Knowledge Graphs and Multi-modal Techniques: A Survey

www.surveyx.cn

Abstract

Knowledge Graphs (KGs) have become indispensable in artificial intelligence and data science, offering structured knowledge representations that enhance AI applications such as information retrieval, recommendation systems, and explainable AI. This survey paper explores the interconnected domains of KGs, multi-modal knowledge graph completion, multi-modal fusion, link prediction, graph embeddings, semantic integration, and data fusion techniques. It highlights the evolution of KGs from foundational projects like WordNet and DBpedia to their current role in integrating diverse data types and addressing incompleteness through link prediction. The paper systematically reviews methodologies and challenges in multi-modal fusion, emphasizing the significance of integrating heterogeneous data types to enrich KGs. Advanced embedding techniques and innovative models such as SGMPT and KeGNN are discussed for their roles in enhancing link prediction and semantic integration. The survey underscores the importance of semantic integration in harmonizing disparate data sources, enhancing the expressiveness and utility of KGs. Future research directions are outlined, focusing on improving the construction and application of KGs in multi-modal contexts, exploring large language models, and refining evaluation frameworks. By advancing these methodologies, the field can further unlock the potential of KGs, driving innovation and efficiency in AI-driven solutions across diverse sectors. Key takeaways include the effectiveness of multi-source embeddings and the potential of dual-view hyper-relational knowledge graphs, as demonstrated by recent studies.

1 Introduction

1.1 The Evolution and Importance of Knowledge Graphs

Knowledge Graphs (KGs) are essential in artificial intelligence and data science, providing structured representations of complex real-world knowledge through entities and their interrelations [1]. Their historical development includes foundational projects such as WordNet, DBpedia, and Freebase, which established their application in diverse AI domains, including information retrieval, recommender systems, question-answering systems, and natural language processing [2]. These initiatives highlighted KGs' potential to enhance machine learning models by offering semantically rich data structures.

Despite their advantages, KGs encounter challenges related to incompleteness, prompting the need for techniques like link prediction to infer missing relationships between entities [2]. Knowledge completion is vital for ensuring the robustness and applicability of KGs across various applications. Additionally, KGs are crucial for linking diverse data sources, creating multilayered structures essential for big data integration [3].

The evolution of KGs is characterized by advancements in integrating unstructured data, which enriches their semantic depth and broadens their applicability, notably in domains like cybersecurity, where they address complex scenarios involving cyber-attacks and defense mechanisms. This

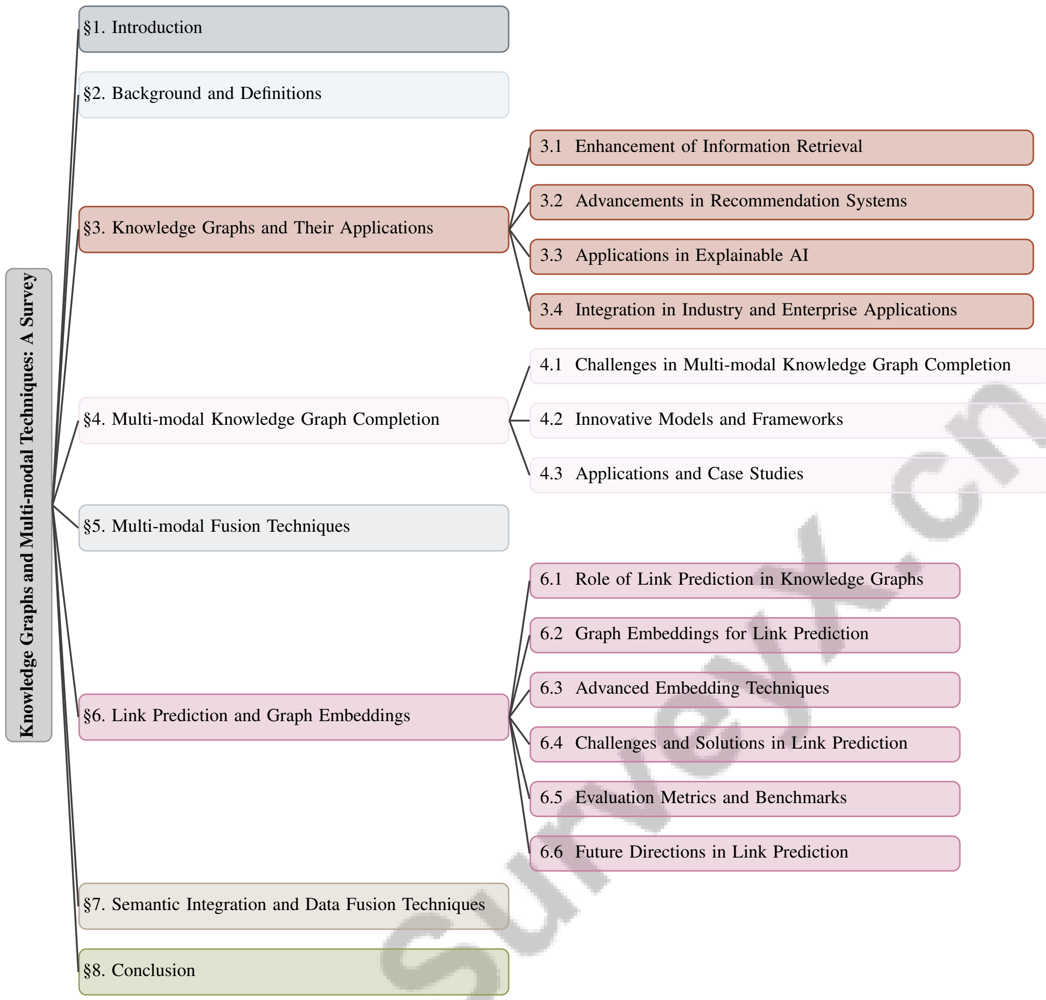


Figure 1: chapter structure

evolution is also driven by the need to overcome challenges in knowledge acquisition from multiple sources, knowledge fusion, and reasoning [1].

1.2 Structure of the Survey

This survey is systematically organized to provide a comprehensive overview of the interconnected domains of knowledge graphs and multi-modal techniques. The initial section introduces the evolution and significance of knowledge graphs, emphasizing their foundational role in AI and data science and their application across various domains. Following this, Section 2 delves into the background and definitions of core concepts, including multi-modal knowledge graph completion and fusion techniques, elucidating their interrelations and significance.

Section 3 explores the diverse applications of knowledge graphs, highlighting their utility in enhancing information retrieval systems and recommendation engines [4]. This section also examines the role of knowledge graphs in explainable AI and their integration into industry and enterprise applications [5]. Section 4 focuses on multi-modal knowledge graph completion, discussing the techniques and challenges involved in integrating diverse data types to enrich knowledge graphs.

The methodologies and challenges of multi-modal fusion are addressed in Section 5, which highlights innovative techniques and future directions in this field [6]. Section 6 examines link prediction and graph embeddings, discussing their role in maintaining and expanding knowledge graphs, with a focus on advanced embedding techniques and evaluation metrics [7].

AI-generated, for reference only.

Section 7 discusses semantic integration and data fusion techniques, emphasizing their importance in harmonizing disparate data sources and the challenges involved [8]. The final section, Section 8, concludes the survey by reflecting on the current state of research and suggesting potential future research directions. This structured approach ensures a thorough understanding of the topics covered, providing insights into both theoretical developments and practical applications.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Background and Definitions

Knowledge Graphs (KGs) are pivotal in structuring entities and their interrelations in artificial intelligence and data science, particularly in clinical decision support systems where advanced embedding techniques are required for medical knowledge graphs [1, 9]. Constructing KGs from unstructured data, especially in geographic contexts, demands rigorous data quality checks and semantic enrichment to ensure accuracy [10].

The development of Multi-modal Knowledge Graphs (MKGs) extends traditional KGs by incorporating diverse data modalities—text, images, and numerical values—thereby overcoming the limitations of symbolic representations and enhancing machine understanding [11]. This integration is crucial in mitigating KG incompleteness, which can hinder applications like web search and natural language processing [12]. The challenge of constructing KGs from free text, particularly under zero-shot conditions, underscores the need for robust models to predict inter-concept relationships [13].

Multi-modal Fusion techniques are essential for synthesizing heterogeneous data types into cohesive, semantically enriched representations, enhancing AI capabilities. These methodologies must effectively handle data heterogeneity while ensuring semantic coherence [14]. The integration of diverse data forms strengthens KGs, leading to more robust knowledge representations and reasoning.

Link Prediction is critical for maintaining and expanding KGs by inferring missing links between entities. This task benefits from combining rule mining and embedding-based methods, enhancing interpretability and predictive accuracy [15]. However, current embedding methods often fail to leverage both local and global cues, limiting their effectiveness [2].

Graph Embeddings facilitate tasks like link prediction by converting KGs into formats compatible with machine learning models, capturing latent features of entities and their interrelations [9]. The challenge of learning effective entity representations in large-scale KGs is exacerbated by incomplete neighborhood information, which conventional algorithms often overlook [16].

Semantic Integration and Data Fusion Techniques are crucial for reconciling disparate data sources into a unified, semantically consistent framework. They address inconsistencies, duplicates, and inaccuracies, essential for applications relying on KGs [17]. Integrating KGs with overlapping but distinct entities and relations complicates merging and updating processes, requiring a balance between correctness and completeness while managing computational costs [18].

These interconnected concepts collectively advance knowledge representation and utilization in AI and data science, enhancing AI systems' ability to process and comprehend complex information landscapes. They contribute to the creation, enrichment, and application of KGs, broadening AI technologies' capabilities across various fields, including temporal knowledge graphs. The dynamic nature of this research area is underscored by the continuous emergence of new knowledge and the integration of temporal information into knowledge evolution processes [19].

3 Knowledge Graphs and Their Applications

In recent years, Knowledge Graphs (KGs) have gained significant attention for their transformative potential across various domains. Their structured representation of information facilitates the integration and analysis of complex datasets, making them invaluable in enhancing both information retrieval and recommendation systems. To fully understand the specific applications of Knowledge Graphs (KGs), it is essential to first examine their significant contributions to enhancing information retrieval processes, particularly in the context of semantic search, where they facilitate concept-based matches and improve the relevance of results in scholarly publication searches, despite the challenges

AI-generated, for reference only.

users may face in navigating complex graphical interfaces. [20, 21, 22, 23, 24]. This foundational understanding will set the stage for examining the subsequent advancements in recommendation systems, where KGs further augment user experience and decision-making capabilities. Thus, we begin with a detailed discussion on the enhancement of information retrieval through Knowledge Graphs.

3.1 Enhancement of Information Retrieval

Knowledge Graphs (KGs) have emerged as pivotal tools in enhancing information retrieval systems, particularly within domains requiring the integration of vast and diverse datasets. In e-commerce, KGs facilitate the seamless integration of extensive information about items, online shops, and users, thereby improving the accuracy and efficiency of information retrieval processes [25]. The structured nature of KGs allows for more precise querying and navigation, which is particularly beneficial in environments characterized by high data volume and complexity [23].

The ability of KGs to address issues such as data sparsity and cold start problems in recommender systems further underscores their utility in information retrieval [26]. By leveraging the rich semantic relationships encoded in KGs, systems can infer user preferences more accurately, even when explicit interaction data is sparse. This capability is exemplified in applications like the Engineering Equipment Recommender (EER), which utilizes KGs to enhance the accuracy and efficiency of product recommendations, thereby streamlining the information retrieval process [27].

