Development and Application of Multimodal Knowledge Graph in Precision Nursing

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Objectives: *This study aims to implement and evaluate a multimodal knowledge graph technology to enhance precision nursing, thereby offering more efficient, accurate, and personalized patient care services.*
Methods: *Data from various sources including clinical databases, nursing training textbooks, and online platforms were collated to create a comprehensive multimodal dataset in the nursing field. Utilizing natural language processing, data mining algorithms, and graph database technology, we constructed a multimodal knowledge graph integrating textual, image, and video data. Visualization tools were employed to facilitate the interaction with and validation of the constructed graph.*
Results: *The developed multimodal knowledge graph encompasses 62,909 entities and 330,285 relationships, covering a wide spectrum of nursing-related aspects such as patient care, disease symptoms, and nursing techniques. This graph has been successfully applied in precision nursing to generate personalized nursing profiles, perform clinical nursing semantic searches, support real-time question-answering, and assist in personalized nursing decision-making. The system demonstrated high accuracy and reliability in clinical nursing applications, particularly in enhancing decision support.*
Conclusions: *The deployment of multimodal knowledge graph technology in precision nursing significantly improves the delivery of personalized care, augments clinical decision-making, and promotes educational excellence. The integration of this technology into nursing practices holds great promise for advancing patient outcomes and fostering more precise and informed healthcare interventions.*

BACKGROUND

Precision nursing is a practice method based on individualization and data-driven approaches, aimed at providing safer, more effective, and personalized nursing services through accurate and professional data and nursing knowledge.[8] Facing the challenges of an aging population and the increasing prevalence of chronic diseases, precision nursing can enhance the quality and efficiency of nursing ser- vices, better meeting the evolving needs of patients.[15]

The key to achieving precision nursing lies in the application of accurate the application the application of accurate and professional data and knowledge. Currently, the nursing field lacks an effective data management platform, which restricts the utilization and dissemination of nursing knowledge.[5]

Therefore, establishing a dedicated nursing knowledge data management platform is crucial for enhancing the accuracy and efficacy of nursing services, promoting the scientification and data orientation of nursing decisions, and improving the overall quality of patient care. In the evolving landscape of healthcare, nurses occupy a pivotal role, embodying a holistic perspective that is fundamental to patient care. This holistic approach is not merely about addressing the immediate medical needs of patients but also encompasses a

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comprehensive understanding of their physical, emotional, social, and environmental well-being. As the healthcare system increasingly embraces precision medicine, the role of nurses becomes even more critical. Precision medicine's promise to tailor treatment and prevention strategies to individual genetic, environmental, and lifestyle factors aligns seamlessly with the nursing ethos of providing personalized care. Nurses, with their unique position at the patient's bedside and in-depth understanding of patient histories and daily needs, are ideally placed to contribute vital insights into the customization of care plans.[8] Their role in collecting and interpreting patient data, advocating for patient needs, and coordinating multidisciplinary care directly supports the implementation of precision medicine, making them indispensable in the realization of its full potential.

Multimodal knowledge graph, as an emerging approach to knowledge storage and management for integrating diverse and heterogeneous data sources, represent a frontier research area in the computer field.[29] Integrating cutting-edge technologies such as big data and artificial intelligence with nursing practices can meet the public demand for personalized and precise nursing services. In this study, clinical nursing databases, nursing training databases, and internet data are utilized as data sources. Various technologies, including natural language processing (NLP), image processing, deep learning, and multimodal data fusion, are employed to extract and represent knowledge from raw data, resulting in a large-scale semantic network knowledge repository encompassing text, images, videos, and more.[29]

The deployment of a nursing multimodal knowledge graph in precision nursing research facilitates the development of bespoke patient care profiles,[10] enables semantic searches within clinical nursing, offers instantaneous access to nursing knowledge, and empowers the analysis and deduction of more precise nursing protocols and individualized nursing services. The ultimate aim is to provide patients with nursing services that are not only more precise and efficient but also attuned to their individual needs, thereby elevating nursing quality and enhancing patient satisfaction.

The main contributions of this paper are summarized as follows:

1. Multimodal Nursing Data Integration: We have integrated diverse data types, including text, images, and videos, into a unified framework, forming a comprehensive dataset crucial for advancing precision nursing. This integration enhances the accuracy and depth of data analysis, supporting complex inferential capabilities.
2. Construction of a Nursing Multimodal Knowledge Graph: A robust multimodal knowledge graph has been constructed, which systematically organizes and represents nursing data. This construction facilitates improved knowledge discovery and management, serving as a foundational tool for advanced nursing informatics.
3. Application in Precision Nursing and Visualization Platform Development: The knowledge graph has been effectively applied in precision nursing to support personalized care and clinical decision-making. Additionally, we have developed a corresponding visualization platform that enables real-time interaction with the graph, significantly enhancing the practical utility of the graph in clinical settings and educational training.

The structure of the remaining sections in this paper

The structure of the remaining sections in this paper is outlined as follows. Section 2 provides an overview of related work in Precision Nursing and knowledge graph. In Section 3, we delve into the details of a method for con- structing a nursing multimodal knowledge graph. Section 4 presents the experimental results, followed by a validation experiment. Section 5 discusses the innovations and limitations of this paper. Lastly, Section 6 offers our conclusions and outlines directions for future research.

