

MEDMKG: Benchmarking Medical Knowledge Exploitation with Multimodal Knowledge Graph

Xiaochen Wang¹ Yuan Zhong¹ Lingwei Zhang¹ Lisong Dai²

Ting Wang³ Fenglong Ma^{1*}

¹Pennsylvania State University, USA

²Renmin Hospital of Wuhan University, China

³Stony Brook University, USA

¹{xcwang, yfz5556, lingwei, fenglong}@psu.edu

²lisong-dai@outlook.com, ³twang@cs.stonybrook.edu

<https://github.com/XiaochenWang-PSU/MedMKG>

<https://huggingface.co/datasets/xcwangpsu/MedMKG>

Abstract

Medical deep learning models depend heavily on domain-specific knowledge to perform well on knowledge-intensive clinical tasks. Prior work has primarily leveraged unimodal knowledge graphs, such as the Unified Medical Language System (UMLS), to enhance model performance. However, integrating *multimodal* medical knowledge graphs remains largely underexplored, mainly due to the lack of resources linking imaging data with clinical concepts. To address this gap, we propose MEDMKG, a **Medical Multimodal Knowledge Graph** that unifies visual and textual medical information through a multi-stage construction pipeline. MEDMKG fuses the rich multimodal data from MIMIC-CXR with the structured clinical knowledge from the Unified Medical Language System (UMLS), utilizing both rule-based tools and large language models for accurate concept extraction and relationship modeling. To ensure graph quality and compactness, we introduce Neighbor-aware Filtering (NaF), a novel filtering algorithm tailored for multimodal knowledge graphs. We evaluate MEDMKG across **three** tasks under **two** experimental settings, benchmarking **twenty-four** baseline methods and **four** state-of-the-art vision-language backbones on **six** datasets. Results show that MEDMKG not only improves performance in downstream medical tasks but also offers a strong foundation for developing adaptive and robust strategies for multimodal knowledge integration in medical artificial intelligence.

1 Introduction

Deep learning has demonstrated remarkable success in the medical domain, enabling tasks such as health risk prediction, disease diagnosis, and mortality forecasting [1]. However, medical data often suffer from noise and missing values, limiting the effectiveness of feature representation learning. To address these challenges, researchers have increasingly integrated *unimodal* medical knowledge graphs into deep learning frameworks. These graphs offer structured and explicit representations of domain knowledge by encoding well-defined medical concepts and their relationships [2]. Incorporating such structured knowledge has led to notable improvements in different tasks, including health risk prediction [3], adverse drug reaction prediction [4, 5, 6], and medical coding [7].

Nevertheless, many important clinical tasks require **multimodal** data as model inputs, such as medical visual question answering (VQA) and text-image retrieval. Relying solely on unimodal

*Corresponding Author.

medical knowledge graphs in these contexts often fails to yield significant performance gains, due to the absence of explicit relationships between visual data and medical concepts. This limitation has hindered the ability of current multimodal deep learning models to fully capitalize on domain knowledge in knowledge-intensive tasks. Addressing this gap necessitates the development of a comprehensive multimodal medical knowledge graph. However, building such a resource introduces the following critical challenges:

- **C1: Quality Concern.** A multimodal medical knowledge graph must be of high quality and practical utility. This includes the accurate identification and representation of diverse intra- and inter-modal relationships, which requires a carefully designed and systematically implemented construction process.
- **C2: Utility Concern.** Beyond quality, it is essential to evaluate whether the graph can effectively enhance model performance on downstream tasks. The graph must encode clinically meaningful multimodal knowledge that directly supports a wide range of knowledge-intensive applications.

To bridge this research gap and address the identified challenges, we introduce MEDMKG, a **Medical Multimodal Knowledge Graph** that unifies visual and textual medical information. To tackle **C1 (Quality Concern)**, we develop a multi-stage construction pipeline that ensures high-fidelity cross-modal integration by combining the rich visual and textual information in MIMIC-CXR [8] with the structured clinical knowledge in the Unified Medical Language System (UMLS) [9]. Our method leverages the domain accuracy of rule-based tools together with the contextual reasoning capabilities of large language models (LLMs), enabling precise extraction of clinical concepts and their relationships. To further ensure conciseness and informativeness, we propose a simple yet effective Neighbor-aware Filtering algorithm (NaF) to enhance the quality of MEDMKG by ranking and filtering medical images. Both expert qualitative evaluations and quantitative benchmarking validate that MEDMKG achieves high quality and is well-suited for practical downstream use.

To address **C2 (Utility Concern)**, we conduct extensive experiments across two complementary settings to demonstrate the practical utility of MEDMKG. First, in the setting of knowledge graph analysis, we assess the intrinsic quality of MEDMKG through a link prediction task. Second, in the setting of knowledge graph augmentation, we integrate MEDMKG into downstream applications including medical text-image retrieval and visual question answering. Our comprehensive evaluation spans 24 baselines, 4 vision-language backbones, and 6 datasets covering 3 distinct tasks. This broad evaluation framework allows us to systematically explore how MEDMKG contributes to downstream performance. From these experiments, we derive several key insights:

- *Model Choice Should Align with Graph Structure:* Effective modeling of multimodal medical knowledge graphs requires selecting well-suited network architectures to handle their heterogeneous and relational nature, underscoring the importance of matching model design to graph characteristics.
- *External Knowledge Improves Downstream Tasks:* Incorporating structured medical knowledge consistently enhances downstream applications such as image–text retrieval and visual question answering, though the extent of improvement depends on the integration strategy and the underlying model architecture.
- *Balancing Knowledge Integration and Model Robustness:* While external knowledge generally improves coverage and reasoning capability, it also introduces challenges related to precision, recall and overfitting, highlighting the need for selective and adaptive knowledge fusion mechanisms.
- *Future Work Needs Unified and Adaptive Frameworks:* Advancing the field will require developing integration strategies that are both backbone-agnostic and adaptable, enabling knowledge graphs to be leveraged effectively across pretraining and fine-tuning stages for robust, generalizable improvements.

In summary, our contributions are threefold:

- **Construction of MEDMKG:** We present MEDMKG, a new medical multimodal knowledge graph that integrates clinical terminology and visual instances, providing a crucial resource for the development of knowledge-intensive multimodal models.
- **Effective Multimodal Knowledge Graph Filtering Algorithm:** We introduce Neighbor-aware Filtering (NaF), a targeted metric for ranking and filtering images in the context of a multimodal knowledge graph, which helps maintain the graph’s quality and conciseness.

- **Extensive Benchmarking:** We conduct comprehensive evaluations spanning 3 tasks, 2 experimental settings, 24 baseline methods, 4 vision-language backbones, and 6 diverse datasets. Our results demonstrate that MEDMKG meaningfully improves performance on knowledge-intensive medical applications and opens the door to new adaptive fusion strategies in multimodal learning.

2 Related Work

Multimodal Learning in the Medical Domain. Multimodal learning has seen widespread application in various medical tasks, including criticality prediction [10, 11, 12, 13, 14, 15], readmission prediction [16, 10, 11], adverse drug reaction prediction [17], and medical visual question answering [18, 19, 20, 21]. Despite their success, most current multimodal methods in the medical domain are predominantly data-driven and rely on task-specific datasets rather than leveraging explicit, structured knowledge. This reliance limits their effectiveness in addressing knowledge-intensive tasks and highlights the need for developing robust, knowledge-reliable approaches and benchmarks.

