Visualizing Human Trafficking and Criminal Networks: A Systematic Mapping Study

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Abstract. Human trafficking is a widespread global crime characterized by decentralized and hidden networks. Addressing this challenge requires not only identifying key individuals but also understanding the structural and temporal dynamics of trafficking operations. This systematic mapping study reviews existing visualization techniques and tools designed to support the analysis of human trafficking data. From an initial set of 519 records, 15 primary studies were selected for a detailed analysis. These studies were examined in three dimensions: data types, visualization approaches, and tool functionalities. Our findings indicate a strong reliance on graph-based and spatio-temporal visualizations, but also reveal significant gaps in data integration, usability, and empirical evaluation. The results underscore the need for more interoperable, accessible, and user-oriented visualization solutions to enhance investigative and preventive efforts.

Keywords: Human trafficking · Visualization · Criminal networks · Data analysis · Graph visualization

1 Introduction

Human trafficking is a pervasive and highly organized form of transnational crime, characterized by complex and decentralized networks. These networks often consist of core actors and loosely affiliated intermediaries, making them difficult to detect, analyze, and dismantle. The associated data, ranging from law enforcement reports to online escort advertisements and social media traces, are vast, heterogeneous, and not amenable to manual analysis [44].

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To address these analytical challenges, visualization tools have emerged as a crucial component in uncovering trafficking operations. Network visualizations help investigators identify key individuals and relational structures, while temporal and spatial maps facilitate pattern recognition and predictive policing [12]. Recent technological advances have further expanded the role of such tools in real-time investigations, victim identification, and strategic interventions [27,16].

Despite the growing importance of these tools, a limited systematic analysis remains of how they are designed, what data they leverage, and how effectively they support anti-trafficking efforts. Visualization solutions vary widely in terms of usability, analytical scope, data modalities, and intended users, making it challenging for researchers to evaluate or select the most suitable tools.

To address this gap, we conducted a systematic mapping study (SMS) to assess the current landscape of visualization tools for human trafficking and criminal network analysis. Specifically, our study addresses the following aims:

- **Survey the State of the Art**: Provide a structured overview of visualization tools explicitly designed for human trafficking networks, distinguishing them from generic criminal network applications.
- **Compare Capabilities**: Analyze tools in terms of visualization techniques, data sources, and analytical functionalities, focusing on applicability.
- **Identify Gaps**: Highlight unresolved challenges, such as poor integration of multimodal data, lack of usability evaluations, and limited support.

This study contributes a synthesized understanding of the field and offers a foundation for future work in visualization system development, empirical evaluation, and cross-agency integration.

The rest of the paper is organized as follows. Section 2 reviews existing literature on visualization methods relevant to criminal and trafficking networks. Section 3 outlines the research methodology and mapping protocol. Section 4 presents the results of our analysis. Section 5 interprets these findings and suggests future directions. Section 6 discusses potential limitations. Finally, Section 7 summarizes our contributions.

2 Related Work

This section reviews existing literature on visualization and tools relevant to criminal network analysis, with an emphasis on their applicability to human trafficking data. This is organized into three categories: (1) traditional graph-based techniques for criminal networks, (2) spatio-temporal and behavioral visualizations, and (3) visual analytics systems tailored for human trafficking.

2.1 Graph-Based Visualization of Criminal Networks

Graph-based representations remain central to criminal network analysis, where individuals and their interactions are encoded as nodes and edges in visual graphs. Among the first and most influential of these is LogAnalysis, introduced by Catanese et al. [8], which constructs social network graphs from mobile phone metadata, where nodes represent individuals and edges denote their communications. This system integrates visual statistical analysis with temporal evolution, enabling investigators to explore dynamic communication patterns before, during, or after criminal events. Ferrara et al. [13] further enhanced this approach by proposing a computational framework that combines network science and forensic methods, utilizing LogAnalysis for phone record-based visualizations.

Later, tools diversified in network structures and interaction modes. Rasheed et al. [30] proposed *PEVNET*, which incorporates structural and temporal visual analytics, including features such as node-link sizing, trend analysis, and composite expansion for the evolution of crime clusters. Zhou et al. [45] developed an interactive process that blends social network analysis and machine learning. Their framework supports iterative hypothesis testing through varying layouts and real-time metric exploration.