Related Work

This section initially presents the advancements in precision nursing research Section 2.1, followed by an exploration of the application background of knowledge graphs in the medical field Section 2.2, and ultimately concludes with a summary of the prospects of multimodal knowledge graphs in the field of nursing Section 2.3.

Advances in Precision Nursing Research

The establishment of the International Society of Nurses in Genetics (ISONG) in 1988 marked the initiation of scientific exploration in the field of nursing within the con- text of the human genome.[7] Under the impetus of the Precision Medicine (PM) trend, precision nursing has seen significant development. In 2008, Clayton Christensen, a business strategist at Harvard Business School, introduced the term "precision medicine" to replace the earlier concept of personalized medicine.[18] In 2011, the National Institutes of Health (NIH) in the United States published the "Toward Precision Medicine" blueprint, garnering global attention for precision medicine.[1] Following closely in 2012, the National Institute of Nursing Research (NINR), a subsidiary of the NIH, established the Precision Nursing Science Advisory Board. This organization, through public input solicitation, evidence review, and expert discussions, identified health issues within the nursing discipline that could benefit from genomic information and issued the Nursing Genomic Science Blueprint.[18] This blueprint emphasized the application of genomics from a nursing perspective for the maintenance of human health.

As nursing professionals incorporate the concept of precision nursing into their daily practice, the definition and scope of precision nursing continue to evolve and expand. Scholars from various disciplines have attempted to elucidate the definition of precision nursing. In 2015, Yuan defined precision nursing as a modernized nursing management model that relies on real-world data to discern patterns in patient care issues, predict nursing risk factors, and implement evidence-based, targeted, individualized, and accurate nursing measures to preempt and mitigate patient health problems.[27] In 2017, Fu et al proposed that precision nursing, rooted in the concepts of precision medicine and precision health, involves precise phenotypic analysis or deep phenotypic analysis by nurses.[6] It results in ac- curate nursing practices tailored to the appropriate patients at the right time, maximizing treatment efficacy. In 2020, Ielapi argued that precision nursing aligns with the objectives of precision health by combining patient information with genomics, lifestyle, environmental factors, and social characteristics.[8] This yields information about disease susceptibility, exposure, characteristics, evolution, and treatment response to enhance disease prevention and nursing strategies.

In 2020, the Precision Medicine Application Society of Guangdong Province issued a group standard for the "System of Precision Nursing," which defined precision nursing as the application of advanced technologies such as genomics, the internet, big data, and artificial intelligence in the development of nursing. It involves the analysis of biological, environmental, and lifestyle factors related to patient symptoms, signs, and disease characteristics throughout the patient's lifecycle, delivering precise, timely, and individualized comprehensive nursing services.[14]

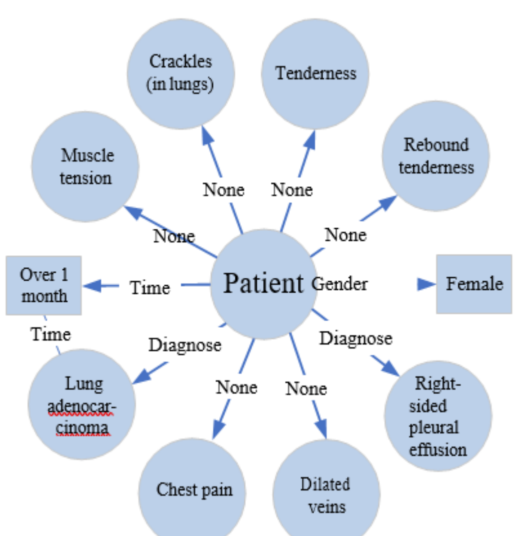
Precision nursing necessitates adherence to fundamental elements such as precision, timeliness, sharing, and individualization, with a strong emphasis on accurately identifying individual characteristics and needs while formulating personalized nursing measures to maximize treatment effective- ness.[27] Among these elements, accurate and specialized nursing knowledge stands as a pivotal factor in realizing precision nursing.

Advances in Knowledge Graph

A knowledge graph is a structured representation of concepts, entities, and their relationships in the objective world. It serves as a means to organize, manage, and understand vast amounts of information data, with broad applications. Initially, knowledge graphs were popularized by Google as a knowledge base, using semantic retrieval to enhance the quality of Google search results.[13] Knowledge graphs possess powerful semantic processing capabilities, making them suitable for the rational representation and utilization of medical knowledge, thereby offering robust support for the advancement of medicine. Volot F structured medical knowledge based on concept graphs.[21] Dai and Guo et al conducted research on predicting drug interactions using similarity mining on a large-scale structured text knowledge graph.[3] Kamsu-Foguemassociated medical concepts with African traditional medicine using a knowledge graph.[9] Dong Xperformed information fusion on the web based on a knowledge graph.4 Paulheim et al surveyed refinement and evaluation methods for knowledge graphs.16 In the field of healthcare in China, there have also been studies related to knowledge graph construction. For example, Zheng used a knowledge graph approach to identify common keywords in medical informatics literature.28 Rotmensch and Halpern organized the content of the "Medical Equipment" journal into a knowledge graph, providing an intuitive representation of the fields and topics covered by the journal.[17] Weng H and colleagues researched the construction of a knowledge graph for traditional Chinese medicine.[24] Yin Y and colleagues, based on the construction of a traditional Chinese medicine knowledge graph, developed intelligent applications for medical knowledge.[26]

