. This study harnesses frameworks like Gordon's functional health patterns for systematic categorization. Despite this, it is recognized that nursing records may also encompass routine details such as gender and weight.

Accordingly, we have adopted three distinct text processing methodologies to ascertain their influence on the predictive accuracy of NANDA diagnoses. The first method, Plain text, operates on the premise that all nurse-documented information is imperative to capture a comprehensive patient profile. It treats both subjective and objective data as a singular textual continuum, preventing fragmentation and maintaining the textual context.

For the second method, the keyword list, morphological analysis was performed on the plain text, and after excluding numerals, nouns, verbs, adjectives, shape verbs, and pronouns were extracted. After extraction, the TF-IDF calculation was applied to extract the 10 most salient keywords. This method assumes that the extraction of nursing diagnoses can be facilitated by focusing on key elements in the documented patterns.

The final method, Important sentences, selects sentences from Plain text that encompass the pivotal words from the Keyword list. This approach was informed by Sitikhu et al., who demonstrated that cosine similarity, when paired with TF-IDF vectors, is notably efficacious in detecting similarities amongst brief news articles.



Plain text : It treats both subjective and objective data as a single textual continuum, preventing fragmentation and maintaining the textual context.
Keyword list : The TF-IDF calculation was applied to extract the 10 most salient keywords.
Important sentences : Selects sentences from the plain text that encompass the pivotal words from the keyword list.

Figure 2. Overview of case processing

This study used a combination of several natural language processing techniques to improve the predictive accuracy of NANDA nursing diagnoses. Specifically, morphological analysis was first used to extract important information from patient records to identify key nouns, verbs, and adjectives. We then calculated the Term Frequency-Inverse Document Frequency (TF-IDF) from these words and used cosine similarity to assess the similarity between texts. This laid the foundation for our analysis by quantifying textual features to predict relevant nursing diagnoses （Fig.2）

4.4. Experiments

The methodology implemented in this research leveraged text vector representations contextualized via deep learning with the BERT model for the analysis of Plain text, Keyword lists, and Semantic Essence Retrieval. The utilized BERT model, pretrained on Japanese text (see: cl-tohoku/bert-base-japanese-char-whole-word-masking), alongside a Sentence-BERT (SBERT) model specifically designed for inter-sentence similarity assessments, draws upon their demonstrated success across a spectrum of Natural Language Processing (NLP) tasks involving Japanese text. Kawazoe et al. developed a clinical-specific BERT model employing a substantial corpus of Japanese clinical texts, showcasing its superior performance in medical text analytics compared to models pretrained on generic domains [18]. SBERT, an adaptation of the original BERT architecture, facilitates direct optimization for similarity comparisons [19], rendering it exceptionally apt for analyzing nursing issue narratives and discerning their relationships with textual depictions.

A matrix was formulated, intertwining nursing diagnoses with corresponding feature vectors derived from this vectorized textual data. Through Cosine similarity computations, the research assessed the congruence between the feature vector of a test instance and those within the dataset, facilitating the prognostication of the nursing diagnosis most akin to the test instance. Furthermore, a matrix amalgamating the feature vector X (integrating the 11 S/O Text patterns) with the binary-encoded Y (NANDA nursing diagnosis labels) was established. This similarity-driven comparative analysis allowed for the evaluation of the textual data’s vectorized representation, pinpointing instances with the highest resemblance in the dataset and enabling the prediction of Y (NANDA nursing diagnoses).

The linkage between the feature vector X (merging the 11 distinct functional health patterns per textual instance) and Y (nursing diagnosis) was vectorized, reflecting the array of functional health patterns unique to each text instance. These feature vectors, coupled with the binary-coded nursing issues (NANDA labels), formed the basis for the matrix construction.

In the predictive phase, the research first generated average feature vectors for each nursing issue from 28 instances, excluding a singular test instance from the total of 29. Subsequently, it calculated the cosine similarity between the test instance’s feature vector and each nursing issue's average feature vector. The average vector computation and cosine similarity calculation are pivotal in this study for quantitatively elucidating the nexus between textual descriptions and nursing issues. By aggregating feature vectors into an average vector for each nursing issue, the method encapsulates the textual features’ central tendencies associated with each issue. This procedure mirrors the creation of representative signatures for each nursing issue, simplifying nuanced comparisons between the test instance and predefined categories.

