

January 22, 2025 (Wednesday)

09:30-10:15

Keynote Speech

General Assembly Room (Hall 1)

The Seal of Cassandra

Şebnem Özdemir

Istinye University, Türkiye

10:15-10:45

Coffee-Break

10:45-12:00

PARALLEL SESSIONS – C

C1 – *General Assembly Room (Hall 1)*

AI and Knowledge Management-2

Moderator: Julien Roche

[C1.1]
AI and Organization of Information: Bridging Tradition and Innovation

Magda El-Sherbini
Ohio State University, USA

[C1.2]
Inclusion Knowledge Graph Approach to Information Retrieval with AI-Driven Systems: Enhancing Search Precision and Relevance

Bahattin Yalçınkaya
Marmara University, Türkiye
Mehmet Oytun Cibaroğlu
Bursa Technical University, Türkiye

[C1.3]
Research on Frontline Technology Trend Identification Integrating Bertopic and Large Language Models

Yunqiang Pu, Tang Chuan and **Deng Hangyu**
Chinese Academy of Sciences, China

[C1.4]
Scientific Literature Recommendation with Knowledge Graph and Collaborative Perception

Jie Li
Shandong University, China
Guobiao Zhang
Soochow University, China

C2 – *Hall of Honor (Hall 2)*
AI and Information Literacy-2
Moderator: Teresa Silveira

[C2.1]
AI Challenging LIS Education: A Focus on Skills Stewardship

Silviu Bors
"Lucian Blaga" University of Sibiu, Romania

[C2.2]
Artificial Intelligence Training Programs for Information and Document Management Students: A Model Proposal

Işıl İlknur Sert and **Jasemin Abdalla**
Istanbul University, Türkiye

[C2.3]
Challenges and Opportunities of Generative Artificial Intelligence for Academic Libraries and LIS Professionals

Isabel Matos and **Liliana Isabel Esteves Gomes**
University of Coimbra, Portugal

[C2.4]
Artificial Intelligence in Library and Information Science Schools: Content Analysis of Curricula

Sanjica Faletar, Borna Petrović and **Irena Poje**
Josip Juraj Strossmayer University of Osijek, Crotia

C3 – Classroom 307 *(Hall 3)*

AI and Information Management-2

Moderator: Tóth Máté

[C3.1]

Exploring the Integration of AI and Digital Technologies in Museum Education: Enhancing Educators' Competencies and Fostering Future Skills

Merle Laurits
Tallinn University, Estonia

[C3.2]

The Impact of Artificial Intelligence in Data Visualization and Common Problems in Information Management Systems

Zeynep Dila Sönmez
Istanbul University, Türkiye

[C3.3]

Towards Global Innovation: Sustainable Development Goal 9 and Innovative Infrastructures in Libraries

Ayşegül Tok
Zonguldak Bülent Ecevit University, Türkiye
Pervin Bezirci
Istanbul University, Türkiye

C4 – Classroom 310 *(Hall 4)*

Inclusion and Diversity

Moderator: Ertuğrul Çimen

[C4.1]

Library as a Third Place: Opportunities and Risks

Gergő Pásztor

[C4.2]

Exploring Multicultural and Indigenous Libraries: An Analysis of Relevant Studies

Lilian Aguilar Teixeira

[C4.3]

Diversity, Equity and Inclusion in European LIS Schools: Short Overview of an Exploratory Study

Eötvös Loránd University, Hungary

University of Coimbra, Portugal/São Paulo State University, Brazil
Ana Lúcia Terra
University of Coimbra, Portugal
Oswaldo Francisco de Almeida Junior
São Paulo State University, Brazil

Sanjica Faletar
Josip Juraj Strossmayer University of Osijek, Croatia
Sara Martinez Cardama
University Carlos III of Madrid, Spain
Kornelija Petr Balog
Josip Juraj Strossmayer University of Osijek, Croatia
Jenny Bronstein
Bar-Ilan University, Israel
Debbie Meharg
Edinburgh Napier University, United Kingdom

C5- Technical Visit – *Registration Desk*
https://bobcatsss2025.org.tr/social-program
10:45-12:00

Istanbul University Central Library
Beyazıt State Library
Istanbul University's Historic Beyazıt Campus

12:00-13:00
Lunch

13:30-14:15

Keynote Speech

General Assembly Room (Hall 1)

The Role of AI in Developing Next Generation Standards for Archives and Records Management

Hamza Kandur
Istanbul 29 Mayıs University, Türkiye

14:15-14:45

Coffee-Break

14:45-16:00

PARALLEL SESSIONS – D

D1 – *General Assembly Room (Hall 1)*

Emerging Technologies and Future Trends-2

Moderator: Merle Laurits

[D1.1]
AI-Driven Cybersecurity: Enhancing the Resilience of Information Systems

Nevzat Özel and **Salih Demir**
Ankara University, Türkiye

[D1.2]
Unveiling the Scroll: What Drives Us to Seek Disaster Information on Social Networking Sites?

Bibi Alajmi and **Omar Khalil**
Kuwait University, Kuwait

[D1.3]
Exploring AI Tool Adoption Among Humanities and Social Sciences University Students

Borna Petrović, Irena Poje and **Snježana Stanarević Katavić**
Josip Juraj Strossmayer University of Osijek, Crotia

[D1.4]
The Trend of Artificial Intelligence in the Research Data Service: A Bibliometric Analysis

Aulia Puspaning Galih
Eötvös Loránd University, Hungary
Ragnar Audunson
Oslo Metropolitan University, Norway
Ágnes Hajdu Barát
Eötvös Loránd University, Hungary

D2 – *Hall of Honor (Hall 2)*
AI Applications in Libraries and Information Centers-3
Moderator: Ina Blümel

[D2.1]
The Role of Information Professionals in the Age of Artificial Intelligence: A Study on University Librarians in Türkiye

[D2.2]
Librarians' Attitudes Toward AI in Hungary

Andor Nagy, Máté Tóth, Dóra Egervári, Katalin Varga and

[D2.3]
Magical Mirrors: AI-Assisted Screens for Storytelling in Children's Library Spaces

Leila Abudraa and **Tünde Oravecz**

[D2.4]
ChatGPT and its Opportunities for Libraries and People with Disabilities

Radoslav Hristov and **Tania Todorova**

Esra Gül, Serpil Avunduk and **Kevser Çiçek**
Istanbul University, Türkiye

Bence Molnár
University of Pécs, Hungary

Eötvös Loránd University, Hungary

University of Library Studies and Information Technologies, Bulgaria

D3 – Classroom 307 *(Hall 3)*

Ethical Considerations and Policy Implications-2

Moderator: Silviu Borș

[D3.1]
Finding the Truth and Trustworthy Online Information: Challenges Encountered by Librarians in Their Professional Practice

Joseph Marmol Yap, Ágnes Hajdu Barát and **Peter Kiszl**
Eötvös Loránd University, Hungary

[D3.2]
Towards a Trustworthy Future for Artificial Intelligence: The Role of Libraries