Moreover, KGs contribute to the robustness and generalization of models across various domains, including computer vision, where they help mitigate distribution shifts and improve model performance [28]. The integration of multimodal information, as demonstrated by models like MR-GCN, further enhances the effectiveness of KGs in information retrieval by providing a more comprehensive understanding of the data [29].

In scholarly domains, KGs offer structured navigation and time-saving features that reduce cognitive overload, facilitating the discovery of relevant publications and enhancing the overall user experience [21]. The dynamic nature of KGs also supports the prediction of future events and the co-evolution of knowledge, which is crucial for maintaining the relevance and accuracy of information retrieval systems in rapidly evolving fields [30].

The integration of Knowledge Graphs (KGs) into information retrieval systems significantly enhances their accuracy and efficiency by providing a structured framework that facilitates the interconnectivity and interoperability of diverse data sources. This improvement not only aids in navigating complex data landscapes but also addresses common challenges such as errors, duplicates, and missing values through a curated approach. As a result, users benefit from more informed decision-making and increased satisfaction, particularly in applications like personal assistants, question-answering systems, and search engines where high-quality KGs are essential for optimal performance. [22, 31]

3.2 Advancements in Recommendation Systems

Knowledge Graphs (KGs) have revolutionized the development of recommendation systems by offering a structured framework that captures intricate relationships between users and items, thereby enhancing both personalization and effectiveness. The integration of KGs into recommendation frameworks enables a deeper understanding of user preferences and item characteristics, facilitating the development of more nuanced and accurate recommendation models [32]. This is particularly beneficial in multi-domain recommendation tasks, where KGs support the evaluation and adaptation of various Knowledge Graph-based Prediction (KGP) models across diverse application areas [33].

Recent advancements have highlighted the need to move beyond traditional Euclidean embedding spaces, which often fail to capture the non-linear and complex interactions inherent in user-item relationships. To address these limitations, innovative methods such as the Multi-modal Knowledge Graph Attention Network (MKGAT) have been developed, leveraging multi-modal data to enhance recommendation quality by integrating diverse types and modalities of information [34]. This approach not only improves the accuracy of recommendations but also enhances their interpretability by providing richer semantic context.

The advent of large language models (LLMs) has further augmented the capabilities of KGs in recommendation systems. Techniques like CoLaKG utilize LLMs to derive semantic embeddings from item-centered knowledge graph subgraphs, thereby improving recommendation accuracy through a more comprehensive understanding of contextual information [35]. Moreover, frameworks such as EDGE incorporate external knowledge to enrich graph embeddings, enhancing the robustness and quality of recommendations [36].

Addressing the balance between accuracy and diversity remains a significant challenge in recommendation systems. KGs play a pivotal role in enhancing recommendation diversity, as demonstrated in studies focusing on context-enhanced and diversified recommendations [37]. In specialized domains, such as vehicle purchase/sale, KGs have been instrumental in constructing personalized recommender systems, overcoming the limitations of existing methods and paving the way for more effective recommendation strategies [38].

Furthermore, the challenges associated with knowledge-aware recommendation systems, particularly the limitations of existing collaborative filtering methods, are being addressed through enhancements in KGs [39]. Differentiating between structured queries and natural language questions (NLQs) is crucial for processing and utilizing KGs effectively in recommendation systems [23].

The integration of knowledge graphs (KGs) into recommendation systems significantly enhances their precision and scalability by facilitating the discovery of associations between items and leveraging contextual information. This approach not only addresses common challenges such as data sparsity and cold start problems but also enables the development of personalized and contextually aware recommendations. Advanced methods like CoLaKG utilize large language models to supplement missing facts and capture both local and global semantic connections within KGs, while techniques such as Multi-modal Knowledge Graph Attention Network (MKGAT) incorporate diverse data types to further enrich recommendations. As a result, these innovations lead to improved user satisfaction and engagement across various application domains, effectively mitigating issues like the "echo chamber" phenomenon through enhanced recommendation diversity. [37, 35, 34]

3.3 Applications in Explainable AI

Knowledge Graphs (KGs) are instrumental in enhancing the interpretability and transparency of AI systems, addressing the critical demand for explainable artificial intelligence (XAI). The integration of KGs with large language models (LLMs) has emerged as a promising advancement, facilitating improved knowledge representation and enabling the development of more comprehensible AI models [40]. This synergy fosters innovation by allowing KGs to enhance machine understanding while simultaneously supporting cross-domain research through the integration of diverse data modalities [41].

In the realm of recommendation systems, KGs contribute significantly to explainability by modeling complex relationships between entities. Knowledge-based multiple adaptive spaces fusion methods, such as MCKG, exemplify the potential of KGs to represent intricate interactions in recommendation tasks, thereby enhancing transparency and user trust [42]. Moreover, explainable knowledge graph attention networks have been developed to predict outcomes by focusing on the relationships between triples, rather than solely relying on embeddings of individual entities and relations [25].

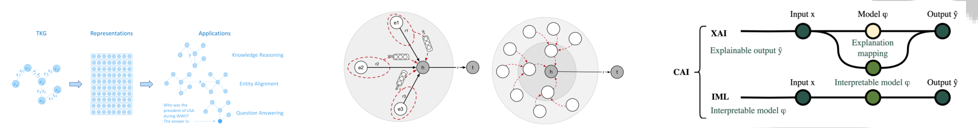
The application of KGs extends to multi-document scientific summarization, where they improve the modeling of content and relationships, leading to more informative and coherent summaries [24]. This capability is crucial for generating summaries that are not only accurate but also easily interpretable by users, thereby enhancing the overall transparency of AI-driven summarization systems.

Cross-domain knowledge graphs, such as DBpedia, Wikidata, and YAGO, further illustrate the versatility of KGs in explainable AI applications. These graphs serve as foundational tools for developing AI systems that prioritize transparency and interpretability [43]. The emphasis on comprehensible artificial intelligence (CAI) methods underscores the importance of KGs in addressing the need for transparent AI decision-making processes [44].

In dialogue systems, KGs facilitate human-like interactions and support exploratory search by leveraging structured knowledge to enhance the user experience and ensure that AI systems provide explanations that are both accurate and user-friendly [45]. This integration exemplifies the potential of KGs to make AI more interpretable and accessible to users.

The development of explainable Knowledge Graph Embedding (KGE) models is critical, as these models are often criticized for their black-box nature. Recent approaches aim to decode latent representations to identify distinct structures in subgraph neighborhoods, translating these into human-understandable symbolic rules and facts [46]. Additionally, the LinkLogic method provides high-quality explanations for link predictions, showcasing its potential to enhance interpretability in knowledge graph applications [47].

Overall, the role of KGs in explainable AI is multifaceted, encompassing the enhancement of recommendation systems, summarization processes, and dialogue interactions. By offering structured and semantically rich representations of knowledge, knowledge graphs (KGs) enhance the capabilities of AI systems, enabling them to provide explanations that are not only transparent and interpretable but also facilitate the discovery of associations between entities. This structured representation helps in addressing challenges such as missing facts and limited scopes within KGs, ultimately fostering greater user trust and engagement in applications like recommender systems, link prediction, and question answering. Additionally, the integration of large language models (LLMs) into KG frameworks further enriches the semantic connections and improves the overall performance of AI-driven applications. [20, 48, 35, 31]



(a) TKG: A Framework for Knowledge Graphs[49]

(b) Dynamic Interaction Network[25]

(c) Interpretable AI: Explaining and Interpreting Machine Learning Models[44]

Figure 2: Examples of Applications in Explainable AI

As shown in Figure 2, In the realm of Explainable AI (XAI), knowledge graphs play a pivotal role in enhancing the interpretability and transparency of machine learning models. The provided examples illustrate how these graphs are leveraged to facilitate understanding and explanation of complex AI systems. The first example, "TKG: A Framework for Knowledge Graphs," demonstrates the transformation of a temporal knowledge graph into a structured representation that highlights the relationships between entities, thus enabling more intuitive applications. The "Dynamic Interaction Network" example showcases a network where entities and their interactions are visualized, revealing intricate patterns that can be analyzed for better insight into dynamic systems. Lastly, the "Interpretable AI: Explaining and Interpreting Machine Learning Models" example underscores the importance of making AI models comprehensible through components like Cross-Entropy AI and Interpretable Machine Learning, which aim to demystify the decision-making processes of AI systems. Together, these examples underscore the critical role of knowledge graphs in advancing the field of Explainable AI by providing clear, structured, and insightful representations of complex data and interactions. [**?**]cai2024surveytemporalknowledgegraph,zhang2021knowledgegraphembeddingecommerce,schramm2024comprehensibleartifici

3.4 Integration in Industry and Enterprise Applications

Knowledge Graphs (KGs) play a transformative role in industry and enterprise applications by providing structured, semantically rich representations of complex datasets, thereby enhancing user interaction and accessibility [50]. In the biomedical sector, KGs facilitate knowledge transfer and improve the applicability of Knowledge Graph Embedding (KGE) models in real-world scenarios, significantly enhancing the efficiency and accuracy of biomedical research [51]. This capability is essential for managing the dynamic nature of biomedical data, where the structural dynamics of KGs are influenced by the superficiality of information [52].

In the educational domain, KGs are employed to construct structured representations that enhance the capabilities of Large Language Models (LLMs) by effectively discovering open intents and relationships [53]. This structured approach not only improves information retrieval and recommendation systems but also supports personalized learning experiences by tailoring content to individual needs. Furthermore, LiveSchema enhances the ability of data scientists to find and utilize relevant relational data, bridging the gap between knowledge representation and machine learning communities [54].

Public safety applications benefit from KGs through advanced anomaly detection and information completion methods, which leverage KGs to enhance situational awareness and decision-making

AI-generated, for reference only.

processes, demonstrating significant potential in improving public safety outcomes [55]. The structured nature of KGs allows for the accurate identification of anomalies and the provision of timely interventions, which are critical in high-stakes environments. In the cyber security domain, KGs are applied in situation awareness, threat detection, attack prediction, and incident response, among others, highlighting their versatility and impact [5].

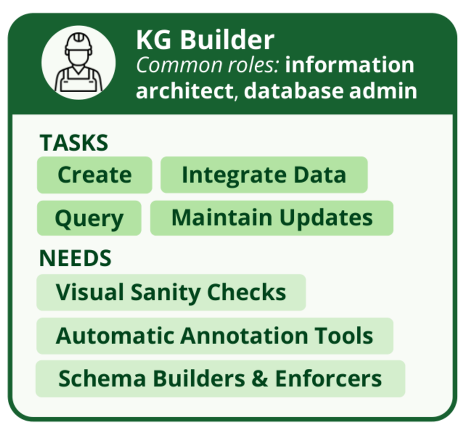
Enterprise solutions are increasingly adopting KGs to streamline operations and enhance decision-making processes. The complexity of many AI models, particularly black-box models, poses challenges for user understanding and interpretation. KGs address this issue by providing transparent and interpretable frameworks that facilitate user comprehension and engagement [44]. This transparency is particularly valuable in sectors where regulatory compliance and accountability are paramount. Additionally, the proposed method for expanding KGs significantly improves the performance of human-algorithm collaboration, leading to faster and more accurate decision-making by human experts [56].

The categorization of KG users into Builders, Analysts, and Consumers highlights the diverse needs and challenges associated with KG usage in enterprise contexts. Builders focus on constructing and maintaining KGs, Analysts leverage KGs for data-driven insights, and Consumers utilize KGs for decision-making and operational improvements. Each persona requires tailored tools and methodologies to maximize the benefits of KGs in their respective roles. The RDF Knowledge Graph Visualization System (RDF-KGVS) exemplifies how KGs enhance user interaction and accessibility in enterprise solutions [50].