Cosine similarity acts as a measure to quantify the alignment between the vector of the test instance and the average vectors for each nursing issue. Thanks to its normalization feature, this metric permit text comparisons based on directional orientation within the feature space rather than size, enabling more semantically concentrated analyses. This strategy, corroborated by Sun et al. through their exploration of BERT's fine-tuning for text classification, underscores the adaptability and effectiveness of BERT embeddings in capturing textual subtleties [20].

Adhering to the outlined methodology, the study compiled nursing issues with the top five and bottom three similarity ratings into a table, pursuant to the conducted calculations.

5. Experiment Results

Upon implementing the proposed methodology, our experiments consistently identified the relevant nursing issues for the test instances across all evaluated patterns. This section explores the results for test instances 4 and 26.

Initially, the findings from the BERT model for instance 4 are outlined in Table 3, while the outcomes from the SBERT model are compiled in Table 4. It should be noted that items in bold within the tables indicate a match with the ground truth, and underlined items signify that the similarity threshold exceeds 0.75. The BERT analysis for instance 4 accurately identified two nursing issues as the ground truth, placing them in the top two positions across Plain text, Keyword list, and Important sentences, with remarkably high similarity scores above 0.9. Nonetheless, it was observed that similarity scores for positions three to five, which did not align with correct answers, remained steadfastly above 0.8. Furthermore, the three lowest-ranked nursing issues demonstrated similarity scores exceeding 0.7.

Table 3. BERT on Case 4

Ground Truth	Plain text		Keyword list		Important sentences	
	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity
Risk for Aspiration	**Imbalanced nutrition: less than body requirements**	0.95	**Imbalanced nutrition: less than body requirements**	0.94	**Imbalanced nutrition: less than body requirements**	0.94
Imbalanced nutrition: less than body requirements	**Risk for Aspiration**	0.94	**Risk for Aspiration**	0.94	**Risk for Aspiration**	0.92
	Ineffective Health Self-Management	0.90	Anxiety	0.89	Ineffective Health Self-Management	0.86
	Risk for impaired skin integrity	0.89	Ineffective Health Self-Management	0.89	Bathing Self-Care Deficit	0.85
	Bathing Self-Care Deficit	0.89	Bathing Self-Care Deficit	0.89	Readiness for enhanced self-care	0.85
	⋮	⋮	⋮	⋮	⋮	⋮
	Disability- associated urinary incontinence	0.78	Fatigue	0.79	Fatigue	0.70
	Chronic confusion	0.78	Hypothermia	0.79	Hypothermia	0.70
	Risk for adult pressure injury	0.77	Delayed surgical recovery	0.79	Risk for impaired oral mucous membrane integrity	0.70

In the case of the SBERT-derived results for instance 4, the model also predicted two nursing issues as the ground truth within the top two ranks across Plain text, Keyword list, and Important sentences. However, the similarity scores slightly decreased, remaining just above 0.8, compared to the BERT experiment. Conversely, for ranks three to five, which did not match the correct answers, similarity scores were recorded at 0.6 for Plain text, Keyword list, and dropped to 0.5 for Important sentences. The three lowest ranks dipped below 0.4 for Plain text, Keyword list, and further declined to below 0.3 for Important sentences.

Table 4. SBERT on Case 4

Ground Truth	Plain text		Keyword list		Important sentences	
	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity
Risk for- Aspiration	**Imbalanced nutrition: less than body requirements**	0.86	**Imbalanced nutrition: less than body requirements**	0.85	**Imbalanced nutrition: less than body requirements**	0.80
Imbalanced nutrition: less than body requirements	**Risk for- Aspiration**	0.80	**Risk for- Aspiration**	0.83	**Risk for- Aspiration**	0.73
	Ineffective Health Self-Management	0.65	Ineffective Health Self-Management	0.67	Anxiety	0.54
	Bathing Self-Care Deficit	0.62	Bathing Self-Care Deficit	0.67	Ineffective Health Self-Management	0.52
	Readiness for enhanced self-care	0.610	Risk for adult falls	0.66	Impaired comfort	0.51
	⋮	⋮	⋮	⋮	⋮	⋮
	Deficient fluid volume	0.40	Risk for deficient fluid volume	0.40	Risk for ineffective lymphedema self-management	0.29
	Constipation	0.39	Parental Role Conflict	0.40	Decisional conflict	0.29
	Risk for impaired oral mucous membrane integrity	0.37	Delayed surgical recovery	0.37	Delayed surgical recovery	0.26

Proceeding to instance 26, the results obtained using the BERT model are presented in Table 5, while those from the SBERT model are detailed in Table 6. The BERT experiment for instance 26 precisely forecasted four nursing issues as the ground truth, securing them within the top four for Plain text, Keyword list, and Important sentences. Similarity scores for Plain text and Keyword list impressively exceeded 0.9 for all four nursing issues. Important sentences revealed similarity scores of 0.89 for two nursing issues. Remarkably, even the fifth-ranked issue, not a correct answer for this instance, showed a similarity score above 0.8. Similar to instance 4's BERT findings, the three lowest-ranked nursing issues-maintained similarity scores above 0.7.