Banu Fulya Yıldırım
Istanbul 29 Mayıs University, Türkiye

[D3.3]
Implementing Artificial Intelligence in Libraries to Detect Fake News and Foster Critical Information Literacy

Marco V. Crivellaro
American Community Schools Athens, Greece

[D3.4]
Artificial Intelligence in Libraries and Information Centers for Data Security: Preventing Data Breaches and Protecting User Privacy

Şimal Karaoğlu and **Elif Sude Özdemir**
Istanbul University, Türkiye

D4 – Club Study Room *(Hall 8)*
Workshop-1

The World Bank Group Library Endeavor into the Artificial Intelligence Ecosystem

Eduardo Quintero
World Bank Group, USA

D5 – **Technical Visit** – *Registration Desk*
https://bobcatsss2025.org.tr/social-program
14:45-16:00

Istanbul University Central Library
Beyazıt State Library
Istanbul University's Historic Beyazıt Campus

16:00-16:30
Poster Sessions
Hall of Honor (Hall 2)

Citation Rules for Content Created by Gen AI
Carmen Köbele, Silke Clausing ve **Ina Blümel**
Hannover University of Applied Sciences and Arts, Germany

AI and Information Management at Deutsche Bahn
Ranwir Singh Josan, Muhammad Murtaza Tarar, Silke Clausing and **Ina Blümel**
Hannover University of Applied Sciences and Arts, Germany

Using Artificial Intelligence Based Applications for Visually Impaired Library Users to Access Information: WeWalk Based Sample Application
Tayyip Enes Gölyeri and **Işıl İlknur Sert**
Istanbul University, Türkiye

The Open Research Knowledge Graph in German Libraries: TIB Hannover
Enes Albayrak, Tom Wieckhorst, Silke Clausing and **Ina Blümel**
Hannover University of Applied Sciences and Arts, Germany

Transkribus: Investigating the Accuracy of AI-supported Handwritten Text Recognition
Janna Freiling, Tanja Rether, Silke Clausing and **Ina Blümel**
Hannover University of Applied Sciences and Arts, Germany

Emerging Trends & Technologies in Library & Information Services
Nabi Hasan
Indian Institute of Technology Delhi, India

Public and Digital Libraries: Germany and Mozambique
Selma Inocencia
Hannover University of Applied Sciences and Arts, Germany

AI-Driven Transformation of Library Services and Operations: Enhancements in user Experience and Engagement
Zita Fekete and **Boglárka Bényei**
Eötvös Loránd University, Hungary

Advancing Gender Inclusion in Information Science: Transformative Approaches in Higher Education
Juan-José Boté
University of Barcelona, Spain

Georgina Martínez
University of Barcelona, Spain
Sylvia Jaki
University of Hildesheim, Germany
Kristina Feldvari
Josip Juraj Strossmayer University of Osijek, Croatia
Alica Kolarić
University of Zadar, Croatia
Hajdarpasic Lejla
University of Sarajevo, Bosnia and Herzegovina
Eithne Knappitsch
Carinthia University of Applied Sciences, Austria

How can AI improve UOC library services? Insights from UOC's Experience
Castellana Mir Natalia, Llussà Vallès Rosa, Casabona Gómez Daniel, Pérez Roig Sandra, De Mon Martín Adrián and **Espín Sánchez Joaquin**
Open University of Catalonia, Spain

Ethics and Privacy in the Use of OSINT and AI for Competitive Intelligence
Gizem Karakoca
Ankara University, Türkiye
Marc Chavarría
University of Barcelona, Spain
Aiman Zbakh
University of Barcelona, Spain

Exploring Gender Equality in Leadership: Business, Research, and Sports
Ariadna Bonnin Jorge
University of Barcelona, Spain

Shaïnez Denfer
Gustave Eiffel University, France
Isaura Felix
Gustave Eiffel University, France
Blanca Gallardo Cabañas
University of Barcelona, Spain
Bernard Mbaye
Gustave Eiffel University, France
Ayoub Mouheb
Gustave Eiffel University, France

Gender Disparities in Educational Achievements Across EU Countries?

Mehmet Pekol
Ankara University, Türkiye
Tetyana Savytska
Gustave Eiffel University, France
Bernat Jordà Ferrer
University of Barcelona, Spain
Margarida Almeida
University of Coimbra, Portugal
Majdi Khelfaoui
Gustave Eiffel University, France
Christiane Mendrika
Gustave Eiffel University, France

Human and Machine: Alliance or Competition

Margaréta Takács and **Gergő Róka**
Eötvös Loránd University, Hungary

Integrating Artificial Intelligence Concepts into Educational Curriculums: International Perspectives

Lucas Dexans
Gustave Eiffel University, France
Dilnavoz Abdulazizova
Ankara University, Türkiye
Romain Dubourguet
Gustave Eiffel University, France
Laura Correia Gurate
University of Coimbra, Portugal

Generative AI and e-Commerce Taxonomies: A Comparative Analysis

Abril Porcar
University of Barcelona, Spain
Ilias Kasmi
Gustave Eiffel University, France
Loriane Messaadi
Gustave Eiffel University, France
Mervenur Sarıgül
Ankara University, Türkiye
Paulo Vicente
University of Coimbra, Portugal
Ana Lúcia Terra
University of Coimbra, Portugal

How to Create a Taxonomy for Your Website using AI tools ? – A Tea Shop's Digital Platform Project

Núria Pujol-Ventosa
University of Barcelona, Spain
Emy Bigirimana
Gustave Eiffel University, France

Elhadj Abdoul Aziz Diop
Gustave Eiffel University, France
Ana Lúcia Terra
University of Coimbra, Portugal

Taxonomy for Spotify by Generative AI Tools: A Methodological Approach

Diewo Diallo
Gustave Eiffel University, France
Sakina Menouar
Gustave Eiffel University, France
Tina Levillain
University of Barcelona, Spain
Ana Borges
University of Coimbra, Portugal
Merve Yaman
Ankara University, Türkiye
Ana Lúcia Terra
University of Coimbra, Portugal

Strategies and Challenges in Fostering AI Understanding: Using Interactive Methods to Teach Critical Skills in the Age of Artificial Intelligence

Benie Guimbi
Gustave Eiffel University, France
Camila Araújo Sá
Gustave Eiffel University, France
Burcu Yılmaz Karahan
Ankara University, Türkiye
Fy Rakotonanahary
Gustave Eiffel University, France

Bernat Montaña Suñé
University of Barcelona, Spain

20:00-23:30
Gala Dinner (Contributed by Mirakıl)
Kabataş Pier – Tosun Pasha Ship
https://bobcatsss2025.org.tr/social-program

© 2024-2025 | BOBCATSSS 2025

BOBCATSSS 2025
The 33rd International Symposium on Artificial Intelligence in Library and Information Science: Exploring the Intersection

Inclusion Knowledge Graph Approach to Information Retrieval with AI-Driven Systems: Enhancing Search Precision and Relevance

Bahattin YALÇINKAYA[*], Mehmet Oytun CİBAROĞLU[**]

