Research on the Empowerment of Knowledge Graphs in the Governance of Cross-Border Online Gambling Crimes

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Abstract: In recent years, cross-border online gambling has witnessed a substantial rise, posing significant threats to national governance, financial order, and public safety. This surge in online gambling activities has introduced a myriad of challenges for regulatory frameworks, necessitating innovative solutions for effective governance. Knowledge graphs, which utilize graph structures to represent knowledge, provide a powerful tool for organizing diverse datasets and creating visual representations of complex information. This capability offers a novel approach to combatting criminal activities associated with online gambling by facilitating a deeper understanding of the underlying networks and relationships.This paper begins by detailing the current status and emerging trends in cross-border online gambling crimes, highlighting the intricate nature of these illicit operations and their impact on society. It further elucidates the technical connotations of knowledge graphs, explaining how they can serve as a framework for data integration and knowledge representation. The application scenarios of knowledge graphs in the context of online gambling regulation are also discussed, demonstrating their potential to enhance data analysis and decision-making processes for law enforcement agencies.The latter sections of the paper delve into the practical applications of knowledge graphs in the governance of online gambling crimes. This includes their role in crime network analysis, financial tracking, and risk assessment, which collectively improve the ability of authorities to respond to and preemptively address criminal activities. Moreover, the paper explores future trends in the application of knowledge graphs, emphasizing the need for continuous innovation and adaptation in regulatory strategies. By leveraging the capabilities of knowledge graphs, stakeholders can better navigate the complexities of cross-border online gambling crimes, ultimately leading to more effective governance and enhanced regulatory outcomes. This comprehensive examination of knowledge graphs in this context not only addresses current challenges but also paves the way for future advancements in regulatory practices.

Keywords: cross-border crime; knowledge graph; crime governance; online gambling

1. Current Status and Development Trends of Cross-Border Online Gambling Crimes

Cross-border online gambling crimes refer to activities that utilize internet and other information technologies to engage in gambling across national or regional boundaries,[1]constituting criminal behavior. Cases of online gambling vary widely, but they share common characteristics, such as tightly organized criminal networks and specialized division of labor. These cases exhibit the following trends[2].

1.1. Chain Structure of Criminal Organizations

In recent years, cross-border online gambling criminal organizations have increasingly adopted a full-chain criminal gang model. Internally, they are segmented into software development, platform operation, online promotion, payment settlement, and gambling agency membership, with offenders classified into four levels. The first level consists of organizers, who provide startup capital, manage personnel, and establish the overall team structure. The second level is the technical team, responsible for building and maintaining the online gambling platform, operating the website, and setting up gambling games. The third level is the promotional team for gambling websites, tasked with advertising, developing agents, and attracting gamblers. The fourth level comprises the payment and settlement team, which illegally facilitates payment processing and money laundering through the purchase of numerous bank cards or the operation of illicit payment platforms.

1.2. Diversification of Criminal Forms

1.2.1. Diversity of gambling targets

Game Gambling: Some offenders recruit software developers to create online gaming platforms or purchase gambling games to attract participants through various methods, such as acquiring gaming equipment, in-game currency, or “room cards.” For example, gambling agents may share game room passwords in WeChat groups, allowing participants to enter their passwords in their apps to gamble.

Short Video Gambling: With the rise of self-media short videos, offenders use platforms like Douyu, Huya, Youku, and Douyin to publish videos about gambling software (e.g., poker), enticing viewers to download gambling applications or use video hosts to showcase gambling activities. These platforms often provide a variety of gambling games, including baccarat, dragon tiger, and color treasure bowl.

1.2.2. Networked betting transactions

Participants transfer funds via mobile payment to third or fourth-party payment platforms, which, according to the gambling companies' requirements, then transfer the accumulated illegal gambling funds to the gambling company's account. Investigations reveal that most of these payment platform accounts are ultimately registered under shell companies.