Medical knowledge graph encapsulates the corpus of knowledge residing within the domain of medicine. For instance, leveraging information extracted from a patient's medical records, one can create a medical knowledge graph, as elucidated in Figure 1. Nevertheless, it is imperative to underscore that these knowledge graphs conventionally comprise unimodal data, predominantly composed of textual information.

Figure 1. A typical medical knowledge graph depicting the complex interconnections among various types of entities such as diseases, symptoms and treatments.



Advances in Multimodal Knowledge Graph

In reality, knowledge is not confined solely to text-based data but extends to diverse modalities such as videos, images, and more. Multi-modal knowledge graphs represent a novel class of knowledge graphs designed to address the diversity of data modalities, garnering significant attention in academia,[10] and showcasing extensive potential applications.[25] These knowledge graphs incorporate various modalities, including text, images, videos, audio, and more, thereby embodying cross-modal and multi-class relation-ships. However, at their core, they remain a form of semantic network-based relational data structure.

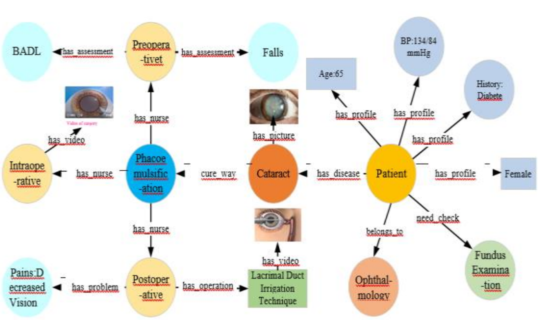
The evolution of multi-modal knowledge graph research has initially revolved around two predominant modes: im- ages and text.[10, 2] Liu laid the foundation by defining multi-modal knowledge graphs, beginning with tasks such as link prediction and ontology matching.[12] These knowledge graphs encompass numerical features, images, and entity alignments across multiple knowledge graphs. multimodal knowledge graphs were constructed based on traditional knowledge graphs, introducing entities in multiple modalities and semantic relationships among entities across various modalities.[22] Sun defined multimodal knowledge graphs as knowledge graphs incorporating multiple data types, such as text and images, integrating visual or textual information into the knowledge graph by treating images or text as entities or entity attributes.[19] While existing research has contributed significantly to the understanding of multi-modal knowledge graphs, their general conceptualization remains relatively straightforward: knowledge graphs enriched with multi-modal ontologies and attributes. Based on these enriched knowledge resources, they serve roles in physical demonstrations, ambiguity resolution, detail augmentation, semantic comprehension, and interpretable inference, thus promoting enhanced knowledge utilization.[20]

In the current medical field, most knowledge graphs are primarily constructed based on textual data, such as medical records and literature. However, within medical systems, there exists a wealth of diverse multimodal information, including images, expressions, videos, and audio, among others, which has not yet been fully leveraged.[29] These multi-modal data can describe objects through various structural features and representations, thereby enabling a more comprehensive and accurate presentation and assessment.[26]

Moreover, current medical knowledge graphs primarily focus on the clinical diagnosis domain, with limited application in nursing field. In fact, there is an equally urgent need for specialized knowledge graphs in the nursing domain. A knowledge graph designed specifically for nursing could encompass information related to nursing guidelines, nursing processes, common nursing issues, and various other aspects, providing invaluable guidance and support to nursing professionals.

In order to explore the application of multimodal knowledge graph in precision nursing, our study includes the following two aspects: (1) The construction of multimodal knowledge graph: This involves collecting and integrating nursing data, performing knowledge extraction, and representing knowledge in the form of (entity, relationship, entity) triples.

Figure 2. Illustration of the proposed nursing multimodal knowledge graph centered around patient, disease and nursing diagnoses entities, integrating diverse data types like text and images into a cohesive structure.



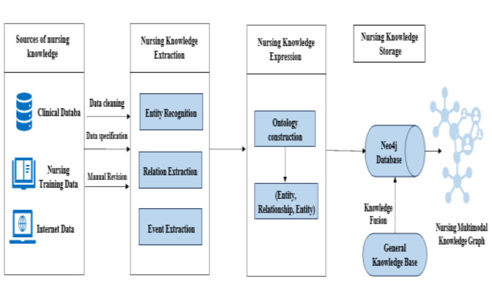
As an illustrative example, we plan to construct a multimodal knowledge graph for the clinical nursing of cataracts, including text, images, videos, and other information, as shown in Figure 2. Figure 2. illustrates the complete nursing process for a patient as recorded through a multimodal knowledge graph, encompassing vital signs, assessments, nursing problems, and the corresponding nursing techniques applied. (2) Precision nursing practices: This includes the creation of personalized nursing records for patients, semantic searches for clinical nursing, real-time nursing Q&A, and the provision of personalized nursing decisions.