In the e-commerce industry, KGs enhance recommendation systems by integrating real-world interaction data and product metadata from various platforms [57]. This integration enables more accurate and personalized recommendations, ultimately improving customer satisfaction and engagement. Comparative analyses of various approaches demonstrate the effectiveness and maturity of KG construction and Natural Language Processing (NLP) tasks in enterprise applications [58].

The integration of Knowledge Graphs (KGs) into industry and enterprise applications significantly improves operational efficiency and decision-making processes by providing a flexible and semantically rich framework for data organization. This integration not only facilitates the development of innovative solutions across diverse sectors, such as enhancing search and recommendation systems in e-commerce and improving the quality of question-answering systems, but also supports the evolution of research ideas into practical applications, ultimately driving advancements in both science and business. Furthermore, the implementation of robust curation frameworks ensures the high quality of KGs, thereby maximizing their utility and effectiveness in various business contexts. [24, 22, 58, 40]. By providing structured and semantically enriched data representations, KGs enable organizations to harness the full potential of their data assets, driving growth and competitiveness in the digital age.

(a) Taxonomy and Product Representation in a Semantic Web Model[40]



(b) KG Builder: A Role for Information Architect and Database Admin[59]

Figure 3: Examples of Integration in Industry and Enterprise Applications

As shown in Figure 3, The integration of knowledge graphs into industry and enterprise applications is exemplified through two distinct yet complementary models depicted in the provided figures. The first image, "Taxonomy and Product Representation in a Semantic Web Model," illustrates a structured semantic web model that organizes and categorizes products through a hierarchical taxonomy. This model emphasizes the relationships and attributes of various product types, showcasing categories such as 'Grocery,' 'Snacks,' 'Drinks,' and 'Candy.' Such a representation facilitates a clearer understanding of product data by aligning it within a semantic framework. The second image, "KG Builder: A Role for Information Architect and Database Admin," highlights the crucial role of the 'KG Builder' in the realm of information architecture and database management. This role is essential for the creation and integration of knowledge graphs, focusing on tasks such as building the graphs and integrating diverse data sources. Together, these examples underscore the practical applications of knowledge graphs in enhancing data organization and management within industry settings, thereby fostering more efficient and insightful enterprise operations. [**?**]dong2023generationsknowledgegraphscrazy,li2024knowledgegraphspracticecharacterizing)

In recent years, the field of Multi-modal Knowledge Graph Completion (MMKGC) has garnered significant attention due to its potential to enhance data integration and reasoning across diverse domains. A comprehensive understanding of this subject necessitates an exploration of its hierarchical structure, which encompasses various challenges, innovative models, and practical applications. Figure 4 illustrates this hierarchical structure, emphasizing the complexities associated with integration and the methodological limitations that researchers face. Notably, innovative models, such as DH-KG and OTKGE, have emerged to address these challenges, significantly improving graph integration and reasoning capabilities. Furthermore, the applications of MMKGC are evident in areas such as geographic data and recommendation systems, where benchmark evaluations underscore its impactful contributions. This multifaceted approach not only highlights the current landscape of MMKGC but also sets the stage for future advancements in the field.

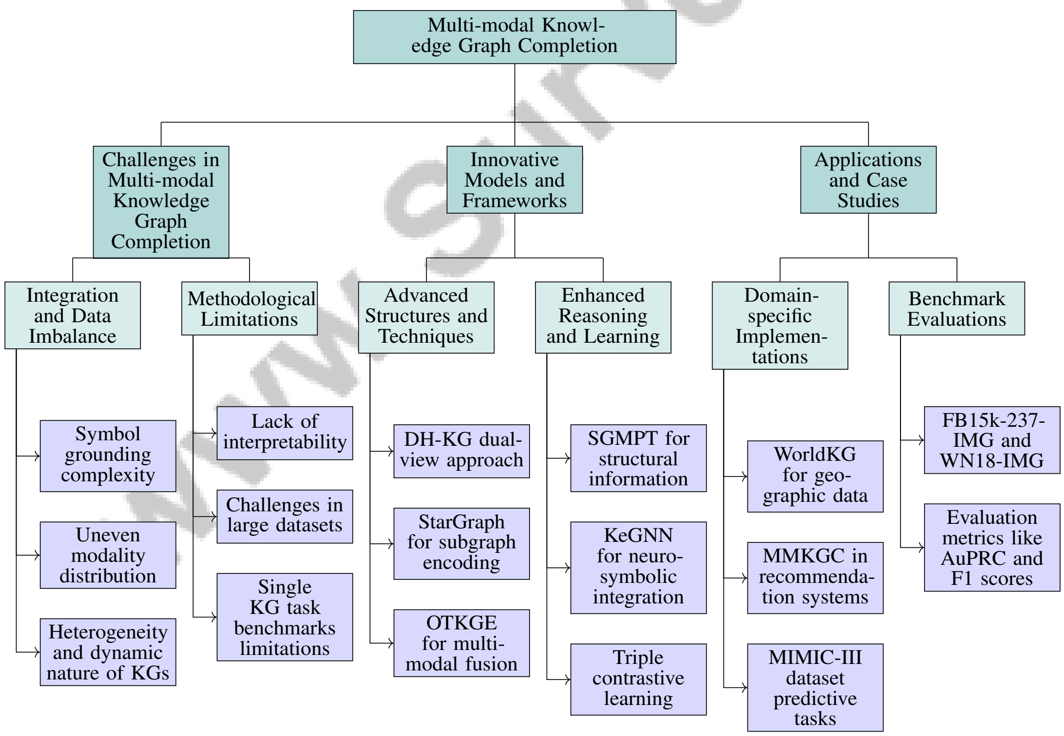


Figure 4: This figure illustrates the hierarchical structure of Multi-modal Knowledge Graph Completion, highlighting the challenges, innovative models, and applications. The challenges include integration complexities and methodological limitations. Innovative models such as DH-KG and OTKGE enhance graph integration and reasoning capabilities. Applications demonstrate the impact of MMKGC in domains like geographic data and recommendation systems, supported by benchmark evaluations.

AI-generated, for reference only.

4 Multi-modal Knowledge Graph Completion

4.1 Challenges in Multi-modal Knowledge Graph Completion

Multi-modal Knowledge Graphs (MKGs) encounter significant challenges due to the integration of diverse data modalities and inherent complexities. A primary issue is symbol grounding to images and other modalities, complicating comprehensive MKG construction [11]. The uneven distribution of modality information often results in missing modalities, reducing the effectiveness of current Multi-modal Knowledge Graph Completion (MMKGC) methods, which frequently fail to address these imbalances [60, 61]. The heterogeneity and dynamic nature of knowledge graphs exacerbate these challenges, necessitating efficient methods for updating and maintaining graph quality, as many methods overlook the intrinsic structure, resulting in suboptimal predictions for missing links [62]. Duplicated data across extensive datasets negatively impacts RDFizers, hindering effective knowledge graph creation [63].

Integrating multimodal information, such as molecular structures and textual descriptions, into completion methods remains a core challenge [64]. Automatic generation of scientific knowledge graphs requires explicit representations from publications, still demanding manual intervention [65]. Aligning entities and relations across continuously updated KGs poses further difficulties [18]. Detecting errors without external validation information is critical [66], and reliance on unavailable query word definitions for taxonomy enrichment diminishes method effectiveness [67]. Existing benchmarks focus on localized extraction methods, failing to capture comprehensive and interconnected knowledge, leading to limited KG accuracy [13].

Addressing these challenges requires innovative methodologies that integrate diverse data types while maintaining semantic coherence and scalability. Traditional embedding algorithms, designed for deterministic relations, do not account for uncertainty in medical knowledge graphs [9], and directly fusing embeddings from different modalities can disrupt spatial structures, resulting in inconsistent representations [68]. Existing methods often lack interpretability or struggle with large datasets, complicating the effective use of prior knowledge [15]. Researchers face challenges in predicting missing relationships due to the vast size of KGs, dynamic information, and complex interrelations [12]. Single KG task benchmarks do not adequately support multi-source KG embeddings, limiting real-world applicability [69]. Methods analyzing single-purpose networks do not consider complexities introduced by multiple layers, significantly altering centrality measures' robustness and interpretation [3]. Overcoming these obstacles necessitates advancements in methodologies that encapsulate semantically rich interactions between entities and their contexts, enhancing MKGs' robustness and applicability across domains.

4.2 Innovative Models and Frameworks

Recent advancements in multi-modal knowledge graph completion have introduced innovative models and frameworks enhancing knowledge graph integration, representation, and utility. The DH-KG structure integrates hyper-relational instance and ontology views, providing a more comprehensive knowledge representation than traditional single-view methods [16]. This dual-view approach improves expressiveness and accuracy, enabling robust applications across diverse domains. StarGraph advances knowledge representation by generating and encoding incomplete 2-hop subgraphs for target nodes, capturing relevant neighborhood information while minimizing computational overhead [69]. Benchmarks like MuTex support this by offering tools for multiple KG tasks, facilitating KG integrations to enhance representation learning.

The Optimal Transport Knowledge Graph Embeddings (OTKGE) method formulates multi-modal knowledge fusion as an optimal transport problem, minimizing the Wasserstein distance between modal distributions to achieve a unified representation that preserves individual modalities' spatial structures [3]. This approach effectively maintains the integrity of multi-modal embeddings during fusion. The Structure-Guided Multimodal Pretrained Transformer (SGMPT) model employs pre-trained transformer architectures to enhance knowledge graph reasoning by utilizing structural information within multi-modal knowledge graphs, significantly improving reasoning capabilities and overall performance in large-scale knowledge networks [70, 22, 13, 65, 71].

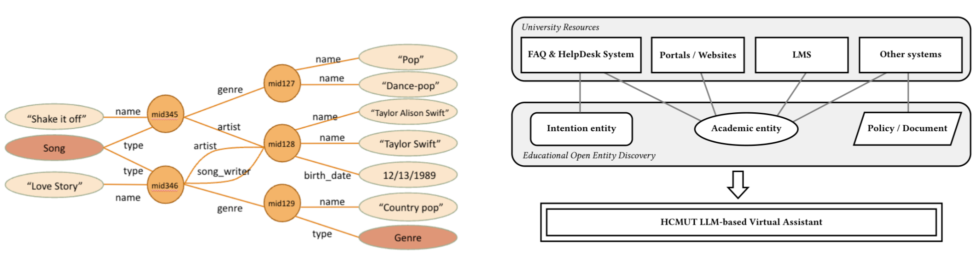
The Knowledge-Enhanced Graph Neural Network (KeGNN) presents a neuro-symbolic framework for graph completion by integrating knowledge enhancement layers with traditional graph neural networks, refining predictions through the incorporation of prior knowledge critical for addressing challenges posed by noisy and incomplete graph data [15, 36, 72]. This design allows for more effective exploitation of graph structure and prior knowledge, enhancing graph-based models' performance. Innovative models and frameworks in multi-modal knowledge graph completion leverage techniques such as triple contrastive learning and dual-phase training strategies to effectively fuse various modalities, addressing challenges in representing complex relationships and attributes of entities. By embedding entities and relations into low-dimensional vector spaces, these approaches improve predictive accuracy for missing links, demonstrating significant potential in applications like recommendation systems and biomedical research [73, 74]. By tackling issues related to data integration, relation pattern capture, and semantic enrichment, they provide robust solutions for enhancing knowledge graphs' accuracy and applicability, paving the way for effective AI-driven applications.