1.2.3. Integration of online and offline activities

Some online organizers use WeChat, QQ groups, and websites to connect and offer free airfare or transportation for participants to cross borders for gambling. Additionally, they lure individuals with all-inclusive accommodations, free tours, high rewards, and lucrative project collaborations, facilitating domestic participants' overseas gambling or providing services for foreign gambling. The primary form of online gambling involves setting up servers in countries where gambling is not prohibited, launching gambling websites, and disseminating gambling information via WeChat and QQ groups to attract domestic gamblers[3].

1.3. Pyramid Scheme-Like Operational Models

Criminals exploit legal loopholes in various countries by establishing their servers in jurisdictions where gambling is not banned, creating gambling websites and domain names on the internet. These overseas gambling companies recruit agents within the country, providing them with relevant gambling URLs and accounts, which agents then use to develop lower-level agents and participating members. This enables online gambling operations within the country through these gambling websites.

2. The Connotation, Principles, and Applications of Knowledge Graphs

2.1. Definition and Structure of Knowledge Graphs

2.1.1. Definition of knowledge graphs

A knowledge graph is a structured semantic knowledge base used to represent concepts and their interrelations in the physical world symbolically. Its fundamental components are "entity-relationship-entity" triples and entity-attribute-value pairs, where entities are interconnected through relationships, forming a web-like knowledge structure. Knowledge graphs enable a shift from hyperlink-based web navigation to concept-based search, allowing users to retrieve information by topic rather than keyword, thus facilitating semantic search. Search engines based on knowledge graphs can provide structured knowledge visually, enabling users to accurately locate and deeply acquire information without sifting through numerous web pages.

2.1.2. Structure of knowledge graphs

The architecture of a knowledge graph includes both its logical structure and the technological framework used for its construction[4].

Logical Structure: Knowledge graphs are divided into two levels: the data layer and the schema layer. In the data layer, knowledge is stored in a graph database as facts. Examples include Google's Graphd and Microsoft's Trinity. Facts are expressed through "entity-relationship-entity" or "entity-attribute-value" triples, creating an extensive network of entity relationships, forming a knowledge "map." The schema layer, sitting above the data layer, is the core of the knowledge graph. It stores refined knowledge and is typically managed by an ontology library, which helps standardize relationships among entities, their types, and attributes through axioms, rules, and constraints. The ontology library functions as a mold for the knowledge base, resulting in minimal redundancy.

Technical Architecture: The construction of a knowledge graph starts from raw data, employing various automated or semi-automated techniques to extract knowledge elements (i.e., facts) and store them in both the data and schema layers. This is an iterative process involving three stages: information extraction, knowledge fusion, and knowledge processing. Knowledge graphs can be constructed using top-down or bottom-up approaches. The top-down approach extracts ontology and schema information from high-quality structured data sources like encyclopedic websites, while the bottom-up approach involves extracting resource patterns from publicly collected data, selecting high-confidence new patterns, and integrating them into the knowledge base after human review. In the early stages of knowledge graph development, many organizations used the top-down approach, exemplified by the Freebase project utilizing Wikipedia as a primary data source. With advancements in automatic knowledge extraction, most contemporary knowledge graphs adopt the bottom-up approach, with notable examples being Google's Knowledge Vault and Microsoft's Satori, both of which leverage massive web data for automated resource extraction and knowledge base enhancement.

2.2. Technical Route of Knowledge Graphs

The construction of knowledge graphs using a bottom-up approach is an iterative updating process comprising three steps: 1) Information Extraction, which involves extracting entities (concepts), attributes, and inter-entity relationships from various data sources to form an ontological knowledge representation; 2) Knowledge Fusion, where newly acquired knowledge is integrated to eliminate contradictions and ambiguities, addressing issues such as multiple representations of the same entity; and 3) Knowledge Processing, where the integrated knowledge undergoes quality assessment (with some human involvement) before being added to the knowledge base, ensuring its quality. Following the addition of new data, knowledge inference and expansion can take place[5].