METHODS

In this study, we proposed a four-stage methodology for constructing a nursing multimodal knowledge graph, based on an analysis of nursing data content and features. This methodology draws parallels with the construction of single- modal knowledge graphs, with the primary distinction lying in the mapping and integration of multi-modal nursing knowledge with existing ontological knowledge. The four stages include "Source Identification, Knowledge Extraction, Knowledge Representation, and Model Evaluation".[16]

The construction of a nursing knowledge graph begins with the extraction and structuring of knowledge from various sources, such as clinical databases, nursing training repositories, and internet data. This process involves leveraging knowledge extraction and fusion techniques. The structured knowledge is then stored in a database, enabling the creation of a nursing knowledge graph. This graph, in turn, supports the development of nursing semantic search engines, nursing question-answering systems, and nursing decision support systems. Please refer to Figure. 3 for a detailed illustration of the construction process.

Figure 3. Workflow for constructing a nursing multimodal knowledge graph.



Knowledge Source Identification

This refers to the process of recognizing and determining the sources of clinical nursing knowledge. It is crucial to identify the data sources for various modalities of informa- tion when constructing a multimodal graph. The primary sources of data for the nursing multimodal knowledge graph are threefold: nursing record sheets (clinical database), Web data (including Wikipedia and Baidu Baike), and nursing training data. Taking "pressure ulcers" as an example, relevant web data related to "pressure ulcers" is obtained from Internet, and empirical data is extracted from clinical nursing materials.

The processing of nursing record sheets mainly involves extracting key terms from the Excel files and storing them in a dictionary format, for example, "Temperature": "37.5". The Web data and nursing guidelines consist of unstructured data written in natural language. The processing of such un- structured textual data primarily employs NLP techniques. Utilizing NLTK's NLP tools, the raw textual data undergoes tokenization and part-of-speech tagging. Referring to Table 1's 17 types of entity labels, the Doccano tool is used to annotate the original text in the BIO format (where, X_B represents the beginning of entity X, X_I represents the end of the entity, and O indicates a segment belonging to no category). The preprocessed textual data is then divided into training, testing, and validation sets in a 7:2:1 ratio, facilitating subsequent named entity recognition tasks.

The processing of images and videos is carried out through semi-automatic and manual methods. If there are titles or descriptive words around the image or video, the keywords from this text are used as the entity name, with the image or video serving as attributes of that entity. If the images and videos exist in isolation, they are defined manually through tagging (entity, image or video attribute). Ultimately, all images and videos are assigned labels.

The preliminary work of data processing and annotation was primarily carried out by three nursing graduate students from our team, while the review process was mainly con- ducted by two senior nurses, taking about one month to complete. The processed data comprises 13,200 text entries, 2,600 images, and 362 videos, all refined for academic purposes.

Nursing Knowledge Extraction

Knowledge extraction is the process of delving deeper into implicit knowledge on top of information extraction, providing raw materials and content for the construction of a nursing multimodal knowledge graph. In the traditional process of constructing knowledge graphs, knowledge extraction primarily focuses on extracting implicit knowledge within a domain and often relies on manual implementation. Based on the structure and modal characteristics of clinical nursing data, knowledge extraction mainly includes entity recognition, and relationship extraction.

In the process of knowledge extraction, defining entities is the most fundamental task. Based on the characteristics of clinical nursing data, nursing entity types are summarized using expert experience and mainly include the following types: disease names and symptom names (e.g., hypertension, diabetes), drug names and treatment methods (e.g., drug names, surgical methods), medical equipment (e.g., respirators, infusion pumps), nursing plans and measures (e.g., turning in bed, vital sign measurement), health indicators (e.g. temperature, blood pressure), patient information (including personal basic information, medical history), nursing records (such as nursing issues, nursing measures), nursing knowledge and guidelines (e.g., nursing procedures, operational standards), and nursing education resources (e.g., training materials, instructional videos).

In this paper, the extraction of nursing knowledge is divided into two steps. First, nursing entities are identified from the data; second, the relationships between these nursing entities are extracted.

Named entity recognition primarily targets unstructured textual data. In this study, we primarily employ a deep learning approach based on BiLSTM-CRF for entity recognition.[11] Specifically, annotated word vectors are input into BiLSTM for bidirectional encoding, obtaining long-sequence semantic features of the text. Sequence decoding is then performed through a Conditional Random Field (CRF) to learn the dependencies between labels, resulting in the optimal label sequence. Ultimately, entities within the nursing field are identified through this sequence.

Relation extraction is conducted using a rule-based template method, utilizing relationships between entities in the nursing field as relational words in the relational triplets. The steps of relation extraction are as follows: First, 20 rule templates are defined based on the concepts in the nursing field entity vocabulary and the relationships between these concepts. For example, the relation (has_measures) represents the relationship between the entities Nursing Problem and Nursing_Measure. Then, if a sentence contains a pair of entities corresponding to a rule, the entity pair and the corresponding relationship are combined to form a relational triplet. If a sentence contains three or more entities, an array is created and named after the entity types to temporarily store the entities. All entity types are first combined pair- wise; if two types of entities correspond to a rule, the entities in the corresponding arrays are combined, otherwise, they are not combined.