However, many of these systems continue to rely on manual data entry and lack the specialized capabilities required for trafficking cases. Si et al. [34] proposed a layered event-based visualization framework leveraging tools such as NETMAP [6], Analyst's Notebook [14], and COPLINK [9], although these systems often suffer from limited automation and high user burden. Similarly, Wiil [40] highlighted key limitations in Crimefighter [28] and in Wiil's work [41], including scalability issues and rigid data models. Haider et al. [15] introduced matrix and graph-based approaches to capture indirect relationships and their temporal evolution, yet these remain constrained in representing complex, dynamic interactions.

While these tools are powerful for generic criminal network analysis, they typically do not incorporate domain-specific features essential for analyzing human trafficking, such as ad metadata or victim-perpetrator role semantics.

2.2 Spatio-Temporal and Behavioral Visualization Approaches

Complementing topological graph representations, several works have explored the visualization of behavioral trends and geographic movement patterns associated with trafficking activity. Sen et al. [33] analyzed police records to identify traffickers' travel paths to Las Vegas, enabling predictive checkpoint placement. Based on temporal metadata, TRAFFICVIS [38] visualizes escort ads using line charts, cluster heatmaps, and movement maps to reveal spatio-temporal regularities and potential trafficking routes. Beyond predictive mapping, tools like *Visilant* [43] provide modular dashboards with timeline tracking and interactive network layouts, supporting real-time investigation workflows. Makin et al. [23] investigated online behavior patterns by visualizing user interactions on prostitution platforms, uncovering temporal engagement trends and site dynamics.

Although these systems offer insight into broad behavioral trends, they often fall short in capturing role-based dynamics, linking identities across platforms, or revealing deeper semantic patterns.

2.3 Visual Analytics for Human Trafficking Data

In recent years, a new class of tools has emerged that specifically focuses on human trafficking networks. TRAFFICVIS [38] and VisPaD [26,25] cluster escort ad data using shared metadata such as phone numbers and location tags. These systems employ dimensionality reduction techniques (e.g., t-SNE [22], UMAP [24]) to visualize meta-clusters, support semi-automated labeling, and enable domain experts to track evolving trafficking patterns.

Spotlight [37] and Traffic Jam [5] are commercial platforms that utilize AI and image analysis to process escort advertisements and prioritize investigative leads. While these tools are in use by law enforcement, their commercial nature and lack of peer-reviewed research make it hard to assess them thoroughly.

Raets et al. [29] conducted a comprehensive review of digital technologies applied to trafficking detection, including machine learning, image recognition, and social media mining. However, their survey primarily focuses on detection technologies and does not explicitly address visualization.

Although these systems represent necessary steps toward trafficking-specific analytics, they often fail to integrate topological, temporal, and semantic layers essential for network-based investigative workflows.

Despite the diversity of previous work, few tools offer integrated views of network topology, spatiotemporal behavior, and semantic data, features that are critical for understanding and disrupting trafficking operations. To bridge this gap, we provide a structured comparison of trafficking-relevant visualization tools, highlighting their methodological strengths, practical trade-offs, and domain-specific capabilities.

3 Research Process

We adopt the three-phase methodology for systematic mapping studies introduced by Kitchenham et al. [18], which consists of planning, conducting, and reporting. During the planning phase, we clarified the study's motivation, developed a review protocol, and outlined our key research questions. In the conducting phase, we executed the search strategy, applied inclusion and exclusion criteria, and synthesized the literature. Finally, we structured our findings around the research questions to ensure clarity and make the results easier to reproduce and extend.

3.1 Research Questions

As outlined in Kitchenham et al. [18], clear research questions help focus the review, determine what to include, and ensure the study stays relevant and on track. Our SMS is framed around the following research questions:

RQ 1: What kind of data is being collected to visualize human/sex trafficking? We aim to identify the primary data sources used in visualizing human trafficking networks and understand why certain data modalities are emphasized in these studies.

