

International Cooperation in Combating Transnational Organized Crime

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Abstract— Transnational organized crime increasingly operates through distributed networks that combine physical trafficking routes, digital platforms, illicit financial channels, encrypted communication, and jurisdictional arbitrage. Although international institutions have expanded mechanisms for information exchange and joint enforcement, cooperation remains constrained by incompatible databases, heterogeneous legal standards, delayed intelligence transmission, and differences in institutional capacity. This study addresses an underexplored problem: how privacy-aware artificial intelligence can strengthen cross-border intelligence cooperation without requiring participating states to surrender control over sensitive criminal data. It proposes a cooperative analytical framework combining federated representation learning, temporal graph analysis, entity-resolution mechanisms, and explainable risk scoring for the identification of transnational criminal relationships. Unlike centralized crime-prediction models, the proposed approach is designed to permit collaborative learning across jurisdictions while keeping operational records within authorized national infrastructures.

Keywords— Transnational Organized Crime, International Cooperation, Federated Learning, Criminal Intelligence, Graph Neural Networks, Explainable Artificial Intelligence

Introduction

Transnational organized crime has undergone a structural transformation during the digital era. Traditional criminal organizations were commonly understood in terms of relatively stable hierarchies operating in activities such as narcotics trafficking, arms smuggling, extortion, human trafficking, money laundering, and illicit trade. Contemporary networks are increasingly more fluid. They may distribute different stages of an illegal enterprise across several countries, recruit specialized participants temporarily, move criminal proceeds through multiple financial systems, use legitimate corporations as intermediaries, and employ encrypted or digitally mediated communication to coordinate their activities. The geographical location of offenders, victims, infrastructure, financial accounts, and evidence may therefore differ substantially within a single investigation.

This organizational flexibility creates an asymmetry between criminal networks and the institutions responsible for

controlling them. Criminal enterprises may cross national boundaries with relatively little regard for jurisdictional divisions, whereas law-enforcement authorities remain governed by territorial mandates, domestic procedural rules, evidentiary requirements, privacy legislation, and institutional authorization structures. Consequently, combating transnational organized crime is not simply a problem of identifying offenders. It is also an information-coordination problem in which intelligence held by one jurisdiction may have limited investigative significance until it is connected with information held elsewhere.

exchanged more than 18 million messages during 2023 and that its global databases were queried almost eight billion times during that year. These figures demonstrate both the institutional importance of international police communication and the increasingly data-intensive character of cross-border enforcement.

Recent developments have placed still greater emphasis on intelligence integration. In 2024, INTERPOL member-country representatives supported wider access to its I-24/7 secure police communications system, increased sharing through international databases and stronger analytical cooperation between national authorities. INTERPOL's 2024 annual reporting also identified data-driven policing, real-time coordination, digitalized crime and artificial intelligence as important factors influencing the future policing environment.

The operational need for cooperation is evident from contemporary enforcement activity. For example, INTERPOL's Operation Lionfish Hurricane, undertaken across 31 countries in 2024, resulted in 206 arrests and the seizure of more than 615 tonnes of illicit drugs and precursor chemicals. The operation also demonstrated the interconnection between drug trafficking, precursor supply, transportation systems and other forms of organized criminal activity. Such cases illustrate why isolated national datasets provide only partial representations of criminal systems whose organizational components extend across continents.