Nursing Knowledge Representation

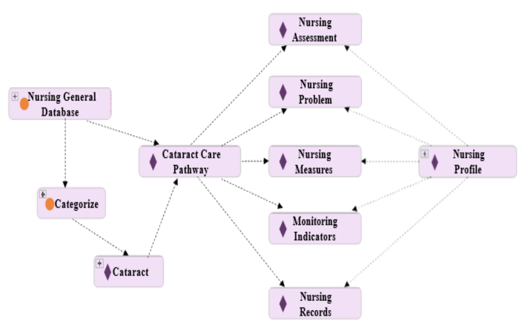
Knowledge representation involves using ontology technology to semantically represent multimodal knowledge. Nursing terminology is described using web ontology language to clearly define classes, properties, and instances related to cataracts. In Protege, OntGraf is used to create classes, instance relationships, and construct a knowledge graph for cataract nursing pathways.

This includes three classes: "Nursing Pathway Information Repository," "Dis- ease," and "Nursing Procedure," along with their corresponding seven instances. Associations between instances such as "Cataract Nursing Pathway" and instances of common nursing procedures are established using properties, as illustrated in Figure. 4.

Nursing Knowledge Storage and Presentation

Once unstructured raw nursing data undergoes knowledge extraction and knowledge representation, structured nursing knowledge Triples can be obtained. Neo4j is a high-performance graph database management system that uses a graph data gemodel to represent data, storing entities and relationships from knowledge triples through nodes and edges. For instance, the nursing measure ’Install bed rails’ for the nursing diagnosis of ’Impaired Physical Mobility’ can be stored in a knowledge base using the triplet (Impaired Physical Mobility, has measure, install bed rails). Additionally, Neo4j provides visualization tools that facilitate knowledge querying and management. Therefore, we adopt Neo4j to store and display the nursing multimodal knowledge graph.

Figure 4. Construction of a nursing knowledge ontology: Taking cataracts as an example, a nursing knowledge pathway was constructed to encompass the disease, nursing processes, and nursing techniques.



RESULTS

Using the knowledge graph construction method deibed in Chapter 3, we utilized clinical databases, nursing training databases, and internet data to construct a nursing multimodal knowledge graph through steps including knowledge extraction, knowledge representation, and knowledge storage. Ultimately, we established a nursing multimodal knowledge graph comprising 62,909 entities and 330,285 relationships. Fig. 5 provides an overview of this knowledge graph. The entities encompass 17 types, including patients, diseases, examinations, medications, nursing techniques, nursing procedures, nursing assessments, nursing measures, images, videos, and more. The relationships consist of 20 types, such as drugs_of, has_assessment, has_disease, has_profile, has_symptom, and others. Table 1 presents statistics on the number of entities and relationships in this nursing multimodal knowledge graph.

For instance, (Patient, has_profile, Profile) is used to storage personal information about patients, including age, gender, and other records. (Disease, has_video, Video) represents teaching videos corresponding to diseases. (Disease, has_nurse, Nursing_Technique) signifies nursing techniques associated with diseases. (Nursing_Technique, has_operation, Nursing_Operation) indicates the operational steps associated with nursing techniques.

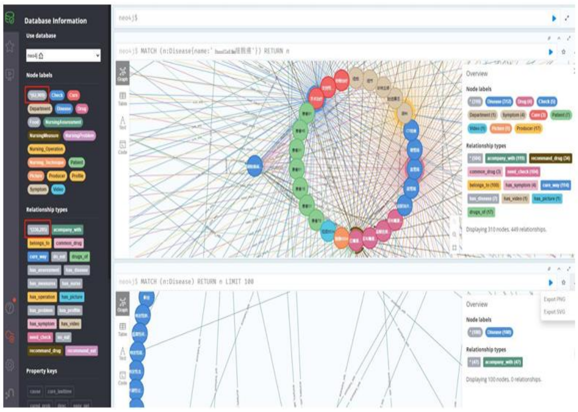


Figure 5. Overview of the constructed nursing multimodal knowledge graph, which includes 62,909 entities and 330,285 relationships.

Table 1. Quantity Statistics of nursing multimodal knowledge graph's Entities and Relationships.

Entities	Quantity	Relationships	Quantity
Patient	100	belongs_to	8864
Profile	2054	cure_way	21050
Check	3353	acompany_with	12029
Cure	544	common_drug	14649
Disease	8808	do_eat	20238
Symptom	5998	drugs_of	17315
Drug	3828	has_assessment	709
Nursing Operation	3929	has_disease	132
Nursing Technique	192	has_measures	728
Nursing Assessment	709	has_nurse	22053
Department	54	has_operation	960
Food	4870	has_picture	7705
NursingMeasure	728	has_problem	756
Nursing Problem	128	has_profile	1276
Producer	12701	has_symptom	54717
Video	7208	has_video	7208
Picture	7705	need_check	39423
		no_eat	22247
		recommand_drug	57990
		recommand_eat	20236
Total: 62909		**Total: 330285**	

Based on the constructed multimodal knowledge graph described above, it can be primarily applied in precision nursing research, with a focus on the following aspects: building personalized patient care profiles, clinical nursing semantic search, nursing question-answering system and nursing decision-making respectively.

