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The Application of Knowledge Graphs in Legal Decision Processes

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Abstract: *Legal knowledge graphs can represent legal entities, concepts, documents, provisions, cases and their relationships in a form that can be queried and interpreted. In this paper, we provide a systematic overview of legal knowledge graphs in legal decision-making processes, focusing on their construction, representation, and application in various downstream tasks. Accordingly, we study the following tasks: predicting legal decisions, predicting legal charges, legal case retrieval, legal statute identification, legal question answering, legal compliance checking, and explainable legal reasoning. Besides, we summarize the pipelines of constructing legal knowledge graphs into three categories, namely, ontology-based manually constructed legal knowledge graphs, knowledge graphs constructed by the NLP techniques, and legal knowledge graph constructed with the help of LLMs. The review identifies the potential of graph-based models to improve retrieval, prediction, matching, and explanation of legal concepts compared to flat-text and keyword-based models. This article presents them as knowledge infrastructures to improve access, traceability, consistency, oversight, automation, and transparency of legal decision-support systems.*

Keywords: knowledge graphs, legal decision-making, artificial intelligence, large language models, explainable legal reasoning.

INTRODUCTION

Legal reasoning can be characterized broadly as the activity of reading, navigating and comparing a great deal of structured, dynamic and complex text. It also includes locating relevant legal concepts, but further tasks such as locating links between rules and case law, identifying amended and repealed law, and analogical reasoning. When multiple jurisdictions and legal systems overlap in a relational manner, this exposes the limits of document-based information retrieval systems when they are tasked with legal reasoning.

The law has also become more complex as a result of the increasing volume of statutes, the digitisation of court records, and the overlap between domestic, regional, and supranational systems of law. For example, legal reasoning in a system influenced by EU law often requires interpretation not only of domestic law, but also of EU legal instruments, administrative practice, and case law. All these trends require systems able to store, retrieve, organize, interpret, and explain legal knowledge clearly, efficiently, and quickly.

Knowledge graphs may provide a promising technical and conceptual basis for structuring and representing legal entities, concepts, documents, provisions, cases, and the relationships between these elements in a machine-readable format. They may therefore support approaches with more accurate retrieval, clearer traceability, and more explainable forms of legal decision support. Indeed, one key function of KGs is to make explicit many relationships that are implicit in legal text, such as that a case applies a provision, an article amends another article, a rule imposes an obligation, a fact satisfies a legal element, or a decision relies on a precedent. Knowledge graphs have been applied across a wide range of legal decision processes including judgment prediction (Gao et al., 2024; Yuan et al., 2025) similar case retrieval (Gao et al., 2023; Bi et al., 2022), statute identification (Shukla et al., 2025; Li et al., 2021), legal question answering (Anhein & Wiharja, 2025; Thomas & Sangeetha, 2022) and compliance verification (Tauqeer et al., 2022), with consistent evidence that graph-based representations of legal knowledge outperform flat-text and keyword-based methods in accuracy, interpretability, and contextual reasoning. Hybrid models that combine KGs with LLMs using RAG or post-training methods have been shown to improve performance on legal reasoning datasets, as well as citation correctness and explanation correctness (Chen et al., 2024; Song et al., 2026; Wang & Zhan, 2026; Zhang et al., 2025). KGs can also encode complex legal knowledge structures that are domain-specific, such as causal chains (Liu et al., 2021), versioning of temporal norms (de Martim, 2025; de Martim, 2025), hierarchical relationships between statutes (Shukla et al., 2025), and cross-jurisdictional concept alignment (Ruan, 2025).

This article has three main contributions. Firstly, it reviews the most prominent construction strategies for legal knowledge graphs: ontology-based approaches, natural language processing-based approaches and the most recently developed LLM-assisted pipelines. Second, it summarizes the main classes of legal entities, relationships and knowledge representation models upon which these representations are based. Third, it surveys the main areas in which knowledge graphs are used in the legal decision-making process, identifying open research challenges and gaps in the literature.

The rest of this article is organized as follows. Background and methods are presented in section II. Section III describes the classical modes to construct legal knowledge graphs. Section IV discusses legal knowledge representation. Section V discusses legally relevant knowledge graph applications for legal decision making. Section VI summarizes the findings and outlines research challenges. Section VII concludes the article and discusses areas for future research.