Medical Knowledge Graphs. Medical knowledge graphs have become indispensable for organizing and interpreting complex biomedical data. Traditional medical knowledge bases have provided critical insights across both comprehensive systems [22, 9, 23] and specialized domains [24, 25]. These systems are typically built through extensive manual annotation, long development cycles, and the sustained involvement of domain experts. However, the labor-intensive nature of annotating medical imaging data presents significant challenges when attempting to generalize these approaches to the construction of multimodal knowledge graphs. To address scalability concerns, several automated methods have been proposed for building medical knowledge graphs. Some works focus on constructing comprehensive graphs [26, 27], while others target specific subdomains, such as pharmacology [6, 5, 4], broader biomedical fields [28, 29, 30], Covid-19 [31], etc. Although these automated approaches offer improved efficiency, they often rely on overly simplified or outdated techniques that compromise accuracy.

Multimodal Knowledge Graphs. Recent research has begun to extend traditional unimodal knowledge graphs into the multimodal realm. Existing approaches for constructing multimodal knowledge graphs typically utilize search engines [32, 33, 34], web crawlers [35, 36], or queries to open-source knowledge bases such as Wikipedia [32, 33]. While these methods perform adequately in general domains where cross-modal alignment is often achievable, the inherent limitations in retrieval accuracy can adversely affect the quality of medical knowledge graphs. This challenge is particularly pronounced in the medical domain, where precision and reliability are paramount.

3 Construction of MEDMKG

3.1 Problem Formulation

Constructing a multimodal radiological knowledge graph from scratch poses significant challenges due to the scale, complexity, and heterogeneity of data modalities. A more practical and reliable strategy is to extend an existing unimodal knowledge graph by systematically incorporating additional modalities. In this work, we formulate the construction of our multimodal radiological knowledge graph as a *modality-wise graph extension* problem.

We begin with the Unified Medical Language System (UMLS) [9], a comprehensive biomedical knowledge base that standardizes and interconnects diverse health-related vocabularies via concept unique identifiers (CUIs). UMLS offers a rich repository of medical concepts and semantic relationships, serving as the foundational backbone for structured medical knowledge integration. For example, the clinical relation “*aspirin is used to treat myocardial infarction*” is represented as a triplet (C0011849, treats, C0020538), where “C0011849” corresponds to “Aspirin” and “C0020538” to “Myocardial Infarction (Heart Attack)”.

We expand the UMLS graph by introducing radiological image nodes and establishing cross-modal edges. The resulting graph contains two types of nodes: (1) **clinical concepts**, inherited directly from UMLS, and (2) **radiological images**. It also includes two types of edges: (1) **intra-modality edges** among clinical concepts (as defined in UMLS), and (2) **cross-modality edges** that link clinical concepts to corresponding images.

To perform the multimodal extension, we leverage the MIMIC-CXR dataset [8], which consists of paired radiology reports and chest X-ray images. Details about the preprocessing of MIMIC-CXR is available in Appendix F.1. From each report, we extract relevant clinical concepts and align them with their associated images, thereby establishing meaningful cross-modal connections. This design enables the extended knowledge graph to seamlessly integrate textual and visual medical information within a unified and structured framework.

3.2 Concept Extraction

A central challenge in constructing MEDMKG lies in accurately establishing cross-modal edges between radiological images and clinical concepts. To address this, we design a two-stage pipeline that leverages the complementary strengths of rule-based systems and large language models (LLMs). Rule-based tools are highly effective in handling clinical terminologies and ontologies, offering broad coverage of domain-specific entities. In contrast, LLMs provide strong contextual understanding and disambiguation capabilities, enabling more accurate interpretation of report-level semantics. By integrating these two approaches, our pipeline achieves both the comprehensive coverage and semantic precision necessary for high-quality concept extraction and reliable cross-modal alignment.

Stage I – Concept Identification. We begin by applying MetaMap [37], a widely used rule-based tool, to each radiology report to identify candidate mentions of UMLS concepts. This step produces an exhaustive set of potential concept mappings for each mention, ensuring comprehensive coverage of clinically relevant entities. To focus on concepts with clinical significance, we filter out irrelevant semantic types based on domain knowledge. A complete list of excluded semantic types is provided in Appendix F.2.

Stage II – Concept Disambiguation. Next, we refine the candidate concepts using ChatGPT-4o [38] that considers both the full radiology report and the list of extracted candidates. For each mention, the LLM is prompted to select the most contextually appropriate concept, leveraging its strong semantic understanding to resolve ambiguity. This stage eliminates spurious or out-of-context candidates, resulting in a clean and accurate set of disambiguated clinical concepts aligned with each image.

This two-stage design enables precise and context-aware mapping of clinical concepts to radiological images, ensuring the construction of high-quality cross-modal edges in the resulting knowledge graph. Aggregating the selected concepts across all mentions in a report yields the final set of clinical concepts associated with each image.

3.3 Relation Extraction

With the clinical concepts identified, we further enrich the knowledge graph by establishing relations:

Intra-Modality Relations. We introduce edges between identified clinical concepts whenever a relation is defined between them in UMLS. Only validated relations connecting distinct concepts are added, ensuring that intra-modality relationships are medically accurate and standardized.

Cross-Modality Relations. Each image is linked to its extracted clinical concepts through cross-modality edges. However, beyond simply linking images and concepts, we also assign a semantic label to each edge to reflect the nature of the relationship. Specifically, each relation is categorized as *Positive*, *Negative*, or *Uncertain*, indicating whether the concept is supported by, contradicted by, or ambiguously discussed in the corresponding report.

While the intra-modality relations are extracted through querying the UMLS knowledge base, the cross-modal relation extraction is performed jointly with concept disambiguation. During the LLM prompting process, the model is additionally instructed to assess the semantic stance (positive, negative, or uncertain) between the image and each concept. These relation labels are used to annotate the edges accordingly. Details concerning the prompting procedure are available in Appendix F.3.

3.4 Neighbor-Aware Filtering for Image Informativeness

The full construction process produces a highly comprehensive multimodal knowledge graph. However, its large scale, with numerous images and associated concepts, creates challenges for storage, computation, and downstream analysis. In particular, many radiological images are *redundant* because they capture similar and homogeneous regions [39]. This redundancy can overwhelm subsequent

analysis and reduce graph efficiency. To improve efficiency without sacrificing knowledge quality, we introduce a filtering strategy that prioritizes the most informative and distinctive images.

Ideally, a representative medical image should be connected to multiple clinical concepts through diverse relations, making the number of its neighboring nodes a key indicator of informativeness. However, relying solely on the number of neighbors may introduce noise, as some medical concepts are linked to a large number of generic or non-discriminative images. To mitigate this, we additionally consider the distinctiveness of an image in the context of its 2-hop neighborhood. Intuitively, if a relation-concept pair is associated with only a few images, those images are likely to carry more unique and clinically informative content.