4.3 Applications and Case Studies

The application of multi-modal knowledge graph completion (MMKGC) techniques has advanced various domains, showcasing their transformative impact on knowledge representation and decision-making. The WorldKG knowledge graph and GeoVectors corpus exemplify effective knowledge graph creation for geographic data, addressing challenges in integrating geographic information [10]. These efforts highlight MMKGC methods' potential in managing complex, multi-modal datasets. Benchmark datasets like FB15k-237-IMG and WN18-IMG, which include multi-modal attributes such as textual descriptions, images, and graph structures, serve as foundational tools for evaluating MMKGC models [14]. Techniques like OTKGE have been tested on multi-modal knowledge graph completion benchmarks, including WN9-IMG and FB-IMG, demonstrating their ability to handle various entities and relationships from real-world knowledge graphs [68]. These benchmarks emphasize the importance of integrating diverse data types to enhance relational learning and link prediction.

In recommendation systems, MMKGC techniques improve personalization and accuracy by integrating diverse data representations into a unified framework. A case study in the vehicle purchase/sale domain evaluated MMKGC methods using metrics such as Precision at n, Recall at n, and Mean Average Precision (MAP), demonstrating superior performance compared to baseline methods [75]. This underscores the potential of MMKGC methods to refine knowledge graph completion processes through innovative data integration strategies. The effectiveness of MMKGC techniques is further illustrated in predictive tasks using the MIMIC-III dataset, where architectures like MMUGL are compared against existing models. Evaluation metrics such as Area under the precision-recall curve (AuPRC) and F1 scores confirm the improved predictive accuracy of MMKGC techniques across multiple downstream tasks [76]. Additionally, the evaluation of KeGNN on benchmark datasets such as Citeseer, Cora, PubMed, and Flickr showcases its performance against baseline methods, validating the robustness of MMKGC approaches [15].

These case studies collectively illustrate significant advancements and practical applications of MMKGC techniques, paving the way for innovative solutions and informed decision-making across diverse sectors. The ongoing development and refinement of MMKGC methods promise to enhance knowledge graphs' integration and utility in complex, real-world scenarios, ultimately leading to improved usability and effectiveness in applications such as question answering and recommendation systems [12].



(a) Music Data Representation[40] (b) Educational Open Entity Discovery System[53]

Figure 5: Examples of Applications and Case Studies

AI-generated, for reference only.

As shown in Figure 5, the integration of diverse data types and systems is crucial for enhancing information utility and accessibility in Multi-modal Knowledge Graph Completion. The provided examples illustrate this concept in two distinct domains: music data representation and educational systems. The first example showcases a graph database model for music data, interconnecting entities like 'Song,' 'Artist,' and 'Genre,' demonstrating how relationships between musical components can be structured for improved data retrieval and analysis. This representation aids in organizing vast musical data and facilitates complex queries and insights into the music industry. The second example highlights an Educational Open Entity Discovery System, employing a virtual assistant to streamline university resource discovery. This system integrates various academic and administrative entities, such as policy documents and learning management systems, into a cohesive framework, enhancing user access to information and supporting educational activities. Together, these examples underscore the versatility and potential of multi-modal knowledge graphs in bridging disparate data sources and enhancing user engagement across different sectors [40, 53].

5 Multi-modal Fusion Techniques

Category	Feature	Method
Methodologies for Multi-modal Fusion	Adaptive Fusion Techniques Contrastive Learning Approaches Ontology and Subgraph Methods Transport-Based Fusion	MoCi[77], MMKGE[78] MyGO[79] RDF-KGVS[50] OTKGE[68]
Applications of Multi-modal Fusion in Knowledge Graphs	Deployment Strategies Fusion Techniques	EEKGC[55] MKGAT[34], NativE[60], OVID[10]
Innovative Techniques in Multi-modal Fusion	Noise and Robustness Enhancement Coherence and Alignment	SNAG[80] KG-MRI[73]
Future Directions in Multi-modal Fusion	Modality Interaction Mechanisms	LAFA[81]

Table 1: This table provides a comprehensive overview of the methodologies, applications, and innovative techniques in multi-modal fusion for knowledge graphs. It categorizes various approaches and highlights specific methods, such as adaptive fusion techniques and ontology-based methods, along with their respective applications and future directions. The table serves as a concise reference for understanding the diverse strategies employed in enhancing the integration and performance of knowledge graphs through multi-modal fusion.

Understanding multi-modal fusion techniques is essential for integrating diverse data types within knowledge graphs. Table 2 provides a comprehensive comparison of various multi-modal fusion methodologies, elucidating their distinct strategies and integration approaches within knowledge graph frameworks. Additionally, Table 1 presents a detailed categorization of methodologies, applications, and future directions in multi-modal fusion, illustrating the diverse techniques employed to enhance knowledge graph capabilities. This section explores various methodologies that enhance knowledge graph integration and performance, focusing on the NativE framework and its relation-guided adaptive fusion strategy.

5.1 Methodologies for Multi-modal Fusion

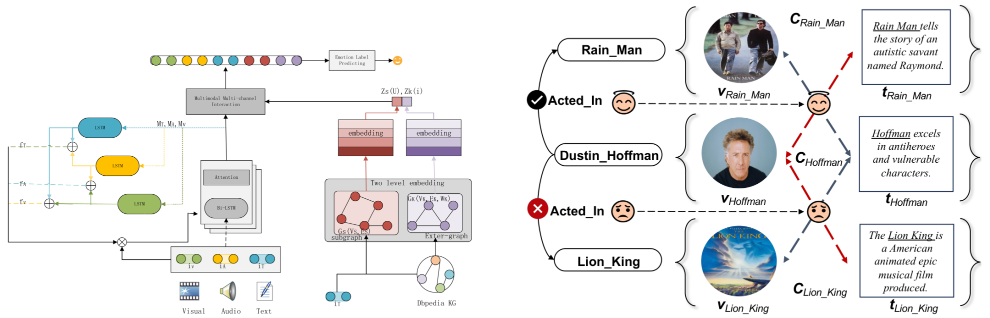
Multi-modal data fusion enhances knowledge graph capabilities by integrating diverse sources effectively. The NativE framework exemplifies this by using relation-guided adaptive fusion and adversarial training to unify diverse modalities into a cohesive embedding space, improving knowledge graph completion [60]. This approach addresses modality imbalance and incomplete data integration challenges.

The LAFA model further advances this field by combining link-aware fusion and aggregation, enhancing entity embeddings for accurate link prediction [81]. By integrating structural and semantic information from multiple modalities, it improves prediction accuracy.

The KG-MRI method employs a triple contrastive learning model and dual-phase training strategy to bolster the robustness of fused knowledge graphs [73]. This method leverages the complementary strengths of various modalities, enhancing the graph's quality and applicability.

MyGO framework tokenizes raw multi-modal data into discrete tokens, using a cross-modal entity encoder to learn fine-grained entity representations, facilitating precise multi-modal information integration [79]. RDF-KGVS enhances clarity and usability by allowing subgraph selection based on ontology features, improving data visualization and interpretability [50].

OTKGE addresses multi-modal fusion challenges by formulating it as an optimal transport problem, minimizing the Wasserstein distance between modalities and the unified embedding space to maintain consistency and comprehensiveness [68]. These methodologies underscore the critical role of multi-modal fusion in augmenting knowledge graphs' capabilities, enabling nuanced understanding of complex scenarios and facilitating applications in AI and data science [73, 41, 65, 82].



(a) A Multimodal Interaction Network for Emotion Label Prediction[78]

(b) Rain Man and The Lion King[77]

Figure 6: Examples of Methodologies for Multi-modal Fusion

The examples in Figure 6 illustrate multi-modal fusion's role in enhancing predictive accuracy and interpretative depth through diverse data integration. The first example integrates visual, audio, and text data for emotion label prediction, employing colored sequences and LSTM layers to improve emotional nuance discernment. The second example maps multi-modal fusion in cinematic data, highlighting connections between movies and actors, demonstrating multi-modal fusion's applicability beyond emotion prediction to broader domains such as media analysis [78, 77].

5.2 Challenges in Multi-modal Fusion

Multi-modal fusion challenges arise from integrating diverse data types into cohesive representations. Representing attributes from multiple modalities and balancing their contributions are significant obstacles [73]. The quality of input data, such as images, impacts fusion model performance, as seen with the LAFA model's sensitivity to image quality and noise assessment [81].

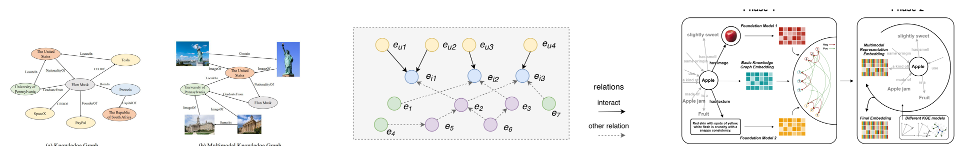
Adaptive fusion strategies are essential for capturing the richness of multi-modal data, enhancing analyses in recommendation systems, knowledge graph representation, and multimedia processing [73, 83, 77, 57]. Addressing these challenges requires innovative approaches that capture each modality's strengths and mitigate weaknesses. Strategies include adaptive weighting schemes, noise reduction techniques, and advanced representation learning frameworks like KG-MRI and SNAG, which leverage foundation models and Transformer architectures to integrate diverse entity features [73, 84, 80, 82].

5.3 Applications of Multi-modal Fusion in Knowledge Graphs

Multi-modal fusion techniques significantly enhance knowledge graphs' ability to integrate diverse data types. In recommendation systems, they improve accuracy and personalization by integrating textual, visual, and structural data [60]. In biomedicine, they combine genomic, clinical, and imaging data for accurate disease diagnosis and treatment recommendations [51].

Geographic knowledge graphs benefit from multi-modal fusion by integrating satellite images, textual descriptions, and geospatial data, enhancing complex geographic information analysis [10]. In public safety, integrating diverse data sources into knowledge graphs supports anomaly detection and situational awareness [55].

These techniques also enhance AI systems' interpretability by providing richer semantic context, crucial for understanding AI-driven decisions [40]. The integration of multi-modal fusion techniques in knowledge graphs results in more powerful AI-driven solutions across fields, as seen in methods like KG-MRI, which use foundation models to enhance multi-modal environments [73, 82, 41, 77, 11].



(a) Multimodal Knowledge Graph for Person-Entity Relationship Extraction[41]

(b) Graph Representation of Interactions and Relations[34]

(c) Multimodal Knowledge Graph Embedding for Semantic Representation Learning[73]

Figure 7: Examples of Applications of Multi-modal Fusion in Knowledge Graphs

The examples in Figure 7 illustrate multi-modal fusion's role in enhancing knowledge graph applications. The first example extracts person-entity relationships using integrated modalities, the second depicts dynamic interactions and relations, and the third focuses on semantic representation learning through knowledge graph embeddings. These examples underscore multi-modal fusion's potential in enriching knowledge graph applications [41, 34, 73].

5.4 Innovative Techniques in Multi-modal Fusion

Recent advancements in multi-modal fusion have introduced innovative techniques that enhance data integration within knowledge graphs. Chen et al.'s Gauss Modality Noise Masking module improves robustness by incorporating noise during training, aligning multi-modal representations [80]. Lu et al.'s triple contrastive learning module enhances coherence and alignment across modalities [73].

These techniques address multi-modal fusion challenges, such as data heterogeneity and alignment, by integrating noise masking and contrastive learning strategies. They enhance knowledge graphs' representational capabilities, enabling better management of complex scenarios and broadening applications across fields like genomics and recommendation systems [73, 46, 36, 80, 71].

5.5 Future Directions in Multi-modal Fusion

Future research in multi-modal fusion aims to enhance system adaptability, robustness, and applicability across domains. Refining noise detection thresholds in fusion models, as seen in the LAFA model, can improve precision and reliability [81]. Expanding modalities integrated into knowledge graphs, such as auditory or physiological signals, enriches semantic depth and contextual understanding, benefiting fields like healthcare [73, 67, 24].