2.2.1. Information extraction

Information extraction is the first step in constructing knowledge graphs, focusing on automatically extracting candidate knowledge units from heterogeneous data sources[6]. This process retrieves structured information from semi-structured and unstructured data, involving key techniques such as entity extraction, relationship extraction, and attribute extraction.

2.2.2. Knowledge fusion

After information extraction, knowledge fusion is necessary to clean and integrate the extracted data, which may contain redundancy and errors. Knowledge fusion comprises two parts: entity linking and knowledge merging. This process resolves conceptual ambiguities and eliminates redundant or erroneous concepts, thereby ensuring knowledge quality.

2.2.3. Knowledge processing

Through information extraction, knowledge elements such as entities, relationships, and attributes are obtained from raw data. Knowledge fusion eliminates ambiguities between entity references and objects, yielding basic factual expressions. However, these facts do not equate to knowledge[7]; a structured and networked knowledge system necessitates further knowledge processing, which includes ontology construction, knowledge inference, and quality evaluation.

2.2.4. Knowledge update

Given that human knowledge and information are continuously increasing, the content of knowledge graphs must also evolve. The updating process involves iterative enhancements, focusing on both conceptual and data layer updates. Conceptual updates entail adding new concepts to the knowledge base, while data layer updates involve adding or updating entities, relationships, and attribute values, considering factors like data source reliability and consistency[8]. Popular methods include utilizing reliable data sources, such as encyclopedic websites, and incorporating frequently occurring facts and attributes. Knowledge updates can adopt a crowdsourced model (e.g., Freebase), while conceptual updates often require manual review by expert teams. There are two primary methods for content updating: comprehensive updates and incremental updates. Comprehensive updates involve rebuilding the knowledge graph from scratch with the updated data, which, while simpler, is resource-intensive. Incremental updates, on the other hand, add new knowledge based on current data, consuming fewer resources but still requiring significant manual intervention, complicating implementation.

2.3 Application Areas of Knowledge Graphs

Knowledge graphs not only allow the representation of internet information in a manner closer to human cognitive understanding, but also provide a superior way to organize, manage, and utilize vast amounts of information. Currently, knowledge graph technology is primarily applied in intelligent semantic search, mobile personal assistants (such as Google Now and Apple Siri), and deep question-answering systems (like IBM Watson and Wolfram Alpha), with the core technology behind these applications being knowledge graphs.

In intelligent semantic search applications, when a user initiates a query, the search engine utilizes knowledge graphs to analyze and infer the keywords, mapping them to one or more concepts within the graph. Based on the hierarchical structure of the knowledge graph, the engine returns a visualized knowledge structure to the user, which includes hyperlinks to resource pages—this is what we see as knowledge cards in search results on platforms like Google and Baidu[9].

In deep question-answering applications, the system first performs semantic and syntactic analysis on the user's natural language questions with the aid of the knowledge graph, transforming them into structured query statements. These queries are typically executed using graph-based query languages (e.g., SPARQL), which may undergo multiple equivalence transformations and reasoning processes to yield equivalent triple queries for retrieving answers from the knowledge graph. Often, deep question-answering systems encounter situations where no direct answer exists in the knowledge base. In such cases, knowledge inference techniques are employed to derive answers. If the knowledge base is insufficient to address user inquiries through reasoning, the deep question-answering system can resort to search engines to provide search results, simultaneously updating the knowledge base with new information to better prepare for future queries.

3. Practical Exploration of Knowledge Graphs Empowering Cross-Border Online Gambling Crimes

When applied to cross-border online gambling crimes, knowledge graphs offer several specific application scenarios and practical explorations:

3.1. Criminal Network Analysis

Criminal network analysis utilizes knowledge graphs to reveal the structure of criminal networks and the relationships among individuals involved in cross-border online gambling. By constructing criminal network graphs, law enforcement can clearly depict the organization's structure and member connections, aiding in tracking criminal activities and organizational frameworks, thus facilitating targeted interventions[10].