RQ 2: What kind of visualizations exist to capture this data? We examine the types of visualizations used to capture patterns or structures in trafficking data.

RQ 3: What tools exist in the industry identified in the literature that visualize human trafficking networks or activities? We aim to catalog visualization tools discussed in the literature and assess their capabilities based on their alignment with data types (RQ1) and visual strategies (RQ2).

3.2 Inclusion/Exclusion Criteria

We adopted standard SMS practices [18] to guide our inclusion and exclusion criteria, ensuring consistency in selecting relevant studies.

Inclusion Criteria:

- Papers on the visualization of human trafficking networks.
- Papers on the visualization of criminal networks that mention human trafficking.
- Papers that discuss the analysis of human trafficking data and mention visualization.

Exclusion Criteria:

- No mention of visualization.
- Does not contain images.
- Papers not in English.
- Opinion papers or vision, road map, or plan papers.
- Secondary studies, like existing SMS or SLR.
- Duplicate papers. In case of duplication, the most recent version was selected.
- Non peer-reviewed.
- No full text available.
- Citation.
- Off Topic.

3.3 Search Process: Identifying Essential Articles

In this work, we included 15 papers published from 2012 to 2023. To identify these papers, we did the following. First, we searched three scientific databases: Scopus, IEEE, and Google/Google Scholar. Our search query was applied to the titles and abstracts of the papers contained in each database; the query is the following:

```
(graph OR "interpretable models" OR visual OR visualization
    OR view OR diagram)
AND (("human traffic" OR "sex traffic") OR
    ("human trafficking" OR "sex trafficking") OR
    ("illicit activity" OR "criminal network"))
```

Our search query was divided into two parts. In the first part, we used the terms *"graph"*, *"interpretable models"*, *"visual"*, *"visualization"*, *"view"*, and *"diagram"* to ensure that papers describing visualizations were being returned from our query. In the second part, we used the terms *"human traffic"*, *"sex traffic"*, *"human trafficking"*, *"sex trafficking"*, *"illicit activity"*, and *"criminal network"* to ensure that all returned papers describing models and diagrams were related to the visualization of human trafficking networks.

We initially retrieved 519 papers using the search query described above. Based on our exclusion criteria, we conducted a title and abstract screening, where each paper was reviewed by two researchers, followed by a third reviewer in cases of disagreement. This screening yielded 85 papers. These were then subjected to full-text review, conducted by a single reviewer, resulting in a final set of 15 studies for analysis.

Fig. 1 shows our search and filtering process. The number of papers returned by search queries for different indexers is shown in Table 1. The complete list of filtered results is listed in Table 2. Once we narrowed down the relevant works to

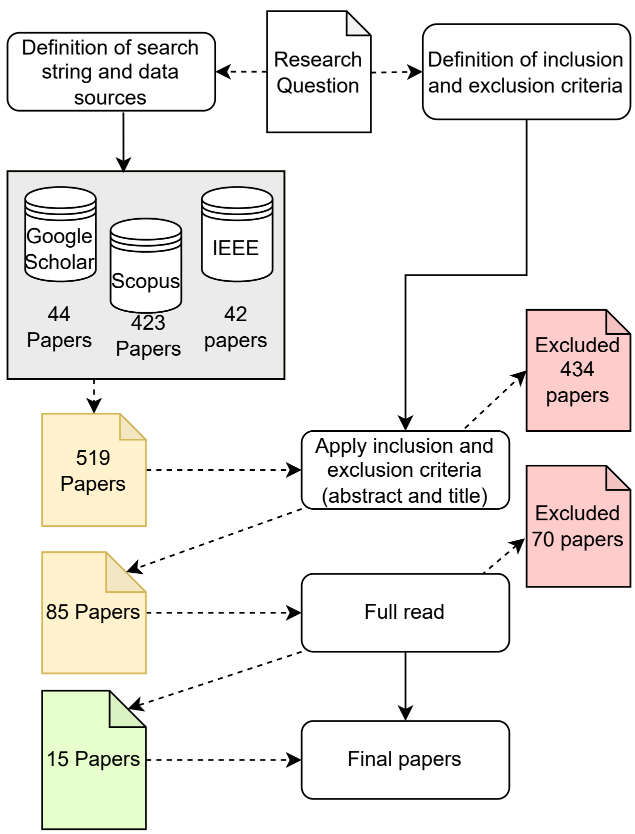

Fig. 1: The summary of the protocol followed during the search process.