Enhancing model adaptability to various knowledge graphs expands multi-modal fusion's applicability. Developing adaptable frameworks can enhance data integration into diverse graph structures, crucial for addressing multi-modal representation challenges. Techniques like KG-MRI leverage foundation models and advanced strategies to improve representation capabilities, aiding applications like NAFLD analysis and scientific knowledge graph creation [73, 83, 65, 85, 24].

Advancements in machine learning and AI hold potential for enhancing multi-modal fusion efficiency and effectiveness. Techniques like deep representation, transfer learning, and knowledge-guided fusion address multi-modal data challenges, enabling improved representation and processing [73, 83, 84]. Future research should focus on noise management, modality integration, model adaptability, and algorithm advancement to enhance knowledge graph applications across sectors, improving AI-driven solutions [1, 20, 22, 65].

Feature	**NativE framework**	**LAFA model**	**KG-MRI**
Fusion Strategy	Relation-guided Adaptive	Link-aware Aggregation	Triple Contrastive Learning
Modality Integration	Cohesive Embedding Space	Structural And Semantic	Complementary Strengths
Training Approach	Adversarial Training	Noise Assessment	Dual-phase Training

Table 2: Comparison of multi-modal fusion methodologies, highlighting the fusion strategies, modality integration approaches, and training techniques for the NativE framework, LAFA model, and KG-MRI. The table provides a concise overview of how each method addresses the challenges of integrating diverse data types within knowledge graphs, contributing to enhanced performance and capability.

AI-generated, for reference only.

6 Link Prediction and Graph Embeddings

Link prediction is a pivotal component in knowledge graphs (KGs), addressing data gaps and enhancing their functionality and precision. As KGs are increasingly applied across various domains, understanding the mechanisms and implications of link prediction becomes crucial. This section delves into the methodologies, advancements, and impacts of link prediction on knowledge representation.

6.1 Role of Link Prediction in Knowledge Graphs

Link prediction is vital for sustaining and expanding KGs by inferring missing connections between entities, thereby enhancing their utility and accuracy, notably in recommendation systems and information retrieval [1]. Performance evaluation of link prediction models typically involves assessing tasks like entity typing and minimizing classification errors to ensure KG reliability [9].

Recent developments address the inefficiencies in single-thread implementations of Knowledge Graph Embedding (KGE) models, especially with large-scale graphs [86]. The dual-view hyper-relational knowledge graph structure (DHGE) significantly enhances link prediction and entity typing by simultaneously modeling hyper-relational facts and hierarchical information [16]. This model improves KG expressiveness and accuracy, facilitating its expansion and maintenance.

Integrating multi-modal data into KGs highlights the importance of link prediction. Models like SGMPT utilize structural information to enhance reasoning capabilities, which is crucial in biomedical KGs for predictive performance [14, 87]. Techniques such as LineaRE manage various connectivity patterns, underscoring the need for comprehensive modeling capabilities [2].

Benchmarks like MuTex facilitate the comparison and analysis of KGE models, crucial for developing effective multi-source KG applications [69]. These benchmarks are essential for evaluating the adaptability and effectiveness of modern link prediction models in dynamic environments requiring continuous information integration.

Ultimately, link prediction is indispensable for KG evolution, ensuring completeness and applicability in AI-driven applications. By enhancing predictive capabilities and precision, link prediction fosters high-quality embeddings that incorporate both structured and unstructured data, supporting diverse applications like entity linking, question answering, and recommender systems. Advancements like KGA further augment KGs by capturing relationship nuances and temporal data, thereby improving link prediction performance [88, 31].

6.2 Graph Embeddings for Link Prediction

Graph embeddings are crucial for link prediction in KGs, transforming entities and relationships into continuous vector spaces that enhance machine learning applications. These embeddings capture latent features and complex relational structures, thereby improving link prediction precision. The RPEST model exemplifies this by predicting predefined relations between nodes using structural and textual information, thereby enriching semantic context and improving accuracy [89].

Models like DeCom refine link prediction by decompressing low-dimensional embeddings into higher-dimensional spaces to capture intricate relational patterns. The IMF framework employs interactive multimodal fusion to integrate commonality and complementarity in multimodal information, enriching the link prediction process [90]. This ensures embeddings reflect a comprehensive integration of diverse data types, leading to improved outcomes.

The TuckERT model incorporates temporal dimensions into graph embeddings, utilizing tensor decomposition for knowledge graph completion [91]. This is crucial for applications requiring an understanding of dynamic relationships. Additionally, LineaRE captures linear relationships between entities and relations, offering a computationally efficient solution for link prediction tasks [2].

Emphasizing topological properties at the individual triple level enhances link prediction accuracy [87]. This granular approach facilitates detailed exploration of structural nuances within KGs, vital for accurate predictions.

Graph embeddings significantly enhance KGs' predictive capabilities by providing structured, semantically rich representations. By integrating diverse methodologies and advanced learning techniques, KGE enhances KGs' precision and versatility in AI applications. These embeddings transform high-dimensional KG data into low-dimensional vector spaces, preserving essential structural and relational information while accommodating both structured and unstructured data, thus supporting tasks like link prediction, entity alignment, and question answering [66, 92, 31, 69, 93].

6.3 Advanced Embedding Techniques

Advancements in graph embedding techniques have significantly improved link prediction accuracy through sophisticated methodologies that capture complex relational and semantic information. Dual-view embedding strategies, such as GRAN encoders and Hypergraph Neural Networks (HGNNs), exemplify innovative approaches that enhance KGs' expressiveness and utility [16]. These methods enable simultaneous modeling of hyper-relational facts and hierarchical information, facilitating accurate link predictions and entity typing tasks.

Decompression-based models like DeCom enhance link prediction by mapping original embeddings into more expressive feature spaces, allowing for detailed exploration of relational patterns within KGs. Advanced decompression techniques improve the representation of entities and relationships, enabling existing models like DistMult and ComplEx to achieve state-of-the-art performance across benchmark datasets [94, 95, 65, 96, 24].

Interactive Multimodal Fusion (IMF) represents a significant advancement in integrating multimodal knowledge for link prediction. This approach employs a two-stage fusion framework that preserves modality-specific information while effectively capturing complex interactions between modalities. Utilizing bilinear pooling and incorporating contrastive learning, IMF enhances knowledge representation across modalities. Empirical evaluations demonstrate its effectiveness, suggesting broad applicability in complex multimodal environments [73, 97]. By leveraging diverse data types, IMF enriches embeddings, leading to improved link prediction outcomes.

The subgraph2vec method introduces a random walk-based algorithm that mitigates biases in prior graph embedding techniques by allowing user-defined subgraph exploration. This approach enhances the ability to capture underlying relationships within KGs, facilitating effective applications like link prediction and providing deeper insights into graph structure and semantics [98, 99, 65]. By focusing on subgraph-level interactions, this method enhances the granularity and accuracy of embeddings.

These advanced techniques highlight ongoing innovations in the field, emphasizing the integration of diverse data types, hierarchical structures, and complex relational information to enhance KGE accuracy and applicability in link prediction tasks. Employing advanced methodologies like Natural Language Processing and Machine Learning can improve knowledge representation in scientific domains, facilitating the extraction of entities and relationships from extensive literature for integration into large-scale KGs. This progress is crucial for driving innovation in AI-driven applications, such as personal assistants and question-answering systems, where high-quality KGs are essential for effective functionality [22, 65].

6.4 Challenges and Solutions in Link Prediction

Link prediction in KGs faces numerous challenges, primarily due to the complexity of accurately inferring missing links while ensuring semantic coherence across diverse datasets. A significant challenge is the time-consuming nature of single-thread implementations, limiting large-scale graph processing efficiency [86]. This computational inefficiency is exacerbated by high dimensionality and extensive tensor calculations required for modeling complex relationships, often leading to suboptimal performance [1].

Additionally, the incomplete nature of knowledge representations in KGs hampers effective knowledge acquisition and integration from diverse sources [1]. This incompleteness is compounded by the absence of negative triples in training datasets, resulting in biases in classification metrics dependent on true negatives and false negatives, ultimately affecting model reliability.

The reliance on monolingual descriptions also poses challenges, potentially leading to the loss of valuable semantic information from multilingual datasets. Current link prediction models struggle with low-frequency relations and sparsity, restricting their capacity to leverage the full spectrum of available data. This inadequacy confines models to coarse-grained positional data of entities, adversely affecting link prediction accuracy and effectiveness, highlighting the need for innovative approaches that integrate richer data representations and address challenges like few-shot learning and data sparsity [100, 101, 102, 36, 65].

Proposed solutions include developing efficient computational frameworks that leverage parallel processing for enhanced scalability and performance. Incorporating adaptive learning strategies and advanced embedding techniques that capture multi-relational graph intricacies may also improve link prediction accuracy. Addressing technical challenges related to KGE, knowledge acquisition, and completion can lead to more robust and reliable link prediction solutions, significantly enhancing KGs' utility and applicability in AI-driven applications like social networks, recommender systems, and scientific research analysis [1, 20, 36, 65].

6.5 Evaluation Metrics and Benchmarks

Evaluating link prediction methods in KGs relies on robust metrics and benchmarks to accurately assess predictive performance. Key metrics include Mean Reciprocal Rank (MRR) and Hits@k, which provide insights into models' abilities to rank correct triples higher among candidates. MRR evaluates predictive performance by calculating the average reciprocal ranks of the first correct answer, while Hits@k measures the percentage of correct triples appearing within the top k ranked positions, offering straightforward assessments of accuracy in link prediction tasks [103, 66, 22, 104].

These metrics are particularly useful when applied to benchmark datasets like WN18, FB15k, WN18RR, and FB15K-237, ensuring consistent and reliable performance assessments across various models and configurations [69]. Utilizing these datasets allows for standardized comparisons, facilitating the identification of strengths and weaknesses in different approaches [16].

In addition to MRR and Hits@k, other metrics such as Mean Rank (MR) and normalized discounted cumulative gain (NDCG@k) provide nuanced insights into model performance across datasets [2]. These metrics assess models' abilities to distinguish between true and false links, enhancing evaluation robustness. Including additional metrics ensures a comprehensive evaluation framework that captures various performance aspects, from ranking accuracy to retrieval effectiveness [16].

The evaluation process typically involves dividing the KG into training, validation, and test sets, with models predicting missing links and ranking them to compute metrics like Hits@10 and MRR [86]. This rigorous approach ensures realistic assessments, reflecting models' potential performance in real-world applications. A comprehensive set of metrics provides valuable insights into different models' predictive capabilities, ultimately driving innovation and improvement in link prediction methodologies across various AI-driven applications.

6.6 Future Directions in Link Prediction

Future research in link prediction within KGs is set to explore promising avenues to enhance model accuracy, scalability, and interpretability. A critical focus will be on implementing sophisticated KGE methods and expanding frameworks like ParaGraphE to diverse graph contexts [86]. This expansion will facilitate exploring diverse graph structures, leading to robust and adaptable link prediction models.

Developing techniques that enhance model resilience to noisy data is vital for improving reliability and accuracy in knowledge extraction, summarization, and analysis across applications like scientific literature management and cybersecurity knowledge representation. Leveraging advanced Natural Language Processing and Machine Learning methods can create robust KGs capable of handling unstructured text complexities and facilitating actionable insights from large datasets [24, 105, 65]. Integrating noise-tolerant algorithms can maintain prediction accuracy despite data imperfections.