3.2. Tracking the Flow of Funds

This involves using knowledge graphs to trace the flow of funds in cross-border online gambling crimes. By analyzing funding pathways, authorities can uncover the origins, destinations, and transfer routes of illicit funds, identifying key nodes and methods associated with money laundering. This enables timely intervention by law enforcement to combat related criminal activities.

3.3. Pattern Recognition of Criminal Activities

Knowledge graphs assist in recognizing activity patterns and characteristics of cross-border online gambling crimes. By analyzing data related to gambling platforms and bettor behaviors, law enforcement can identify trends and common tactics, such as peak crime periods and methods employed by criminals. This insight helps predict the evolution of criminal activities and informs targeted enforcement measures[11].

3.4. Risk Assessment and Early Warning

Risk assessment and early warning systems leverage knowledge graphs to evaluate the risks associated with cross-border online gambling crimes and establish preventive mechanisms. By analyzing the likelihood and potential impact of criminal activities, authorities can detect emerging risks and proactively implement preventive strategies to mitigate losses[12].

3.5. International Cooperation and Information Sharing

Knowledge graphs serve as a platform for international cooperation and information sharing, facilitating collaboration among law enforcement agencies across countries. By sharing data from knowledge graphs, nations can enhance joint efforts to combat cross-border online gambling crimes, increasing the efficiency of international cooperation and creating a unified front against criminal activities.

3.6. Intelligent Decision Support

Intelligent decision support refers to using knowledge graphs to provide law enforcement with data-driven recommendations for optimal intervention strategies. By analyzing relevant data, these systems can suggest effective action plans, improving the efficacy of efforts to tackle cross-border online gambling crimes.

4. Future Trends of Knowledge Graphs Empowering Cross-Border Online Gambling Crimes

4.1 Existing Issues and Challenges

Governance of cross-border online gambling crimes presents complex challenges, and while knowledge graphs are powerful tools, their application still faces several issues:

4.1.1. Diversity of data sources

Cross-border online gambling crimes are characterized by strong information concealment and lengthy criminal chains. Constructing knowledge graphs requires processing vast amounts of heterogeneous data from various countries and platforms, raising concerns about data quality and completeness.

4.1.2. Data processing and analysis capability

Building and maintaining knowledge graphs demand significant human and material resources, including data collection, cleansing, and modeling. Enhancing processing efficiency and reducing modeling costs remain critical challenges.

4.1.3. Inefficient international cooperation mechanisms

Cross-border gambling often necessitates multi-country collaboration; however, existing international cooperation frameworks are underdeveloped, leading to barriers in information sharing. Establishing more robust cooperation mechanisms is essential for future efforts.

4.1.4. Privacy and security protections

The governance process must address issues of data privacy and security. Balancing the need for information sharing and data analysis while ensuring data protection is a significant concern that requires further research.

4.2. Future Development and Improvement

To address the challenges associated with the application of knowledge graphs in combating cross-border online gambling, several key directions for future development include:

4.2.1. Enhancing data sharing and cooperation

Building mechanisms for international data sharing and cooperation is crucial. Such systems will facilitate information exchange among law enforcement agencies, enabling coordinated efforts against cross-border gambling crimes.

4.2.2. Improving data processing and analysis efficiency

As data volume and diversity increase, rapidly and accurately processing large datasets becomes a challenge. Future efforts should focus on advancing data processing technologies, including artificial intelligence and machine learning, to enhance efficiency and accuracy in knowledge graph construction.

4.2.3. Strengthening privacy and security protections

Ensuring data security and privacy is vital for the credibility of knowledge graph initiatives. Research and application of secure data encryption, transmission, and storage technologies will be necessary to protect sensitive information related to cross-border gambling.

4.2.4. Promoting technological innovation and talent development

Encouraging innovation and enhancing the effectiveness of knowledge graphs in governance can better equip law enforcement to respond to evolving criminal activities. Additionally, training professionals with expertise in cross-border gambling governance is a critical task for future initiatives.

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