Based on this insight, we propose a **Neighbor-aware Filtering (NaF)** strategy that balances both connectivity and distinctiveness. The informativeness score of an image m is defined as:

$$\text{NaF}(m) = \sum_{(r,c) \in \mathcal{N}_m} \log \frac{M}{|\mathcal{N}_{(r,c)}|}, \quad (1)$$

where each triplet (m, r, c) represents a connection between image m , relation r , and concept c ; \mathcal{N}_m denotes the 1-hop neighbors of m ; M represents the number of medical images in the knowledge graph; and $\mathcal{N}_{(r,c)}$ is the set of images linked to concept c via relation r .

By combining these two dimensions, the designed NaF strategy effectively prioritizes images that are both rich in clinical content and contribute unique, informative knowledge to the graph. After computing the informativeness scores, we rank all images in descending order and select them from top to bottom until the full set of concepts is covered. This strategy ensures that the final graph retains maximal clinical richness and diversity while eliminating redundant or overly generic images, thereby improving scalability and downstream utility. More details of the NaF strategy algorithm are available in Appendix F.4.

3.5 Quantitative and Qualitative Analysis

To acquire an intuitive understanding of MEDMKG’s statistical characteristics and soundness of MEDMKG, we performed both quantitative and qualitative analyses.

Quantitative Analysis. MEDMKG’s statistics are detailed in Table 1. The moderate scale of MEDMKG facilitates convenient utilization in diverse application scenarios with different computational budgets. Additionally, images and concepts are intensively connected with intra- and cross-modal neighbors, promoting rich multimodal reasoning. Furthermore, Figure 2 shows the distribution of semantic types between the clinical concepts involved, indicating a broad and balanced coverage of the areas of clinical knowledge.

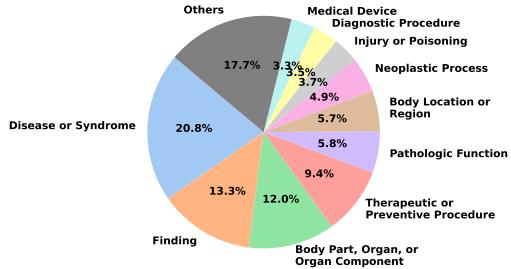
Qualitative Analysis. To further assess the quality of MEDMKG, we conducted a human evaluation with experienced radiologists. The experts reviewed a set of sampled subgraphs and assigned quality scores across three key dimensions, each rated on a scale from 1 to 10: (1) *concept coverage* — whether the graph captures the key image-related clinical concepts; (2) *relation correctness* — whether the cross-modal relations are accurately identified; and (3) *image diversity* — whether the linked images reflect a broad range of clinical scenarios. Higher scores indicate better performance on each metric. As illustrated in Figure 1, MEDMKG achieves an average of approximately 80% across all three metrics, indicating its reliability and practical utility as a multimodal medical knowledge source. Further details on the evaluation protocol are provided in Appendix G. An illustration of the constructed MEDMKG is available in Appendix F.5.

4 Benchmark

In this section, we evaluate MEDMKG under two complementary scenarios: **knowledge graph analysis** and **knowledge graph augmentation**. In the knowledge graph analysis setting, we assess tasks that directly utilize the internal structure and semantics of the graph. Specifically, we focus on the widely adopted task of *link prediction*, which serves as a standard benchmark for evaluating the quality of knowledge graph embeddings and relational representations. In the knowledge graph augmentation setting, MEDMKG is employed as auxiliary knowledge to enhance the performance of external multimodal applications. We consider two representative tasks—*multimodal text-image*

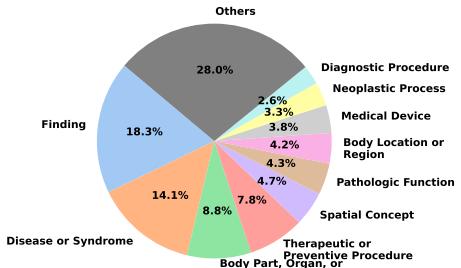
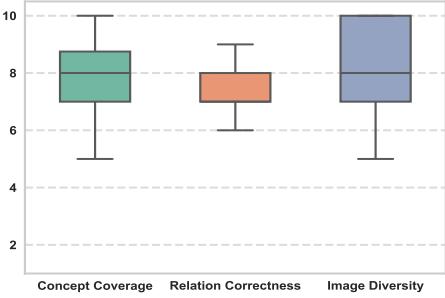
Table 1: Data Statistics Summary

Statistic	Count
Total Number of Edges	35,387
Number of Concepts	3,149
Number of Images	4,868
Number of Relations	262
Number of Cross-modality Edges	20,705
Number of Intra-modality Edges	14,682
Image-to-Concept Ratio	1.55
Average Edges per Image	4.25
Average Edges per Concept	11.24



(a) Distribution of Head Concepts per Semantic Types

Figure 1: Human assessment results.



(b) Distribution of Tail Concepts per Semantic Types

Figure 2: Distribution of entities involved in MEDMKG. The top 10 semantic types are shown individually, and rare types are grouped as “Others.”

retrieval and multimodal visual question answering (VQA)—to demonstrate the practical benefits of integrating structured knowledge into diverse and complex clinical tasks. These evaluations highlight MEDMKG’s effectiveness in both structural understanding and knowledge-enhanced model performance.

4.1 Link Prediction

The link prediction task [40] focuses on inferring missing links between entities by predicting either the head entity, the tail entity, or the relation connecting them. Specifically, given two known components of a triple, such as a relation and one entity, or two entities, the goal is to predict the missing element that completes the triple. This task helps improve the completeness and utility of knowledge graphs by filling in missing entities or relations between entities.

Baselines. We benchmark 17 widely-used link prediction models on our constructed KG, grouped into the following representative categories: (1) *Translation-based models*: TransE [40], TransH [41], TransR [26], TransD [42] and RotatE [43]. (2) *Tensor factorization models*: RESCAL [44], DistMult [45], ComplEx [46], SimplE [47], and TuckER [48]. (3) *Convolution-based models*: Hyper [49], ConvE [50], and ConvR [51]. (4) *Manifold-based models*: AttH [52], MurP [53], and MurE [53]. (5) *Neural tensor model*: NTN [54]. More details about these baselines can be found in Appendix H.1.

Evaluation Metrics. We evaluate the performance of the models using widely accepted metrics for link prediction, namely Mean Rank (MR), and Hits@ K (with K set to 3, 5, and 10). Detailed descriptions of these metrics are provided in Appendix H.2.

Implementation. All models are optimized using the AdamW optimizer [55] with a batch size of 2,048 and a learning rate of 0.001. The training is run for a maximum of 500 epochs with an early stopping mechanism (patience set to 5 epochs) to prevent overfitting. Data are split into training, validation, and test sets with an 8:1:1 ratio.

Evaluation Results. Table 2 reports the performance of 17 link prediction baselines across head, relation, and tail prediction tasks on our MEDMKG. A clear performance gap emerges between head and tail prediction, reflecting the distinct structural challenges posed by the created multimodal

Table 2: Performance of 17 approaches on the three types of link prediction tasks.