** Assoc. Prof. Dr., Marmara University, Department of Information and Records Management, İstanbul, Turkey, bahakaya@gmail.com*
*** Lecturer, Bursa Technical University, Department of Information Technology, Bursa, Turkey, oytun.cibaroglu@btu.edu.tr*

Abstract

Traditional information retrieval systems have several problems such as limited understanding of user intentions, lack of flexibility in natural language queries, static indexing, scalability, relevance and ranking limitations. Artificial Intelligence (AI) is now integrated into various aspects of life, from search engines to archive systems. If the precision and relevance of the results of traditional information retrieval systems are increasing day by day, it is thanks to the integration of AI. However, given that AI is ultimately composed of algorithms with a certain bias, it is anticipated that there may be many types of data or information that it misses or omits. A Knowledge Graph (KG) approach to be integrated into AI-based search engines could provide more data and therefore more relevance and precision. While search engines with AI are largely capable of solving these problems, integrating KGs would add additional features such as semantic search, annotation, context-sensitive retrieval, complex query understanding, etc., and could further improve existing high scores. The function of the KGs approach here is to be fully inclusive to further improve contextual retrieval. It would be integrated into classical AI phenomena such as Machine Learning (ML) and Natural Language Processing (NLP), thus contributing to more efficient results through its inclusion function. Compared to alternatives such as relational or NoSQL databases found in various applications, the KGs based approaches are known to be particularly useful in abstraction. The main research question in this study is how KGs can improve relevance and precision scores in information retrieval. The paper initially reviews the literature on KGs and provides a basic definition of it, then evaluates the functioning of AI-driven search engines in terms of relevance and precision scores and discusses how the proposed approach can be integrated into these processes. In the conclusion, inferences are drawn in terms of relevance metrics (precision, sensitivity, F1) and semantic metrics (entity disambiguation accuracy, information completeness), which are the main metrics that can be used to evaluate the KGs approach. The study provides an insight into different aspects of the use of AI in information retrieval and thus knowledge discovery, and provides an updated perspective on both traditional and new AI-driven knowledge discovery applications, as well as new future prospects.

Keywords: Knowledge Graphs; Information Retrieval; AI Driven Systems, Precision, Relevance

1. Introduction

The fact that information in digital environments is expanding day by day and the Information Technologies (IT) are frequently used in almost all processes creates both an opportunity and a prejudice. The cost and effects of

wider access to information have made the critical issues of sensitivity, relevance and inclusiveness in information retrieval systems more frequently discussed. Traditional information retrieval systems are structures that mostly provide access to information by matching keywords and static indexing. However, the high relevance and accuracy provided by the integration of Artificial Intelligence (AI) applications into various structures cannot meet the various needs of users (dynamic etc.) in traditional systems. Therefore, traditional systems work with both sensitivity and relevance problems and cannot ensure that user information search behavior results in complete satisfaction. In addition, in a world where end users are increasingly diversifying, traditional systems are also inadequate in this respect. The most fundamental problem here is that a single-type search strategy has been designed that bypasses users' individual and unique needs, various tastes and backgrounds. This type of restriction can lead not only to search results that are far from individual preferences, but also to the user accessing results that do not match a specific information context.

In addition, the existence of "insensitive" content that includes culturally biased and various exclusionary results stands out as an important factor in the decrease in trust in IT. The design of traditional information retrieval systems with this static approach remains an old technology feature when compared to today's AI-driven systems. While there are wide variety of retrieval systems that reflect instant and dynamic results, traditional system design is not a choice to use. The relevance problem is equally important, too. Traditional information retrieval systems mostly work on the logic of keyword matching, ignoring the relationship between terms and the real intention behind users' information search behavior. Such a situation brings superficial or approximate results beyond the results that the user exactly desires. In addition, the limited contextual understanding of traditional systems prevents a successful distinction between different meanings of comparable queries in multilingual and multicultural communities. In other words, the query intent is not fully understood. Traditional models prioritize popularity over actual relevance when ranking, which can fuel existing biases. To solve the aforementioned challenges, an approach that requires adaptation to smarter, more inclusive, and dynamic-adaptive information retrieval infrastructures is required. This study argues that such an approach can be further enhanced by the AI-driven Knowledge Graph (KG) approach.

2. Issues on Challenges

As mentioned in the introduction section, the challenges of traditional information retrieval systems can be prioritized as sensitivity and relevance. Stating in Table 1, problems related to sensitivity include lack of personalization, insensitive content, static information, and privacy concerns, while relevance problems arise from limitations in keyword matching, contextual understanding, lack of understanding of query intent, and ranking of results.

Table 1. Challenges with Traditional Information Retrieval Systems

Sensitivity	**Relevance**
Lack of personalization	Keyword matching
Insensitive content	Contextual understanding
Static knowledge	No understanding of query intent
Privacy	Ranking limitations

2.1. Sensitivity Issues

Personalized results often fail in traditional information retrieval systems. Such systems cannot provide results that fully take into account personal needs without mechanisms to "adapt" to the user's search behavior (White & Marchionini, 2007). This deficiency is often experienced in communities where multiple languages or cultures prevail.

Traditional search engines also face issues with insensitive content. Traditional systems often fail to flag results that are biased, discriminatory, or harmful to underrepresented communities, and are also at a disadvantage when it comes to ethical sensitivities (Noble, 2018). Failure to accept or host such content systematically perpetuates inequalities and also reduces the reliability of information retrieval technologies. Such limitations prevent adaptation to dynamic contexts, including new trends, various societal crises, or evolving terminologies, thus

limiting their ability to provide timely, accurate, and relevant information (Baeza-Yates & Ribeiro-Neto, 2011).

In traditional systems where personalization strategies cannot be applied, the privacy problem becomes more complex. Some information retrieval systems attempt to reveal the end user's information search intentions through methods such as cookies, query logs, and behavioral profiling techniques. Such approaches can optimize personalization, but they often require a balance between user autonomy and privacy protection (Teevan, Dumais, & Horvitz, 2005). Recently, there has been increasing interest in information retrieval models that support end users' rights to remain "anonymous" and to have control over information about themselves.

2.2. Relevance Issues

Traditional models, which are heavily dependent on keyword matching algorithms, often do not consider the "semantic" connections between words, resulting in "superficial" matches that fail to adequately capture the "implicit" meanings in user queries (Manning, Raghavan, & Schütze, 2008). In other words, end users may receive only minimally important information and documents that match words. Such a problem leads to contextual semantic problems. Many traditional systems have difficulty distinguishing between synonymous terms and, accordingly, fail to parse words or word pairs with ambiguous meanings. Traditional information retrieval systems cannot provide query results in a specific information context because they cannot grasp end users' search history, location, or target (Liu & Toubia, 2018).

