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Implementing large language model and retrieval augmented generation to extract geographic locations of illicit transnational kidney trade

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Abstract

Background Illicit kidney trade networks, operating globally, involve intricate interactions among various players, most notably buyers, sellers, brokers, and surgeons. A comprehensive understanding of these trade networks is, however, hindered by the lack of systematically amassed data for analysis. Further, extracting the geographic locations of buyers, sellers, brokers, transplant surgeons, and medical facilities in all relevant publications often involves extensive, time-consuming, manual labelling that is very costly. Although current techniques such as Named Entity Recognition (NER) tools can potentially automate the process, they are limited to identifying country names and often fail to associate the roles (i.e., offering buyer, seller, broker and/or surgery) that each country played.

Methods This study employed state-of-the-art technologies, including Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-Trained Transformers (GPT) model Llama3.3 from Meta in developing a kidney trade country database. We first extracted news articles reporting illicit kidney trade from the LexisNexis database (2000–2022). BERT and Llama3.3 with chain-of-thought prompt tuning strategies were then applied to the materials to determine the relevance of articles to the illegal kidney trade and to identify the roles those different countries played in kidney trade cases over the past 23 years. The specific country classes recorded in the final kidney trade database included: a) countries of origin for kidney sellers; b) countries of origin of kidney buyers; c) countries performing illegal transplant surgeries; and d) countries of origin of organ trafficking brokers.

Results The BERT classification model achieved an accuracy of 88.75%, ensuring that only relevant articles were analyzed. Additionally, the Llama3.3-70B model with chain-of-thought prompt tuning strategies extracted location-based roles with an accuracy of 86.30% for sellers, 88.89% for buyers, 93.33% for brokers, and 95.93% for surgeries, supporting these observed patterns. We observed in the final database that the kidney trade networks change and evolve dynamically where the primary role played by each country (as a host of either sellers, buyers or surgeries) change over time. About half of the top 10 countries playing each role gets replaced by other countries within a decade. The final database also demonstrated that developing countries were more likely to be a host of kidney sellers while that played by developed countries was a host of kidney buyers.

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Conclusion The current study developed a geospatial database describing transnational kidney trade country networks over the past two decades. The new approach for geographic location extraction that is more precise compared to conventional NER and machine learning methods.

Keywords Geographic feature extraction, Geospatial data, Large language model, Retrieval augmented generation, Organ trafficking, Kidney transplantation, Public health, Media

Introduction

Chronic kidney disease impacts 843.6 million individuals worldwide in 2017 [1]. Prior research underscores that kidney transplantation is the primary and most favoured treatment for end-stage kidney disease (ESRD) [2]. Despite the growing demand for kidney transplants as the best existing remedy for ESRD, the supply of kidneys has not matched the needs in decades. Globally, only 13.5 transplants are performed on average for every 255 patients in need of a kidney transplant [3]. As the average wait time has extended to 5 years, approximately 7% of patients either die on the waitlist or drop out from the list due to exacerbated conditions every year [4]. Owing to the scarcity of legally obtainable kidneys and the prolonged waiting period for a kidney transplant, there's a notable interest among these patients in locating kidney donors quickly, bypassing the lengthy waitlist process. Consequently, illicit kidney transplantation or so-called "transplant tourism" or "organ trafficking" has come into existence.

Over the past few decades, international health authorities and law enforcement agencies have taken substantial initiatives to counteract illicit kidney transplants. These endeavours reflect a collective commitment to address the pressing issue of organ trafficking, which preys on vulnerable individuals and undermines ethical medical practices. In the 1980s and onwards, the World Health Organization (WHO) has been instrumental in formulating guidelines for human organ transplantation, emphasizing the importance of voluntary donations, transparency, and ethical sourcing [5]. A pivotal milestone was the adoption of the Declaration of Istanbul on Organ Trafficking and Transplant Tourism in 2008, which united experts across disciplines to condemn organ trafficking and establish ethical transplantation principles [6]. Alongside these efforts, the United Nations Office on Drugs and Crime (UNODC) established a global database to document human trafficking, including organ trafficking, enhancing international collaboration, and supporting law enforcement actions [7]. Notably, INTERPOL launched Operation Organs in 2016, targeting criminal networks engaged in organ trafficking and emphasizing cross-border cooperation [8].

Despite the concerted global efforts to combat the kidney trade, instances of such illicit activities persist. For instance, the "Kosovo Organ Trafficking Allegations" in 2008 unveiled allegations of kidney sales by a criminal group during the Kosovo conflict. These claims implicated the forceful removal of organs from prisoners of war for sale on the black market [9]. In addition, the "Gurgaon Kidney Scandal" in 2008 revealed a kidney transplant racket in India, wherein impoverished donors were coerced into selling their kidneys to affluent recipients [10]. The kidney trade remains a complex and multifaceted phenomenon involving various transnational actors, including sellers, buyers, brokers, as well as medical professionals and facilities. A prominent characteristic of this trade is the intricate network that enables the transactions. Affluent buyers typically do not directly engage with financially disadvantaged sellers. Instead, kidneys procured from economically marginalized individuals are passed through intermediaries, commonly referred to as brokers, who operate internationally as part of a transnational crime organization [11]. Subsequently, medical facilities responsible for the surgical procedures and testing are identified, contacted, and engaged by brokers or buyers.

Given the inherent challenges to demonstrate the intricate multi-agent nature of the trade and to effectively eradicate illicit transactions, it is critical to establish a robust and comprehensive spatiotemporal database capturing key attributes of these operations. A previous study introduced a quantitative methodology aimed at uncovering patterns within transnational kidney trade networks, utilizing agent information derived from news articles [12]. However, the scope of this study was confined to South Asia, and the methodologies employed were limited in sophistication. For a more comprehensive, global-level investigation of these networks, it is imperative to automate the extractions of geographic locations as well as the roles played by each participating country. Challenges persist, however, in extracting geographic locations because location descriptions in text data often lack direct mentions of the exact location. Named Entity Recognition (NER) is a feature of Natural Language Processing (NLP) that involves locating and categorizing predefined entities in text into specific groups, such as names of people, organizations, locations, etc. [13]. However, traditional NER tools lack the capability to identify the country name solely based on detailed location descriptions. Consequently, NER tools need to be implemented in conjunction with other deep learning methods to detect associated elements with detected geographic features, thereby increasing the complexity of our goals in this study [14, 15].

To advance beyond traditional methods of extracting geographic entities and capitalize on the capabilities of Artificial Intelligence (AI), the current study introduces a novel framework for the extraction of geographic features from text. This framework streamlines the process of extracting geographic features and discerning the roles of these features within a given context. Specifically, we employed state-of-the-art models such as Bidirectional Encoder Representations from Transformers (BERT) to determine whether an article pertains to illegal kidney activities [16]. Furthermore, the Meta's open-sourced Generative Pre-Trained Transformer (GPT), Llama3.3-70B [17], and fine-tuning method Retrieval Augmented Generation (RAG) [18] was deployed to extract country names and identify intricate agent relationships, including buyers, sellers, brokers, and surgeons for all extracted countries. Compared to traditional NER approaches, BERT and GPT models leverage the attention mechanism to capture richer contextual information, bidirectionally in BERT and left-to-right in GPT [16, 19, 20]. This enables them to understand the meaning of a word based on its surrounding words while weighing the importance of different words in a sentence. As a result, these models can focus on the most relevant parts of the text for identifying entities in context. Additionally, BERT and GPT are pretrained on large corpora, allowing them to learn more nuanced language patterns [16, 20]. In contrast, NER models are typically trained on smaller, task-specific datasets, limiting their ability to generalize across diverse contexts. RAG further enhances GPT's capabilities by integrating a retrieval mechanism that enables the model to query an external corpus of documents (in this study, news articles), extracting relevant information that may not have been part of the model's pretraining [18]. This leads to more accurate and up-to-date responses. The combination of RAG and GPT has been successfully applied in domains such as biomedicine and geosciences, demonstrating significant improvements in biomedical text processing and extracting geospatial knowledge, such as measurements of population density and economic livelihoods [21, 22]. This augmentation enabled us to explore a broader spectrum of articles spanning worldwide regions. By doing so, we constructed a more comprehensive spatiotemporal database of kidney trade networks, fostering a deeper understanding of its intricate dynamics and interconnections across different countries.

Data sources

The study systematically gathered English news articles encompassing the timeframe from January 1st, 2000, to December 31st, 2022. This expansive collection of text data was culled from LexisNexis, a globally renowned purveyor of legal, regulatory, and business information, recognized for offering analytical solutions tailored to a plethora of industries [23]. We extracted relevant articles by employing a curated array of keywords, i.e., "kidney trafficking", "kidney trade", "kidney buy", "kidney sell", "kidney market", "kidney bazaar", "kidney sale", and "kidney illegal transplant". To eliminate articles that are unrelated to kidney trade, the Boolean search logic was applied. The logic was developed using the prior knowledge regarding the articles that are unrelated to kidney trade, e.g., articles discussing trade of kidney beans as well as commercial or agricultural products linked to kidney failure, cases of kidney disease arising from sex trafficking, advertisements pertaining to kidney disease treatment, and all other articles deviating from the focal point of our study. Particularly those articles with keywords such as "agriculture", "commerce", "pesticides", "hair dye", and "sex", were purposefully excluded. The specific logic is expressed as follows:

> *(trafficking OR trade OR buy* OR sell* OR market* OR bazaar OR sale* OR 'illegal transplant') AND NOT (bean OR agriculture OR commerce* OR pesticide OR 'hair dye' OR sex)*

The above process generated 50,228 raw data entries. A subsequent phase of data refinement involved the extraction of key attributes of the raw data, including title, date, source name, and main content, from the raw data (Table 1). These efforts resulted in the assembly of a comprehensive CSV file housing pre-processed data, primed for subsequent analysis and investigation.

Methodologies

Figure 1 outlines our sequential steps in developing the database. Upon extraction of research data via the LexisNexis API, a manual labelling process was performed, followed by Implementing the BERT model to discern

Table 1 Definition of the attributes that are used in the pre-processed datasets

Attribute	Definition
Title	The title of the extracted article
Date	The date that the extracted article was published
Source Name	The publisher of the extracted article
Main Content	The news content reported in the extracted new article