Refining evaluation metrics is another key area of exploration. Developing comprehensive performance metrics that consider dataset size and hub entities' roles in KGs is essential for accurately evaluating model performance, particularly in large, complex datasets with high entity and relationship volumes. This enhancement will improve KGs' quality and utility, critical for applications like personal assistants and question-answering systems, addressing common issues like errors, duplicates, and missing values that compromise effectiveness [22, 65].

Expanding link prediction to include multimodal attributes is also promising. Future research could focus on incorporating a broader range of attributes into multimodal datasets and developing efficient

AI-generated, for reference only.

models for capturing these attributes. This expansion would lead to more nuanced knowledge representations, improving link prediction accuracy by integrating external textual information with existing KGs, addressing sparsity issues, and enhancing embeddings' overall quality [36, 65].

Extending existing link prediction models to incorporate various literals, such as string literals, and refining their application to larger, more diverse KGs will enhance versatility and effectiveness across domains. This enhancement is crucial, as KGs often contain valuable unstructured information, including multilingual entity descriptions and numerical values, significantly improving predictive accuracy. Recent advancements in embedding methods that integrate literal-aware terms and hyper-relational facts indicate potential for improved link prediction performance, suggesting that a comprehensive approach to incorporating structured and unstructured data will yield robust, scalable models [88, 62, 31, 106, 107].

Investigating advanced pruning strategies and creating hybrid language models that balance computational efficiency with performance efficacy presents opportunities for future research, particularly in developing sophisticated KGs and enhancing semantic search capabilities in scholarly literature. These advancements could significantly improve the management, analysis, and dissemination of scientific knowledge by enabling accurate extraction of entities and relationships from research publications and facilitating user-friendly exploration of complex data through conversational search systems [21, 65]. Such strategies could enhance link prediction models' efficiency, making them suitable for real-time applications.

Additionally, future research could investigate enhancements to decompression functions and explore their application to other model types and datasets. This approach aims to improve link prediction models' efficiency and scalability by effectively managing and analyzing increasingly complex data structures. Leveraging advanced techniques like Natural Language Processing and Machine Learning can enhance knowledge extraction and integration from vast scientific literature into KGs, facilitating the extraction of more expressive features and leading to better performance in relationship prediction within large-scale KGs [95, 65, 102].

Finally, exploring lightweight fusion models and additional components for predicting missing modalities could enhance IMF's applicability in various real-world tasks. By incorporating cutting-edge techniques like transductive and inductive embeddings and knowledge graph augmentation methods, future research can significantly improve link prediction models' accuracy and scalability. This advancement enhances these models' predictive capabilities and increases KGs' overall effectiveness in AI-driven applications, including scientific literature analysis and social network interactions. Leveraging Natural Language Processing and Machine Learning for entity and relationship extraction from research publications can create comprehensive KGs that facilitate scientific knowledge management and dissemination, while optimized embedding strategies can better utilize available node features, even in privacy-sensitive contexts [88, 65, 102].

7 Semantic Integration and Data Fusion Techniques

7.1 Importance of Semantic Integration

Semantic integration is essential for unifying diverse data sources, thereby enhancing the expressiveness and utility of knowledge graphs (KGs). It improves cognitive interoperability, enabling more effective data utilization across applications [108]. A significant challenge is the underutilization of semantic information due to existing methods' limitations in leveraging rich KG semantics and the absence of standardized evaluation metrics [44]. Developing benchmarks for better comparisons among KGs is crucial for guiding design improvements and ensuring effective semantic integration [109]. Understanding embeddings' capabilities to represent complex semantic relationships is vital for advancing KG embeddings [110].

Current research is predominantly monolingual, restricting semantic richness. Incorporating multilingual data could enhance semantic depth and interoperability [107]. Integrating logic rules into KG embeddings through frameworks like algebraic learning strengthens relational representation and supports robust semantic integration [111]. Methods like SDK leverage hyper-relational semantics and dynamic hypergraph structures, maintaining rich feature representations and enhancing integration in dynamic environments [39]. Improving decision-making speed and accuracy while reducing cognitive load on experts highlights semantic integration's value in expanding and utilizing KGs [56].

Semantic integration is crucial for harmonizing diverse data sources, facilitating the development of KGs that are expressive, interoperable, and capable of driving innovation across sectors. Advanced NLP and ML techniques enable KGs to represent complex relationships and entities from extensive scientific literature, addressing challenges posed by the growing volume of research publications. Organizing KGs into semantically meaningful units enhances usability through improved data management, access control, and alignment, supporting the FAIR principles critical for modern data practices [112, 65].

7.2 Challenges in Semantic Integration and Data Fusion

Semantic integration and data fusion face challenges in harmonizing disparate data sources while ensuring semantic consistency and accuracy. Evaluating semantic consistency is a significant obstacle, as existing benchmarks often focus on link prediction, neglecting broader aspects of integration [113]. This narrow focus can hinder comprehensive integration methodologies. Structural metrics may overlook critical quality dimensions like data accuracy and consistency [109], necessitating holistic evaluation frameworks with a wider range of quality metrics.

Capturing all relational structures within multi-relational data is another hurdle, as existing benchmarks may not fully account for inherent nuances [114], affecting data fusion processes. The quality and diversity of candidate KGs significantly influence semantic integration and extension performance [115]. Handling modality-missing scenarios remains a challenge, as current methods may not reflect real-world conditions where data from multiple modalities is incomplete or missing [90]. Efficiency challenges arise with methods having higher parameter counts, particularly with large embedding dimensionalities [91]. The study of centrality measures in multi-layered contexts is limited, focusing primarily on degree and betweenness centrality [3].

Addressing these challenges requires innovative methodologies to integrate diverse data types while ensuring semantic coherence and scalability, enhancing KGs' utility in browsing, analyzing, and forecasting scientific research. NLP and ML techniques, coupled with robust curation frameworks, can tackle quality, errors, and heterogeneity issues, optimizing KG construction and maintenance for improved performance and reliability in research applications [115, 22, 65].

7.3 Evaluation Frameworks and Benchmarks

Evaluating semantic integration and data fusion in KGs requires robust frameworks and benchmarks to assess effectiveness and accuracy comprehensively. Understanding structural quality is crucial for ensuring integrated data maintains semantic integrity and usability [109]. Structural quality metrics, such as node classification benchmarks, provide insights into KGs' ability to represent complex semantic relationships and support effective data fusion [110]. However, existing benchmarks often focus on link prediction, neglecting broader semantic integration aspects like aligning diverse data types and preserving coherence [113].

Comprehensive evaluation frameworks encompassing a wider range of quality metrics, including data accuracy, consistency, and the ability to handle multi-relational data, are needed [114]. Developing benchmarks for better comparisons among KGs is essential for guiding design improvements and ensuring effective semantic integration [109]. These benchmarks should consider candidate KGs' quality and diversity, significantly impacting integration and extension performance [115].

Evaluating semantic integration techniques must account for modality-missing scenarios, where data from multiple modalities may be incomplete or missing [90]. Efficiency is another critical evaluation aspect, particularly for methods with higher parameter counts and large embedding dimensionalities [91]. Establishing comprehensive evaluation frameworks and benchmarks is vital for improving semantic integration and data fusion techniques, facilitating high-quality KG development, enhancing data interoperability, and optimizing knowledge extraction and management from diverse scientific literature [17, 21, 22, 63, 65].

7.4 Future Research Directions

Future research in semantic integration and data fusion within KGs should explore several promising avenues to enhance effectiveness and applicability. Investigating additional logic rules and entity embedding designs within the algebraic framework could yield robust and versatile KG embeddings, facilitating accurate semantic integration [111]. Developing methods that utilize multilingual embeddings to enhance KGE models can improve the richness and diversity of semantic information captured by KGs, enhancing expressiveness across languages and cultural contexts [107].

Robust evaluation frameworks incorporating a broader spectrum of quality metrics, extending beyond traditional link prediction methodologies, are necessary. This should include integrating rank-based metrics for improved interpretability and comparability across diverse datasets and establishing quality metrics for KG curation addressing errors, duplicates, and missing values. Leveraging advancements in NLP and ML can facilitate extracting entities and relationships, enriching evaluation processes and providing insights into research trends [22, 104, 103, 65, 85].

Investigating sophisticated learning algorithms capable of addressing KGs' complexities and scale is critical, especially concerning missing information, limited scopes, and robust semantic connections in applications like recommender systems and scientific summarization. Recent advancements such as CoLaKG and KGSum1 demonstrate potential for innovative approaches to these limitations. Developing algorithms that manage and enrich dynamic structures for various AI applications, including search engines and question-answering systems, is essential [24, 20, 22, 35].

Addressing modality-missing scenarios is crucial for developing robust approaches in multi-modal knowledge graph completion (MMKGC). These approaches must integrate incomplete data from various modalities to enhance accuracy and reliability of predictions regarding missing triples in KGs. Tackling imbalance and incompleteness of modality information, as highlighted in recent advancements like AdaMF-MAT and MACO, can significantly improve MMKGC models' performance [90, 73, 83, 116]. Future research should focus on creating methodologies that effectively manage these scenarios, ensuring KGs maintain semantic integrity and usability even when faced with incomplete data.

Exploring innovative research avenues in semantic integration and data fusion can significantly enhance KGs' capabilities, particularly in managing and analyzing the expanding body of scientific literature. This advancement will streamline entity and relationship extraction from research publications using cutting-edge NLP and ML techniques, improving user experience through conversational search systems that facilitate effective scholarly discovery. Ultimately, these developments will drive substantial innovation and improvements across diverse KG applications, benefiting researchers, policymakers, and organizations alike [21, 65].

8 Conclusion

The investigation into knowledge graphs (KGs) and multi-modal methodologies underscores their significant impact across diverse sectors, enhancing functionalities in areas such as information retrieval, recommendation systems, and explainable AI. The fusion of varied data types within KGs has bolstered the resilience and applicability of AI solutions, with models like SGMPT demonstrating exceptional capabilities in multi-modal knowledge graph reasoning. This underscores the effectiveness of integrating structural information for improved reasoning processes. Similarly, KeGNN has shown its potential by enhancing node classification through the incorporation of prior knowledge, thus benefiting simpler neural models.

In the realm of recommendation systems, the amalgamation of KGs with conventional methods has proven beneficial in elevating both model transparency and performance. However, additional research is required to fully understand their advantages within enterprise environments. The LineaRE model exemplifies this by outperforming existing link prediction techniques across multiple datasets, highlighting its role in advancing knowledge graph embeddings. This calls for a holistic approach to knowledge graph completion that leverages multimodal data and sophisticated machine learning techniques to improve precision and efficiency.

Future research directions should focus on refining KG construction and application in multi-modal settings, exploring the emerging trends in large language models (LLMs), and addressing the current study limitations. Developing reasoning tools for semantic units and examining diverse applications across various domains remain crucial. Models such as DHGE, which excel in link prediction and entity typing, illustrate the potential of dual-view hyper-relational knowledge graphs to enhance KG utility.

Recent studies have emphasized the importance of multi-source embeddings in augmenting knowledge graph-related tasks, as demonstrated by the efficacy of μKG. Furthermore, OTKGE has achieved state-of-the-art results in multi-modal knowledge graph completion tasks, showcasing its ability to learn unified representations while tackling the challenges of spatial heterogeneity in multi-modal embeddings.

By advancing methodologies and discovering new applications, the field can further harness the capabilities of KGs and multi-modal techniques, fostering innovation and efficiency in AI-driven solutions across various industries. Future investigations should also aim at developing error approximations for larger sets of additional layers and exploring alternative graph structures that may affect centrality stability.

AI-generated, for reference only.