Table 1: Search Query Results for Various Index Sites

Indexer	Search Results	Title and Abstract Filtered	Final Results
Scopus	423	62	14
Google Scholar	44	7	1
IEEE	52	16	0

Table 2: Final list of 15 primary studies identified by search process protocol.

Ref	Year	Title
[38]	2023	TRAFFICVIS: Visualizing Organized Activity and Spatio-Temporal Patterns for Detecting and Labeling Human Trafficking
[31]	2022	Analysis and Visualization Features in PEVNET
[26]	2022	VisPaD: Visualization & Pattern Discovery for Fighting Human Trafficking
[33]	2022	Human Trafficking Interdiction Problem: A Data Driven Approach to Modeling and Analysis
[29]	2021	Trafficking and Technology: Exploring the Role of Digital Communication Technologies in the Belgian Human Trafficking Business
[4]	2021	Integrated framework for criminal network extraction from Web
[7]	2021	Q -Rung Orthopair Fuzzy Matroids with Application to Human Trafficking
[11]	2021	Women trafficking networks: Structure and stages of women trafficking in five Dutch small-scale networks
[32]	2020	Generalized fuzzy graph connectivity parameters with application to human trafficking
[10]	2019	Understanding law enforcement strategies and needs for combating human trafficking
[21]	2019	Connectivity index of a fuzzy graph and its application to human trafficking
[20]	2019	Coupled clustering of time-series and networks
[36]	2015	Building and Using a Knowledge Graph to Combat Human Trafficking
[35]	2014	Data integration from open internet sources and network detection to combat underage sex trafficking
[39]	2012	Data integration from internet sources to combat sex trafficking of minors

15 papers, we studied them to discover different forms of human trafficking data, the ways they are visualized, and the tools that accomplish those visualizations.

3.4 Data Extraction and Analysis Procedures

We conducted a full-text review of each selected study to extract information relevant to our three research questions. Articles were assessed for alignment with RQ1 (types of data), RQ2 (visualization techniques), and RQ3 (tools or platforms), and were systematically coded accordingly.

To identify conceptual patterns and support consistent classification, we organized the extracted data along two primary axes: theoretical visualization models and implemented visualization tools. This distinction enabled us to distinguish between general visualization frameworks and practical software applications.

Through thematic clustering, we organized the findings into coherent categories. These insights were synthesized into structured sections in the results and discussion, focusing on coverage gaps and future research opportunities.

4 Results

This section presents the results of the mapping study, aligned with the three research questions in Section 3. Findings are organized by data types, visualization techniques, and tools, accompanied by a summary. Of the 519 papers identified, only a small subset met the relevance and accessibility criteria, reflecting the sensitive nature of trafficking data and the limited methodological diversity in law enforcement research. 15 papers were selected for analysis (see Table 2), supplemented by two tools evaluated through developer interviews.

4.1 RQ1: Types of Human Trafficking Data

Two main types of data are commonly used to support human trafficking visualizations. The first category comprises law enforcement and case records, which include incident reports, wiretap transcripts, and various official documents. These sources provide verified and well-documented information on trafficking operations. For example, Sen et al. [33] used incidence data from the Las Vegas Metropolitan Police Department to analyze traffickers' movement patterns and inform checkpoint placement strategies. Their analysis was limited to routes ending in Las Vegas, but they noted that incorporating data from other cities could support a more comprehensive reconstruction of the paths. Similarly, Diviák et al. [11] examined five trafficking cases involving women and extracted actor networks from wiretap transcripts, suspect and witness statements, and police reports. The researchers mapped relationships between individuals, such as facilitators and traffickers, by tracing their roles within the same cases.