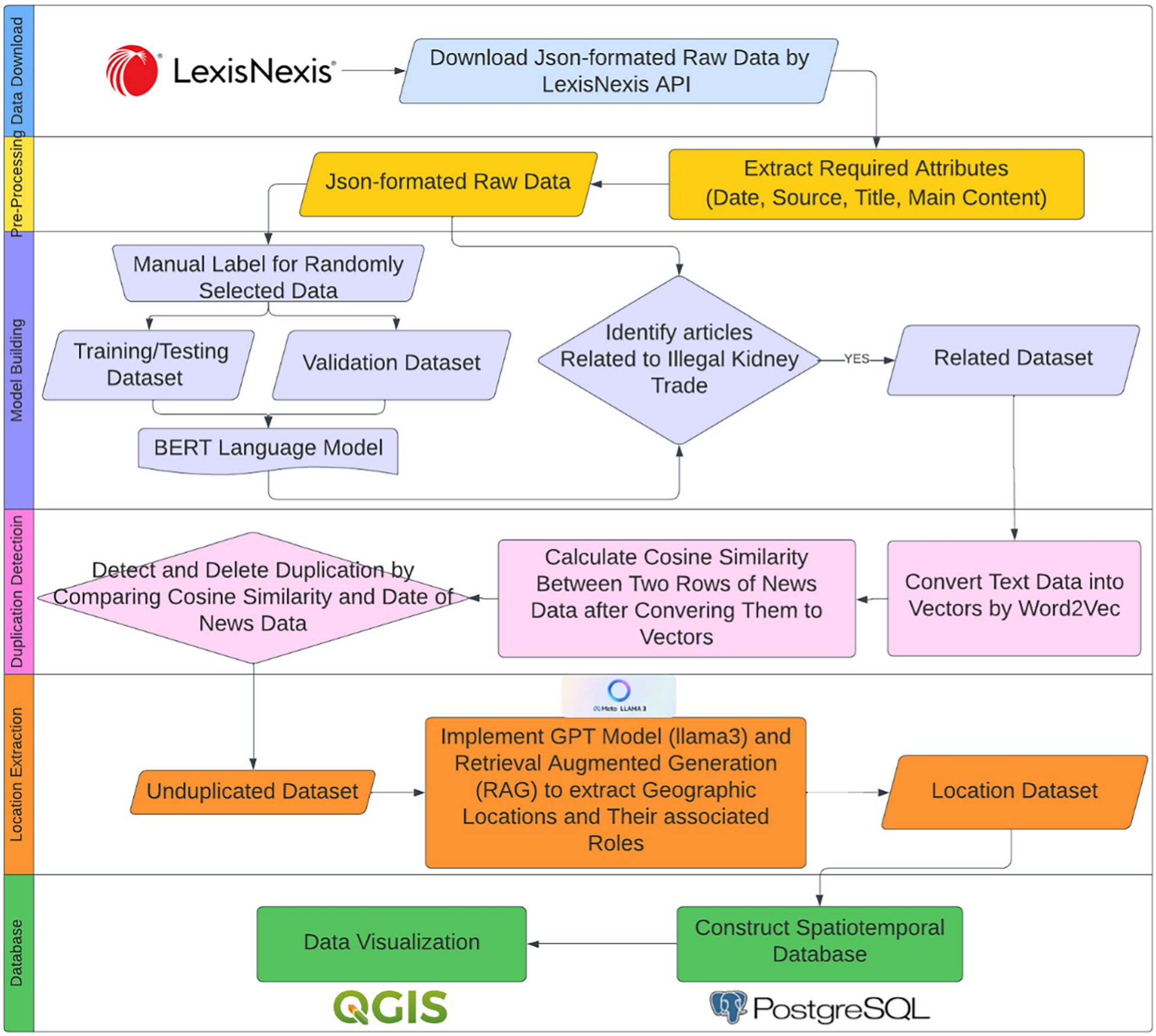

Fig. 1 Workflow of Constructing a Spatiotemporal Database for Analyzing Illegal Kidney Trade Using NLP-Driven Deduplication and Geographic Location Extraction by Implementing Large Language Models

and exclude irrelevant articles. Next, the deployment of word2vec and cosine similarity techniques facilitated the identification and removal of duplicated articles [24, 25]. After this step, the application of GPT Model Llama3.3-70B and RAG enabled the extraction of pertinent trading-related information as embedded within the articles. The final stage established a comprehensive PostgreSQL database structured across multiple tables. To visually render the data stored in the database, the QGIS software was used.

Article classification

While the dataset was initially refined through keyword-based searches in the LexisNexis database, a certain proportion of unrelated articles persisted in the data. To address this issue, we leveraged BERT, an NLP model rooted in transformer architecture [16] to create a classification model capable of effectively distinguishing between articles pertinent to illegal kidney trade and those that are unrelated. The BERT model has been shown to perform well on text classification tasks, even with small datasets [26, 27]. In this study, a manually labelled dataset of 800 rows was compiled, with 720 entries used for training and 80 reserved for validation.

To ensure that the training data was randomly sampled and balanced, we selected data spanning different years from a 23-year period. The training set comprised 435 entries labelled as "unrelated" and 285 as "related." Similarly, the validation set consisted of 40 rows, evenly distributed between the two categories. To further assess the model's performance under conditions that reflect the actual distribution of the full dataset, we conducted a second evaluation using a separate, imbalanced dataset of 1,003 rows—comprising 90 related and 913 unrelated articles—sampled across all 23 years. This imbalanced set was not used during training and was specifically designed to mirror the skewed distribution of related versus unrelated articles in the original data collection.

Duplication detection

In the subset of news articles identified as relevant, a significant portion of the articles described identical events. To address these duplicates, we leveraged word-to-vector techniques [24]. The process began with the transformation of the content of each article into a vectorized format. This allowed us to quantify the similarity between articles by utilizing cosine similarity [25]. Cosine similarity is widely used for text comparison tasks, particularly in high-dimensional spaces like those encountered in document analysis [28, 29]. It effectively measures the angle between two vectors representing documents, focusing on their direction rather than magnitude [25]. This makes cosine similarity more robust when dealing with documents of varying lengths, as it disregards differences in scale, which are common in news articles [30]. As depicted in Eq. (1), where A and B are the vector representations of two articles' content. ||A|| and ||B|| denote the magnitudes (Euclidean norms) of the vectors A and B, respectively.

$$\text{Cosine Similarity } = (A \cdot B)/(||A|| * ||B||) \tag{1}$$

Cosine similarity typically ranges from -1 to 1. In text analysis, however, A and B represent non-negative vectorized representations of the text content, meaning the cosine similarity score ranges from 0 (completely dissimilar) to 1 (completely similar). A score closer to 1 indicates a higher degree of similarity between the articles. Similarity scores above 0.7 are often considered strong indicators of near-duplicate or highly similar texts. Conversely, lower similarity scores, such as 0.2 to 0.3, can capture broader, less exact matches, potentially identifying articles discussing similar events [31]. In this study, we define duplicates as articles that report on the same event, rather than focusing on exact word matching. Therefore, a threshold of 0.2 was chosen to capture this broader concept of duplication. When the criteria are met, and if the articles were published within a narrow temporal window (less than 7 days apart), we consider them to refer to the same event. In such cases, only one of the duplicate articles is retained in the database.

Location extraction

We implemented the Llama3.3-70B model and deployed RAG to fine-tune the language model for answering questions. Llama3.3-70B is a pre-trained GPT model [17] used in this study to identify the roles of countries involved in illegal kidney trade. As illustrated in Fig. 2, the process begins by inputting the article text and a prompt specifying the target role identification task. This input is first tokenized and passed through an embedding layer, converting tokens into numerical vectors. Since the Transformer architecture doesn't inherently capture sequence order, positional encoding is added to the embeddings to incorporate information about each token's position, preserving word order. The encoded input is then processed through a stack of decoder layers, each containing Multi-Headed Attention and Positionwise Feed-Forward components, with layer normalization applied throughout for stability. Within the Multi-Headed Attention Layer, the model simultaneously attends to different parts of the sequence, enabling it to understand contextual relationships. Attention scores are computed using Scaled Dot-Product Attention, which calculates relevance between tokens through linear transformations into Query (Q), Key (K), and Value (V) vectors. In this study, attention scores specifically highlight the relationships between country names and their target roles. The highest scoring country-role associations are selected, as shown in the right panel of the figure. The processed outputs from each decoder layer eventually pass through a linear layer and a SoftMax function, generating output probabilities for each country-role pair. The final output consists of the most probable country-role associations, generated token by token [17, 19, 20].

A pre-trained GPT model is trained on its own corpus, providing a foundational ability to reason and understand language. RAG enhances this by introducing an additional data source, which is retrieved based on specific queries [18]. In this study, we implemented RAG by converting news articles related to the illegal kidney trade into vectors using Llama3.3-70B embeddings and integrating a vector database into the Llama3.3 model. This extended the model's original knowledge, enabling it to answer questions focused on extracting country names and identifying their roles in the illegal kidney trade. As illustrated in Fig. 3, during the deployment of RAG, we utilized FAISS, a vector database building tool developed by Meta, to construct the vector database [32]. This process involves inputting all illegal kidney trade articles into the embedding base model (Llama3.3-70B), converting

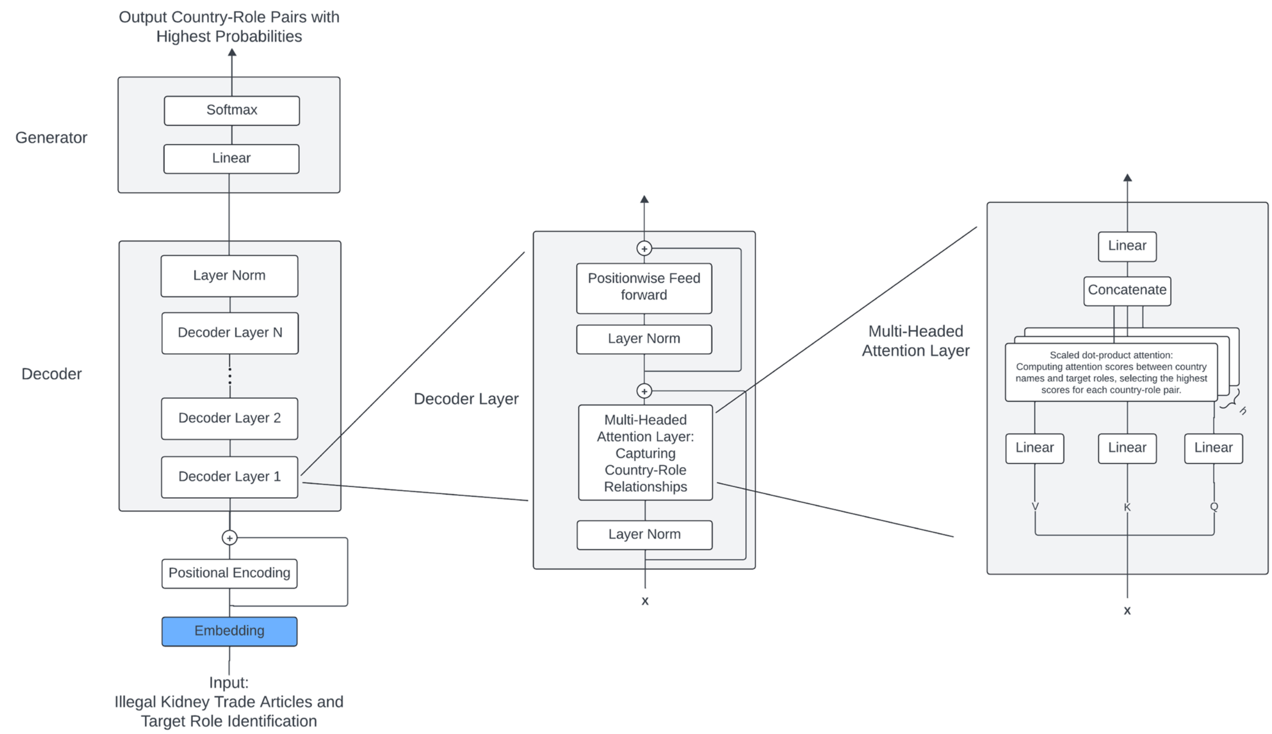

Fig. 2 Architecture of the Decoder Module in Transformer Models with Multi-Headed Attention and Output Generation

them into numerical vectors, and storing them in the database. When a query is input as a prompt, it is also processed through the embedding model to retrieve relevant information from the vector database. We inputted the prompt for several rounds to find the best prompt. By using vectorized news articles and the chain-of-thought prompt, we fine-tune the LLM to extract geographic information from each illegal kidney trade article. we used the prompt attached-in Appendix II:

In this study, each news article was processed through this predefined template, wherein terminologies such as “seller,” “buyer,” “broker,” and “surgery” were strategically replaced to facilitate the extraction of critical attribute information pertinent to the kidney trade. The scale of the geographic location extraction is fixed on countries