References

[1] Ciyuan Peng, Feng Xia, Mehdi Naseriparsa, and Francesco Osborne. Knowledge graphs: Opportunities and challenges. *Artificial Intelligence Review*, 56(11):13071–13102, 2023.

[2] Yanhui Peng and Jing Zhang. Lineare: Simple but powerful knowledge graph embedding for link prediction, 2021.

[3] Jens Dörpinghaus, Vera Weil, Carsten Düing, and Martin W. Sommer. Centrality measures in multi-layer knowledge graphs, 2022.

[4] Sven Hertling and Heiko Paulheim. Dbkwik++ – multi source matching of knowledge graphs, 2022.

[5] Kai Liu, Fei Wang, Zhaoyun Ding, Sheng Liang, Zhengfei Yu, and Yun Zhou. A review of knowledge graph application scenarios in cyber security, 2022.

[6] Zhuo Chen, Yichi Zhang, Yin Fang, Yuxia Geng, Lingbing Guo, Xiang Chen, Qian Li, Wen Zhang, Jiaoyan Chen, Yushan Zhu, Jiaqi Li, Xiaoze Liu, Jeff Z. Pan, Ningyu Zhang, and Huajun Chen. Knowledge graphs meet multi-modal learning: A comprehensive survey, 2024.

[7] Wen Zhang, Chi-Man Wong, Ganqinag Ye, Bo Wen, Hongting Zhou, Wei Zhang, and Huajun Chen. Pkgm: A pre-trained knowledge graph model for e-commerce application, 2022.

[8] Lei Jiang and Zuqiang Meng. Knowledge-based visual question answering using multi-modal semantic graph. *Electronics*, 12(6):1390, 2023.

[9] Linfeng Li, Peng Wang, Yao Wang, Jinpeng Jiang, Buzhou Tang, Jun Yan, Shenghui Wang, and Yuting Liu. A method to learn embedding of a probabilistic medical knowledge graph: Algorithm development, 2020.

[10] Elena Demidova, Alishiba Dsouza, Simon Gottschalk, Nicolas Tempelmeier, and Ran Yu. Creating knowledge graphs for geographic data on the web, 2023.

[11] Xiangru Zhu, Zhixu Li, Xiaodan Wang, Xueyao Jiang, Penglei Sun, Xuwu Wang, Yanghua Xiao, and Nicholas Jing Yuan. Multi-modal knowledge graph construction and application: A survey. *IEEE Transactions on Knowledge and Data Engineering*, 36(2):715–735, 2022.

[12] Satvik Garg and Dwaipayan Roy. A birds eye view on knowledge graph embeddings, software libraries, applications and challenges, 2022.

[13] Rui Yang, Boming Yang, Sixun Ouyang, Tianwei She, Aosong Feng, Yuang Jiang, Freddy Lecue, Jinghui Lu, and Irene Li. Graphusion: Leveraging large language models for scientific knowledge graph fusion and construction in nlp education, 2024.

[14] Ke Liang, Sihang Zhou, Yue Liu, Lingyuan Meng, Meng Liu, and Xinwang Liu. Structure guided multi-modal pre-trained transformer for knowledge graph reasoning, 2023.

[15] Luisa Werner, Nabil Layaïda, Pierre Genevès, and Sarah Chlyah. Knowledge enhanced graph neural networks for graph completion, 2023.

[16] Haoran Luo, Haihong E, Ling Tan, Gengxian Zhou, Tianyu Yao, and Kaiyang Wan. Dhge: Dual-view hyper-relational knowledge graph embedding for link prediction and entity typing, 2023.

[17] Paul Cuddihy, Justin McHugh, Jenny Weisenberg Williams, Varish Mulwad, and Kareem S. Aggour. Semtk: An ontology-first, open source semantic toolkit for managing and querying knowledge graphs, 2018.

[18] Walid S. Saba. Towards ontologically grounded and language-agnostic knowledge graphs, 2023.

[19] Jiapu Wang, Boyue Wang, Meikang Qiu, Shirui Pan, Bo Xiong, Heng Liu, Linhao Luo, Tengfei Liu, Yongli Hu, Baocai Yin, and Wen Gao. A survey on temporal knowledge graph completion: Taxonomy, progress, and prospects, 2023.

[20] Amit Sheth, Swati Padhee, and Amelie Gyrard. Knowledge graphs and knowledge networks: The story in brief, 2020.

[21] Phillip Schneider and Florian Matthes. Conversational exploratory search of scholarly publications using knowledge graphs, 2024.

[22] Elwin Huaman and Dieter Fensel. Knowledge graph curation: A practical framework, 2022.

[23] Arijit Khan. Knowledge graphs querying, 2023.

[24] Pancheng Wang, Shasha Li, Kunyuan Pang, Liangliang He, Dong Li, Jintao Tang, and Ting Wang. Multi-document scientific summarization from a knowledge graph-centric view, 2022.

[25] Wen Zhang, Shumin Deng, Mingyang Chen, Liang Wang, Qiang Chen, Feiyu Xiong, Xiangwen Liu, and Huajun Chen. Knowledge graph embedding in e-commerce applications: Attentive reasoning, explanations, and transferable rules, 2021.

[26] Yue Deng. Recommender systems based on graph embedding techniques: A comprehensive review, 2022.

[27] Sarika Jain. Exploiting knowledge graphs for facilitating product/service discovery, 2020.

[28] Sebastian Monka, Lavdim Halilaj, and Achim Rettinger. A survey on visual transfer learning using knowledge graphs, 2022.

[29] W. X. Wilcke, P. Bloem, V. de Boer, and R. H. van t Veer. End-to-end learning on multimodal knowledge graphs, 2023.

[30] Cristóbal Esteban, Volker Tresp, Yinchong Yang, Stephan Baier, and Denis Krompaß. Predicting the co-evolution of event and knowledge graphs, 2015.

[31] Genet Asefa Gesese, Russa Biswas, Mehwish Alam, and Harald Sack. A survey on knowledge graph embeddings with literals: Which model links better literal-ly?, 2020.

[32] Gengyue Zhang, Hao Li, Shuangling Li, Beibei Wang, and Zhixing Ding. Mmkg-par: Multimodal knowledge graphs-based personalized attraction recommendation. *Sustainability*, 16(5):2211, 2024.

[33] Yichi Zhang, Binbin Hu, Zhuo Chen, Lingbing Guo, Ziqi Liu, Zhiqiang Zhang, Lei Liang, Huajun Chen, and Wen Zhang. Multi-domain knowledge graph collaborative pre-training and prompt tuning for diverse downstream tasks, 2024.

[34] Rui Sun, Xuezhi Cao, Yan Zhao, Junchen Wan, Kun Zhou, Fuzheng Zhang, Zhongyuan Wang, and Kai Zheng. Multi-modal knowledge graphs for recommender systems. In *Proceedings of the 29th ACM international conference on information & knowledge management*, pages 1405–1414, 2020.

[35] Ziqiang Cui, Yunpeng Weng, Xing Tang, Fuyuan Lyu, Dugang Liu, Xiuqiang He, and Chen Ma. Comprehending knowledge graphs with large language models for recommender systems, 2025.

[36] Saed Rezayi, Handong Zhao, Sungchul Kim, Ryan A. Rossi, Nedim Lipka, and Sheng Li. Edge: Enriching knowledge graph embeddings with external text, 2021.

[37] Xiaolong Liu, Liangwei Yang, Zhiwei Liu, Mingdai Yang, Chen Wang, Hao Peng, and Philip S. Yu. Knowledge graph context-enhanced diversified recommendation, 2024.

[38] Ngoc Luyen Le, Marie-Hélène Abel, and Philippe Gouspillou. A personalized recommender system based-on knowledge graph embeddings, 2023.

[39] Yi Liu, Hongrui Xuan, Bohan Li, Meng Wang, Tong Chen, and Hongzhi Yin. Self-supervised dynamic hypergraph recommendation based on hyper-relational knowledge graph, 2023.

[40] Xin Luna Dong. Generations of knowledge graphs: The crazy ideas and the business impact, 2023.

[41] Yong Chen, Xinkai Ge, Shengli Yang, Linmei Hu, Jie Li, and Jinwen Zhang. A survey on multimodal knowledge graphs: Construction, completion and applications. *Mathematics*, 11(8):1815, 2023.

[42] Meng Yuan, Fuzhen Zhuang, Zhao Zhang, Deqing Wang, and Jin Dong. Knowledge-based multiple adaptive spaces fusion for recommendation, 2023.

[43] Nicolas Heist, Sven Hertling, Daniel Ringler, and Heiko Paulheim. Knowledge graphs on the web – an overview, 2020.

[44] Simon Schramm, Christoph Wehner, and Ute Schmid. Comprehensible artificial intelligence on knowledge graphs: A survey, 2024.

[45] Phillip Schneider, Nils Rehtanz, Kristiina Jokinen, and Florian Matthes. From data to dialogue: Leveraging the structure of knowledge graphs for conversational exploratory search, 2023.

[46] Christoph Wehner, Chrysa Iliopoulou, and Tarek R. Besold. From latent to lucid: Transforming knowledge graph embeddings into interpretable structures, 2024.

[47] Niraj Kumar-Singh, Gustavo Polleti, Saee Paliwal, and Rachel Hodos-Nkhereanye. Linklogic: A new method and benchmark for explainable knowledge graph predictions, 2024.

[48] Shurong Wang, Yufei Zhang, Xuliang Huang, and Hongwei Wang. Harmonizing human insights and ai precision: Hand in hand for advancing knowledge graph task, 2024.

[49] Li Cai, Xin Mao, Yuhao Zhou, Zhaoguang Long, Changxu Wu, and Man Lan. A survey on temporal knowledge graph: Representation learning and applications, 2024.

[50] Fadhela Kerdjoudj and Olivier Curé. Rdf knowledge graph visualization from a knowledge extraction system, 2015.

[51] Aryo Pradipta Gema, Dominik Grabarczyk, Wolf De Wulf, Piyush Borole, Javier Antonio Alfaro, Pasquale Minervini, Antonio Vergari, and Ajitha Rajan. Knowledge graph embeddings in the biomedical domain: Are they useful? a look at link prediction, rule learning, and downstream polypharmacy tasks, 2023.

[52] Loïck Lhote, Béatrice Markhoff, and Arnaud Soulet. The structure and dynamics of knowledge graphs, with superficiality, 2024.

[53] Tuan Bui, Oanh Tran, Phuong Nguyen, Bao Ho, Long Nguyen, Thang Bui, and Tho Quan. Cross-data knowledge graph construction for llm-enabled educational question-answering system: A case study at hcmut, 2024.

[54] Mattia Fumagalli, Marco Boffo, Daqian Shi, Mayukh Bagchi, and Fausto Giunchiglia. Towards a gateway for knowledge graph schemas collection, analysis, and embedding, 2023.

[55] Fan Lu, Quan Qi, and Huaibin Qin. Edge-enabled anomaly detection and information completion for social network knowledge graphs, 2024.

[56] Emaad Manzoor, Jordan Tong, Sriniketh Vijayaraghavan, and Rui Li. Expanding knowledge graphs with humans in the loop, 2023.

[57] Anna Wroblewska, Jacek Dabrowski, Michal Pastuszak, Andrzej Michalowski, Michal Daniluk, Barbara Rychalska, Mikolaj Wieczorek, and Sylwia Sysko-Romanczuk. Multimodal embedding fusion-based recommender, 2020.

[58] Phillip Schneider, Tim Schopf, Juraj Vladika, and Florian Matthes. Enterprise use cases combining knowledge graphs and natural language processing, 2024.