The second category comprises web-scraped and media-based data, which are more readily accessible to researchers. These include escort advertisements, news articles, and public images. Afra et al. [4] compiled a set of 84 crime-related keywords to identify potential trafficking content across media sources. Their method achieved a 95% accuracy rate in identifying crime-related data, from which additional keywords and personal names were extracted for visualization. Deeb-Swihart et al. [10] applied a similar approach to analyze escort advertisements, utilizing both textual and image-based cues to detect suspicious postings. Silva et al. [35] detailed a scraping procedure targeting escort websites, including categorizing location-specific directories and conducting automated crawls multiple times daily using rotating IP addresses to avoid detection. Wang et al. [39] adopted a comparable approach, emphasizing that some advertisements are intentionally poorly formatted to appear more approachable or to evade automated detection systems.

Although law enforcement data are typically more detailed and reliable, they are often inaccessible due to legal and privacy restrictions. Consequently, researchers frequently rely on web-scraped data, which, while more accessible, present challenges related to quality, completeness, and standardization. As a result, researchers often tailor their visualization methods to the available data.

4.2 RQ2: Visualization Techniques for Human Trafficking Data

The selected studies apply diverse visualization methods, each aimed at analyzing different aspects of trafficking data. These techniques fall into several categories, including structural network visualization, geospatial mapping, temporal trend analysis, and cluster-based or stage-based representation.

Among these methods, graph-based visualization is the most prevalent, used to depict relationships among individuals by encoding entities as nodes and their interactions as edges. In these visualizations, entities such as traffickers or victims are represented as nodes, and their interactions, such as co-involvement in the same case or communication links, are shown as edges. Studies such as Diviák et al. [11], Afra et al. [4], and Deeb-Swihart et al. [10] use this approach to reconstruct criminal networks from structured records or web-scraped data. Some models go further by linking individuals to specific roles or tasks, enabling the identification of central figures and operational hierarchies.

In addition to structural representations, several studies incorporate spatial dimensions to capture geographic patterns in trafficking activity. Temporal and behavioral trends are explored using line charts, time-series plots, and clustering techniques, which help reveal peaks, recurring behaviors, and long-term shifts in trafficking activity [31,38]. Some studies further support forensic analysis by allowing users to trace these patterns back to individual ads or actors. Predictive visualizations have also been employed to estimate how trafficking activity may evolve in the near future [31].

Cluster-based or stage-based visualizations are also applied to uncover hidden patterns or operational phases. Liu et al. [20] integrate temporal and structural clustering to group actors with similar behavioral signatures. Diviák et al. [11] segment the trafficking process into distinct stages, recruitment, transport, and exploitation, allowing visual separation of roles and functions within the network.

A few studies also present conceptual models grounded in fuzzy logic and graph theory [7,21,32]. While not tested on real data, these frameworks suggest promising directions for future research.

4.3 RQ3: Visualization Tools

Through our literature research and a few personal interviews with experts, we discovered seven tools that utilize human trafficking data to construct graphs for analysis. Each tool is described below, followed by a comparison.

TRAFFICVIS: TRAFFICVIS [38] is designed to identify trafficking patterns in escort advertisements by combining metadata and clustering techniques. Implemented in Python, it enables both pattern detection and user-driven labeling. The system first applies text clustering to form micro-clusters of similar ads, then links them into higher-level meta-clusters using shared metadata [19].

Its interface includes five main panels that visualize spatial trends, posting timelines, and ad content:

1. **Micro-cluster**: Displays posting behavior of top-active ad clusters.
2. **Timeline**: Presents time series of posting frequency and location shifts.
3. **Map**: Illustrates geographic distribution of ads.
4. **Text**: Lists and compares ad text content within clusters.
5. **Labeling**: Enables classification of meta-clusters into predefined categories such as Trafficking, Scam, or Spam.

The system focuses on textual and metadata analysis; image data is not included. Expert evaluation confirmed the system's usability and labeling efficiency, with tasks typically completed within three minutes, faster than other tools. The tool is built with the Streamlit framework and is publicly available.

VisPaD: Developed by the creators of TRAFFICVIS, VisPaD [26] is a Python-based tool designed to analyze escort advertisement data with enhanced analytical features. It retains TRAFFICVIS's two-level clustering structure, but focuses on exploratory analytics and feature-driven comparison.