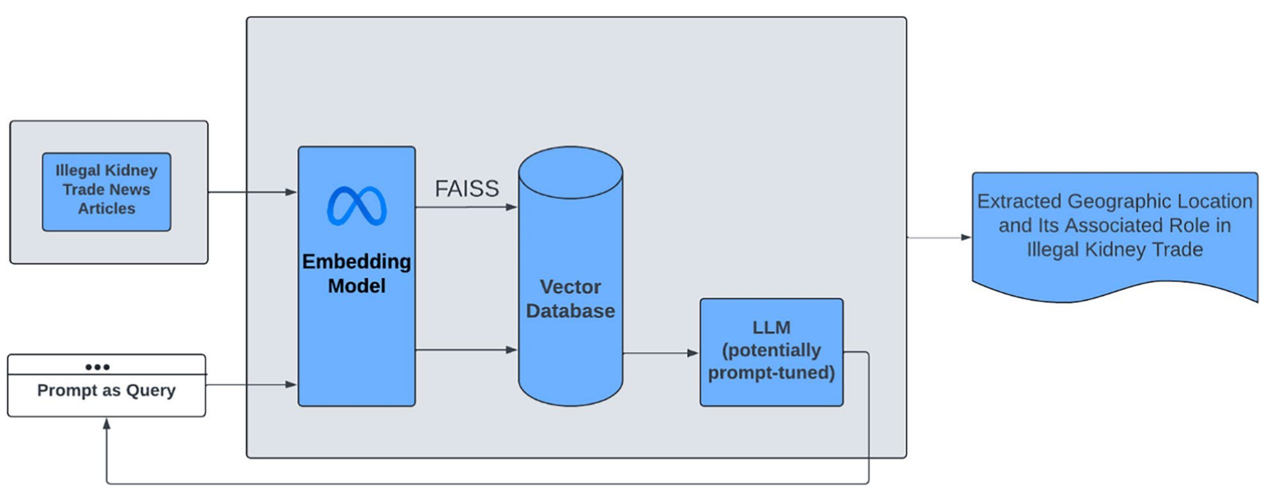

Fig. 3 Pipeline for Extracting Geographic Locations and Roles from Illegal Kidney Trade News Articles Using Large Language Model Embeddings and Vector Database FAISS

level, since scope of this study majorly focuses on global network of illegal kidney trade instead of focusing on specific locations in each country. To ensure the efficacy of the location extraction capabilities of Llama3.3-70B, a manual labelling process was employed for all articles, serving to validate the applicability of this methodology for precise location identification. During the validation phase, the comparison was strictly limited to entries with valid values in both datasets—one produced by the Llama3.3-70B model, and the other comprising manually assigned labels. This approach entailed the exclusion of any data points containing null values, thereby refining the process of evaluating precision by focusing solely on comparably reliable information.

Database construction and data visualization

A spatial database was constructed utilizing PostgreSQL to store and manage data related to kidney trade cases [33]. Each case was recorded with attributes that capture the spatiotemporal dimensions, such as the location of occurrence and the time of the event. Although this project is designed to utilize LLMs to identify related datasets and extract countries' roles in the kidney trade, the accuracy of the database is ensured through manual verification of all data output from the LLM. The manually verified dataset forms the foundation of the database, ensuring that all entries are relevant to the illegal kidney trade and that each country's role is accurately labeled, so that the verified data can be utilized for future studies such as network analysis of illegal kidney trade in the last two decades. The use of PostgreSQL, particularly its PostGIS extension, was instrumental in handling complex queries involving geographical data and visualizing the spatiotemporal attributes of kidney trade cases. The maps were generated through a series of steps: first, by querying the spatial database to extract relevant data; then, by applying geospatial analysis techniques, including implementing corresponding world map layers, assigning attributes such as trading role, trade frequency, and trade year to each country element in the attribute table, and categorizing them by decade, role, and frequency, we were able to interpret the spatial and temporal patterns; and finally, by using mapping software to create visual representations that convey the findings in an accessible and impactful manner.

The kidney trade mapping was performed using two methods. First, we counted the number of kidney trade activities each country was involved in and then plotted them on the corresponding maps based on their role. For example, India appeared 259 times (36.17%) as a seller host, 64 times (8.94%) as a buyer host, 207 times (28.91%) as a broker host, and 186 times (25.98%) as a surgery host. Thus, India was plotted on all four maps as a seller, buyer, broker, and surgery host. Second, we determined the primary role played by each country in the kidney trade. This classification was based on the role that appeared most frequently, excluding countries where the occurrence was less than two times. In the case of India, it was involved in four different kidney trade activities. However, its role as a seller host accounted for the largest proportion (36.17%) of all kidney trade roles. Therefore, we determined that India's primary role in the kidney trade was a seller host. The list of the countries by primary role is summarized in Appendix I.

Lastly, we visualized the primary roles of the countries in the global kidney trade network, focusing on cases involving at least two countries. The global kidney trade networks were then generated using Gephi [34], an open-source software, and its various layout algorithms, including Fruchterman Reingold, Noverlap, Expansion, Contraction, and Rotation, to better represent the complex interactions within the network.

Results

Overall quantity and accuracy of data extraction by LLM

The PRISMA workflow (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) is a standardized framework widely used for reporting systematic reviews and meta-analyses across various disciplines [35]. Figure 4 displays the PRISMA workflow for the quantity of data in each step introduced in the previous methodology section. Initially, a comprehensive collection of 50,228 articles was retrieved from the LexisNexis database. By inputting the 50,228 articles into the BERT classification model, this corpus was narrowed down to 3,105 articles that were directly related to illegal kidney trade. Table 2 presents the classification model constructed using BERT demonstrated an accuracy of 88.75%, alongside a sensitivity of 88.75% and a specificity of 90.0%. From the data independently selected apart from the training dataset, we also recognized that the raw retrieved data (50,228 articles) was imbalanced, with far more unrelated than related articles. To account for this, we selected a total of 1,003 validation samples across all 23 years—comprising 90 related and 913 unrelated articles—ensuring that each year contributed approximately equal proportions of data. After testing, all model outputs were manually reviewed by human evaluators. As shown in Table 3, two evaluation tables are presented: one based on a balanced dataset (39 related, 41 unrelated) and the other on an imbalanced dataset (90 related, 913 unrelated). The results indicate that the model performs particularly well in correctly identifying unrelated

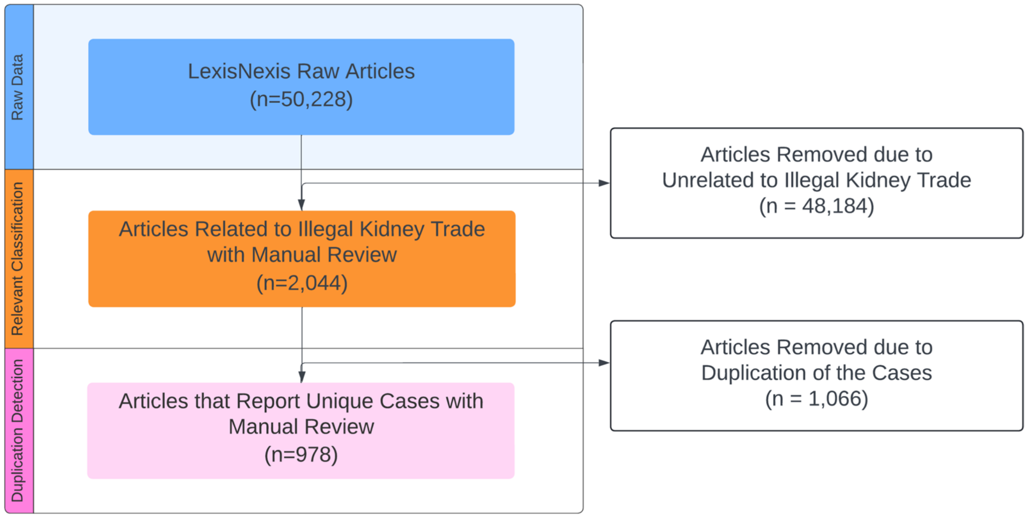

Fig. 4 Filtering Pipeline for Illegal Kidney Trade News Articles: From Raw Data to Unique Case Identification

Table 2 Confusion matrix for BERT classification: balanced vs. imbalanced testing results

Balanced Dataset	**Actual related (40)**	**Actual unrelated (40)**	**Measures**
Predicted related (39)	True Positive (35)	False Positive (4)	PPV: 89.7%
Predicted unrelated (41)	False Negative (5)	True Negative (36)	NPV: 87.8%
Measures	Sensitivity: 88.75%	Specificity: 90.0%	Accuracy 88.75%
Imbalanced Dataset	**Actual related (90)**	**Actual unrelated (913)**	**Measures**
Predicted related (90)	True Positive (88)	False Positive (2)	PPV: 97.8%
Predicted unrelated (913)	False Negative (2)	True Negative (911)	NPV: 99.8%
Measures	Sensitivity: 97.78%	Specificity: 99.78%	Accuracy 99.60%

PPV positive predictive values, *NPV* Negative predictive values

Table 3 Accuracy of Location Extraction by Llama3.3-70B across Different Roles

	Sellers (%)	**Buyers (%)**	**Brokers (%)**	**Surgery (%)**
Accuracy	86.30	88.89	93.33	95.93
Precision	74.37	79.21	86.16	89.32
Recall	75.65	77.5	70.42	84.25
F1 Score	71.19	74.5	72.84	83.28

articles. Following manual review of all 3,105 articles, we identified and retained 2,044 news articles related to illegal kidney trade. Subsequently, to ensure the uniqueness of the dataset, the duplication detection phase was employed, which further refined the selection to 978 articles after manual review. Lastly, 978 articles were inputted into the Llama3.3 GPT model to identify countries that have been involved and their roles in the illegal kidney trade. Table 3 summarizes the accuracy of the methodology across different roles involved in the trade. Compared to traditional Named Entity Recognition (NER) approaches, which can only extract location entities that explicitly appear in the text and fail to identify the roles countries play within the context of the article, the integration of RAG with the GPT model offers a significant improvement. For example, in an article stating, "a 27-year-old Chinese citizen wants to sell his kidney to the UK," traditional NER could not recognize "Chinese" as "China" or "UK" as "United Kingdom." Additionally, it couldn't identify which country was the buyer or seller. By understanding the broader context of the news article, the integration of RAG with the GPT model effectively extracts geographic locations and identifies the roles of countries involved, demonstrating more robust and insightful results.

During the evaluation of the GPT model's output, we removed all rows containing empty or null values. In many cases, we found the role information to be ambiguous. Therefore, during manual review, if a country's role was not clearly stated, we intentionally left the corresponding field empty. For example, consider the following article excerpt: "*BERLIN: Internet auction house eBay has said it had put a stop to an auction of a human kidney on its German website which drew a bid of almost $160,000. The offer was posted on the United States auctioneer's site (*www.ebay.de*) by an anonymous seller who said it could be picked up in the Swiss city of Zurich. The bid was made on February 18.*" From a human reviewer's perspective, the seller is not explicitly stated. However, the buyer appears to be browsing the German website, while the United States and Switzerland could be considered brokers—the former as the host of the auction platform and the latter as the pickup location. The surgery location is also clearly mentioned. In contrast, the LLM interpreted Switzerland as the seller, the United States as the buyer, Germany and the United States as brokers, and no country as the surgery location. While this interpretation diverges from our own, we acknowledge that the LLM's reasoning is also plausible—for instance, one could reasonably infer that a seller in Switzerland posted a kidney trade listing on both German and American platforms.

Due to such ambiguity, we limited our evaluation to a subset of cases where all four roles—seller, buyer, broker, and surgery—were explicitly and unambiguously stated. This approach enabled a more reliable assessment of the model's ability to accurately identify clearly defined role information. Specifically, we evaluated the LLM's performance on 270 cases that contained complete role annotations. As shown in Table 3, the model correctly identified 233 seller roles (86.30%), 240 buyer roles (88.89%), 252 broker roles (93.33%), and 259 surgery roles (95.93%).

Although a deduplication step was included in our preprocessing pipeline to remove repeated articles, we later realized that some of these articles, while describing the same incident, provided different pieces of role information. For example, one article might mention the seller's country, while another referring to the same case might reveal the buyer or surgery location. To ensure comprehensive labelling, we manually revisited all potential duplicates and consolidated information across articles describing the same case. This process allowed us to extract more complete role data and ultimately resulted in a refined dataset of 978 unique cases, each with the most comprehensive role information available.

Country involvement in kidney trade

Most of the 978 reviewed articles mentioned kidney sellers' nationalities, while mentions of buyers' and brokers' nationalities as well as the countries where surgeries took place were less frequent. More specifically, 798 (81.60%) articles revealed sellers' nationalities, while the number of articles listing buyers' or brokers' nationalities, or surgery locations were 378 (38.65%), 612 (62.58%), 548 (56.03%respectively. The numbers reflect the fact that many of the reviewed articles focused most heavily on victims (i.e., sellers), and then on accused (i.e., brokers or surgery locations) of kidney trade. There appears to be less emphasis on buyers who tend to be perceived as less to be blamed in the crime.