Since end users often make queries with vague, short and poorly defined words, a retrieval system that lacks models that model the intent of these queries has a negative impact on the level of relevance (Keyvan & Huang, 2022). Traditional information retrieval systems; as stated by Croft, Metzler and Strohman (2015), since they do not include advanced Natural Language Processing (NLP) and end-user search modeling techniques, they cannot understand exactly what the query means (definition, comparison or concept). In this regard, ranking restrictions also constitute a significant obstacle. Rankings brought about by click-through rates or link popularity cannot represent the level of relevance of the content as desired. For example; some pages may be represented in search results quite a lot even if they are not relevant, and this situation may be seen lower in the rankings because they are more relevant to the query but have a small number of clicks (Joachims, 2002). The solution to such challenges is a more effective information retrieval system. Such a system should include a multi-approach such as inclusiveness, personalization, context and ethics.

AI-powered information retrieval systems, on the other hand, can perform "semantic" searches that include the underlying intent and importance of the query rather than simply matching keywords, and can effectively rank the results. In other words, results can be ranked according to the end user's intent, goals, systemic or cultural conditions, and past searches (Chen et al., 2022). In addition, AI can determine whether a query is related to sensitive content such as health, politics, or personal issues, and adapt its responses accordingly. Since AI will provide more precise and robust results as it learns from more diverse data sets, its integration with traditional retrieval systems can help reduce the aforementioned problems and deliver more inclusive and culturally "aware" results.

3. Traditional Information Retrieval Systems and AI Support for Challenges

Although the integration of AI into traditional information retrieval systems can overcome most of the challenges, AI also has several important problems such as characteristic bias, memorization and inability to generalize (Adelakun, 2024). Since these problems are not the subject of this study, the focus is on the potential disadvantages as well as the benefits of AI support for information retrieval systems. For example; user privacy and data protection are very important issues in all AI-driven systems (Devineni, 2024). The collection and analysis of a lot of personal data about user experience for more accurate and correct results today leads to privacy

violations or negative biases. Another important issue is the difficulties related to contextual accuracy of overly complex queries, especially when the exact intention of the end user is unclear. As mentioned before, since AI systems are trained on datasets that may contain historical biases depending on their algorithms, they can also lead to unbalanced or unfair results. Again, such problems are actually solved in AI itself. For example, contributing to contextual integrity by making sense of changing end-user preferences can be achieved by continuously retraining and "evolving" AI models to some extent.

Since Deep Learning (DL) models can explain both context and semantic understanding, they increase the level of recall and relevance by using contextualized word representations, as emphasized by Devlin et al. (2019). In addition, recommendation systems and algorithms for modeling end-user search intentions provide highly successful personalization by learning from end-users' behaviors, preferences, and search histories, as described by Ricci, Rokach, and Shapira (2015). KGs and ontology-based retrieval are widely used to increase adaptability and relevance by enabling static knowledge to be dynamicized and integrated with real-world situations, as stated by Hogan et al. (2021). Despite the successful results achieved in the mentioned fields, the integration of AI into traditional information retrieval systems has not yet solved certain problems and brings some additional difficulties.

Personalization appears to be a rather complex topic in both traditional systems and AI. AI models can suggest content based on observed user behavior, but just like traditional systems, due to the algorithm used, they may ignore the underlying end-user intent, individual context changes, and some limitations of personalization. Empowering filters by overemphasizing past behavior may prevent a broad perspective (Nguyen et al., 2014).

Machine Learning (ML) models trained with biased or incorrect data often cause major problems and can reduce performance by reinforcing social, cultural and political biases that exist in search engine results regardless of the platform (Binns, 2018). Also known as "black boxes," AI algorithms may not be perceived by end users or even software developers, and in this case, the goal of fairness, transparency and inclusiveness is far from being achieved.

Continuous adaptation also presents significant challenges. Adapting AI models to dynamic information environments or user needs that emerge in real time results in high computational costs due to the continuous and repetitive training process. Long-term calculations, especially on very large data sets, are also expensive processes to model methodologically (Liu et al., 2022).

In addition, the inability to understand the end user's purpose and intent is also among the problems that have not yet been solved. Despite the significant achievements in the field of NLP in recent years, some AI-driven systems do not fully understand unspecific, multi-purpose or "exploratory" search behaviors. Uncertainty is especially evident when end users are not sure what they are looking for or use terminology that even the algorithm cannot recognize (Clarke et al., 2016).

In summary, although AI enhances the capabilities of traditional information retrieval systems, its integration comes with the aforementioned limitations. In order to further reduce these problems, the KG approach, which has been frequently used in recent years, can be integrated into AI-driven retrieval systems.

4. Knowledge Graph Approach

A KG can be defined as a complex data structure for representing, storing and evaluating the connections and properties of entities within a given topic or across various related topics. Unlike traditional databases that store data in tables or basic key-value pairs, a KG is structured with nodes representing entities and edges representing the connections between these entities, and the output is a graph. Such an approach captures the complex connections between the entities themselves, thus providing a much more efficient and detailed level of "knowledge representation".

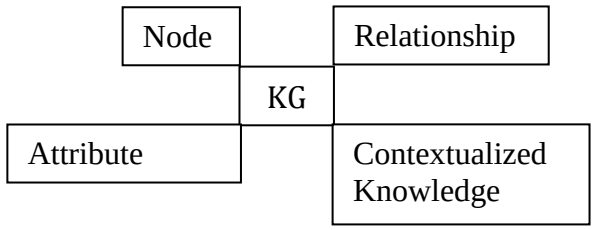


Figure 1. Components of a Knowledge Graph

4.1. Key Components of a KG

The KG approach can be thought of as a "semantic" layer that increases the accessibility capabilities of information retrieval systems by allowing them to think "critically" about structured knowledge representations. A KG structures the entities, properties, and their connections in a graphical form that is clearly and explicitly defined and easily understood by machines (Hogan et al., 2021). An approach using KGs is a great idea to address the challenges and limitations mentioned in the previous section: Improving contextual understanding, facilitating semantic search, and more complex personalization (Ehrlinger & Wöß, 2016).

KGs consist of four basic components as shown in Figure 1: Node, relationship, attribute, and contextualized information.

Node (Entity): Nodes can be represented by entities that contain real-world concepts (objects, people, locations, events, ideas, etc.). These representations can be represented in the graph as each entity, both uniquely identifiable and also as a separate semantically defined node (Nickel et al., 2016).

Relation (Edge): A relationship is a component that outlines the relationships between the entities mentioned in the nodes. These relationships are defined by directed and labeled connections between two nodes. For example; location, class, etc. information can be used to explain the relationship of a pair of nodes (Ji et al., 2022).

Attribute: Each node has unique properties that provide descriptive information. For example; Michael Jordan as an entity can contain various properties such as birth date, origin, team, and place of residence.

Contextualized Information*:* KGs can provide insightful context by combining time, space, and usage-based data in their nodes. In other words, it becomes possible to distinguish between different meanings of concepts and can adapt information retrieval processes according to time, space or end-user purpose (Xu et al., 2021).

4.2. The Process of Constructing a KG

The process of creating a KG consists of four steps, showing in Figure 2, namely data extraction, entity linkage, relationship establishment and graphical representation, especially because unstructured or semi-structured data is in a graphical representation.