Alongside panels for viewing ad frequency, metadata trends, and geo-textual content, VisPaD introduces two additional modules for advanced cluster exploration. In addition to these, VisPaD introduces two advanced data exploration panels. The first panel reduces the high-dimensional cluster feature space to 2D using ICA [17], t-SNE [22], or UMAP [24], enabling visual comparison and label-based coloring. The second panel displays feature-level summaries and correlations, allowing users to explore variable distributions across selected clusters. The tool is built with Dash and Plotly and remains publicly available [25].

PEVNET: PEVNET [31] is a desktop-based visualization framework implemented in C# using the FLEX tool in Visual Studio.Net. Its key innovation lies in capturing temporal repetition in criminal behavior, an aspect often overlooked by traditional network tools. The system addresses this challenge by integrating multi-dimensional visual analytics to reveal structural and temporal patterns in complex criminal datasets. To support this, PEVNET offers the following:

1. **Network Visualization Features:** These include centrality detection, node customization, detail-on-demand overlays, cluster-based summaries, and inter-subnetwork detection.
2. **Temporal Visualization Features:** The system enables trend and temporal pattern analysis through calendar-based filtering and graphical overlays, helping analysts examine repeated behaviors and coordinated activity.
3. **Composite Features:** These support high-level structural abstraction through encircle, expand, and collapse functionalities, allowing sub-networks to be grouped or isolated for focused investigation.

The interface supports drag-and-drop editing, filtering, and layered views, enabling analysts to transition between detailed inspection and global pattern recognition. Analysts can customize calendar views to compare activity across timeframes or detect periods of overlap between different criminal entities.

PEVNET's feature set is further organized into three hierarchical levels, basic, prerequisite, and primary, based on their role in supporting investigative tasks. Primary features (e.g., sub-cluster detection, timeline overlays) are designed to provide core analytical value, while prerequisite and basic features ensure usability and flexibility. Although not publicly accessible, PEVNET is a robust tool for law enforcement handling complex, time-sensitive data.

i2 Analyst's Notebook: i2 Analyst's Notebook is a desktop platform widely used by investigators to visualize and analyze structured data in complex cases developed by IBM. It is extensively used in law enforcement, intelligence, military, and financial sectors for uncovering complex relationships, events, and patterns across large-scale networks. Given its wide deployment, the system allows analysts to construct association, temporal, spatial, statistical, and spreadsheet-based views, supporting multi-modal analysis of up to 50,000 entities. Users can define custom entities and relationships across more than 550 types, without adhering to a fixed schema. Structured data can be imported via CSV, Excel, or drag-and-drop interfaces using a visual import wizard.

Beyond the desktop client, i2 Online offers web-based integration with a wide range of external sources, including open platforms like Twitter and the Wayback Machine, as well as licensed datasets such as LexisNexis Accurint and Shadow Dragon, enabling IP tracing, dark web mining, and cross-platform entity resolution. Some important features include:

1. **Flexible Data Acquisition:** Supports diverse data types such as call logs, financial transactions, IP addresses, and forensic records. Data import is enabled via wizard-based tools or direct drag-and-drop, with extensibility for live database connections.
2. **Custom Data Modeling:** Empowers users to construct association and timeline charts tailored to investigative needs, with visual cues like link thickness, node coloring, and annotations.
3. **Multi-View Analysis:** Offers synchronized views, association, temporal, spatial, statistical, and augmented by integrated social network analysis capabilities for identifying key actors, clusters, and communication pathways.
4. **Briefing and Dissemination:** Facilitates creation of visual briefing charts, including redacted versions for varying security levels. Outputs are easily shareable via the free i2 Chart Reader, even with non-licensed users.

The i2 suite also integrates with specialized tools such as Fivecast [1] for behavioral profiling and TexChart [2] for NLP-based document analysis and entity extraction. A 30-day trial version is available, making it accessible for institutional evaluation and training use.