Construction of Personalized Patient Care Profiles

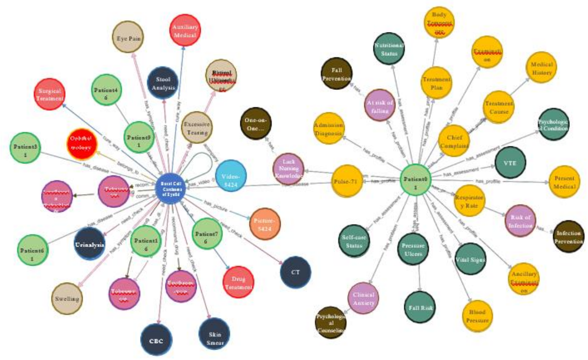
Data collection for personalized patient care profiles involves gathering information from various sources, including hospital information systems, health records, laboratory results, and medical imaging data. These data can take the form of text, images, videos, or other formats, creating a multimodal dataset. The collected data undergoes preprocessing to ensure accuracy, completeness, and consistency. Additionally, the raw patient data is subjected to anonymization (medical number) and encoding processes, adhering to strict privacy and data security regulations and standards to safeguard sensitive patient information. Using knowledge graph technology, different types of data are connected and related. For instance, linking a patient's basic information.

symptoms, diagnostic results, and treatment plans forms a comprehensive knowledge graph. Attributes and labels are added to each node and edge to enrich the knowledge graph's information. For symptom nodes, attributes such as time information, severity, and frequency can also be included. Since a patient's health status may change over time, personalized care profiles are continually updated by continuously adding new data and information to maintain accuracy and utility.

Ultimately, personalized patient care profiles are created, providing a solid foundation for clinical nursing decision- making. Figure. 6 illustrates some personalized care profile information we have constructed for Patient01. Centered

around the patient, relationships such as has_profile, has_assessment, has_nurse, and has_disease are used as edges to build Patient 01's personalized care profile. The use of the has_disease relationship bridges connections to disease knowledge repositories centered around Disease, incorporating relationships like has_symptom, drugs_of, need_check, and others. Together, these components form a knowledge graph that can be directly applied to clinical nursing. Through a nursing multimodal knowledge graph, various physiological indica- tors, clinical diagnoses, nursing assessments, and nursing interventions of patients can be systematically documented. This facilitates the subsequent provision of precise nursing plans for patients.

Figure 6. Personalized nursing profiles of patient 01.



Clinical Nursing Semantic Search

In the context of precision nursing research based on a multimodal knowledge graph, clinical nursing semantic search refers to the process of using the graph as a database. It involves defining keywords and terms and employing query languages or tools to retrieve information related to specific clinical nursing questions within the knowledge graph. Through semantic search, healthcare professionals can rapidly identify nodes and edges related to particular medical conditions, symptoms, or nursing issues, thereby obtaining comprehensive and accurate nursing advice and decision support. Additionally, semantic search can employ semantic inference techniques to expand the search scope and locate other nodes and information associated with the search target, providing healthcare professionals with more comprehensive nursing support.

Moreover, clinical healthcare providers can conveniently use semantic search for knowledge retrieval and skill training. Figure. 7 illustrates nursing techniques related to common ophthalmic diseases such as cataracts and retinal detachment. For instance, if a novice nurse wishes to understand the nursing procedures for cataracts, they can perform a search using keywords like "cataracts" and "has_nurse." This allows them to quickly access nursing guidance for that particular disease.

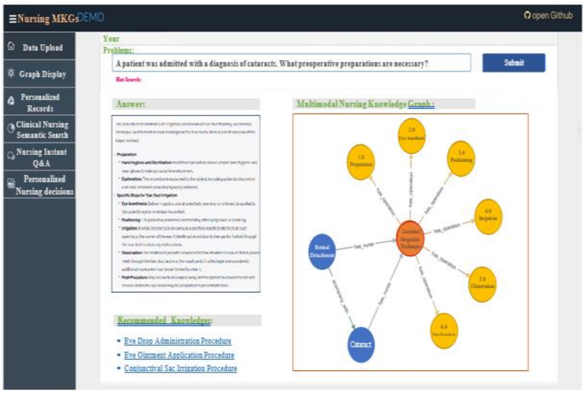
Figure 7. Semantic search for clinical care of cataracts.

Clinical Nursing Instant Question-Answering

In precision nursing research based on a nursing multi- modal knowledge graph, a nursing question-answering system is a crucial application tool. This system leverages in- formation and data from the nursing multimodal knowledge graph to provide real-time and accurate answers and guidance to healthcare professionals for nursing-related questions. Healthcare providers can input keywords or problem descriptions, and the system utilizes the nursing multimodal knowledge graph to conduct semantic searches and provide corresponding nursing advice and solutions.