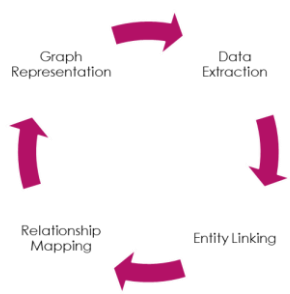


Figure 2. The Process of Constructing a Knowledge Graph

Data Extraction: In this first step data is collected from a wide variety of different sources (online or offline content, text files, databases, APIs, etc.). Information extraction and especially NLP are used to determine the relationships between entities (Luo, 2024).

Entity Linking: After the extraction process of all entities is completed, they need to be connected to a standardized structure or reference in a knowledge database. This process requires the elimination of ambiguities in the query, such as distinguishing between the technology company "Apple" and the fruit "apple", and even the normalization process (Shen, Wang, & Han, 2015).

Relationship Mapping: In this step, the semantic connections contained in the entities are determined and the entities are connected to each other. Certain relationships between entities; are defined using techniques such as dependency parsing, co-occurrence analysis, semantic role labeling or learned relational representations (Wang et al., 2017). The output is a graph structure with nodes representing the entities and meaningful and labeled edges connecting these nodes.

Graph Representation: The final stage is to represent the relationships, mostly using Resource Description Framework (RDF), feature graphs or embedding-based formats. This representation, which can be called structured, facilitates effective and efficient querying, reasoning and integration with AI-driven systems for subsequent applications, including semantic search and recommendation (Paulheim, 2017).

KGs increase the accuracy and importance of the information retrieval process by providing not only the process information of the data but also the underlying meaning behind the data. The integration of KGs with AI models can serve as a basis for the development of information retrieval systems that are both inclusive and responsive to context and user intent.

In Table 2, the stages' explanation and using techniques during construction.

Table 2. Knowledge Graph Creation Process

Order	Stage	Explanation	Techniques
1	Data Extraction	Collecting various information (text, web, APIs, etc.) online	Information Extraction (IE), Natural Language Processing (NLP)
2	Entity Linking	Matching extracted entities with scenic forms in the knowledge base	Entity Disambiguation, Entity Normalization
3	Relationship Making	Discovering deep semantic connections between entities to create meaningful connections	Dependency Parsing, Co-occurrence Analysis, Semantic Role Labeling, Embeddings
4	Graph Representation	Graph-based structuring and storage of data for querying and AI	RDF, Property Graphs, Knowledge Graph Embeddings

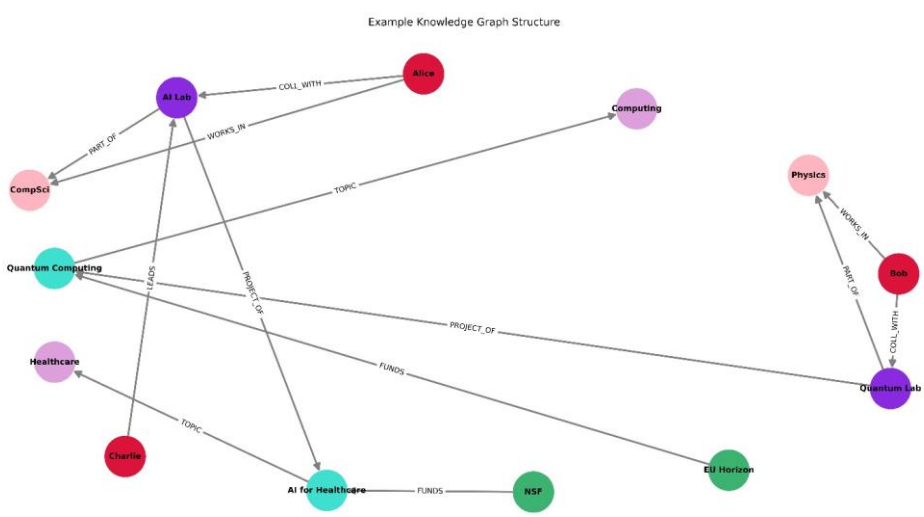


Figure 3. The Example of KG

The example KG shown in the Figure 3 describes an academic collaboration ecosystem that includes researchers, departments, laboratories, projects, funding organizations and various research areas in a university and shows the multidimensional relationships that provide the production of "knowledge" in the university. For example; Alice, Bob and Charlie represent researchers in the university and the department in which each researcher works is modeled through the "WORKS_IN" relationship. Charlie is the top manager in the "AI Lab" as seen in the "LEADS" relationship. "AI Lab" and "Quantum Lab" represent sub-research laboratories and are connected to the department they are affiliated with through the "PART_OF" relationship. "AI for Healthcare" and "Quantum Computing" represent the projects carried out by the laboratories and the "TOPIC" relationship is connected to the subject concepts. "NSF" is the funding organization that finances the "AI for Healthcare" project. "EU Horizon" supports "Quantum Computing". All of these are connected with the "FUNDS" edges. The "COLL_WITH" edge represents collaboration connections.

4.3. Inclusiveness in KGs

According to Nguyen (2021), digital inclusivity can be defined as the access and use of Information and Communication Technologies (ICT) such as the internet and its infrastructure, hardware, software and digital literacy education by all people, regardless of age, gender, ethnicity, mobility, physical and cognitive abilities, and cultural and socioeconomic backgrounds, as a reflection of the democratic nature of information. Another definition is the creation of systems that can reflect the diversity of data sources and social perspectives in the digital environment and the ability to use them in the same way (O'Neil, 2016; Noble, 2018).

AI-driven systems are playing an increasingly important role in information retrieval, and although they have several disadvantages, they can equally strengthen inclusivity in how information is represented. For example; taking cultural and linguistic diversity into account, gradually reducing system and end-user biases, ensuring digital accessibility for all segments of society, and promoting equality in the depiction and access of information are all possible through the collaboration of information graphics and AI (Hajian et al., 2016; Biega, Gummadi, & Weikum, 2018).

4.4. Key Dimensions of Inclusiveness in KGs

Inclusiveness in KGs can be evaluated by considering the origin, structure and functionality of the graphs.

Biases: Digital models and structures are naturally prone to biases originating from end users, circulating content or the algorithms themselves. When evaluated in terms of inclusiveness, the more these situations are reduced, the more success can be achieved. For example; personal and cultural biases can often be reflected quite comfortably and easily in the content created by the end user. If this is not corrected, biases naturally spread to entity representations and relationships (Mehrotra et al., 2018). In the design of KGs, factors such as the selection of sources, the relationships of entities to each other and even the algorithm itself can lead to systematic biases that favor certain demographic characteristics or perspectives over oppressed and disadvantaged groups (Binns, 2018).

Representational Diversity: Inclusiveness also relies on the representations in the KG. Entities representing different groups based on gender, ethnicity, and socioeconomic status should be represented "proportionally" to accurately reflect the pure truth and to avoid ignoring underrepresented disadvantaged groups (Hovy & Spruit, 2016). Including different geographic regions in the global representation allows for healthier integration into the structure of the graph and retrieval processes (Heeks, 2021). An inclusive KG should also meet various linguistic accessibility needs. Providing end users with the opportunity to search for and retrieve information in their native or preferred languages will naturally expand information retrieval (Hellmann et al., 2013). In addition, the system should include translation mechanisms and cross-language entity matching processes. KG-based interfaces should

comply with various basic accessibility rules, including compatibility with the demands of individuals with disabilities and accessible alternative text interaction methods (Zhu et al., 2025).