CONCEPTUAL BACKGROUND AND METHODOLOGICAL APPROACH

In general terms, knowledge graphs are structured, machine-readable representations of real-world entities and their relationships, containing metadata, document structures, textual content, and relations between legal resources. (Abdurahman et al., 2021) They enhance accessibility and support semantic querying, serving as knowledge-intensive components for predictive machine learning applications, with practical applications such as improving access to legal information and enabling complex queries. (Markovich et al., 2025; D'Amato et al., 2025).

As Pham et al. (2026) describe, knowledge graphs, after being built based on the content from legal documents to build the system's knowledge base or from questions entered by users, act as an intermediate knowledge layer. They support the matching and inference process to accurately retrieve relevant information from the knowledge base to answer questions effectively. They provide a structured, clear, and organized way of representing knowledge of legal documents. In addition, because knowledge graphs can easily identify legal concepts and relationships in users' questions, knowledge graphs can improve the performance of legal research and the accuracy of answers given by legal question and answer systems when individuals input legal questions. (Pham et al., 2026) Entities and relationships in the legal knowledge graph are presented in Li et al. (2024). (Li et al., 2024)

This article reviews recent work applying knowledge graphs, semantic networks, graph-based legal ontologies, and graph reasoning at one or more of the following stages of the legal decision-making process: legal information retrieval, legal provision prediction, decision or charge prediction, legal question answering, compliance checking, and the explanation of legal reasoning processes. We included articles dealing with graph-based legal knowledge representation, decision support, legal reasoning, legal information retrieval, legal compliance, and legal explanation, as long as they made empirical evaluations or had a clear methodological contribution to the field.

KNOWLEDGE GRAPH CONSTRUCTION APPROACHES

Ontology-based construction remains one of the first approaches to legal KGs. The first such applications required humans to construct the ontologies, with legal experts being the ones doing this work (Casanovas et al., 2005); more recent approaches are, however, a hybrid between ontology-based and extraction. Several studies construct ontologies tailored to their legal domains. Such ontologies include the CargO-S ontology for maritime law based on the Unified Foundational Ontology (UFO) (El Ghosh & Abdulrab, 2020) , the LATO ontology in SKOS, which is a base ontology in CRIKE (Crime Knowledge Extraction) , a data-science-oriented approach and tool environment to extract and improve legal knowledge from a corpus of court decisions (Castano et al., 2020) , and a three-layer legal knowledge architecture developed (Zhang et al., 2025) .

Automated and semi-automated information extraction pipelines are becoming common, with natural language processing (NLP) based pipelines gaining in popularity. Named entity recognition and relation extraction are core building blocks for many automated information extraction pipelines (Ma, 2025; Han, 2024; Zhou et al., 2024). In general, BERT-based models were commonly used for entity extraction (Zhou et al., 2024; Ershov, 2023). Other alternatives include CasRel and BiLSTM-CRF joint-relation models (Han, 2024), as well as key case element extraction using a combination of RoBERTa-CRF (Wu, 2025).

In addition, there is a growing use of LLMs. Prompt-based LLMs have been used to extract components of legal reasoning from court decisions (Kondo et al., 2025), to automate knowledge graph construction from case texts (Chen et al., 2024), and to generate fundamental knowledge components from legal codes (Huy et al., 2025). Two complementary approaches, a bottom-up structured method and an LLM-based method, were compared for constructing a knowledge graph on violence against women cases, with the bottom-up approach excelling in precision and the LLM approach offering adaptability and speed (D'Amato et al., 2025).

LEGAL KNOWLEDGE REPRESENTATION STRUCTURES

The representation of legal knowledge within different graphs varies in sophistication and scope. At the entity level, the most commonly captured types include laws and legal provisions (Ruan, 2025; Shukla et al., 2025; Li et al., 2021), court cases and courts (Vuong et al., 2023), legal articles and statutes (Shao, 2024; Huy et al., 2025), violations and criminal behaviors (Gao et al., 2024; Huy et al., 2025) and penalties (Huy et al., 2025). More specialized systems capture even entities such as carriers and shippers in maritime law (El Ghosh & Abdulrab, 2020), contractual terms and obligations in GDPR compliance (Tauqeer et al., 2022), or forensic evidence entities in digital forensics (Ramadan et al., 2025).