Table 4 lists the top 10 countries with the highest counts of involvement in the kidney trade. The counts were very skewed: One country (India) was involved in 352 reported cases, while the majority of the 89 countries (N = 50) appeared in less than 10 reported cases. The median count of kidney trade involvement was 6 with the min and max values being 1 and 352 respectively and the interquartile range (IQR) being 18 (= 20–2). Figure 5 presents the global country map showing the counts of kidney trade involvement for each country, where darker coloured countries correspond to the countries with a higher count of involvement.

Of the 89 countries, 71 (79.78%) countries hosted seller(s) in at least one case. Sixty (67.42%) countries hosted buyer(s) at least once, 60 (67.42%) countries hosted broker(s) at least once, and 49 (55.06%) countries hosted surgeries at least once.

Countries hosting kidney sellers

Figure 6 presents the world map of countries hosting reported kidney sellers between the first (2000–2011) and the second (2012–2022) decades. The countries with the darkest shade of red correspond to the category with the highest number of times that the country hosted sellers, while those with the lightest red correspond to the

Table 4 Counts of Involvement in Kidney Trade Cases

Country Name	Cases Count (%)
India	352 (36.25)
Pakistan	160 (16.48)
China	123 (12.67)
Israel	114 (11.74)
United Kingdom	82 (8.44)
United States	68 (7.00)
Turkey	67 (6.90)
Philippines	44 (4.53)
Sri Lanka	42 (4.33)
Moldova	41 (4.22)

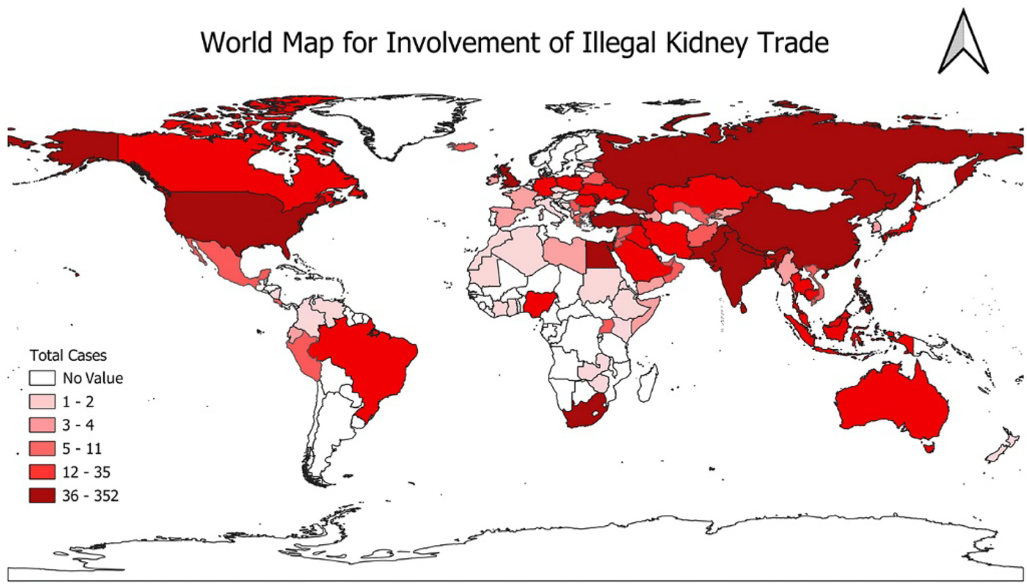

Fig. 5 A world map representing the number of illegal kidney trade cases reported in the news articles worldwide between January 1st, 2000, to December 31st, 2022. The countries with at least one case of illegal kidney trade case were classified into 5 groups using quantiles. Countries with a darker red shade correspond to more cases of reported illegal kidney trade cases

lowest frequency of appearance as a seller host. In the first decade, the countries that belonged to the highest frequency category were India, Pakistan, China, Moldova, Brazil, the United Kingdom, Israel, the Philippines, Indonesia, and Turkey. In the second decade, the countries of India, China, Pakistan, Nepal, Bangladesh, Israel, Nigeria, the Russian Federation, Turkey, Ukraine, and Sri Lanka were found to be in the highest frequency category (Fig. 7).

Table 5 presents how the top 10 seller countries changed between the first and the second decades. Five of the top 10 countries bolded in the table (India, Pakistan, China, Israel and Turkey) appeared as top 10 seller countries in both decades, while Moldova, Brazil, the United Kingdom, the Philippines, and Indonesia were replaced by Nepal, Bangladesh, Nigeria, Russia and Ukraine. India dominated as the top seller country with more cases seen in the second decade. In the first decade, 16% (N = 92) of the total seller cases involved India, while this share increased to 33% (N = 167) in the second decade. Most sellers were from Southern (India, Pakistan, Bangladesh, Nepal) or South-eastern Asia (Indonesia, the Philippines). In fact, these countries shared 44% (= 477/1,083) of the entire reported kidney seller cases. Other regions included Western Asia (Israel and Turkey), Western Africa (Nigeria), Eastern Europe (Russian Federation, Ukraine, and Moldova), Latin America and the Caribbean (Brazil), Eastern Asia (China), and Northern Europe (United Kingdom).

Countries hosting kidney buyers

Figure 6 presents the countries reported as a host of kidney buyers between the first and the second decades. The darkest blue shading represents the highest concentration of buyer cases, whereas the lighter shading corresponds to the lowest reported number of buyers. In the first decade, the countries that fell into the highest frequency category were Israel, the United States, the United Kingdom, Singapore, India, Canada, Australia, and Japan. In the second decade, the highest frequency category included India, Israel, the United States, Canada, Pakistan, the United Kingdom, and Germany.

Table 6 presents the top 10 buyer countries by decade, revealing significant shifts in buyer country patterns between the two decades. In the first decade, Israel, the United States, and the United Kingdom emerged as the primary buyers, with Israel leading at 16% (N = 46), followed by the United States (12%, N = 35) and the United Kingdom (10%, N = 29). Singapore and India also featured prominently, accounting for 9% (N = 26) and 6% (N = 17) of cases, respectively. In the following decade, however, India surged to prominence, becoming the top buyer with 20% (N = 47) of cases, followed by Israel (9%, N = 20) and the United States (7%, N = 17). When analysing the geographic regions, the top buyer countries were distributed across various parts of the world. In the earlier decade, buyers were notably concentrated in regions such as North America (United States and Canada), Europe (United Kingdom and Germany), and Asia (Israel, Singapore, India, Japan, Saudi Arabia, and Pakistan). In

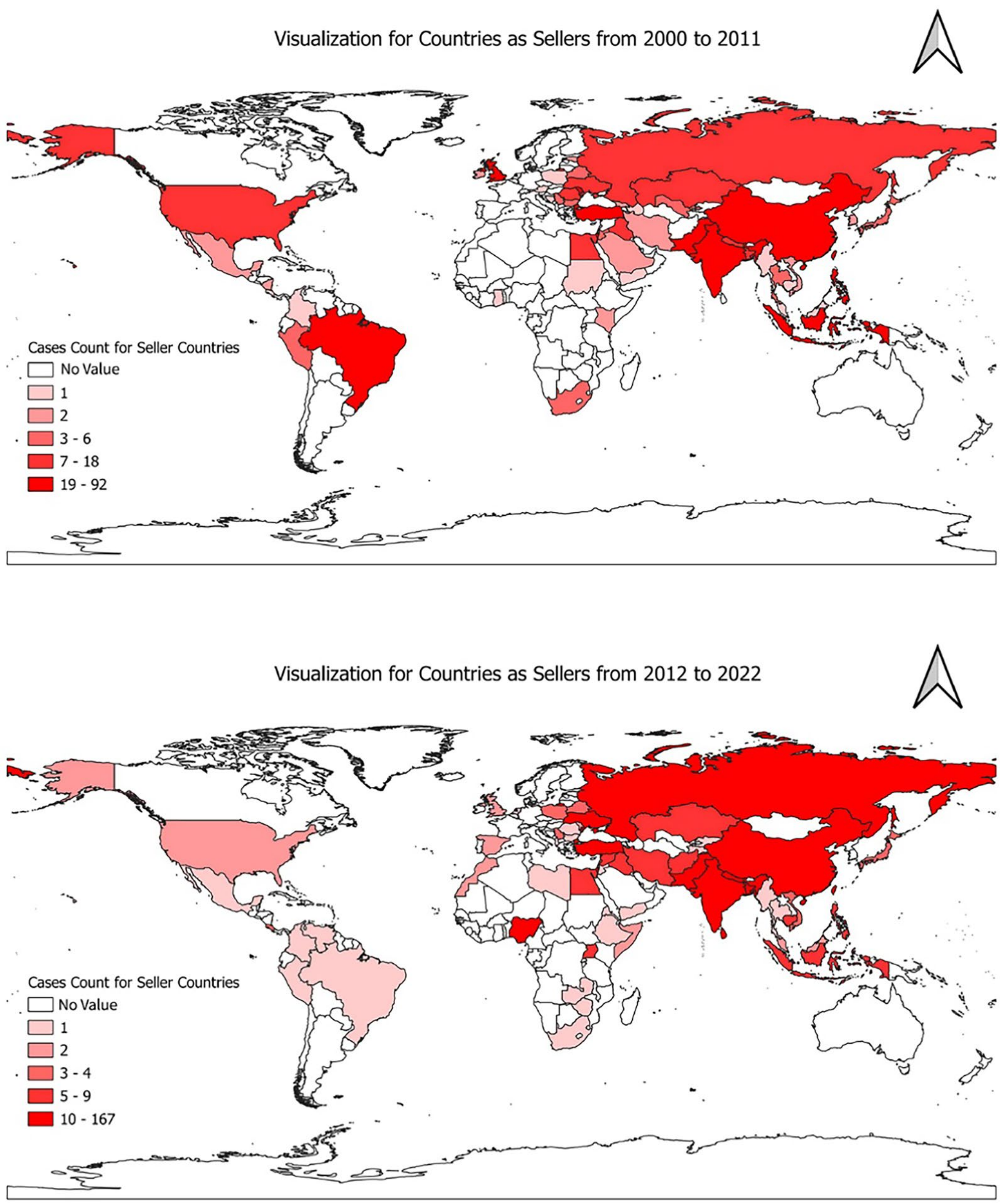

Fig. 6 A world map representing the number of illegal kidney trade cases in which countries were reported as a kidney seller provider. The upper panel shows the map for the first decade (2000–2011) while the lower panel shows the map for the second decade (2012–2022). In each panel, the countries with at least one case serving as a kidney seller provider were classified into 5 groups using quantiles. Countries with a darker red shade correspond to more cases in which they appeared as a kidney seller provider

contrast, the subsequent decade witnessed a more globally dispersed pattern, with India and Israel leading from Asia, the United States from North America, and Canada from North America. Additionally, significant buyer countries were found in Europe (the United Kingdom and Germany), Africa (Nigeria), and Asia (Pakistan, China, and Oman).