Justice and Ethics: If the design of KGs is to be inclusive, it must also be based on fairness and ethical principles. KGs are also used in decision-making processes, while algorithms should ensure fairness to users and prevent biased treatment and discrimination (Barocas, Hardt, & Narayanan, 2023). Software developers and developers should respect potential users' right to privacy when designing (Crawford, 2021). Accepting inclusivity as a fundamental design element allows KGs to support more equal access, context-sensitive retrieval, and informed decision-making processes, and can strengthen the positive impact of AI-driven systems on users and communities.

4.5. How KGs Improve the Results: Agents and Fine Tuning

KGs provide a structured framework of interconnected knowledge that can be used by various agents and AI models to improve information retrieval processes and increase the performance of the results obtained. Significant improvements are facilitated primarily by the use of intelligent agents and fine-tuning methods, many of which are made through DL, representation learning, and neural-symbolic integration techniques. An agent acts as an intermediary between end users and knowledge bases by using knowledge graph structures to facilitate reasoning, content matching, and ranking. Agents are basically divided into three:

Rule-Based Agents: This type of agents operate in accordance with predefined rules, ontologies, and logical inference mechanisms. Grau et al. (2008) emphasize that rule-based agents provide precise and interpretable results by directly matching queries to specified entities or relations in a predictable and well-defined environment. Their performance may also deteriorate when the platform is uncertain or very noisy.

Learning-Based Agents: It is known as ML agents, can "reason" without predefined rules by using supervised and unsupervised methods to develop representations of entities and relationships within KGs. Such agents use entity embeddings, semantic similarity, and contextual representations (Nickel et al., 2016). In dynamic or data-rich domains, when it is not practical to create a set of rules, learning-based agents are more effective.

Hybrid Agents: This type usually works with techniques based on learning symbolic reasoning methods. It often applies rules for high-precision constraints, and neural networks for flexibility and generalization ability. This integration with deep learning methods adapts to unpredictable queries or evolving dynamic knowledge (Hitzler, 2021).

5. Fine-Tuning and Knowledge-Aware Learning

KGs also support fine-tuning of ML models through various embedding techniques and hybrid architectures. There are several strategies to directly transfer the knowledge of KGs to the training of the model:

Embedding-Based Fine-Tuning: KGs can be represented using entity and relation embeddings such as TransE and DistMult, which are very low-dimensional vectors that preserve semantic relationships. These embeddings are also frequently used to fine-tune retrieval models to improve entity disambiguation and ranking (Bordes et al., 2013; Yang et al., 2014).

Graph Embedding Models: Graph embedding models such as Node2Vec or GraphSAGE learn contextual node representations by randomly sampling local areas of the graph and are highly effective in link prediction, semantic retrieval, and recommendation tasks (Hamilton, Ying, & Leskovec, 2017).

Task-Specific Loss Functions: Using task-sensitive loss functions such as contrastive loss or triplet loss during fine-tuning of retrieval models increases the ability to distinguish between relevant and irrelevant KG entities (Yao, Mao, & Luo, 2019). The performance of the model can be balanced and improved by losses that prioritize more contextual and relevant elements.

Knowledge Augmented Language Models: Recent developments in transformer-based architectures, including BERT and T5, have been developed to integrate knowledge based on KGs. Techniques such as K-BERT and KnowBERT directly incorporate triplet structure into attention layers to add text-based reasoning to structured knowledge (Liu et al., 2019; Peters et al., 2019).

Retrieval-Augmented Generation (RAG): In KG based RAG systems, retrieval and generation components dynamically retrieve knowledge from external KGs and transfer it to the generation process. For example, it provides more accurate and detailed contextual results in tasks such as open-ended question answering and text summarization (Lewis et al., 2020).

5.1. Graph Neural Networks and Their Fine-Tuning

Graph Neural Networks (GNNs), related the KG approach, are special types of Artificial Neural Networks (ANNs) developed for tasks whose inputs are some kind of graph. A GNN can also be thought of as an optimized transformation on all attributes of the graph (nodes, edges, global context) that preserves graph symmetries (Ward et al., 2020). GNNs adopt the "graph-input, graph-output" architecture, that is, such models accept a graph as input, impute information to its nodes, edges, and global context, and gradually transform these embeddings without changing the connectivity of the input graph. For example, fine-tuning applied to GNNs in tasks such as entity classification or link prediction enables the discovery of domain-specific relevance patterns (Ye et al., 2022). Graph Attention Networks (GAT) and Relational Graph Convolutional Networks (R-GCN) architectures provide more selective weighting of neighborhood information or relation-specific transformations (Velickovic et al., 2018; Schlichtkrull et al., 2018). Information retrieval models enhanced with GNN technology combine text and multimedia inputs and have made significant advances in verifying semantic results of queries, recommendation systems, and facts.

6. Expected Benefits of the Approach

Integrating KGs into information retrieval systems should be seen as a very important factor in increasing both the accuracy, precision and relevance of search results. KGs offer “contextual intelligence” with semantic relationships in a structure that goes beyond traditional retrieval systems (Singhal, 2012; Ehrlinger & Wöß, 2016). One benefit of the approach is enhanced contextual understanding. KGs enable information retrieval systems to understand both semantic and contextual relationships beyond simple keyword matching by modeling the meaning and connections of entities. Search systems can identify conceptually similar content by applying entity embeddings and relationship types, even if the lexicon used is different (Wang et al., 2014). Greater semantic depth enables more effective ranking of information that is compatible with the purpose and intent of end users. Context-aware query processing is another one. KGs also demonstrate the representability of situational and domain-specific knowledge by adding contextualized nodes and edges to the existing structure. The system can distinguish between ambiguous user queries using the resulting context and user history. For example; the interpretation of the query "NASA" may vary depending on the context, depending on whether it is related to astrology, physics, spacecraft, or government agency information, etc. (Shen, Wang, & Han, 2015). This greatly minimizes redundant results by increasing the retrieval accuracy for matching relevant words connected to the context. Personalization and adaptability is important benefit. KGs can also be designed to include a wide range of personalization strategies, such as profiles, preferences, and past actions, to customize the displayed results. Personalized access paths can also be supported by system adaptability, which enables dynamic and instantaneous responses to end-user needs (Liu et al., 2024). Since the retrieval system uses detailed user profiles, personal “relevance” becomes more responsive. Handling ambiguity also another one. In natural language, ambiguity is a significant disadvantage for traditional information retrieval systems. KGs allow the elimination of entity ambiguity and the detailed resolution of meaning by connecting queries to an entity network and the connections of these networks, thus ensuring that the system outputs accurately represent the intended meaning of the end user (Nickel et al., 2016). It stands out as a useful feature, especially in text files where words have multiple meanings. Multilingual and multicultural support is side of social benefits of KGs. Multilingual ontologies and language-independent entity

identifiers can be used when designing KGs, thus increasing cross-lingual recall and cultural inclusiveness. A query in one natural language can retrieve content comparable to another natural language, thus increasing accessibility and relevance for end users (Navigli & Ponzetto, 2012; Auer et al., 2007). The last one is enhanced sensitivity to underrepresented knowledge. Traditional information retrieval systems often struggle due to "bias" towards dominantly represented concepts and topics. When KGs are designed with inclusivity in mind, they can make "underrepresented knowledge" accessible by incorporating it into the algorithmic graph structure (Binns, 2018). By using ontologies and design principles organized with ethical concerns, KGs can ensure that underrepresented communities and concepts in search results are represented fairly and equally.