The nursing question-answering system based on the nursing multimodal knowledge graph offers healthcare professionals a convenient and rapid means of accessing nursing information and knowledge. It assists them in making more scientific and personalized nursing decisions, thereby enhancing nursing quality and patient treatment outcomes. Furthermore, the system promotes knowledge sharing and exchange in the nursing field Figure. 8 displays an interface for a question-answering system built upon the nursing multimodal knowledge graph. The interface includes modules on the left side for data upload, patient record management, clinical semantic search knowledge question-answering, and more. The central part of the interface is dedicated to the question-answering module, featuring question input at the top, answers and the display of relevant knowledge graph below, and knowledge recommendations at the bottom. This system integrates data collection, knowledge question-answering, and intelligent decision-making and has demonstrated excellent application results in clinical practice within our ophthalmology department.

Figure 8. Nursing knowledge instant Q&A interface, which integrates NMKG.



Personalized Nursing Decision-Making

Utilizing the nursing multimodal knowledge graph, it is possible to construct a nursing decision support system for automated diagnosis. This system can provide nursing diagnoses and care plans based on symptoms and signs, assisting nurses in making timely and accurate nursing diagnoses and thereby enhancing the quality of nursing work. The nursing decision support system based on the nursing knowledge graph primarily completes the decision support process through an inference engine. When users input symptoms and signs, the inference engine uses the knowledge graph and user input to provide diagnostic results or suggest the next steps for nursing care.

According to the nursing multimodal knowledge graph, if Patient 02 is over 65 years old, has experienced falls in the past three months, and has more than one medical diagnosis, the nursing decision system can assess the patient's fall risk and provide corresponding nursing measures. It

Experimental Validation

To evaluate the application effectiveness of the multi- modal knowledge graph in nursing practice, we utilized the clinical nursing question-answering system from Section 4.3 as the experimental platform. This allowed us to measure the reliability of the inference-based question-answering results derived from the nursing multimodal knowledge graph. For comparative reference, we utilized the expert historical ex- periential knowledge provided by three senior nurses. The reliability of the answers was measured using the Normal- ized Discounted Cumulative Gain (NDCG),[23] a common metric in search and recommendation tasks. The calculation formula is described as following:

$$NDCG = \frac{DCG}{IDCG} \tag{1}$$

where, Discounted Cumulative Gain (DCG) refers to the sequence of answers to clinical questions generated by the nursing question-answering system. The ideal DCG (IDCG) represents the optimal sequence of answers to clinical questions based on expert historical experience. NDCG indicates the ratio of the answer sequence generated by the question- answering system to the ideal answer sequence provided by experts. The closer the ratio is to 1, the more reliable the system’s answers to clinical questions are deemed. The calculation formula for DCG is as following:

$$DCG_k = \sum_{i=1}^{k} \frac{rel(i)}{\log_2(i+1)} \tag{2}$$

where, $rel(i)$ represents a relevance score associated with the inference result; i denotes the current position in the sequence of clinical question results.

Taking the clinical question "What are the nursing measures for a patient nursing diagnosed with ’Impaired Physical Mobility’ during the acute phase?" as an example, based on expert experience, table 2 provides the top 4 nursing measures for the acute phase of "Impaired Physical Mobility" ranked by importance and scored. Subsequently, IDCG is calculated as 1.97 to serve as the evaluation criterion.

Table 2. Top 4 Nursing Measures for "Impaired Physical Mobility", Ranked and Scored Based on Expert Experience (IDCG).

I	rel(i)	log2(i+1)	rel(i)/ log2(i+1)
1=Install bed rails	0.9	1	0.9
2= Provide 24-hour bedside assistance	0.8	1.59	0.5
3=Regularly change the patient’s position	0.7	2	0.35
4=Guide the patient in passive exercises	0.5	2.32	0.22
IDCG			1.97

Meanwhile, the top 4 nursing measures for "ImpairedPhysical Mobility" during the acute phase, as ranked and scored by the nursing question-answering system, are shown in Table 3, resulting in a DCG of 1.94.

Based on this, the NDCG is calculated as NDCG = DCG / IDCG = 1.94 / 1.97 = 0.984. This indicates that the answers calculated by the nursing question-answering system, based on the multimodal knowledge graph for the nursing measures corresponding to "Impaired Physical Mobility", closely align with expert experience. This is be- cause the knowledge graph stores entities labeled as "nursing diagnoses" and entities labeled as "nursing measures", along with their corresponding relationship "has_measure". Nurses can query and display relevant results through the nursing question-answering system, offering crucial profes- sional knowledge support to enhance their ability to analyse and solve clinical problems.