Model	Head Prediction				Relation Prediction				Tail Prediction			
	MR ↓	Hits@3 ↑	Hits@5 ↑	Hits@10 ↑	MR ↓	Hits@3 ↑	Hits@5 ↑	Hits@10 ↑	MR ↓	Hits@3 ↑	Hits@5 ↑	Hits@10 ↑
TransR	1379.06	1.98	4.58	8.81	129.08	5.59	9.63	16.36	836.28	3.19	6.70	12.94
TransD	1231.34	3.79	7.57	11.89	47.44	28.50	36.55	48.53	594.07	6.24	11.81	18.87
TransE	1254.46	3.73	6.30	9.58	39.81	17.54	26.95	41.05	547.75	4.27	8.90	14.21
TransH	1269.10	2.99	5.93	9.15	40.72	20.23	28.62	41.61	556.27	4.66	9.21	15.03
RotatE	1609.24	1.13	2.32	4.38	132.36	0.65	1.33	2.94	767.87	1.24	2.80	5.68
DistMult	3571.00	0.03	0.11	0.28	118.26	1.64	3.28	6.58	3562.13	0.03	0.11	0.20
Simple	3927.09	0.00	0.06	0.09	129.73	0.73	1.41	3.67	3924.18	0.03	0.03	0.14
TuckER	1522.89	2.51	4.15	6.92	41.43	47.88	56.78	65.28	1183.13	3.62	5.73	9.75
ComplEx	3929.15	0.03	0.06	0.11	130.16	0.25	0.45	1.44	3923.04	0.06	0.14	0.23
RESCAL	3883.04	0.03	0.09	0.09	128.35	0.28	1.05	2.43	3880.00	0.00	0.00	0.06
HypER	3000.66	0.62	1.10	2.01	108.95	2.32	3.96	7.29	1541.50	2.71	4.38	7.63
ConvE	2064.17	1.47	2.54	4.27	58.59	25.57	32.71	41.02	764.86	4.29	6.47	10.79
ConvR	3605.00	0.09	0.11	0.31	112.96	2.03	4.18	8.05	802.00	3.81	6.27	10.59
AttH	3144.07	0.06	0.09	0.20	20.80	29.35	46.33	63.08	567.94	5.57	9.21	14.80
MurE	1266.26	3.62	6.22	9.63	40.50	19.27	27.71	41.38	567.77	4.92	8.67	15.79
MurP	3926.74	0.14	0.45	0.73	112.20	5.40	7.15	10.99	561.80	1.58	3.19	7.35
NTN	4047.60	0.09	0.11	0.20	138.08	0.17	0.48	1.13	4030.05	0.00	0.06	0.14

knowledge graph. Tail prediction consistently outperforms head prediction, with models achieving notably higher Hits@ K scores and lower mean ranks. This can be attributed to the more homogeneous nature of tail entities, which consist solely of clinical concepts, compared to the mixed-modal head entities that include both images and concepts. The latter introduces additional complexity, as models must reconcile heterogeneous representations in a shared embedding space.

Among the baselines, translation-based models (e.g., TransD, TransE, and TransH) deliver the strongest results on both head and tail prediction, highlighting their ability to effectively capture cross-modal and intra-modal relationships. Notably, TransD achieves the best overall performance, including the top Hits@10 scores across head, relation, and tail tasks. In contrast, while TuckER achieves relatively strong performance on relation prediction, other tensor factorization models (e.g., SimpIE and RESCAL) generally perform poorly across both relation and entity prediction tasks. This suggests that although tensor factorization methods may effectively capture relational patterns in some cases, their general ability in entity linking is limited and often inconsistent across models.

These findings emphasize the importance of selecting models that align with the multimodal and relational structure of medical knowledge graphs. Future work may explore combining translation-based and tensor factorization-based models to leverage their complementary strengths and enhance the overall capability of knowledge graph representation learning.

4.2 Knowledge-Augmented Text-Image Retrieval

The knowledge-augmented text-image retrieval task aims to enhance conventional medical text-image retrieval [56] by leveraging domain knowledge encoded in a multimodal medical knowledge graph.

Datasets. We leverage two representative datasets for the medical text-image retrieval task, i.e., OpenI [57] and MIMIC-CXR [8], following previous work [11]. To prevent any potential data leakage regarding MIMIC-CXR, we only select text-image pairs that were not used during the curation of MEDMKG, and we randomly sample a fixed set of 10,000 pairs from these remaining examples. Since no predefined splits exist, both datasets are divided into training, validation, and test sets with an 8:1:1 ratio.

Backbone Models. To comprehensively assess the impact of knowledge augmentation, we employ four open-sourced vision-language models as backbones: CLIP [58], PubMedCLIP [59], BioMedCLIP [60], and MedCSPCLIP [11]. Additional details about these models are available in Appendix I.

Baselines. For benchmarking, we consider two knowledge-augmented retrieval methods: KnowledgeCLIP [61] and FashionKLIP [62]. More information about these baselines is available in Appendix J.1.

Evaluation Metrics. We comprehensively evaluate retrieval performance using standard metrics, i.e., precision@ K and recall@ K , with K set to 10, 20, and 100. Detailed metric descriptions can be found in Appendix J.2.

Implementation. All models are optimized using the AdamW optimizer [63]. The hidden state dimension is uniformly set to 512, and the learning rate is configured to 0.0001. Training is conducted for a maximum of 30 epochs with an early-stopping patience of 3 epochs.

Table 3: Results (%) on Text-image Retrieval Task for OpenI and MIMIC-CXR Datasets. Metrics highlighted with green indicate improvement over backbone, while red refers to drop.

Methods	OpenI						MIMIC-CXR					
	Precision @K ↑			Recall @K ↑			Precision @K ↑			Recall @K ↑		
	10	20	100	10	20	100	10	20	100	10	20	100
CLIP	1.17	1.00	0.56	11.10	19.24	53.48	1.11	0.98	0.58	11.11	19.52	58.26
+ FashionKLIP	1.29	1.16	0.63	12.64	22.75	60.46	1.19	0.99	0.56	11.91	19.82	56.06
+ KnowledgeCLIP	2.63	1.99	0.79	25.56	38.83	76.16	2.33	1.73	0.74	23.32	34.53	74.37
PubMedCLIP	1.17	0.98	0.51	10.81	18.47	48.46	0.69	0.65	0.43	6.91	13.01	42.79
+ FashionKLIP	1.54	1.21	0.70	15.10	23.38	67.73	0.73	0.72	0.49	7.31	14.41	49.20
+ KnowledgeCLIP	1.49	1.17	0.61	14.33	22.61	59.41	1.26	1.13	0.60	12.61	22.62	59.96
BioMedCLIP	1.04	0.79	0.42	9.90	15.10	40.45	2.02	1.59	0.66	20.12	31.63	65.77
+ FashionKLIP	1.46	1.15	0.60	14.33	22.47	58.22	2.02	1.49	0.68	20.12	29.63	67.77
+ KnowledgeCLIP	1.26	0.95	0.49	12.50	18.61	47.54	2.64	1.94	0.71	26.33	38.74	70.77
MedCSPCLIP	1.60	1.10	0.54	15.73	21.35	52.14	3.77	2.59	0.82	37.69	51.65	81.58
+ FashionKLIP	1.81	1.36	0.60	17.84	26.54	57.65	4.02	2.69	0.85	40.19	53.75	84.98
+ KnowledgeCLIP	1.90	1.40	0.62	18.61	27.18	59.55	4.95	3.14	0.89	49.50	62.66	88.99

Evaluation Results. Table 3 shows that knowledge augmentation consistently improves retrieval performance across both OpenI and MIMIC-CXR, particularly in low-K settings. This indicates that external knowledge enhances the model’s ability to identify the most relevant matches at top ranks. Among the two strategies, KnowledgeCLIP (pretraining-based) shows strong and consistent gains across most settings, especially on MIMIC-CXR, while FashionKLIP (joint fine-tuning) provides more noticeable improvements on OpenI relative to its effect on MIMIC-CXR.