7. Conclusion

The structuring of KGs helps to communicate complex connections between entities in an orderly and efficient manner, allowing traditional systems to process data contextually and semantically rather than through basic keyword searches. Interpreting queries within specific and relevant contexts allows AI to more accurately understand the meaning of the query, thus reducing the likelihood of misinterpretation of the query. In other words, the accuracy of the answers increases.

KGs enable personalization by using interconnected data to customize recommendations, predictions, or choices based on end users' preferences, past actions, and "digital" behaviors. These features increase the accuracy of system outputs by more closely aligning user goals with the underlying meanings of the information. The transparency feature of KGs also enables AI systems to detect and correct biases in data, thus enforcing fairness and demonstrating that equal treatment can be achieved between different user groups. It also plays a crucial role in improving AI outputs and ensuring the ethical and responsible use of AI in various fields (such as healthcare, finance, and education). The need for accurate, customized, and responsible information retrieval in an era of disinformation and information overload is driving the transition from traditional systems to AI systems powered by KGs. Modeling end-user preferences and behaviors in a graphical way helps provide more effective personalization and enables the system to adjust its responses in real time to suit each user's unique goals.

References

Adelakun, N.O. (2024). Exploring the Impact of Artificial Intelligence on Information Retrieval Systems. *Information Matters*, 4(5), Retrieved from https://informationmatters.org/2024/05/exploring-the-impact-of-artificial-intelligence-on-information-retrieval-systems/

Auer, S. et al. (2007). DBpedia: A Nucleus for a Web of Open Data. In: Aberer, K. (ed.), *The Semantic Web Lecture Notes in Computer Science*, 4825, 722-735, Springer, Berlin, Heidelberg, doi: https://doi.org/10.1007/978-3-540-76298-0_52

Baeza-Yates, R. & Ribeiro-Neto, B. (2011). *Modern Information Retrieval: The Concepts and Technology Behind Search (2nd ed.)*. New York: Addison-Wesley.

Barocas, S., Hardt, M., & Narayanan, A. (2023). *Fairness and Machine Learning: Limitations and Opportunities*. Cambridge: The MIT Press.

Biega, A.J., Gummadi, K.P., & Weikum, G. (2018). Equity of Attention: Amortizing Individual Fairness in Rankings. In *Proceedings of the 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* (pp. 405-414), doi: https://doi.org/10.1145/3209978.3210063

Binns, R. (2018). Fairness in Machine Learning: Lessons from Political Philosophy. *ArXiv:1712.03586*, 149-159, doi: https://doi.org/10.48550/arXiv.1712.03586

Bordes, A. et al. (2013). Translating Embeddings for Modeling Multi-Relational Data. *In NIPS'13: Proceedings of the 27th International Conference on Neural Information Processing Systems in Advances in Neural Information Processing Systems*, 2, (pp. 2787-2795).

Chen, B. et al. (2022). Towards Improving the Explainability of Text-based Information Retrieval with Knowledge Graphs. *ArXiv:2301.06974*, 1-7, doi: https://doi.org/10.48550/arXiv.2301.06974

Clarke, C.L. et al. (2008). Novelty and Diversity in Information Retrieval Evaluation. *In Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp.659-666), doi: https://doi.org/10.1145/1390334.1390446

Crawford, K. (2021). *The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven: Yale University Press, doi: https://doi.org/10.2307/j.ctv1ghv45t

Croft, W.B., Metzler, D., & Strohman, T. (2015). *Search Engines: Information Retrieval in Practice (2nd ed.).* New York: Pearson.

Devineni, S.K. (2024). AI in Data Privacy and Security. *International Journal of Artificial Intelligence & Machine Learning*, 3(1), 35-49, doi: https://doi.org/10.17605/OSF.IO/WCN8A

Devlin, J. et al. (2018). BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding. *ArXiv:1810.04805*, 1-16, doi: https://doi.org/10.48550/arXiv.1810.04805

Ehrlinger, L. & Wöß, W. (2016). Towards a Definition of Knowledge Graphs. *SEMANTICS 2016: Posters and Demos Track*, 1-4, Retrieved from https://ceur-ws.org/Vol-1695/paper4.pdf

Grau, B.C. et al. (2008). OWL 2: The next step for OWL. *Journal of Web Semantics*, 6(4), 309-322i doi: https://doi.org/10.1016/j.websem.2008.05.001

Hajian, S., Bonchi, F., & Castillo, C. (2016). Algorithmic Bias: From Discrimination Discovery to Fairness-Aware Data Mining. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 2125-2126), doi: https://doi.org/10.1145/2939672.2945386

Hamilton, W., Ying, Z., & Leskovec, J. (2017). Inductive Representation Learning on Large Graphs. *In NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems*, 1025-1035.

Heeks, R. (2021). From Digital Divide to Digital Justice in the Global South: Conceptualising Adverse Digital Incorporation. *Digital Development Working Paper no:90*, 1-15, doi: http://dx.doi.org/10.2139/ssrn.3907633

Hellmann, S. et al. (2013). Integrating NLP Using Linked Data. In: H. Alani et al. (eds.). *The Semantic Web-ISWC 2013. Lecture Notes in Computer Science*, 8219, 98-113, Springer, Berlin, Heidelberg, doi: https://doi.org/10.1007/978-3-642-41338-4_7

Hitzler, P. (2021). Neuro-Symbolic Artificial Intelligence: Current Trends. *ArXiv:2105.05330*, 1-11, doi: https://doi.org/10.48550/arXiv.2105.05330

Hogan, A. et al. (2021). Knowledge Graphs. *ACM Computing Surveys*, 54(4), 1-37, doi: https://doi.org/10.1145/3447772

Hovy, D. & Spruit, S.L. (2016). The Social Impact of Natural Language Processing. *In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics* (pp. 591-598), doi: 10.18653/v1/P16-2096

Ji, S. et al. (2022). A Survey on Knowledge Graphs: Representation, Acquisition, and Applications. *IEEE Transactions on Neural Networks and Learning Systems*, 33(2), 494-514, doi: 10.1109/TNNLS.2021.3070843

Joachims, T. (2002). Optimizing Search Engines Using Clickthrough Data. *In Proceedings of the 8th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 133-142). Association for Computing Machinery, New York, USA, doi: https://doi.org/10.1145/775047.775067