Table 5. BERT on case 26

Ground Truth	Plain text		Keyword list		Important sentences	
	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity
Bathing Self-Care Deficit	**Risk for surgical site infection**	0.958337009	**Risk for surgical site infection**	0.956047058	**Risk for surgical site infection**	0.940807343
Acute pain	**Acute pain**	0.952272415	**Acute pain**	0.942031145	**Acute pain**	0.924515188
Risk for surgical site infection	**Bathing self-care deficit**	0.937564015	**Ineffective Health Self-Management**	0.911164165	**Bathing Self-Care Deficit**	0.897566795
Ineffective Health Self-Management	**Ineffective Health Self-Management**	0.933083236	**Bathing Self-Care Deficit**	0.911138654	**Ineffective Health Self-Management**	0.891524434
	Toileting care deficit	0.926025867	Anxiety	0.891421974	Toileting care deficit	0.875628471

⋮	⋮	⋮	⋮	⋮	⋮
Disability-associated urinary incontinence	0.796358943	powerlessness	0.785867631	Death anxiety	0.707535207
Chronic coufusion	0.796358943	Risk for decreased activity tolerance	0.785867631	Fatigue	0.707535207
Risk for adult pressure injury	0.789653659	Risk or powerlessness	0.779423654	Hypothermia	0.707535207

The SBERT analysis for instance 26 also correctly identified the four ground truth nursing issues within the top four ranks for Plain text, Keyword list, and Important sentences. While the predictions remained at the forefront, the results for Plain text and Keyword list indicated the top two issues had similarity scores above 0.8, and the subsequent two scored above 0.7. For Important sentences, the highest-ranking issue achieved a similarity of 0.8, but the second rank fell to 0.7, with the third and fourth ranks at 0.6. Where the fifth rank did not correspond to the correct answer, similarity scores reduced to 0.7 for Plain text, 0.6 for Keyword list, and 0.5 for Important sentences. Echoing instance 4's SBERT results, the three lowest ranks exhibited scores below 0.4 for Plain text and Keyword list, and below 0.3 for Important sentences.

Table 6. SBERT on case 26

Ground Truth	Plain text		Keyword list		Important sentences	
	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity	Diagnosis	Degree of similarity
Bathing Self-Care Deficit	**Risk for surgical site infection**	0.842952669	**Risk for surgical site infection**	0.870051861	**Risk for surgical site infection**	0.850353003
Acute pain	**Acute pain**	0.816089392	**Acute pain**	0.809403062	**Acute pain**	0.778760195
Risk for surgical site infection	**Bathing self-care deficit**	0.759753883	**Ineffective Health Self-Management**	0.711817086	**Bathing Self-Care Deficit**	0.671874285
Ineffective Health Self-Management	**Ineffective Health Self-Management**	0.756038547	**Bathing Self-Care Deficit**	0.71033442	**Ineffective Health Self-Management**	0.667933822
	Feeding self-care deficit	0.715617359	Readiness for enhanced self-care	0.640454113	Readiness for enhanced self-care	0.585806668
	⋮	⋮	⋮	⋮	⋮	⋮
	Risk for unstable blood glucose level	0.409294546	Risk or powerlessness	0.408281505	Risk for decreased activity tolerance	0.344676703
	Risk for decreased activity tolerance	0.381339401	Risk for deficient fluid volume	0.397819459	powerlessness	0.344676703
	powerlessness	0.381339401	Parental Role Conflict	0.397819459	Risk for adult pressure injury	0.323548555

6. DISCUSSION

6.1. Impact of Preprocessing Techniques and Models on Nursing Problem Prediction

The research presented herein validates the potential for predicting NANDA nursing diagnoses by correlating feature vectors, derived from Gordon's Functional Health Patterns, with nursing diagnoses. Utilizing a combination of subjective and objective data recorded by nurses, and employing an 11-dimensional feature vector X, our proposed method demonstrated considerable predictive accuracy. The adoption of BERT and SBERT models, along with preprocessing techniques such as Plain text, Keyword list, and Important sentences, proved to be effective in accurately forecasting nursing issues across all evaluated cases.