The overall trend suggests that integrating external knowledge—whether through pretraining or joint fine-tuning—can significantly benefit medical retrieval tasks. However, the effectiveness varies with the backbone and integration method, underscoring the importance of alignment between knowledge signals and visual-language representations.

Future work may explore tighter coupling between knowledge and model training by involving medical knowledge graphs in both pretraining and fine-tuning stages. Such unified frameworks could offer deeper semantic grounding and more robust generalization across diverse clinical retrieval scenarios.

4.3 Knowledge-Augmented Visual Question Answering

The knowledge-augmented visual question answering task aims to improve medical visual question answering task [64] by integrating domain knowledge contained in multimodal medical knowledge graphs, enabling more accurate and clinically meaningful question answering over medical images.

Datasets. To benchmark current knowledge-augmented visual question answering methods with our proposed MEDMKG, we adopt three widely used medical VQA datasets, following previous work [18]. These datasets include VQA-RAD [65], Slake [66], and Path-VQA [67]. For the fair comparison, we select closed-set questions from the datasets, which can be equally tackled by methods with different sophistication.

Backbone Models. We use the same set of backbone models as in Section 4.2, namely CLIP [58], PubMedCLIP [59], BioMedCLIP [60], and MedCSPCLIP [11]. For more details, please refer to Appendix I.

Baselines. We evaluate five models that integrate knowledge graphs to enhance visual question answering: KRISP [68], MKBN [69], K-PathVQA [70], EKGRL [71], and MR-MKG [72]. Detailed descriptions of these approaches are provided in Appendix K.2.

Evaluation Metrics. We adopt four widely accepted metrics for the visual question answering task: Accuracy, Precision, Recall, and F1 score. More detailed metric descriptions can be found in Appendix K.3.

Implementation. We use the same implementation configuration as described in Section 4.2.

Evaluation Results. Table 4 summarizes the performance (%) of knowledge-augmented VQA models across VQA-RAD, SLAKE, and PathVQA. Incorporating external knowledge from our multimodal medical knowledge graph consistently improves model performance, particularly on

Table 4: Results (%) on Medical Visual Question Answering with Knowledge Graphs. Metrics highlighted with green indicate improvement over backbone, while red refers to drop.

Methods	VQA-RAD				SLAKE				PathVQA			
	Acc↑	Prec↑	Rec↑	F1↑	Acc↑	Prec↑	Rec↑	F1↑	Acc↑	Prec↑	Rec↑	F1↑
CLIP	64.94	62.71	62.71	62.71	65.07	62.09	74.86	67.88	81.89	88.37	76.54	82.03
+ KRISP	73.71	78.89	60.17	68.27	56.90	55.00	69.14	61.27	84.21	89.83	79.79	84.51
+ MKBN	70.12	70.87	61.86	66.06	70.14	73.47	61.71	67.08	84.68	89.35	81.33	85.15
+ K-PathVQA	66.14	62.79	68.64	65.59	69.30	73.57	58.86	65.40	84.15	85.74	84.75	85.24
+ EKGRL	67.73	65.04	67.80	66.39	70.70	71.01	68.57	69.77	84.77	86.38	85.24	85.81
+ MR-MKG	73.71	77.08	62.71	69.16	76.34	79.74	69.71	74.39	84.30	84.85	86.34	85.59
PubMedCLIP	66.14	64.35	62.71	63.52	63.94	59.59	83.43	69.52	81.26	86.65	77.20	81.65
+ KRISP	76.10	76.85	70.34	73.45	75.77	79.47	68.57	73.62	84.41	88.13	82.21	85.07
+ MKBN	67.33	67.31	59.32	63.06	70.70	75.18	60.57	67.09	84.56	90.15	80.18	84.87
+ K-PathVQA	72.51	76.34	60.17	67.30	68.17	67.03	69.71	68.35	83.76	87.62	81.44	84.42
+ EKGRL	76.49	75.21	74.58	74.89	75.49	73.40	78.86	76.03	84.59	90.41	79.96	84.86
+ MR-MKG	78.88	76.86	78.81	77.82	77.75	78.57	75.43	76.97	84.18	86.07	84.36	85.21
BioMedCLIP	66.93	61.74	77.97	68.91	70.14	70.18	68.57	69.36	84.56	94.03	76.27	84.22
+ KRISP	76.10	79.59	66.10	72.22	57.18	54.77	75.43	63.46	85.46	93.74	78.30	85.33
+ MKBN	68.53	64.66	72.88	68.53	67.89	75.63	51.43	61.22	85.78	88.32	84.91	86.58
+ K-PathVQA	65.34	71.23	44.07	54.45	70.70	73.20	64.00	68.29	85.93	90.57	82.54	86.37
+ EKGRL	75.70	71.76	79.66	75.50	86.20	89.38	81.71	85.37	85.46	89.66	82.60	85.98
+ MR-MKG	77.29	74.80	77.97	76.35	80.28	79.66	80.57	80.11	87.24	90.06	85.85	87.91
MedCSPCLIP	68.13	61.59	85.59	71.63	66.20	83.95	38.86	53.12	77.72	73.37	92.24	81.73
+ KRISP	80.08	84.00	71.19	77.06	70.70	91.76	44.57	60.00	83.19	94.71	72.96	82.43
+ MKBN	69.72	65.44	75.42	70.08	67.32	75.21	50.29	60.27	85.37	86.17	86.84	86.51
+ K-PathVQA	67.73	75.34	46.61	57.59	71.55	74.03	65.14	69.30	85.31	89.35	82.65	85.87
+ EKGRL	76.10	73.39	77.12	75.21	69.30	78.95	51.43	62.28	84.92	92.75	78.19	84.85
+ MR-MKG	78.49	77.59	76.27	76.92	83.94	83.15	84.57	83.85	86.53	89.74	84.75	87.17

Accuracy and F1 metrics, confirming the utility of structured domain-specific knowledge in enhancing medical visual reasoning.

Among the evaluated methods, MR-MKG achieves the highest and most stable performance across datasets and backbones, underscoring the effectiveness of contrastive learning in promoting robust cross-modal alignment. By explicitly optimizing visual–knowledge representations, MR-MKG demonstrates superior generalization across varying task difficulties and data scales. Attention-based fusion methods (K-PathVQA and MKBN) show less consistent gains, with noticeable performance degradation on smaller datasets (VQA-RAD and SLAKE), likely due to overfitting. However, their improvements stabilize on larger datasets (e.g., PathVQA), suggesting that attention-driven integration requires sufficient data to avoid overfitting to noisy or spurious knowledge signals.