Other Tools: In addition to the tools discussed above, several other tools utilize human trafficking data for visualization. One such tool is Spotlight. Using machine learning and big data analytics, Thorn's Spotlight tool [3], developed in collaboration with law enforcement and technology companies, facilitates the identification of human trafficking victims. It helps law enforcement prioritize leads and has drastically shortened investigative timeframes by reviewing over 150,000 daily online escort ads. The success of Spotlight is demonstrated by the over 62,000 cases in which it was used to identify traffickers and victims.

Another visualization tool, Traffic Jam [5], created by Marinus Analytics, is designed to assist law enforcement organizations in combating human trafficking. It analyzes enormous volumes of data from internet advertisements using artificial intelligence, which includes facial recognition technology, to find possible victims of human trafficking. By facilitating faster and more efficient searches across millions of documents, Traffic Jam expedites the investigative process and significantly reduces the time required to identify victims. By offering a data-driven strategy to direct resources toward solving the most serious dangers of human trafficking, this technology represents an advancement in the fight against organized crime, human trafficking, and the search for missing persons.

Tool Comparison: The visualization tools reviewed above differ in their usability, analytical scope, technical architecture, and accessibility. Table 3 summarizes these differences. Below, we highlight the main comparative insights:

- **Usability:** TRAFFICVIS and VisPaD are designed for ease of use by non-technical users, featuring intuitive workflows and interfaces. In contrast, PEVNET and i2 Analyst's Notebook require greater manual input but offer advanced analytical capabilities that are better suited for experienced users.
- **Analytical and Visualization Scope:** TRAFFICVIS and VisPaD focus on clustering escort ads and visualizing spatial-temporal patterns. PEVNET and i2 Analyst's Notebook support broader functions, including multi-level network modeling, timeline overlays, and detection of criminal substructures.
- **Development Environment:** TRAFFICVIS and VisPaD are implemented in Python, enabling rapid customization and prototyping. PEVNET is developed in C#, which also allows for extensibility in academic settings. In contrast, i2 Analyst's Notebook is a proprietary system, which may restrict modification, integration, or open-source collaboration.
- **Adoption and Evaluation:** TRAFFICVIS has received positive expert feedback, particularly regarding its interface efficiency. i2 Analyst's Notebook is widely adopted in law enforcement and military sectors. Although formal evaluations of PEVNET and VisPaD are limited, both have been effectively applied in research contexts.

Overall, graph-based visualizations are the most consistently supported feature across tools. Only TRAFFICVIS and VisPaD offer full public access with integrated spatial, temporal, and clustering functionality. However, most tools have not been subjected to systematic usability testing or cross-tool benchmarking, indicating a clear gap for future empirical evaluation.

Table 3: Comparison of Tools Across Key Dimensions

Tool	**Data Source**	**Graph**	**Map**	**Time Series**	**Clustering**	**Public?**
TRAFFICVIS	Ads	✓	✓	✓	✓	Yes
VisPaD	Ads	✓	✓	✓	✓	Yes
PEVNET	Law records	✓	–	✓	Partial	No
i2 Analyst's NB	Mixed	✓	Partial	Partial	–	No
Spotlight	Ads	✓	–	–	Partial	No
Traffic Jam	Ads + Face	✓	–	–	Partial	No
TexChart	Text	✓	–	–	–	No

5 Discussion

This study reviews current visualization methods and tools for analyzing human trafficking networks, identifying several limitations that hinder their effectiveness in real-world applications. One persistent challenge is integrating diverse data sources. Law enforcement records offer accurate and structured information, but access is restricted due to legal and privacy concerns. On the other hand, web-scraped advertisement data are more readily available but often noisy and inconsistent. Without standardized frameworks for combining these heterogeneous sources, comprehensive analysis remains limited. Future research should explore privacy-preserving methods, such as federated learning or synthetic data generation, to support secure and responsible data sharing among stakeholders.

Another concern is the lack of systematic evaluation for existing tools. While systems such as TRAFFICVIS and i2 Analyst's Notebook are widely referenced, few have been tested using standardized benchmarks. Usability, scalability, and analytical effectiveness are seldom assessed in comparative studies. The development of open benchmarks and datasets would enable more rigorous evaluation and inform improvements in tool design.