The observed discrepancy in performance between the BERT and SBERT models underscores the importance of domain-specific optimization in the nursing sector. Although BERT models are adept at capturing detailed contextual information within texts, they are not inherently designed to distinguish directly between the semantic similarities of different texts [21]. This led to uniformly high similarity scores across all nursing issues, indicating BERT's profound contextual comprehension but suggesting potential limitations in its specificity for direct nursing issue prediction.

In contrast, the direct optimization for similarity calculations by SBERT enables more nuanced capture of semantic nuances, yielding a wider array of similarity scores that more accurately reflect semantic distances between sentences. This proves its effectiveness in discerning the relationships between nursing issues and their textual depictions, underlining the advantage of employing a specialized approach like SBERT for detailed analysis and predictions in niche areas such as nursing.

The preprocessing methodologies—Plain text, Keyword list, and Important sentences—significantly influenced predictive accuracy across all patterns, underscoring the critical role of systematic text analysis in extracting meaningful patterns from nursing records. The application of cosine similarity, known for its efficacy in analyzing short texts and domain-specific texts, showcased its utility in deepening the understanding of nursing records. This highlights the potential of cosine similarity to enhance insights into nursing documentation significantly.

Nonetheless, this investigation was constrained by the modest dataset size of 29 instances, highlighting the challenges associated with leveraging actual hospital data due to privacy considerations. The data imbalance—from nursing diagnoses appearing in just one instance to those in ten—suggests a variability in the extent to which each nursing diagnosis label's feature vector reflects individual or multiple instances. This indicates that feature vector generation via plain text may have been particularly effective owing to the limited data scope. Conversely, important sentences yielded lower similarity scores for test instances than plain text, yet demonstrated decreased similarity for incorrect nursing issues, emphasizing the precision of BERT and SBERT models in excluding irrelevant nursing issues.

Given the nature of nursing issues, overprediction could lead to inefficiencies in nursing workload, whereas underprediction might degrade the quality of care. Therefore, offering a balanced array of predictive candidates is imperative for optimizing nursing workload and enhancing the quality of patient care.

6.2. Utilizing Data Science Techniques in the Nursing Field

The results of this study suggest that effectively leveraging the information documented in daily nursing records by nurses can lead to more accurate predictions of nursing diagnoses. It implies that the nursing process, from assessment to planning, could be conducted more efficiently and accurately with support from AI. Utilizing NLP and AI technologies for selecting nursing diagnoses and planning nursing care could support decision-making, thus alleviating the burden on individual nurses faced with the challenge of nursing shortages and enhancing the quality of patient care.

Future research should focus on constructing a larger dataset incorporating diverse nursing records and further optimizing and evaluating NLP models tailored for the nursing domain. Moreover, automating the manual tasks of categorizing data patterns and assigning NANDA nursing diagnoses is necessary for system development.

Conducting empirical studies to verify the applicability and effectiveness of these models in actual nursing settings is crucial. Through such efforts, this study aims to utilize AI and NLP technologies effectively as decision-support tools in nursing, ultimately improving the quality of patient care.

7. Conclusion

This study has substantiated the feasibility of employing advanced natural language processing (NLP) models, specifically BERT and SBERT, for the prediction of NANDA nursing diagnoses. By integrating feature vectors derived from Gordon's Functional Health Patterns with textual data meticulously recorded by nurses, we have demonstrated enhanced accuracy in diagnosing nursing issues across multiple test instances. This underscores the critical importance of domain-specific adaptations in model training and the rigorous analysis of textual data within the nursing domain. Our results highlight the transformative potential of NLP technologies in refining nursing diagnostics and improving care planning processes. The study advocates for the expansion of data diversity and further model refinement specifically engineered for applications within nursing to bolster predictive performance. Moreover, the automation of data classification and the assignment of diagnoses are proposed as innovative approaches to streamline nursing operations and enhance the quality of patient care. Future research should prioritize the empirical validation of these models within real-world nursing settings to confirm their utility as effective decision-support tools.

Future investigations should also focus on the development of AI frameworks capable of autonomously identifying urgent cases through the analysis of real-time patient data and integrating predictive models to assist nursing professionals in their daily duties. Such technological advancements could significantly empower nursing personnel, enabling more informed and strategic decision-making processes, and ultimately raising the standard of nursing care.

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