[59] Harry Li, Gabriel Appleby, Camelia Daniela Brumar, Remco Chang, and Ashley Suh. Knowledge graphs in practice: Characterizing their users, challenges, and visualization opportunities, 2024.

[60] Yichi Zhang, Zhuo Chen, Lingbing Guo, Yajing Xu, Binbin Hu, Ziqi Liu, Wen Zhang, and Huajun Chen. Native: Multi-modal knowledge graph completion in the wild. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 91–101, 2024.

[61] Pouya Pezeshkpour, Liyan Chen, and Sameer Singh. Embedding multimodal relational data for knowledge base completion, 2018.

[62] Jason Youn and Ilias Tagkopoulos. Kglm: Integrating knowledge graph structure in language models for link prediction, 2023.

[63] Samaneh Jozashoori and Maria-Esther Vidal. Mapsdi: A scaled-up semantic data integration framework for knowledge graph creation, 2019.

[64] Derong Xu, Jingbo Zhou, Tong Xu, Yuan Xia, Ji Liu, Enhong Chen, and Dejing Dou. Multimodal biological knowledge graph completion via triple co-attention mechanism. In *2023 IEEE 39th International Conference on Data Engineering (ICDE)*, pages 3928–3941. IEEE, 2023.

[65] Danilo Dessì, Francesco Osborne, Diego Reforgiato Recupero, Davide Buscaldi, and Enrico Motta. Generating knowledge graphs by employing natural language processing and machine learning techniques within the scholarly domain, 2020.

[66] Yaqing Wang, Fenglong Ma, and Jing Gao. Efficient knowledge graph validation via cross-graph representation learning, 2020.

[67] Irina Nikishina, Mikhail Tikhomirov, Varvara Logacheva, Yuriy Nazarov, Alexander Panchenko, and Natalia Loukachevitch. Taxonomy enrichment with text and graph vector representations, 2022.

[68] Zongsheng Cao, Qianqian Xu, Zhiyong Yang, Yuan He, Xiaochun Cao, and Qingming Huang. Otkge: Multi-modal knowledge graph embeddings via optimal transport. *Advances in neural information processing systems*, 35:39090–39102, 2022.

[69] Xindi Luo, Zequn Sun, and Wei Hu. μKG: A library for multi-source knowledge graph embeddings and applications, 2022.

[70] K M Annervaz, Somnath Basu Roy Chowdhury, and Ambedkar Dukkipati. Learning beyond datasets: Knowledge graph augmented neural networks for natural language processing, 2018.

[71] Albert Sawczyn, Jakub Binkowski, Piotr Bielak, and Tomasz Kajdanowicz. Empowering small-scale knowledge graphs: A strategy of leveraging general-purpose knowledge graphs for enriched embeddings, 2024.

[72] Binbin Hu, Zhiyang Hu, Zhiqiang Zhang, Jun Zhou, and Chuan Shi. Kgnn: Distributed framework for graph neural knowledge representation, 2022.

[73] Yuxing Lu, Weichen Zhao, Nan Sun, and Jinzhuo Wang. Enhancing multimodal knowledge graph representation learning through triple contrastive learning. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence*, pages 5963–5971, 2024.

[74] Mohamad Zamini, Hassan Reza, and Minou Rabiei. A review of knowledge graph completion, 2022.

[75] Hongzhu Li, Xiangrui Gao, Linhui Feng, Yafeng Deng, and Yuhui Yin. Stargraph: Knowledge representation learning based on incomplete two-hop subgraph, 2023.

[76] Liyi Chen, Zhi Li, Yijun Wang, Tong Xu, Zhefeng Wang, and Enhong Chen. Mmea: entity alignment for multi-modal knowledge graph. In *Knowledge Science, Engineering and Management: 13th International Conference, KSEM 2020, Hangzhou, China, August 28–30, 2020, Proceedings, Part I 13*, pages 134–147. Springer, 2020.

[77] Jing Yang, Shundong Yang, Yuan Gao, Jieming Yang, and Laurence T Yang. Multimodal contextual interactions of entities: A modality circular fusion approach for link prediction. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 8374–8382, 2024.

[78] Shaohua Dong, Xiaochao Fan, and Xinchun Ma. Multichannel multimodal emotion analysis of cross-modal feedback interactions based on knowledge graph. *Neural Processing Letters*, 56(3):190, 2024.

[79] Yichi Zhang, Zhuo Chen, Lingbing Guo, Yajing Xu, Binbin Hu, Ziqi Liu, Wen Zhang, and Huajun Chen. Tokenization, fusion, and augmentation: Towards fine-grained multi-modal entity representation, 2024.

[80] Zhuo Chen, Yin Fang, Yichi Zhang, Lingbing Guo, Jiaoyan Chen, Jeff Z. Pan, Huajun Chen, and Wen Zhang. Noise-powered multi-modal knowledge graph representation framework, 2025.

[81] Bin Shang, Yinliang Zhao, Jun Liu, and Di Wang. Lafa: Multimodal knowledge graph completion with link aware fusion and aggregation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 8957–8965, 2024.

[82] Zhuo Chen, Yichi Zhang, Yin Fang, Yuxia Geng, Lingbing Guo, Xiang Chen, Qian Li, Wen Zhang, Jiaoyan Chen, Yushan Zhu, et al. Knowledge graphs meet multi-modal learning: A comprehensive survey. *arXiv preprint arXiv:2402.05391*, 2024.

[83] Wenwu Zhu, Xin Wang, and Hongzhi Li. Multi-modal deep analysis for multimedia, 2020.

[84] Yichi Zhang, Zhuo Chen, Lei Liang, Huajun Chen, and Wen Zhang. Unleashing the power of imbalanced modality information for multi-modal knowledge graph completion, 2024.

[85] Angelo Salatino, Andrea Mannocci, and Francesco Osborne. Detection, analysis, and prediction of research topics with scientific knowledge graphs, 2021.

[86] Xiao-Fan Niu and Wu-Jun Li. Paragraphe: A library for parallel knowledge graph embedding, 2017.

[87] Alberto Cattaneo, Stephen Bonner, Thomas Martynec, Carlo Luschi, Ian P Barrett, and Daniel Justus. The role of graph topology in the performance of biomedical knowledge graph completion models, 2024.

[88] Jiang Wang, Filip Ilievski, Pedro Szekely, and Ke-Thia Yao. Augmenting knowledge graphs for better link prediction, 2022.

[89] Sakher Khalil Alqaaidi and Krzysztof Kochut. Knowledge graph completion using structural and textual embeddings, 2024.

[90] Yichi Zhang, Zhuo Chen, Lei Liang, Huajun Chen, and Wen Zhang. Unleashing the power of imbalanced modality information for multi-modal knowledge graph completion. *arXiv preprint arXiv:2402.15444*, 2024.

[91] Pengpeng Shao, Guohua Yang, Dawei Zhang, Jianhua Tao, Feihu Che, and Tong Liu. Tucker decomposition-based temporal knowledge graph completion, 2020.

[92] Tianxing Wu, Arijit Khan, Melvin Yong, Guilin Qi, and Meng Wang. Efficiently embedding dynamic knowledge graphs, 2022.

[93] Wen Zhang, Xiangnan Chen, Zhen Yao, Mingyang Chen, Yushan Zhu, Hongtao Yu, Yufeng Huang, Zezhong Xu, Yajing Xu, Ningyu Zhang, Zonggang Yuan, Feiyu Xiong, and Huajun Chen. Neuralkg: An open source library for diverse representation learning of knowledge graphs, 2022.

[94] Alberto Garcia-Duran, Antoine Bordes, Nicolas Usunier, and Yves Grandvalet. Combining two and three-way embeddings models for link prediction in knowledge bases, 2015.

[95] Xiang Kong, Xianyang Chen, and Eduard Hovy. Decompressing knowledge graph representations for link prediction, 2019.

[96] Hung Nghiep Tran and Atsuhiro Takasu. Meim: Multi-partition embedding interaction beyond block term format for efficient and expressive link prediction, 2022.

[97] Xinhang Li, Xiangyu Zhao, Jiaxing Xu, Yong Zhang, and Chunxiao Xing. Imf: Interactive multimodal fusion model for link prediction, 2023.

[98] Elika Bozorgi, Saber Soleimani, Sakher Khalil Alqaiidi, Hamid Reza Arabnia, and Krzysztof Kochut. Subgraph2vec: A random walk-based algorithm for embedding knowledge graphs, 2024.

[99] Feng Xia, Ke Sun, Shuo Yu, Abdul Aziz, Liangtian Wan, Shirui Pan, and Huan Liu. Graph learning: A survey, 2021.

[100] Dora Jambor, Komal Teru, Joelle Pineau, and William L. Hamilton. Exploring the limits of few-shot link prediction in knowledge graphs, 2021.

[101] N'Dah Jean Kouagou, Arif Yilmaz, Michel Dumontier, and Axel-Cyrille Ngonga Ngomo. Improving rule mining via embedding-based link prediction, 2024.

[102] Chitrank Gupta, Yash Jain, Abir De, and Soumen Chakrabarti. Integrating transductive and inductive embeddings improves link prediction accuracy, 2021.

[103] Filip Cornell, Yifei Jin, Jussi Karlgren, and Sarunas Girdzijauskas. Are we wasting time? a fast, accurate performance evaluation framework for knowledge graph link predictors, 2024.

[104] Charles Tapley Hoyt, Max Berrendorf, Mikhail Galkin, Volker Tresp, and Benjamin M. Gyori. A unified framework for rank-based evaluation metrics for link prediction in knowledge graphs, 2022.

[105] Ryan Barron, Maksim E. Eren, Manish Bhattarai, Selma Wanna, Nicholas Solovyev, Kim Rasmussen, Boian S. Alexandrov, Charles Nicholas, and Cynthia Matuszek. Cyber-security knowledge graph generation by hierarchical nonnegative matrix factorization, 2024.

[106] Mehdi Ali, Max Berrendorf, Mikhail Galkin, Veronika Thost, Tengfei Ma, Volker Tresp, and Jens Lehmann. Improving inductive link prediction using hyper-relational facts, 2021.

[107] Genet Asefa Gesese, Mehwish Alam, and Harald Sack. Semantic entity enrichment by leveraging multilingual descriptions for link prediction, 2020.

[108] Lars Vogt. Semantic units: Increasing expressivity and simplicity of formal representations of data and knowledge in knowledge graphs, 2024.

[109] Sumin Seo, Heeseon Cheon, Hyunho Kim, and Dongseok Hyun. Structural quality metrics to evaluate knowledge graphs, 2022.

[110] Jan Portisch and Heiko Paulheim. The dlcc node classification benchmark for analyzing knowledge graph embeddings, 2022.

[111] Tong Yang, Yifei Wang, Long Sha, Jan Engelbrecht, and Pengyu Hong. Knowledgebra: An algebraic learning framework for knowledge graph, 2022.

[112] Lars Vogt, Tobias Kuhn, and Robert Hoehndorf. Semantic units: Organizing knowledge graphs into semantically meaningful units of representation, 2023.

[113] Nicolas Hubert, Heiko Paulheim, Armelle Brun, and Davy Monticolo. Do similar entities have similar embeddings?, 2024.

[114] Yanjie Wang, Rainer Gemulla, and Hui Li. On multi-relational link prediction with bilinear models, 2017.

[115] Daqian Shi. Knowledge graph extension by entity type recognition, 2024.

[116] Yichi Zhang, Zhuo Chen, and Wen Zhang. Maco: A modality adversarial and contrastive framework for modality-missing multi-modal knowledge graph completion. In *CCF International Conference on Natural Language Processing and Chinese Computing*, pages 123–134. Springer, 2023.

AI-generated, for reference only.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.