Countries hosting kidney brokers

Figure 8 shows the countries that hosted an alleged kidney broker. The darkest purple shading represents the highest concentration of broker cases, whereas the lighter shading corresponds to the lowest reported number of brokers in a given country. Across both periods, a handful of countries stood out as clear outliers: India, Pakistan, China, Israel, Turkey, Egypt, and the United States. The global broker distribution was also sparser

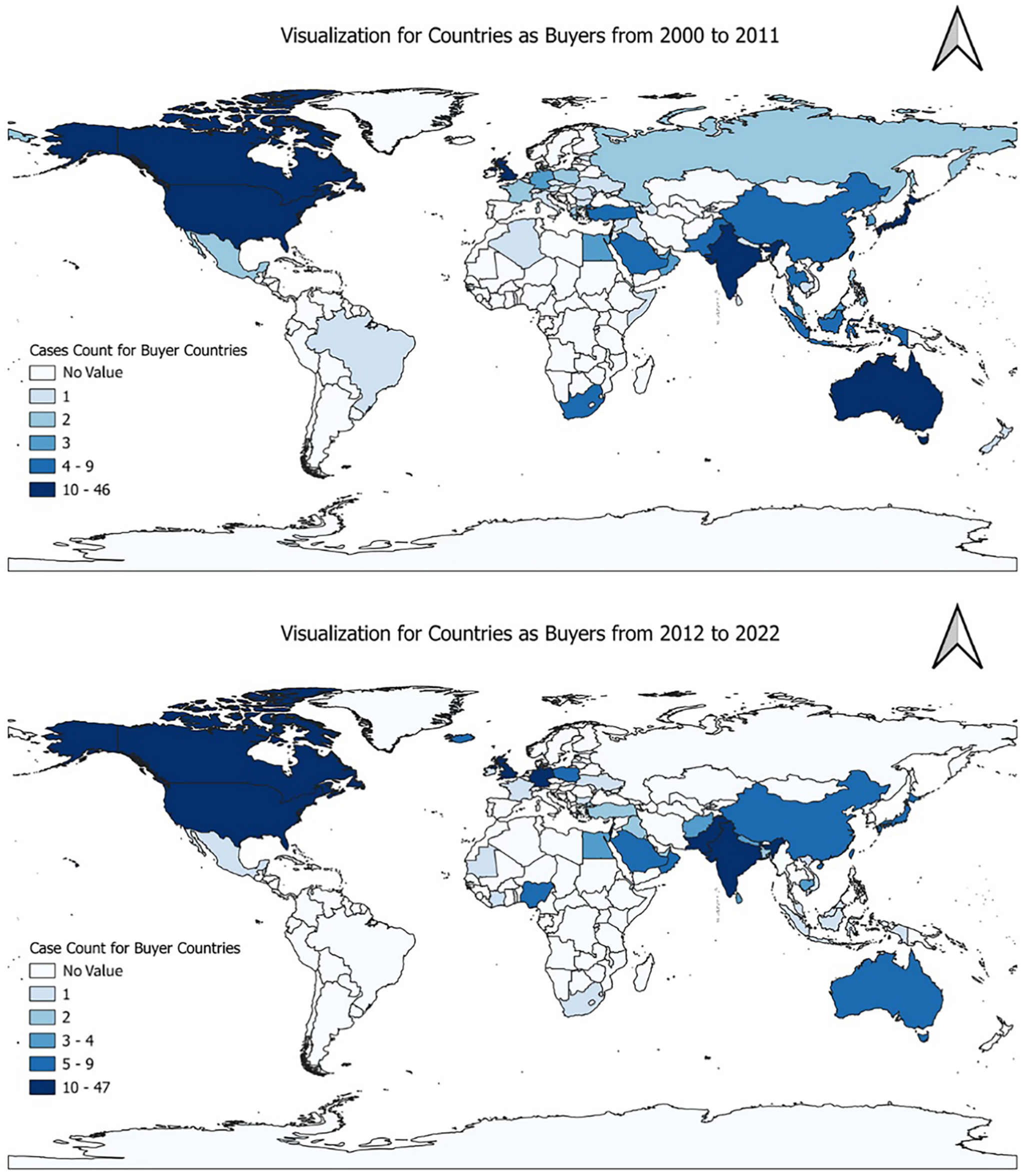

Fig. 7 A world map representing the number of illegal kidney trade cases in which countries were reported as a kidney buyer provider. The upper panel shows the map for the first decade (2000–2011) while the lower panel shows the map for the second decade (2012–2022). In each panel, the countries with at least one case serving as a kidney buyer provider were classified into 5 groups using quantiles. Countries with a darker blue shade correspond to more cases in which they appeared as a kidney buyer provider

in the first decade than the second decade. Sub-Saharan Africa, South America, North America, and the Oceania regions all reported significantly fewer cases in the later-half of our analysis.

Table 7 reports the top 10 broker countries in the first and second decade of our study. These results further corroborate the visual concentration of broker activity apparent in our global map (Fig. 8). Six of the top 10 countries listed (India (15%, N = 47), Israel (9%, N = 29), Pakistan (8%, N = 24), China (7%, N = 23), Turkey (7%, N = 21), and Egypt (3%, N = 10)) stood out clear outliers in our dataset, identified as part of the top 10 broker countries across both decades. In all, 63% (N = 462) of all broker cases were from these six countries. South Africa (7%, N = 21), the United States (6%, N = 20), Singapore (6%, N = 19), and the United Kingdom (4%, N = 12) were global leaders in the earlier decade of our study. These nations were replaced by Nepal (5%, N = 19), Bangladesh (3%, N = 13), Cambodia (2%, N = 10), and Sri Lanka (2%, N = 9) in the latter decade. India dominated as the top

Table 5 Top 10 Seller Countries by Decade

2000–2011		2012–2022	
Country Name	**Cases Count (%)**	**Country Name**	**Cases Count (%)**
India	92 (16.17%)	**India**	167 (32.55%)
Pakistan	51 (8.96%)	**China**	63 (12.28%)
China	42 (7.38%)	**Pakistan**	40 (7.80%)
Moldova (Republic of)	39 (6.85%)	Nepal	21 (4.09%)
Brazil	34 (5.98%)	Bangladesh	19 (3.70%)
United Kingdom	32 (5.62%)	Nigeria	13 (2.53%)
Israel	31 (5.45%)	Russian Federation	13 (2.53%)
Philippines	28 (4.92%)	**Israel**	13 (2.53%)
Indonesia	25 (4.39%)	**Turkey**	12 (2.34%)
Turkey	22 (3.87%)	Ukraine	11 (2.14%)

Table 6 Top 10 Buyer Countries by Decade

2000–2011		2012–2022	
Country Name	**Cases Count (%)**	**Country Name**	**Cases Count (%)**
Israel	46 (16.37%)	**India**	47 (20.00%)
United States	35 (12.46%)	**Israel**	20 (8.51%)
United Kingdom	29 (10.32%)	**United States**	17 (7.23%)
Singapore	26 (9.25%)	**Canada**	13 (5.53%)
India	17 (6.05%)	Pakistan	13 (5.53%)
Canada	14 (4.98%)	**United Kingdom**	12 (5.11%)
Australia	11 (3.91%)	Germany	10 (4.26%)
Japan	11 (3.91%)	Nigeria	9 (3.83%)
Saudi Arabia	9 (3.20%)	China	8 (3.40%)
Pakistan	7 (2.49%)	Oman	8 (3.40%)

broker country, significantly expanding its global broker share by nearly 23 percentage points (N = 113) from the first to the second decade. No immediate regional broker trends stand out in our analysis. Brokers were mostly working from Southern Asia (India, Pakistan, Bangladesh, Nepal), Middle East/Northern Africa (Turkey, Egypt, Israel), or North America (United States, Canada). Instead, a handful of nations disproportionately dominated the overall broker market. Our analysis found the top ten countries accounted for 72% (= 266/314) of all cases in the first decade and 85% (= 359/422) in the second decade included in our dataset.

Countries hosting illegal transplant surgeries

Figure 9 shows that countries were reported as kidney surgery countries between the first and the second decades. The darkest green shading represents the highest concentration of surgery cases, whereas the lighter shading corresponds to the lowest reported number of surgeries. In the first decade, the countries that fell into the highest frequency category were India, Pakistan, China, South Africa, Turkey, United States, and Philippines. In the second decade, the highest frequency category included India, Pakistan, China, Sri Lanka, Turkey, Thailand, and Egypt.

Table 8 illustrates the analysis of the top 10 surgery countries by decade, revealing significant shifts in surgery patterns over the periods from 2000 to 2011 and from 2012 to 2022. In the first decade, India (17%, N = 50), Pakistan (14%, N = 41), China (12%, N = 36), and South Africa (10%, N = 30) emerged as the primary surgery countries, with Turkey leading at 8% (N = 24), followed by the United States 5% (N = 14) and the Philippines (4%, N = 11). In the following decade, India (36%, N = 136), Pakistan (13%, N = 49), and China (12%, N = 45) were still the primary surgery countries, followed by Sri Lanka (8%, N = 30) and Turkey (4%, N = 14). When analysing the geographic regions, the top surgery countries were distributed across various parts of the world. 17% (N = 50) of the total surgery cases involved India as a host while this share increased to 36% (N = 136) in the second decade. Most surgery countries were from Southern Asia (India, Pakistan, Sri Lanka, Nepal), Eastern Asia (China) or South-eastern Asia (Thailand, Philippines, Indonesia). In fact, these countries shared 66% (= 443/668) of the entire reported kidney surgery cases. Other regions included Sub-Saharan Africa (South Africa), Europe and Northern America (the United Kingdom, and the United States), Eastern Asia (Japan), and Western Asia (Turkey, Israel, Egypt), reflecting a more globally dispersed pattern of surgery activity.

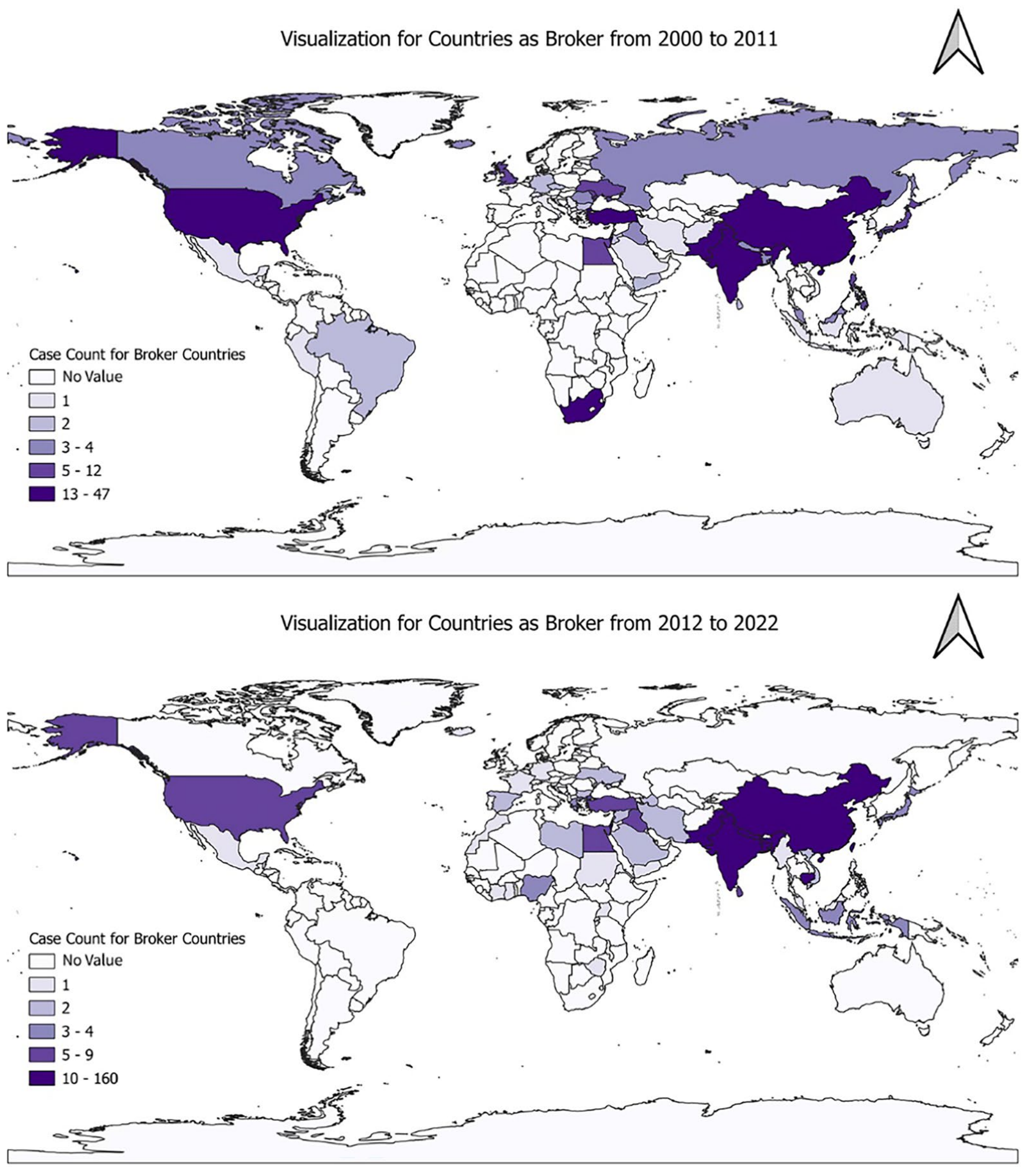

Fig. 8 A world map representing the number of illegal kidney trade cases in which countries were reported as a kidney broker provider. The upper panel shows the map for the first decade (2000–2011) while the lower panel shows the map for the second decade (2012–2022). In each panel, the countries with at least one case serving as a kidney broker provider were classified into 5 groups using quantiles. Countries with a darker purple shade correspond to more cases in which they appeared as a kidney broker provider

Primary role of countries

To identify the primary role (seller, buyer, broker or surgery) played by each country, we classified the countries into one of these classes based on the largest number of times that the country appeared by playing the specific role. For instance, India appeared 259 times (36.17%) as a seller host, 64 times (8.94%) as a buyer host, 207 times (28.91%) as a broker host, and 186 times (25.98%) as a surgery host. Thus, we determined that the primary role played by India was a seller host.