Additionally, while external knowledge improves Accuracy and F1 broadly, its impact on either Precision or Recall is more variable, indicating a trade-off between broader answer coverage and precision specificity. This highlights the need for more selective fusion strategies that can dynamically balance knowledge contribution during inference.

In conclusion, the results confirm that incorporating our multimodal medical knowledge graph effectively enhances performance in medical VQA tasks. The graph’s clinical specificity, image-aware relational structure, and semantic richness contribute to the stronger multimodal understanding. Future work should explore adaptive, backbone-agnostic fusion mechanisms to further improve stability and generalizability across diverse datasets and model architectures.

5 Conclusion

In this work, we present MEDMKG, a novel multimodal medical knowledge graph that integrates clinical text and medical imaging data to capture rich inter- and cross-modality relationships. To ensure the graph’s quality and conciseness, we introduce a novel neighbor-aware filtering algorithm tailored to multimodal knowledge graphs. Extensive experiments on knowledge graph analysis and downstream augmentation tasks validate the effectiveness of MEDMKG and highlight its value in enhancing medical knowledge representation. Beyond providing a valuable resource, MEDMKG also opens new research opportunities, underscoring the need for adaptive and efficient strategies to integrate multimodal knowledge into real-world clinical applications.

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Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

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Justification: We have provided links to our code and the curated knowledge graph at the beginning of this paper.

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- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
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6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

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Justification: Please check Section 4, Appendix H and Appendix K and Appendix J,

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7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: Considering that this benchmark study contains quite a number of comprehensive experiments, multiple runs of each experiment would result in a significant computational burden. Instead, we set fixed random seed and provide reproducible source codes to ensure the fair comparison.

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- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
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Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

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- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
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Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: This paper does not propose the risk as all the data have been de-identified.

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- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

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A Broader Impact

Beyond offering a high-quality research resource, MEDMKG has the potential to broadly impact medical AI by enabling the development of multimodal learning algorithms that leverage both imaging and clinical text. This can ultimately enhance diagnostic tools, decision support systems, and clinical research by providing models with richer contextual understanding. Furthermore, MEDMKG lowers the entry barrier for institutions and researchers working on multimodal healthcare applications by providing a ready-to-use, well-curated dataset. By facilitating broader access to multimodal medical data and advancing AI methods in healthcare, MEDMKG contributes to the long-term goal of improving patient outcomes, supporting personalized medicine, and enabling more equitable healthcare innovations.

Nevertheless, there are potential risks associated with the use of MEDMKG. When models trained on the knowledge graph are deployed in real-world clinical settings, incorrect or outdated associations may lead to diagnostic errors or biased decision support, especially if not carefully validated. Moreover, misuse of the resource, such as training models that reinforce existing health disparities or deploying systems without appropriate clinical oversight, could result in unintended harm. To mitigate these risks, we recommend that users validate model outputs against expert clinical judgment, employ mechanisms to monitor system behavior over time, and adopt usage restrictions to prevent inappropriate or unverified clinical deployment.

B Compute and Environment Configuration

All experiments were conducted on an NVIDIA A100 GPU with CUDA version 12.0, running on an Ubuntu 20.04.6 LTS server.

C Dataset Repository

We have released a public dataset repository for MEDMKG, available on Github at <https://github.com/XiaochenWang-PSU/MedMKG> and on Hugging Face at <https://huggingface.co/datasets/xwangpsu/MedMKG>. The MEDMKG dataset can be loaded using the Hugging Face datasets module, alongside the MIMIC-CXR dataset, which requires separate download following the instructions provided in the Hugging Face repository README file. The GitHub repository includes runnable code for data processing, baseline models, environment configuration, and example execution scripts. We are committed to regularly updating the repository with additional modalities, datasets, and tasks to further support the research community.

D Author Statement

As authors of this dataset and article, we take full responsibility in the event of any violation of rights or licenses. We have included a disclaimer in the repository inviting original dataset creators to open issues regarding any license-related concerns.

E Limitations

Despite its contributions, MEDMKG has several limitations. Due to data privacy policies and access restrictions of the MIMIC-CXR dataset (PhysioNet Credentialled Health Data License 1.5.0), sensitive medical images in MEDMKG cannot be released directly along with other components. Instead, we provide the index of the images. Users are required to independently obtain the MIMIC-CXR dataset and follow our reconstruction instructions², which may present a barrier to accessibility.

In addition, privacy constraints prevent us from conducting detailed analyses of specific radiological images or reporting case-level findings. While aggregate analyses and quantitative evaluations are feasible, visual inspection or discussion of individual examples is restricted to comply with ethical and legal requirements.

²<https://huggingface.co/datasets/xwangpsu/MedMKG>

Table 5: Filtered Semantic Types. The semantic types listed below are disallowed; all others are considered allowable.

Occupation or Discipline	Intellectual Product	Age Group
Biomedical Occupation or Discipline	Classification	Patient or Disabled Group
Organization	Regulation or Law	Geographic Area
Health Care Related Organization	Language	Conceptual Entity
Professional Society	Group Attribute	Idea or Concept
Self-help or Relief Organization	Group	Temporal Concept
Professional or Occupational Group	Qualitative Concept	Quantitative Concept
Population Group	Functional Concept	Body System
Family Group		

F Details of Knowledge Graph Construction

E.1 Pre-processing of MIMIC-CXR

To ensure the quality of the constructed multimodal knowledge graph, we perform targeted pre-processing on the raw data in the MIMIC-CXR database. Each radiological report may correspond to images in different views, including anteroposterior, posteroanterior, lateral, etc. Involving multiple images with the same set of concepts could result in significant redundant edges within the knowledge graph. Therefore, we only maintain images in the anteroposterior view for graph conciseness; similarly, radiological reports usually contain abundant information such as diagnostic history that is not directly relevant to the content of the corresponding radiological image, therefore, extracting concepts from these similar reports can also result in redundancy.

To mitigate this problem, we only preserve sections of Impression and Findings, two major sections that contain the most informative content, and stick to existing works in clinical report analysis [7]. We perform semantic filtering using DBSCAN [73] and MedCSPCLIP [11]. To be specific, we encode all the radiological reports with the text encoder of MedCSPCLIP, then perform clustering on the reports based on their semantics. Based on the clustering results, we select the ones near the centroid of each cluster as representative of a group of similar radiological reports.

These approaches function together, ensuring that our pipeline referred to in Section 3 receives high-quality data for processing, producing the multimodal knowledge graph with sufficient information, negligible noise, and minimal redundancy.

E.2 Filtering per Semantic Type of Medical Concepts

In order to eliminate concepts that are overly abstract or lack practical value, we filter concepts based on their semantic types. Table 5 lists the semantic types that are not preferred thus filtered, while all other semantic types in the UMLS vocabulary ³ are allowed.

E.3 Prompt for Concept Disambiguation and Relation Extraction

To leverage the LLM’s contextual understanding for effective concept disambiguation and relation extraction, we designed an instructive prompt that guides the model through these tasks. The prompt is presented in Example F.3.

E.4 NaF Algorithm

We propose the Neighbor-Aware Filtering (NaF) algorithm for effective image filtering to boost the conciseness of MEDMKG. More details are presented in Algorithm 1.