Keyvan, K. & Huang, J.X. (2022). How to Approach Ambiguous Queries in Conversational Search: A Survey of Techniques, Approaches, Tools, and Challenges. *ACM Computing Surveys*, 55 (6), 1-40, doi: https://doi.org/10.1145/3534965

Lewis, P. et al. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks *ArXiv:2005.11401*, 1-19, doi: https://doi.org/10.48550/arXiv.2005.11401

Liu, J. & Toubia, O. (2018). A Semantic Approach for Estimating Consumer Content Preferences from Online Search Queries. *Marketing Science*, 37(6), 930-952, doi: https://doi.org/10.1287/mksc.2018.1112

Liu, S. et al. (2023). An Effective Learning Evaluation Method Based on Text Data with Real-time Attribution: A Case Study for Mathematical Class with Students of Junior Middle School in China. *ACM Transactions on Asian and Low-Resource Language Information Processing*, 63, 1-22, doi: https://doi.org/10.1145/3474367

Liu, G. et al. (2024). Knowledge-Enhanced Recommendation with User-Centric Subgraph Network. *ArXiv:2403.1437*, 1-13, doi: https://doi.org/10.48550/arXiv.2403.14377

Liu, W. et al. (2019). K-BERT: Enabling Language Representation with Knowledge Graph. *ArXiv:1909.07606*, 1-8, doi: https://doi.org/10.48550/arXiv.1909.07606

Luo, Y. (2024). Recent Advances in Knowledge Graph Completion. *Applied and Computational Engineering*, 73, 236-245, doi: https://doi.org/10.54254/2755-2721/73/20240404

Manning, C.D., Raghavan, P. & Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge: Cambridge University Press.

Mehrotra, R. et al. (2018). Towards a Fair Marketplace: Counterfactual Evaluation of the Trade-off between Relevance, Fairness & Satisfaction in Recommendation Systems. *In CIKM '18: Proceedings of the 27th ACM International Conference on Information and Knowledge Management* (pp. 2243-2251), doi: https://doi.org/10.1145/3269206.3272027

Navigli, R. & Ponzetto, S.P. (2012). BabelNet: The Automatic Construction, Evaluation and Application of a Wide-Coverage Multilingual Semantic Network. *Artificial Intelligence*, 193, 217-250, doi: https://doi.org/10.1016/j.artint.2012.07.001

Nickel, M. et al. (2016). A Review of Relational Machine Learning for Knowledge Graphs. *Proceedings of the IEEE*, 104(1), 11-33, doi: https://doi.org/10.1109/JPROC.2015.2483592

Nguyen, A. (2021). Digital Inclusion. In: Liamputtong, P. (ed.). *Handbook of Social Inclusion* (pp. 1-15). Cham: Springer, doi: https://doi.org/10.1007/978-3-030-48277-0_14-1

Nguyen, T.T. et al. (2014). Exploring the Filter Bubble: The Effect of Using Recommender Systems on Content Diversity. In *Proceedings of the 23rd International Conference on World Wide Web* (pp. 677-686), doi: https://doi.org/10.1145/2566486.2568012

Noble, S.U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York: New York University Press.

O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. New York: Crown Publishing.

Paulheim, H. (2017). Knowledge Graph Refinement: A Survey of Approaches and Evaluation Methods. *Semantic Web*, 8(3), 489-508, doi: https://doi.org/10.3233/SW-160218

Peters, M.E. et al. (2019). Knowledge Enhanced Contextual Word Representations. *ArXiv:1909.04164*, 1-14, doi: https://doi.org/10.48550/arXiv.1909.04164

Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender Systems: Challenges, Solutions and Research Opportunities. In F. Ricci, L. Rokach, B. Shapira, P.B. Kantor (eds.), *Recommender Systems Handbook* (pp. 1-34), Boston: Springer, doi: https://doi.org/10.1007/978-0-387-85820-3_1

Schlichtkrull, M. et al. (2018). Modeling Relational Data with Graph Convolutional Networks. *ArXiv:1703.06103*, 1-9, doi: https://doi.org/10.48550/arXiv.1703.06103

Shen, W., Wang, J., & Han, J. (2015). Entity Linking with a Knowledge Base: Issues, Techniques, and Solutions. *IEEE Transactions on Knowledge and Data Engineering*, 27(2), 443-460, doi: 10.1109/TKDE.2014.2327028

Singhal, A. (2012). *Introducing the Knowledge Graph: Things, Not Strings*. Official Google Blog. Retrieved from: https://blog.google/products/search/introducing-knowledge-graph-things-not/

Teevan, J., Dumais, S.T., & Horvitz, E. (2005). Personalizing Search via Automated Analysis of Interests and Activities. *In Proceedings of the 28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 449-456). Association for Computing Machinery, New York, USA, doi: https://doi.org/10.1145/1076034.1076111

Velickovic, P. et al. (2018). Graph Attention Networks. *ArXiv:1710.10903*, 1-12, doi: https://doi.org/10.48550/arXiv.1710.10903

Wang, Q. et al. (2017). Knowledge Graph Embedding: A Survey of Approaches and Applications. *IEEE Transactions on Knowledge and Data Engineering*, 29(12), 2724-2743, doi: 10.1109/TKDE.2017.2754499

Wang, Z. et al. (2014). Knowledge Graph Embedding by Translating on Hyperplanes. In *AAAI'14: Proceedings of the 28th AAAI Conference on Artificial Intelligence*, 1112-1119.

Ward, I.R. et al. (2020). A Practical Tutorial on Graph Neural Networks. *ArXiv:2010.05234*, 1-35, doi: https://doi.org/10.48550/arXiv.2010.05234

White, R.W. & Marchionini, G. (2007). Examining the Effectiveness of Real-Time Query Expansion. *Information Processing & Management*, 43(3), 685-704, doi: https://doi.org/10.1016/j.ipm.2006.06.005

Xu, C. et al. (2021). Contextual Knowledge Graph. *ArXiv:2406.11160*, 1-19, doi: https://doi.org/10.48550/arXiv.2406.11160

Yang, B. et al. (2014). Embedding Entities and Relations for Learning and Inference in Knowledge Bases. *ArXiv:1412.6575*, 1-12, doi: https://doi.org/10.48550/arXiv.1412.6575

Yao, L., Mao, C., & Luo, Y. (2019). Graph Convolutional Networks for Text Classification. In *EAAI'19: Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, Article No: 905, 7370-7377, doi: https://doi.org/10.1609/aaai.v33i01.33017370

Ye, Z. et al. (2022). Comprehensive Survey of Graph Neural Networks for Knowledge Graphs. *IEEE Access*, 10, 75729-75741, doi: 10.1109/ACCESS.2022.3191784

Zhu, R. et al. (2025). The KnowWhereGraph: A Large-Scale Geo-Knowledge Graph for Interdisciplinary Knowledge Discovery and Geo-Enrichment. *ArXiv:2502.13874*, 1-31, doi: https://doi.org/10.48550/arXiv.2502.13874