The list of the countries by primary role is summarized in Appendix I. Figure 10 presents the map of the countries with their primary roles coded in different colours. The map shows that, as expected, most seller countries are in less developed regions including South America, Africa, South Asia and the Former Soviet Union, while buyer countries are concentrated in richer countries in Western Europe, North America, the Middle East, Japan and Australia.

Table 7 Top 10 Broker Countries by Decade

2000–2011		2012–2022	
Country Name	**Cases Count (%)**	**Country Name**	**Cases Count (%)**
India	47 (14.97%)	**India**	160 (37.91%)
Israel	29 (9.24%)	**Pakistan**	62 (14.69%)
Pakistan	24 (7.64%)	**China**	47 (11.14%)
China	23 (7.32%)	**Israel**	22 (5.21%)
Turkey	21 (6.69%)	Nepal	19 (4.50%)
South Africa	21 (6.69%)	Bangladesh	13 (3.08%)
United States	20 (6.37%)	Cambodia	10 (2.37%)
Singapore	19 (6.05%)	**Egypt**	9 (2.13%)
United Kingdom	12 (3.82%)	Sri Lanka	9 (2.13%)
Egypt	10 (3.18%)	**Turkey**	8 (1.90%)

Figure 11 visualizes the international kidney trade networks for the two decades. The node size in the networks represents the number of cases in which each country was involved, while the edge width indicates the volume of kidney trade between the connected countries. To enhance the readability of the network graphs, only the edges involved in more than one case were displayed. In the first decade, the United States and Israel played crucial roles as buyer countries in the kidney trade network. However, these two countries displayed contrasting network patterns. The United States received illicit kidney supplies from various countries in a relatively even distribution. In contrast, Israel was frequently connected to two seller countries, Moldova and Brazil. Also, Turkey and South Africa were the key countries that operated kidney transplants for this Israel-centric network. In the second decade, the United States continued to be an important buyer country with a more balanced distribution of kidney supplier countries compared to Canada and Germany. However, Israel's role has shifted from that of a buyer to that of a broker country, playing a significant role in abetting kidney trade among the United States (buyer), Canada (buyer), Germany (buyer), Russian Federation (seller), and Turkey (seller). Lastly, it is worth noting that Sri Lanka emerged as an important surgical country, performing kidney transplants on victims from India.

Discussions and conclusion

There are several limitations to our method. First, we only collected English articles from around the world using LexisNexis. To construct a more comprehensive network, the dataset can be expanded by incorporating more sources and including articles in different languages. Second, our dataset might not represent the actual total cases. Removing duplicates effectively and capturing the actual number of cases of illegal transplants proved to be challenging as some notorious cases tend to be mentioned for a long period of time. Third, although the RAG tuning method has improved extraction accuracy compared to regular prompts, it still falls short of achieving 95% accuracy or higher when compared to human-evaluated results. Further research into additional tuning methods is necessary to enhance the accuracy of LLM for extracting geographic locations. Lastly, we acknowledge the inherent limitations of using news articles as a representative sample. Newspaper publishers and their reporters may have different regional as well as topical focuses, which could generate bias in demonstrating the true prevalence of illegal kidney transplant cases in individual countries. In our previous work, for instance, we have learned that Indian newspapers tend to report cases involving and not involving India, while Pakistani newspapers tend to be more Pakistan-centric. We have observed similar trend in newspapers and countries where some newspapers and countries are more likely to report kidney trafficking cases than the others. Despite these limitations, we believe that the high accuracy in discerning target articles and texts demonstrate that media analysis and NLP can offer the promise of extracting spatiotemporal insights from objective and accessible sources.

We acknowledge that the current paper is not the first to demonstrate this. Wang, for instance, harnessed social media NLP techniques to explore public sentiments concerning COVID-19 vaccines, uncovering various patterns across states, ethnicities, and topics [36]. The contribution of the current paper lies in that the deployment of such methodologies to construct illicit kidney trade networks has not been explored in prior literature with the exception of the work focusing on South Asia [12]. Our approach aimed to unravel a more comprehensive and intricate illegal kidney trade network while elucidating the encompassing spatiotemporal patterns that have shaped this phenomenon over the past 23 years. Further, the current study is the first to use BERT and Llama3.3 to extract geographic information in constructing the kidney trade database. Previous studies have employed a range of methodologies for geographic location extraction, typically falling into three categories: Geocoding services, Geoparsing, and Geotagging [37]. Geocoding services, exemplified by the Google Geocoding API, offer likely location references that correspond to input phrases, providing users with longitude and latitude coordinates for specific locations [37]. Geoparsing involves the recognition of toponyms in text, often employing existing Named Entity Recognition (NER) tools like Stanford NER, which is particularly adept at identifying country and city names [38]. Geotagging, frequently

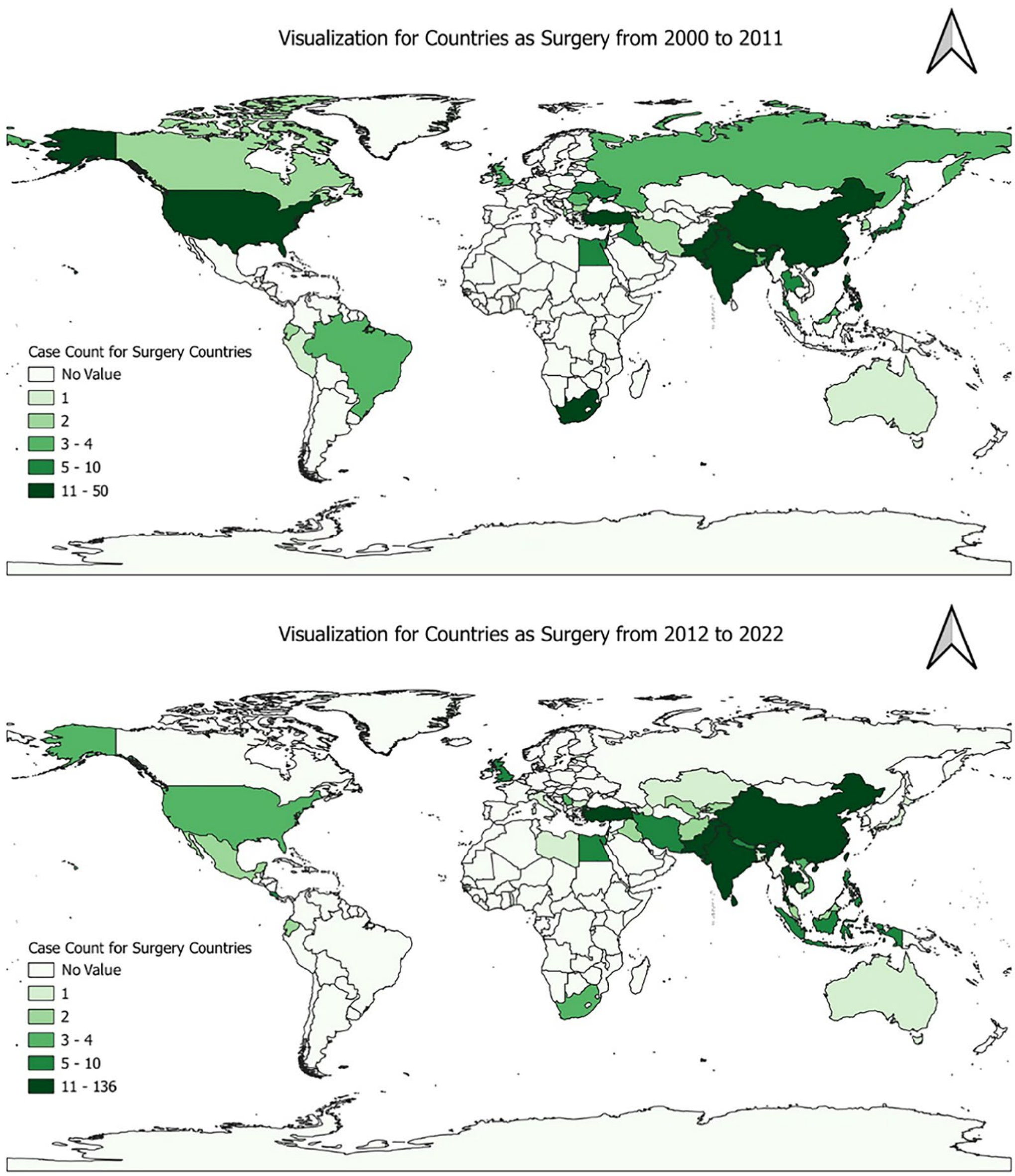

Fig. 9 A world map representing the number of illegal kidney trade cases in which countries were reported as an illegal transplant surgery provider. The upper panel shows the map for the first decade (2000–2011) while the lower panel shows the map for the second decade (2012–2022). In each panel, the countries with at least one case serving as an illegal transplant surgery provider were classified into 5 groups using quantiles. Countries with a darker green shade correspond to more cases in which they appeared as an illegal transplant surgery provider

utilized in social media platforms like Twitter, relies on users to directly provide geographic information [39]. In recent years, researchers have developed innovative techniques by incorporating neural network models like Bidirectional Long Short-Term Memory (BiLSTM) and fine-tuning transformer models to enhance the performance of location information comprehension [14, 15]. However, these approaches resolved the location extraction problem primarily from an NER perspective. While these methodologies have found application in numerous research studies, they are primarily suited for the interpretation of simple location information. Furthermore, the intertwining of geographic locations with specific topics presents additional complexities, with a single article often referencing multiple geographic locations and diverse topics. These methodologies struggle to associate relevant topics with each location. Although recent research has used large language models (LLMs) to identify geographic locations with zero-shot and few-shot prompt strategies [40, 41], we have implemented RAG to

Table 8 Top 10 Surgery Countries by Decade

2000–2011		2012–2022	
Country Name	**Cases Count (%)**	**Country Name**	**Cases Count (%)**
India	50 (17.06%)	**India**	136 (36.27%)
Pakistan	41 (13.99%)	**Pakistan**	49 (13.07%)
China	36 (12.29%)	**China**	45 (12.00%)
South Africa	30 (10.24%)	Sri Lanka	30 (8.00%)
Turkey	24 (8.19%)	**Turkey**	14 (3.73%)
United States	14 (4.78%)	Thailand	11 (2.93%)
Philippines	11 (3.75%)	**Egypt**	10 (2.67%)
Egypt	8 (2.73%)	United Kingdom	7 (1.87%)
Israel	7 (2.39%)	Nepal	5 (1.33%)
Japan	7 (2.39%)	Indonesia	5 (1.33%)

enhance the accuracy of geographic location extraction. Additionally, there are still limitations in implementing RAG with LLMs. While an accuracy of over 73% was achieved, with the highest role-specific accuracy reaching 86.76%, manual verification of all results remains necessary to ensure the accuracy of the database. This step is critical to make the database reliable for future studies, such as network analyses and predictions of international illegal trade.