Regarding legal relationships, citation and cross-reference relationships are widely modelled (de Martim, 2025; Ruan, 2025; Shukla et al., 2025). Hierarchical structures, representing the nesting of titles, chapters, sections, and articles are captured in several constitutional and statutory knowledge graphs (de Martim, 2025; Shukla et al., 2025; Barron et al., 2026). Temporal relations in general, including change of law over time, are as well addressed by a number of approaches, as well as causal relationships between legal events and resulting effects. The IRAC framework (Issue, Rule, Analysis, Conclusion) provides a conceptual approach that organizes the components of legal reasoning (Song et al., 2026).

Formal ontologies, for example the UFO-L formal ontology of Alexy's Theory of Constitutional Rights, showed to be a better representation of the semantics of court decisions in cases of normative omissions or principle collision than the LKIF-Core ontology which is based on a Kelsenian positivist theory of law (Griffo et al., 2020). Fermat's Fuzzy Graph Framework tabulates fuzzy truth and contradictory evidence in models of law and fact using non-linear dual-membership functions (Nishad et al., 2025). Heterogeneous graph models link multiple types of entities (cases, domains, courts, laws) through typed relations. Contrastive learning methods have also been used to identify correspondences between legal concepts across jurisdictions (Ruan, 2025). Legal semantics is a major challenge. Solutions include legal domain embeddings, semantic alignment modules (Bi et al., 2022), attention mechanisms to highlight relevant legal information (Yuan et al., 2025), and various granularity of concept retrieval, which identify relevant legal concepts at different levels within an ontological hierarchy (Zhang et al., 2025). In addition, in several knowledge graph completion methods, pre-trained language models are used as factual knowledge to assist or guide the graph reasoning (Li et al., 2021; Qin et al., 2021).

KEY APPLICATIONS

Multiple works apply knowledge graphs to predict legal outcomes such as the charges (articles of law applied) (Xu et al., 2025) and the sentences. CP-KG, which applies criminal behavior knowledge graphs to predict charges, achieves large improvements over baselines (Gao et al., 2024). Fine-grained element graphs have also been used in tasks such as predicting articles of law, charges and penalties

(Guo et al., 2024). However, predictive accuracy must be treated carefully. Legal judgment prediction is not legal reasoning, since a model may learn statistical correlations from past decisions that do not correspond to doctrinal reasoning, evidentiary burdens, or fairness concerns. For this reason, prediction systems should be framed as decision-support tools rather than autonomous adjudicative systems.

Similar-case retrieval is one of the most natural applications of legal knowledge graphs. Legal reasoning by analogy depends on forms of similarity that are not purely textual. Some cases may be similar with respect to the legal statutes and case law they address, or with respect to procedural aspects, even if they do not share the same keywords. Graph-based representation methods may capture and represent such similarities more transparently than keyword-based methods.

The Legal-GMN model uses graph matching for similar-case retrieval and reports improvements in retrieval precision and efficiency compared with baseline methods, while also generating visualised retrieval process graphs (Gao et al., 2023). L-HetGRL, a heterogeneous graph representation learning model, outperformed competitive baselines on similar case matching and charge prediction tasks (Bi et al., 2022). Node2vec-based judgment similarity using case-article knowledge graphs automated comparisons that previously required extensive labor hours (Shao, 2024).

Legal provision identification concerns the selection of the legal rules applicable to a factual situation. Text-guided graph reasoning shows improvement over text-only methods (Li et al., 2021). NyayGraph, a KG of Penal Code provisions, is shown to improve recall without losing precision with explicit KG inference (Shukla et al., 2025). Benefits have been identified benefits when combining KGs with LLMs for recommending legal articles (Chen et al., 2024), providing evidence that there is value in combining a semantic understanding of text with structured legal authority.

KG-augmented systems for retrieving legally relevant and accurate information link legal questions to legal concepts, legal provisions, legal cases, and legal relations. This provides context for the retrieved legal information. In terms of answering legal questions, KG-RAG systems outperform other approaches on direct questions and show lower, yet substantial, performance on semantically related questions (Anhein & Wiharja, 2025). In another legal case KG, it is reported improvement of the F1 score compared to baseline retrieval models (Vuong et al., 2023).