³https://www.nlm.nih.gov/research/umls/META3_current_semantic_types.html

Prompt for Concept Disambiguation and Relation Extraction (F.3)

Report Text: [Report Text]

Candidate Concepts: [Candidate Concepts]

For each phrase, evaluate the concept candidates and select the most relevant concept based on the context provided in the report. Your decision should account for the specific context of a radiological image.

After selecting the appropriate concept for each phrase, classify the relation between the selected concept and the image using the following categories:

Positive - The concept is clearly represented in the image (e.g., anatomical structures, specific findings).

Neutral - Concepts that are structural, general terms (like "findings", "normal", "changes"), meta-concepts, adjectives, or unrelated to clinical insight.

Negative - The concept is the opposite of what is shown in the image (e.g., when the image shows no abnormalities but the concept implies pathology).

Uncertain - The concept's presence in the image is unclear based on the report (e.g., the reporter uses language like "possible" or "could be").

Return only concepts with a positive, negative, or uncertain relation. Do not include any neutral concepts in the final output.

Provide the final output in the following format: ***start***

(Concept ID only (digits start with C), Relation)

end

Ensure that:

- Neutral concepts are excluded entirely from the output.
- Concepts like "findings" and any general or structural terms are categorized as neutral and omitted.
- Double-check that each remaining concept is evaluated accurately based on the context of the radiological image.

E.5 Illustration of MEDMKG

Figure 3 shows a subgraph of MEDMKG, provided to facilitate a better understanding of its structure and content. As shown in Figure 3, the medical multimodal knowledge graph integrates both intra- and cross-modal edges, offering rich multimodal medical knowledge that can potentially support a wide range of applications.

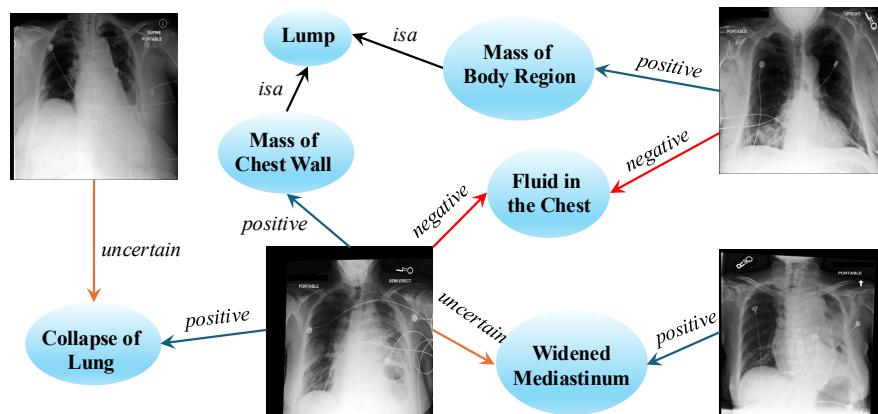


Figure 3: An illustration of MEDMKG.

Algorithm 1 Neighbor-Aware Filtering Algorithm

```
1: Input:
    • A set of images  $\mathcal{M} = \{m_1, m_2, \dots, m_N\}$ .
    • For each image  $m_i$ , its associated triplets  $T_i = \{(m_i, r_{ij}, c_{ij})\}$ .
    • The set of filtered clinical concepts  $\mathcal{C}$ .
2: Output: Selected image set  $\mathcal{M}^*$ .
3:  $\mathcal{M}^* \leftarrow \emptyset$  and  $\mathcal{C}^* \leftarrow \emptyset$ .
4: for each image  $m_i \in \mathcal{M}$  do
5:     Compute  $\text{Score}(m_i) \leftarrow \sum_{(r,c) \in T_i} \log \frac{N}{N_{(r,c)}}$ .
6: end for
7: Sort  $\mathcal{M}$  in descending order by  $\text{Score}(m_i)$ .
8: for each image  $m_i$  in sorted order do
9:     if  $\mathcal{C}^* \neq \mathcal{C}$  then
10:         $\mathcal{M}^* \leftarrow \mathcal{M}^* \cup \{m_i\}$ .
11:         $\mathcal{C}^* \leftarrow \mathcal{C}^* \cup \{c \mid \exists r \text{ such that } (r, c) \in T_i\}$ .
12:     else
13:         break
14:     end if
15: end for
16: return  $\mathcal{M}^*$ .
```

G Details of Human Assessment

G.1 Assessment Criteria

We conducted a human evaluation to assess the quality of MEDMKG. Three key metrics were used:

- **Concept Coverage** measures how comprehensively the extracted concepts capture the clinically meaningful findings present in the image.
- **Relation Correctness** assesses whether the relationships between images and extracted concepts are accurately modeled, correctly identified with positive, negative, or uncertain associations.
- **Image Diversity** evaluates whether the set of images associated with each concept reflects a diverse range of clinical scenarios, rather than highly homogeneous ones.

These metrics were selected to capture complementary aspects of performance: *Concept Coverage* ensures clinical relevance and completeness; *Relation Correctness* ensures accurate representation of image-concept associations; and *Image Diversity*: ensures the robustness and generalizability of concept representations. Together, they provide a holistic evaluation of both precision and breadth of MEDMKG.

G.2 Assessment Procedure

For the metrics of concept coverage and relation correctness, we randomly sample 30 images in MEDMKG, choose all their concept neighbors, and the relation connecting them for assessment. For image diversity, we randomly choose 30 concepts in MEDMKG and provide all the images positively linked with them to the evaluator. The evaluator performs the assessment along with detailed guidance. The guidebook is available for check ⁴.

⁴https://docs.google.com/document/d/1Z--FL3-eEN4JtYosiMd07Xa_yiudQOPAuAE2wx0PNg4/edit?usp=sharing

H Details of Link Prediction

H.1 Link Prediction Baselines

We benchmark MEDMKG with the following baseline models in the task of link prediction:

- **AttH** [52] is a hyperbolic knowledge graph embedding model designed to capture hierarchical structures by leveraging the Lorentz model.
- **DistMult** [45] is a bilinear factorization model for knowledge graphs that represents relations as diagonal matrices, enabling efficient computation.
- **TransR** [26] extends TransE by introducing separate relation-specific entity spaces, allowing better modeling of diverse relationships.
- **HypER** [49] applies hypernetworks to generate relation-dependent transformation matrices for entity embeddings, improving flexibility.
- **Simple** [47] is an extension of Canonical Polyadic (CP) decomposition that enables each entity representation to be used in two different ways.
- **TuckER** [48] is based on Tucker decomposition and factorizes the knowledge graph tensor into entity and relation embeddings with a core interaction tensor.
- **MurP** [53] embeds knowledge graphs in the Poincaré ball model, enabling effective representation of hierarchical data.
- **MurE** [53] embeds knowledge graphs in Euclidean space using multiple relational constraints to improve predictive performance.
- **NTN** [54] introduces a neural tensor network for knowledge graph embedding, modeling entity interactions through a bilinear tensor layer.
- **TransD** [42] extends TransE and TransH by introducing entity- and relation-specific projection matrices for dynamic embedding transformation.
- **TransE** [40] models relationships as translations in the embedding space, assuming that the sum of the head and relation embeddings approximates the tail embedding.
- **RESCAL** [44] models multi-relational data using a bilinear tensor factorization approach that captures pairwise interactions.
- **RotatE** [43] represents relations as rotations in a complex vector space, capturing symmetric and antisymmetric relations effectively.
- **TransH** [41] introduces relation-specific hyperplanes to improve the representation of diverse relational properties.
- **ConvE** [50] applies 2D convolutional neural networks to entity embeddings, capturing complex interactions between entities and relations.
- **ComplEx** [46] extends DistMult by using complex-valued embeddings, enabling the representation of asymmetric relations.
- **ConvR** [51] applies relation-specific convolutional filters to entity embeddings, enhancing the modeling of complex interactions.