The primary objective on the current study was to explore the new approach involving NLP and LLM to efficiently construct a geospatial database of illicit kidney trade. Thus, in-depth analysis of the extracted kidney trade networks is beyond the scope of the current study. We would like to note, however, that several anecdotal evidence or common conjectures about kidney trade were confirmed by the data gathered under the current study. First, as expected, the primary role played by developing countries were more likely to be a host of kidney sellers while that played by developed countries was a host of kidney buyers. Second, the spatial temporal trend of the data indicated that primary roles played by individual countries change over time, and kidney trade networks change and evolve dynamically. Our data indicated that about half of the top 10 countries playing each role gets replaced by other countries within a decade, possibly in response to exogenous factors such as enforcement or establishment of transplant laws that force their citizens to buy kidneys elsewhere as well as wars and poverty that force their citizens to sell their kidneys to get a secure passage to a safer location. Third, many of the countries highlighted in the current study are studied in qualitative literature on kidney trafficking. India is by far the most studied country [42–46], followed by other countries such as China [47–50], Bangladesh [51–55], Nepal [56–59], Pakistan [60–63] Egypt [55, 64] and South Africa [65–67]. While Turkey and Israel were also found to be major players in the study, they were less studied [68–71]. Finally, the immediate next steps should include quantitative analyses of the data, investigating the country characteristics and other external factors associated with the primary role played by these countries. Equally important would be to identify the factors influencing the configuration of the country networks, i.e., investigating why certain seller countries are connected to specific buyer or surgery countries and how the country networks dynamically change or evolve over time.

Supplementary material

https://github.com/wangfarmer/IllegalKidneyNetwork

Appendix 1

Primary Role of Countries 2000–2011			
Sellers	**Buyers**	**Brokers**	**Surgery**
India	**Israel**	**Iceland**	**South Africa**
Pakistan	**United States**	**Czechia**	**Turkey**
China	**Singapore**	**Sri Lanka**	**Albania**
Moldova	**Canada**	**Yemen**	**Ecuador**
Brazil	**Australia**		
United Kingdom	**Japan**		
Philippines	**Saudi Arabia**		
Indonesia	**South Korea**		
Russian Federation	**Oman**		
Egypt	**United Arab Emirates**		
Romania			
Bangladesh	**Germany**		
Nepal	**Greece**		
Kazakhstan	**Poland**		
Ukraine	**France**		
Iraq			
Jordan			
Peru			
Uzbekistan			
Bulgaria			
Serbia			
Belarus			
Georgia			
Ireland			
Nicaragua			
Vietnam			
Estonia			
Kenya			

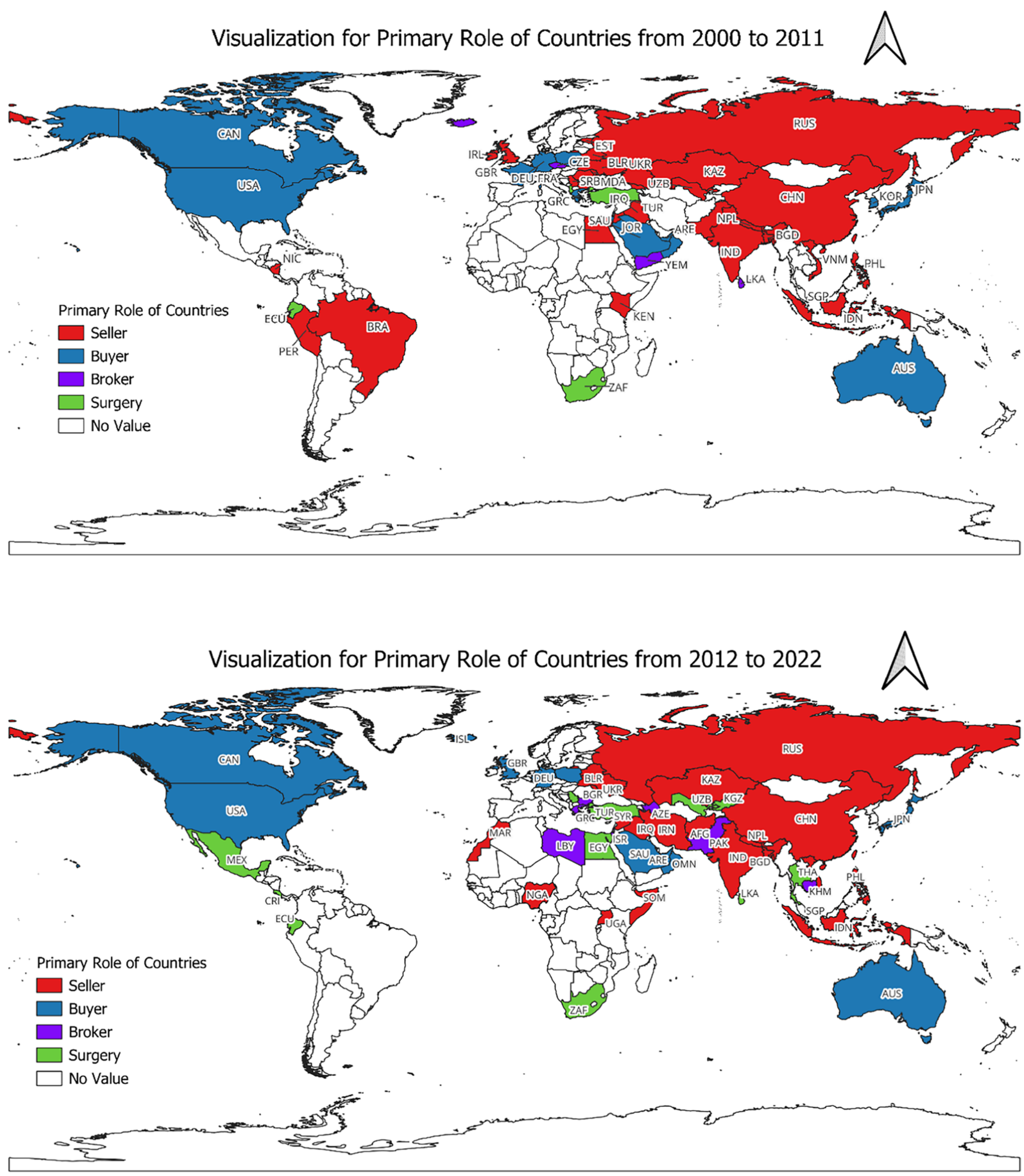

Fig. 10 A world map representing the major role that each country played in illegal kidney trade cases. The upper panel shows the map for the first decade (2000–2011) while the lower panel shows the map for the second decade (2012–2022). In each panel, countries shown in red are the countries with more cases reported as a kidney seller provider than a kidney buyer, broker, or surgery provider. Countries shown in blue are the countries with more cases reported as a kidney buyer provider. Countries shown in purple are the countries with more cases reported as a kidney broker provider. Countries shown in green are the countries with more cases reported as an illegal transplant surgery provider

(See figure on next page.)

Fig. 11 Global ilicit kidney trade network diagram demonstrating the networks among kidney seller, buyer, broker and surgery countries by decade. The upper panel shows the diagram for the first decade (2000–2011) while the lower panel shows the diagram for the second decade (2012–2022). The networks were displayed only when country pairs had at least one trade reported. In each panel, the countries shown in blue and red are kidney seller and buyer providers respectively, while those shown in brown and green are kidney broker and illicit transplant surgery providers respectively. The node size in the networks represents the number of illicit kidney trade cases in which each country was involved, while the edge width indicates the volume of kidney trade between the connected countries

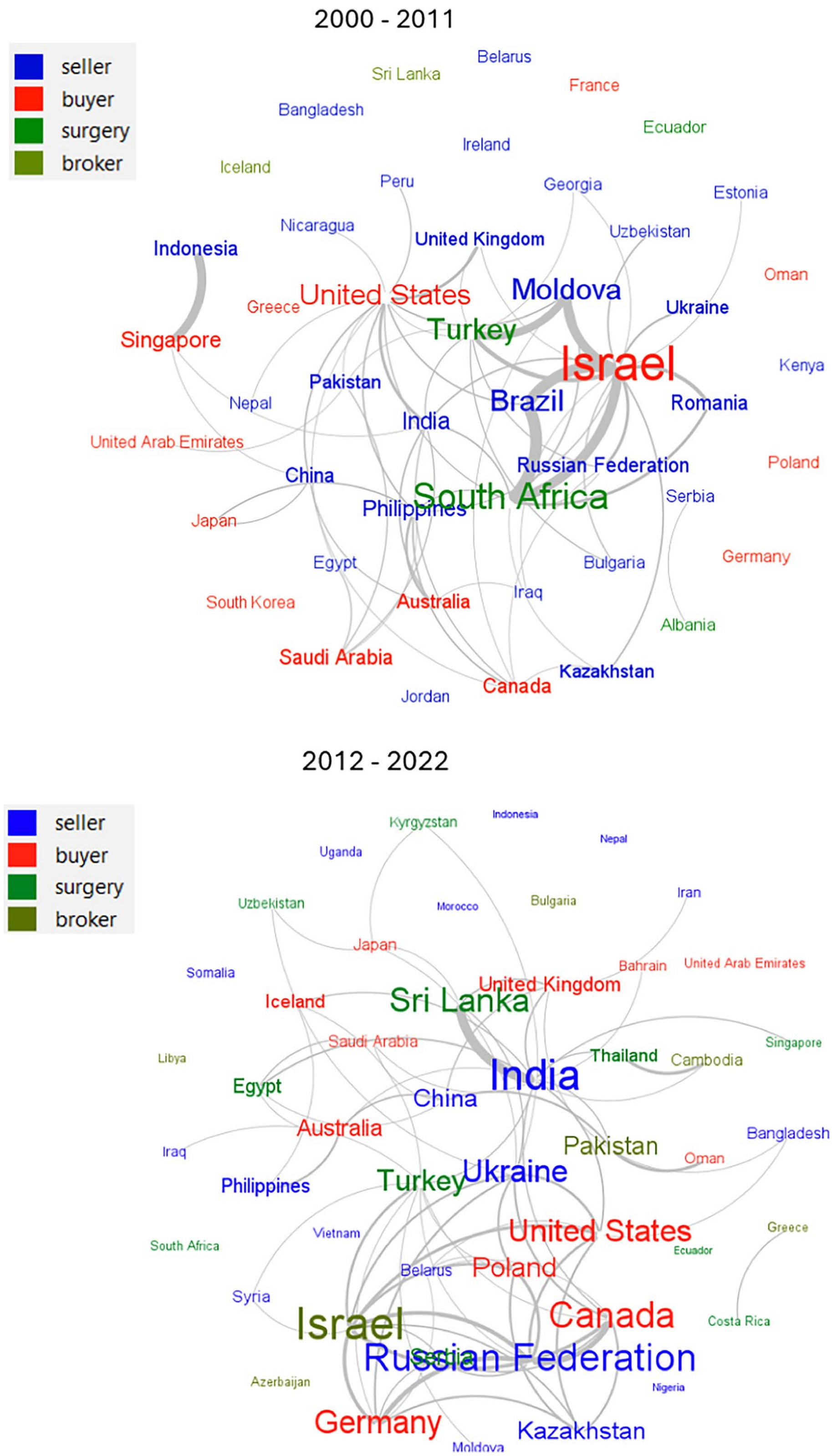

Fig. 11 (See legend on previous page.)