Several knowledge graph applications are used for compliance checking and regulatory analysis. For instance, a knowledge graph of GDPR laws showed improved contract creation time and compliance management processes (Tauqeer et al., 2022), while the Lynx Legal Knowledge Graph offered multilingual compliance for labor law, contract management and geothermal energy (Kaltenboeck et al., 2022 ; Appleby et al., 2024). As well, a regulatory knowledge graph for financial regulations offered automated compliance interpretation (Ershov, 2023).

A cross-cutting theme is the use of knowledge graphs to enhance the explainability of legal AI systems. JuriFusion reports improvements in accuracy and explanation fidelity over baselines by fusing multimodal knowledge graphs with large foundation models (Wang & Zhan, 2026). The integration of prompt engineering with multidimensional knowledge graphs improved citation accuracy (Zhang et al., 2025). In addition, KG-assisted LLM post-training using the IRAC framework produced models that achieved the best score on 4 of 6 reasoning tasks (Song et al., 2026).

DISCUSSION

Beyond performance alone, a knowledge graph in the domain of legal decision-making is most useful when it connects legal texts and concepts, factual information, and authoritative sources, while also providing a framework for auditing, updating, and explaining legal information. In this respect, legal knowledge graphs can support the integration of machine-derived outputs with human legal expertise. No single construction method is suitable for all legal tasks. Ontology-based construction provides conceptual clarity and semantic precision, but it is labour-intensive. NLP-based extraction enables scalability, but requires verification, normalization, and quality control. LLM-assisted pipelines are flexible and efficient, but must be constrained by verified sources, ontological rules, and legal review. For real-world applications, the strongest systems will be hybrids of expert-created legal ontologies, automated extraction, graph-enabling reasoning, and human review and validation of results.

Data quality is one of the most important conditions for the success of legal knowledge graphs, because if their sources are outdated, incomplete, or poorly structured, their output is not legally relevant. This is aggravated by the temporal character of law and the evolution of legal rules: the meaning, substance, and scope of legal concepts may differ from jurisdiction to jurisdiction, legal system to legal system, and procedure to procedure. Thus, a legal knowledge graph must be able to represent legal concepts and the conditions under which these concepts apply.

Another issue relates to evaluation. Although many of these methods perform well on particular data sets, it remains challenging to compare models across tasks, languages, jurisdictions, benchmarks, and metrics.

Finally, there is the institutional and ethical challenge: legal knowledge graphs in decision-support applications should be under human control, assisting but not replacing. They can provide legal practitioners with a more efficient, consistent and transparent way of working, but cannot displace legal responsibility or obfuscate accountability. They should be fair, contestable and accountable in key decision support areas, such as criminal justice systems, administrative sanctions, social assistance, and migration.

CONCLUSIONS AND FUTURE WORK

Knowledge graphs can be used for the representation, linking and reasoning over legal knowledge, thus supporting legal decision making tasks such as legal information retrieval, legal prediction, legal statute retrieval, legal question answering, compliance checking and explainable legal decision making. A key feature that distinguishes legal knowledge graphs is the ability to abstract the relationship of legal concepts as done by legal practitioners. They include legal facts and rules, legal provisions and case law, legal concepts and evidence, states of the law at present and in the past, and judgments and the reasoning applied to reach them.

Ontology-based, NLP-based, and LLM-assisted approaches each have their own advantages. Ontology-based construction provides semantic precision and clear conceptual structuring. NLP-based approaches are scalable and enable the automatic extraction of information from large quantities of legal text. LLM-assisted approaches provide greater flexibility in identifying and structuring complex legal reasoning patterns. Thus, future systems are likely to be hybrid systems, supported by appropriate mechanisms for control, validation, and verification.

Future work should focus on the temporal validity and versioning of legal norms in legal knowledge graphs, as well as on multilingual and cross-jurisdictional legal reasoning, particularly in jurisdictions where supranational legal instruments have direct effect. Third, future hybrid KG-LLM systems should strengthen source verification, legal grounding, and traceability capabilities within legal knowledge graphs.

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