There is also a noticeable disconnect between theory and application. Several papers propose novel frameworks based on fuzzy logic or graph theory, but these models are rarely implemented or validated with real-world data. Bridging this gap requires more emphasis on translating conceptual models into deployable systems and evaluating them in operational contexts.

In terms of visualization strategy, graph-based methods continue to dominate, but are often used in isolation. Temporal and spatial dimensions are underutilized, and few tools support multimodal integration of text, imagery, location, and time. Visualization platforms that combine these modalities within interactive interfaces could greatly enhance analytical depth and interpretability.

Finally, current tools often fail to accommodate the diverse roles and expertise of their users. While TRAFFICVIS and VisPaD focus on ease of use for non-specialists, and PEVNET and i2 Analyst's Notebook offer more advanced capabilities for trained investigators, few systems are adaptable across different user needs. Role-specific customization and modular interfaces could improve accessibility and impact across various domains, from policy analysis to investigative journalism.

In general, although progress has been made, the field would benefit from more robust data integration, standardized evaluation practices, practical validation of theoretical models, and more inclusive, user-centered design.

6 Threats to Validity

Following the framework by Wohlin et al. [42], we discuss four validity threats that may affect this study: construct, internal, external, and conclusion validity.

Construct Validity Construct validity examines whether the study reflects the intended concepts. To address this, we refined the search query iteratively with expert input to ensure relevance across key databases. Inclusion and exclusion criteria were applied consistently. To minimize the risk of missing relevant studies, we employed backward snowballing during the screening process.

Internal Validity Internal validity concerns potential biases during data extraction, particularly due to inconsistent terminology, incomplete reporting, or absence of relevant information in primary studies. Since Phase 4 of our SMS involves extracting nuanced and often implicit content, this stage is especially error-prone. To mitigate these risks, we cross-validated the extracted data against prior surveys and meta-analyses to ensure alignment with established classifications. Additionally, multiple researchers independently reviewed the qualitative synthesis to minimize subjective interpretation and to ensure that our summaries remain faithful to the original studies without introducing analytical bias.

External Validity This study focuses specifically on visualization tools used in human trafficking research. Therefore, the findings may not be generalizable to broader domains. Moreover, limitations inherent in the reviewed studies are carried into this synthesis, affecting its external applicability.

Conclusion Validity Conclusion validity concerns the accuracy and reproducibility of results. We mitigated this threat by including a larger set of primary studies than previous reviews, ensuring statistical robustness. Descriptive findings are based on multiple sources, reducing sensitivity to individual classification errors. The methodology is thoroughly documented to ensure reproducibility.

7 Conclusion

This study systematically maps existing visualization tools and methods used to investigate human trafficking networks. Through a structured review of 15 relevant studies, we examined how visualization techniques have been applied to reveal the structure and dynamics of trafficking activities.

While human trafficking generates extensive data, it remains difficult to visualize and interpret such information effectively. Researchers have explored various methods, including spatial mapping, temporal analysis, and graph-based network visualizations, to analyze the complex relationships embedded in trafficking operations. These tools are intended to support predictive modeling and guide law enforcement interventions.

We identified four major tools, TRAFFICVIS, VisPaD, PEVNET, and i2 Analyst's Notebook, that reflect different priorities and user bases. TRAFFICVIS and VisPaD emphasize accessibility and ease of use, catering to non-technical stakeholders, while PEVNET and i2 Analyst's Notebook provide more advanced analytical functionality for professional investigators. This variation underscores the need for role-specific interfaces and flexible interaction designs.

The review also highlights several gaps, including limited data integration, lack of standardized evaluation, and insufficient support for multimodal inputs or diverse user needs. Effective visual analytics depend on the availability and combination of data from disparate sources, such as law enforcement records, online advertisements, and social media, which are often siloed due to privacy and access constraints.

Our findings highlight the importance of visualization in understanding and combating human trafficking, while identifying key areas for future improvement. Advancing this field will require the development of better data-sharing frameworks, comparative evaluations of existing tools, and user-centered system design tailored to operational needs.

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