Primary Role of Countries 2012–2022

Sellers	Buyers	Brokers	Surgery
India	**United States**	**Pakistan**	**Sri Lanka**
China	**Canada**	**Israel**	**Turkey**
Nepal	**United Kingdom**	**Cambodia**	**Thailand**
Bangladesh	**Germany**	**Greece**	**Egypt**
Russian Federation	**Oman**	**Azerbaijan**	**Costa Rica**
Nigeria	**Australia**	**Libya**	**Singapore**
Ukraine	**Saudi Arabia**	**Bulgaria**	**South Africa**
Syria	**Japan**		**Serbia**
Iraq	**Poland**		**Uzbekistan**
Philippines	**Iceland**		**Ecuador**
Afghanistan	**United Arab Emirates**		**Mexico**
Indonesia	**Bahrain**		**Kyrgyzstan**
Iran			
Kazakhstan			
Uganda			
Vietnam			
Belarus			
Somalia			
Morocco			
Moldova			

Example 1: Sellers are implied to be local kidney providers or donors.

→ Seller Country: Moldova

Example 2: "Police have arrested nine people, including two doctors, three donors, three recipients and one person who arranged these operations, for illegal transplant of purchased kidneys in New Delhi."

Sellers are implied to be local kidney providers or donors.

Sellers are located in New Delhi.

New Delhi is a city; it's located in India.

→ Seller Country: India

Example 3: Three Latin American men in Toronto are offering to sell their kidneys for transplant.The National Post reports the three are advertizing their organs in a Spanish-language newspaper.

Sellers are implied to be local kidney providers or donors.

Latin America is identified as the seller location, but it is a region, not a specific country.

→ Seller Country: None

"""

Chain-of-Thought System Prompt for Buyer

"""

Step 1: Identify individuals who received or purchased a kidney in the context of the kidney trade.

Step 2: Determine their country of origin or nationality based on the text.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the individual is a recipient or buyer, and not a seller, broker, or surgeon.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to sellers. No explanation.

Example 1: "INTERPOL is co-ordinating a worldwide hunt for a woman from Moldova, who has been accused of making tens of thousands of pounds by encouraging at least 100 people from Moldova to sell their kidneys for transplants in Turkey"

Buyers are implied to be local kidney recipients or patients

→ Buyer Country: Turkey

Example 2: "Police have arrested nine people, including two doctors, three donors, three recipients and one person who arranged these operations, for illegal transplant of purchased kidneys in New Delhi."

Buyers are implied to be local kidney recipients or patients.

Buyers are identified in New Delhi.

New Delhi is a city; it's located in India.

→ Buyer Country: India

Example 3: "There they are said to have agreed to have their left kidneys removed in return for Pounds 1,800. The organs were given to patients from western countries who are believed to have paid up to Pounds 15,000 each"

Buyers are implied to be local kidney recipients or patients.

Western countries is identified as the buyer location, but it is a region, not a specific country.

→ Buyer Country: None

"""

Chain-of-Thought System Prompt for Broker

"""

Step 1: Identify individuals or entities who arranged, coordinated, or facilitated the kidney trade (e.g., recruiting sellers, matching buyers, arranging travel or surgeries).

Step 2: Determine the country where each broker is based, operates from, or where the coordination activities took place.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the individual or organization is a broker or intermediary, and not a seller, buyer, or surgeon.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to brokers. No explanation.

Example 1: "INTERPOL is co-ordinating a worldwide hunt for a woman from Moldova, who has been accused of making tens of thousands of pounds by encouraging at least 100 people from Moldova to sell their kidneys for transplants in Turkey".

Brokers are implied to be persons who arranging the operations.

→ Broker Country: Moldova.

Example 2: "Police have arrested nine people, including two doctors, three donors, three recipients and one person who arranged these operations, for illegal transplant of purchased kidneys in New Delhi."

Brokers are implied to be persons who arranging the operations.

Buyers are identified in New Delhi.

New Delhi is a city; it's located in India.

→ Broker Country: India.

Example 3: "Sharma now got involved in the illegal kidney transplant business in cahoots with the notorious Dr Amit Kumar, who ran a multi-nation racket in South Asia".

Brokers are implied to be persons who arranging the operations.

South Asia is identified as the broker location, but it is a region, not a specific country.

→ Broker Country: None.

"""

Chain-of-Thought System Prompt for Surgery.

"""

Step 1: Identify the locations where kidney transplant surgeries were physically performed.

Step 2: Look for keywords like hospital, clinic, transplant, operation, surgery, or doctors performing the surgery that clearly indicate where the procedure took place.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the location is linked to the transplant procedure, and not to the seller, buyer, or broker.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to surgery locations. No explanation.

Example 1: "Thailand's Medical Council has revoked the license of one doctor and suspended those of four others after finding they had illegally traded in human organs, the council's officers said Friday"

Surgery are implied to be locations where kidney transplant surgeries were physically performed.

→ Surgery Country: Thailand

Example 2: "Police have arrested nine people, including two doctors, for illegal transplant of purchased kidneys in New Delhi."

Surgery are implied to be locations where kidney transplant surgeries were physically performed.

The involvement of doctors and illegal transplants links New Delhi to the surgeries.

New Delhi is a city; it's located in India.

→ Surgery Country: India

Example 3: "Then they were flown to Europe, South America or Southeast Asia, where the medical surgeries were performed in illegal procedures."

Surgery are implied to be locations where kidney transplant surgeries were physically performed.

Europe, South America or Southeast Asia are identified as the broker locations, but they are regions, not specific countries.

→ Surgery Country: None.

"""

Appendix 2

Chain-of-Thought System Prompt for Seller

"""

Step 1: Identify individuals who sold or lost a kidney in the context of the kidney trade.

Step 2: Determine their country of origin or nationality based on the text.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the person is a donor or victim who lost a kidney, and not a broker, buyer, or surgeon.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to sellers. No explanation.

Example 1: "INTERPOL is co-ordinating a worldwide hunt for a woman from Moldova, who has been accused of making tens of thousands of pounds by encouraging at least 100 people from Moldova to sell their kidneys for transplants in Turkey"

Sellers are implied to be local kidney providers or donors.

→ Seller Country: Moldova

Example 2: "Police have arrested nine people, including two doctors, three donors, three recipients and one person who arranged these operations, for illegal transplant of purchased kidneys in New Delhi."

Sellers are implied to be local kidney providers or donors.

Sellers are located in New Delhi.

New Delhi is a city; it's located in India.

→ Seller Country: India

Example 3: Three Latin American men in Toronto are offering to sell their kidneys for transplant.The National Post reports the three are advertizing their organs in a Spanish-language newspaper.

Sellers are implied to be local kidney providers or donors.

Latin America is identified as the seller location, but it is a region, not a specific country.

→ Seller Country: None

""""

Chain-of-Thought System Prompt for Buyer

""""

Step 1: Identify individuals who received or purchased a kidney in the context of the kidney trade.

Step 2: Determine their country of origin or nationality based on the text.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the individual is a recipient or buyer, and not a seller, broker, or surgeon.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to sellers. No explanation.

Example 1: "INTERPOL is co-ordinating a worldwide hunt for a woman from Moldova, who has been accused of making tens of thousands of pounds by encouraging at least 100 people from Moldova to sell their kidneys for transplants in Turkey"

Buyers are implied to be local kidney recipients or patients

→ Buyer Country: Turkey

Example 2: "Police have arrested nine people, including two doctors, three donors, three recipients and one person who arranged these operations, for illegal transplant of purchased kidneys in New Delhi."

Buyers are implied to be local kidney recipients or patients.

Buyers are identified in New Delhi.

New Delhi is a city; it's located in India.

→ Buyer Country: India

Example 3: "There they are said to have agreed to have their left kidneys removed in return for Pounds 1,800. The organs were given to patients from western countries who are believed to have paid up to Pounds 15,000 each"

Buyers are implied to be local kidney recipients or patients.

Western countries is identified as the buyer location, but it is a region, not a specific country.

→ Buyer Country: None

""""

Chain-of-Thought System Prompt for Broker

""""

Step 1: Identify individuals or entities who arranged, coordinated, or facilitated the kidney trade (e.g., recruiting sellers, matching buyers, arranging travel or surgeries).

Step 2: Determine the country where each broker is based, operates from, or where the coordination activities took place.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the individual or organization is a broker or intermediary, and not a seller, buyer, or surgeon.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to brokers. No explanation.

Example 1: "INTERPOL is co-ordinating a worldwide hunt for a woman from Moldova, who has been accused of making tens of thousands of pounds by encouraging at least 100 people from Moldova to sell their kidneys for transplants in Turkey".

Brokers are implied to be persons who arranging the operations.

→ Broker Country: Moldova.

Example 2: "Police have arrested nine people, including two doctors, three donors, three recipients and one person who arranged these operations, for illegal transplant of purchased kidneys in New Delhi."

Brokers are implied to be persons who arranging the operations.

Buyers are identified in New Delhi.

New Delhi is a city; it's located in India.

→ Broker Country: India.

Example 3: "Sharma now got involved in the illegal kidney transplant business in cahoots with the notorious Dr Amit Kumar, who ran a multi-nation racket in South Asia".

Brokers are implied to be persons who arranging the operations.

South Asia is identified as the broker location, but it is a region, not a specific country.

→ Broker Country: None.

"""

Chain-of-Thought System Prompt for Surgery.

"""

Step 1: Identify the locations where kidney transplant surgeries were physically performed.

Step 2: Look for keywords like hospital, clinic, transplant, operation, surgery, or doctors performing the surgery that clearly indicate where the procedure took place.

Step 3: If only a city, village, or state is mentioned, identify the country that location belongs to and return the country name only.

Step 4: Confirm that the location is linked to the transplant procedure, and not to the seller, buyer, or broker.

Step 5: If no country or identifiable location is provided, return None.

Step 6: If identified location is too vague, such as "Western countries", "African Countries" or "Latin America", return None.

Step 7: only Output the names of countries specifically linked to surgery locations. No explanation.

Example 1: "Thailand's Medical Council has revoked the license of one doctor and suspended those of four others after finding they had illegally traded in human organs, the council's officers said Friday"

Surgery are implied to be locations where kidney transplant surgeries were physically performed.

→ Surgery Country: Thailand

Example 2: "Police have arrested nine people, including two doctors, for illegal transplant of purchased kidneys in New Delhi."

Surgery are implied to be locations where kidney transplant surgeries were physically performed.

The involvement of doctors and illegal transplants links New Delhi to the surgeries.

New Delhi is a city; it's located in India.

→ Surgery Country: India.

Example 3: "Then they were flown to Europe, South America or Southeast Asia, where the medical surgeries were performed in illegal procedures."

Surgery are implied to be locations where kidney transplant surgeries were physically performed.

Europe, South America or Southeast Asia are identified as the broker locations, but they are regions, not specific countries.

→ Surgery Country: None.

"""

Abbreviations

LLM	Large Language Model
NER	Named Entity Recognition
GPT	Generative Pre-Trained Transformer
BERT	Bidirectional Encoder Representations from Transformers

RAG	Retrieval-Augmented Generation
BiLSTM	Bidirectional Long Short-Term Memory
NLP	Natural Language Processing
ESRD	End-Stage Kidney Disease
WHO	World Health Organization
UNODC	United Nations Office on Drugs and Crime

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

Supplementary Material 3.

Supplementary Material 4.

Supplementary Material 5.

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Author contributions
Z.W. and N.K. wrote the main manuscript text. Z.W. and M.L. collected the raw data. N.K., M.L., P.B., J.W., and V.K. reviewed and labeled the training and validation datasets. Z.W., Q.Z., and M.L. designed and implemented the BERT to identify related articles Z.W. and M.L. designed and implemented the GPT models with RAG and automatically extract geographic entities. Z.W. produced all the maps and tables for the trading statistics. N.K., M.L., P.B., and V.K. wrote the description of each map and table for trading statistics. O.Z. conducted the network analysis for the trading network. C.Y. contributed the idea of using a large language model and provided the GPU machine. N.K. and C.Y. oversaw the overall quality of the article.

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Availability of data and materials
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Declarations

Ethics approval and consent to participate
Not applicable.

Competing Interests
The authors declare no competing interests.

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