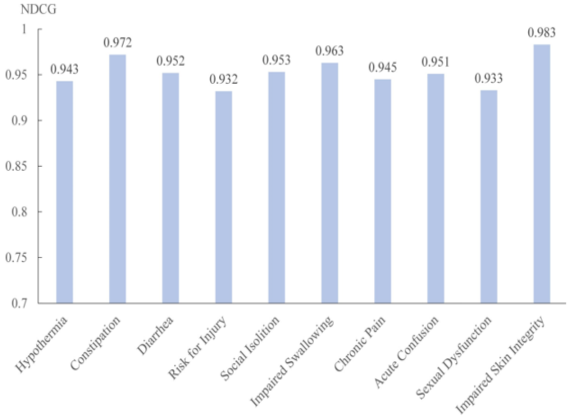
We further assessed the NDCG of this nursing

Table 3. Top 4 Nursing Measures for "Impaired Physical Mobility" as Ranked by the Nursing Question-Answering System (DCG)

I	rel(i)	log2(i+1)	rel(i)/ log2(i+1)
1= Provide 24-hour bedside assistance	0.8	1	0.8
2= Install bed rails	0.9	1.59	0.57
3=Regularly change the patient's position	0.7	2	0.35
4=Guide the patient in passive exercises	0.5	2.32	0.22
DCG			1.94

question- answering system for 10 common nursing diagnoses in different departments, which include Hypothermia, Constipation, Diarrhea, Risk for Injury, Social Isolation, Impaired Swallowing, Chronic Pain, Acute Confusion, Sexual Dysfunction, and Impaired Skin Integrity. The reliability evaluation of the inference answer results is shown in Figure 9. The horizontal axis corresponds to 10 different nursing problems, and the vertical axis corresponds to the NDCG calculation results for individual nursing problems. As evident, the inferential performance of this question-answering system on 10 types of nursing problems is not less than 0.932, with an average reaching 0.953. This demonstrates not only the reliability of the system in computing individual nursing diagnosis inference results but also its robustness and generalization ability in inferential analysis across multiple nursing diagnoses.

Figure 9. NDCG valuation results for 10 typical nursing diagnoses.



DISCUSSION

In this study, we have successfully constructed a mul- timodal knowledge graph consisting of 60,000+ nodes. Our experimental results demonstrate that the multimodal knowledge graph exhibits considerable accuracy and relia- bility in clinical nursing question-answering. The primary objective of our research was to explore the potential appli- cations of this knowledge graph in the realm of precision nursing. Our findings suggest that the utilization of multi- modal knowledge graphs in precision nursing holds great promise and could significantly impact clinical practice and patient care.

One of the key advantages of the nursing multimodal knowledge graph lies in its ability to effectively integrate a wide array of data types, including clinical databases, nurs- ing training databases, and internet-sourced data. This amal- gamation creates comprehensive patient health records and extensive nursing knowledge repositories. These valuable resources empower nursing professionals to gain a deeper and more accurate insight into patients' medical conditions, thereby facilitating the formulation of highly personalized nursing interventions.

Moreover, our research indicates that the incorporation of multimodal knowledge graphs in precision nursing has the potential to yield substantial improvements in clinical outcomes. By leveraging multimodal data analysis, nursing professionals can proactively predict disease risks, develop tailored care plans, and swiftly identify patients' unique requirements. This not only reduces unnecessary medical interventions but also enhances treatment efficacy, reduces overall healthcare costs, and ultimately enhances the quality of life for patients. Utilizing knowledge graphs to store patient care records and associated nursing knowledge facilitates the efficient creation of a tailored nursing system. This approach empowers nursing staff to effectively manage and monitor patients' clinical statuses via a nursing multimodal knowledge graph, thereby enabling the customization of care plans to meet individual patient needs.

To apply multimodal knowledge graphs in precision nursing, providing nurses with a user-friendly interface is essential.

The development of such an interface facilitates nursing staff to easily access and interpret information from the knowledge graph, as well as conveniently upload knowledge with quality control measures in place. Furthermore, the use of advanced analytics and retrieval algorithms is crucial for extracting meaningful insights from multimodal data and predicting potential nursing interventions. Additionally, integrating nursing multimodal knowledge graph into general large language models (LLMs) for knowledge enhancement, thereby fine-tuning LLMs specific to the nursing domain, represents significant research.

However, T this study has several limitations. First, approximately 85% of the original nursing data was sourced from publicly available data on the internet, with only about 15% derived from professional materials internal to hospitals. Consequently, the quality and professionalism of the nursing knowledge extracted from these sources may not be as robust. Second, due to the limited capabilities of our team and time constraints, we only verified the reliability of the nursing multimodal knowledge graph in clinical question-answering scenarios.

Its full validation in clinical nursing to assess its impact on patient quality of life has not yet been conducted.

Third, this paper lacks comparable literature for discussion, resulting in an absence of a comparison with peers. Despite these shortcomings, our research still holds considerable innovativeness and practical clinical relevance.

CONCLUSIONS

In conclusion, our research underscores the transformative possibilities that multimodal knowledge graphs offer in the field of precision nursing. By integrating various types of data to establish a nursing multimodal knowledge graph, nursing professionals can manage and perceive patients' clinical conditions, thereby formulating personalized care plans. Concurrently, nursing staff can utilize this knowledge graph to query and learn diverse nursing knowledge, enhancing the efficiency of clinical care.

While challenges exist in terms of data integration and infrastructure requirements, the potential benefits far out- weigh these limitations. As we move forward, further refinement and expansion of the nursing multimodal knowledge graph will be a priority. This will enable us to explore its application across various nursing domains, ultimately advancing the frontiers of precision nursing and healthcare delivery.

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