H.2 Evaluation Metrics

For the link prediction tasks, we utilize Mean Rank (MR) and Hits@K for assessing the baselines. Let \mathcal{T} denote the set of test triples and, for each test case i , let r_i be the rank of the ground-truth entity among all candidate entities (with a lower rank indicating better performance). The metrics are defined as follows:

Mean Rank (MR) The Mean Rank is the average rank of the ground-truth entities over all test cases:

$$MR = \frac{1}{|\mathcal{T}|} \sum_{i=1}^{|\mathcal{T}|} r_i. \quad (2)$$

Hits@K Hits@K measures the proportion of test cases for which the ground-truth entity is ranked within the top K predictions:

$$\text{Hits}@K = \frac{1}{|\mathcal{T}|} \sum_{i=1}^{|\mathcal{T}|} \mathbb{I}(r_i \leq K), \quad (3)$$

where $\mathbb{I}(\cdot)$ is the indicator function that returns 1 if the condition is true and 0 otherwise.

A lower MR and a higher MRR or Hits@K value indicate better performance.

I Backbone Models in Knowledge-augmented Tasks

The following advanced visual language models are adapted as the standard backbone for knowledge-augmented methods:

- **CLIP** [58] is a vision-language model trained on large-scale internet data using contrastive learning. It aligns images and text embeddings in a shared latent space, enabling zero-shot image classification and retrieval. The model is under the MIT License.
- **PubmedCLIP** [59] is a domain-specific adaptation of CLIP trained on PubMed articles and biomedical images. It enhances the alignment of biomedical images with textual descriptions, improving zero-shot performance in medical imaging tasks. The model is under the MIT License.
- **BioMedCLIP** [60] is a biomedical contrastive pretraining model trained on a large-scale corpus of biomedical images and text. It is designed to improve multimodal understanding in healthcare applications, particularly for retrieval and classification tasks. The model is under the MIT License.
- **MedCSPCLIP** [11] is a medical-specific adaptation of CLIP that incorporates the MedCSP framework for contrastive scalable pretraining. It learns generalizable medical image representations, enabling improved zero-shot performance and transfer learning in clinical applications. The model is under the MIT License.

J Details of Knowledge-augmented Image-text Retrieval

J.1 Baselines

In the task of knowledge-augmented image-text retrieval, we benchmark with the following baseline models:

- **KnowledgeCLIP** [61]: This model extends CLIP by integrating external knowledge graphs. By adding knowledge-based objectives during pre-training, it leverages structured relational data (e.g., from ConceptNet or VisualGenome) to improve semantic alignment between images and text.
- **FashionKLIP** [62]: Designed for the fashion domain, FashionKLIP automatically constructs a multimodal conceptual knowledge graph (FashionMMKG) from large-scale fashion data. By injecting domain-specific knowledge into the pre-training process, it learns fine-grained representations that enhance image-text alignment and retrieval performance.

J.2 Evaluation Metrics

For this task, we leverage Precision k and Recall k as the metrics for evaluation. Let \mathcal{Q} denote the set of queries. For each query $q \in \mathcal{Q}$, let $R(q)$ be the set of relevant items, and let $\hat{R}_k(q)$ be the set of top- k items retrieved by the model. Then, the metrics are defined as follows:

Precision k Precision k is the fraction of the top- k retrieved items that are relevant. Formally, it is given by:

$$\text{Precision}@k = \frac{1}{|\mathcal{Q}|} \sum_{q \in \mathcal{Q}} \frac{|\hat{R}_k(q) \cap R(q)|}{k}. \quad (4)$$

Recall k Recall k is the fraction of the relevant items that are retrieved in the top- k results. It is defined as:

$$\text{Recall}@k = \frac{1}{|\mathcal{Q}|} \sum_{q \in \mathcal{Q}} \frac{|\hat{R}_k(q) \cap R(q)|}{|R(q)|}. \quad (5)$$

A higher Precision k indicates that a larger proportion of the retrieved items are relevant, whereas a higher Recall k suggests that a greater proportion of all relevant items have been retrieved. These metrics together provide a comprehensive evaluation of the retrieval performance.

K Details of Knowledge-augmented Visual Question Answering

K.1 Datasets

We compare the baselines on three medical visual question answering dataset, including VQA-RAD, SLAKE and PathVQA. We extract closed questions in these datasets for benchmarking.

K.2 Baselines

In the task of knowledge-augmented visual question answering, we evaluate five models that incorporate external knowledge graphs to improve visual reasoning and answer prediction:

- **KRISP [68]**: This model integrates structured knowledge graphs into the VQA pipeline, refining both image representations and question understanding to boost answer accuracy.
- **MKBN [69]**: Originally designed for medical VQA, MKBN leverages domain-specific knowledge graphs to align visual and textual features, thus enhancing performance in specialized settings.
- **K-PathVQA [70]**: By incorporating multi-hop reasoning over a knowledge graph, K-PathVQA enables the model to infer complex relationships and answer questions that require multi-step deductions.
- **EKGRL [71]**: This framework combines graph-based representation learning with reinforcement learning to effectively integrate external knowledge, thereby improving reasoning capabilities in visual question answering.
- **MR-MKG [72]**: MR-MKG utilizes contrastive loss to capture diverse semantic interactions between visual content and questions, leading to enhanced cross-modal alignment and VQA performance.

K.3 Evaluation Metrics

For the visual question answering task, we adopt four standard metrics: Accuracy, Precision, Recall, and F1 score. Let \mathcal{D} denote the set of VQA examples. For each example $i \in \mathcal{D}$, let y_i be the ground-truth answer and \hat{y}_i the predicted answer. The metrics are defined as follows:

Accuracy Accuracy measures the proportion of correctly answered questions:

$$\text{Accuracy} = \frac{1}{|\mathcal{D}|} \sum_{i \in \mathcal{D}} \mathbb{I}(\hat{y}_i = y_i), \quad (6)$$

where $\mathbb{I}(\cdot)$ is the indicator function.

Precision Precision is the fraction of true positive answers among all answers predicted as positive. In a binary (or thresholded) setting, it is given by:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad (7)$$

with TP and FP denoting the numbers of true positives and false positives, respectively.

Recall Recall is defined as the fraction of true positive answers among all actual positive answers:

$$\text{Recall} = \frac{TP}{TP + FN}, \quad (8)$$

where FN represents false negatives.

F1 Score The F1 score is the harmonic mean of Precision and Recall:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (9)$$

Together, these metrics provide a comprehensive evaluation of model performance on the knowledge-augmented visual question answering task.