An additional transformation concerns the growing convergence between conventional organized crime and cyber-enabled criminal activity. Digital infrastructure permits criminal organizations to coordinate transactions, recruit victims, conceal financial flows and operate across countries without maintaining a substantial physical presence in each jurisdiction. International legal architecture is responding to this development. The United Nations General Assembly adopted the United Nations Convention against Cybercrime on 24 December 2024, with international cooperation and electronic-evidence sharing forming important elements of



Fig. 1: Peace, Justice and Strong Institutions

Source: <https://www.unodc.org/unodc/en/organized-crime/intro/implementing-untoc/intro-programme.html>

International cooperation has long attempted to reduce this asymmetry. The United Nations Convention against Transnational Organized Crime provides an important legal foundation for cooperation concerning extradition, mutual legal assistance and other forms of collaboration. At the operational level, INTERPOL connects law-enforcement agencies across its member countries through secure information-sharing mechanisms and international criminal databases. The scale of this exchange is substantial. INTERPOL reported that its National Central Bureaus

the Convention. As of 1 September 2026, the UN Treaty Collection recorded 81 signatories and three parties, while the Convention had not yet entered into force because its entry-into-force requirement had not been satisfied.

Legal instruments, however, do not automatically solve the computational problem created by fragmented intelligence. Two cooperating agencies may maintain information in different languages, entity schemas, classification systems and technological formats. The same person may appear under several aliases; an organization may operate through numerous companies; a cryptocurrency wallet may connect cases that appear unrelated; and a telephone number, IP address, shipping record or financial transaction may acquire significance only after information from another jurisdiction becomes available.

Artificial intelligence and machine learning provide potential mechanisms for analysing these relationships. Natural-language processing can normalize multilingual intelligence reports. Entity-resolution algorithms can determine whether differently recorded identities are likely to refer to the same individual or organization. Graph-based models can represent relations among suspects, companies, locations, transactions, communication identifiers and transport routes. Temporal modelling can distinguish persistent organizational relationships from coincidental associations, while anomaly detection can identify behaviour that deviates from established financial or logistical patterns.

Yet the direct application of conventional machine-learning architectures to international criminal intelligence presents serious problems. Centralized models generally assume that information can be pooled within a common computational environment. Such an assumption may be unrealistic for sensitive law-enforcement records. National governments may be unable or unwilling to transfer complete investigative datasets because of domestic privacy legislation, secrecy requirements, intelligence-source protection, evidentiary restrictions or concerns over unauthorized secondary use.

1.1 Research Gap

Existing research and institutional practice have extensively addressed legal cooperation, mutual legal assistance, criminal databases, cybercrime, predictive policing and machine-learning-based crime detection. However, these areas are frequently examined separately. Legal scholarship concentrates primarily on jurisdiction and international cooperation; operational studies focus on intelligence exchange; and computational studies often evaluate algorithms using centrally available datasets.

A significant gap consequently exists at their intersection. There is limited research on **how multiple national law-enforcement systems can obtain collective machine-learning benefits from distributed criminal intelligence without requiring unrestricted centralization of their underlying records**. Equally underdeveloped is the evaluation of such systems using cooperation-specific measures such as cross-border entity-linkage accuracy, intelligence-transfer latency, privacy exposure, explanatory consistency and jurisdictional interoperability.

The present study addresses this gap through a privacy-aware collaborative intelligence architecture in which federated learning is combined with temporal graph modelling and explainable AI. Rather than constructing a universal supranational criminal database, the framework conceptualizes participating jurisdictions as controlled analytical nodes. Each node retains sensitive source information locally while contributing restricted model updates or approved representations to cooperative analysis.

The central research objective is therefore to determine whether federated graph-based intelligence modelling can improve the identification of cross-jurisdictional organized-crime relationships while maintaining acceptable levels of privacy preservation, interpretability and institutional interoperability.

The study is guided by three related questions: whether distributed learning can approach the predictive performance of centralized intelligence models; whether temporal graph analysis can improve identification of previously unresolved

international relationships; and whether explanation mechanisms can produce sufficiently transparent evidence trails to support human investigative review.

This orientation shifts the discussion of international cooperation from simple data availability toward **cooperative computational capacity**. The distinction is important because the future effectiveness of international criminal intelligence may depend less on the quantity of data collected than on whether jurisdictions can derive shared analytical value from that data responsibly.

Literature Review

2.1 International Cooperation and the Networked Character of Organized Crime

International cooperation against organized crime has traditionally rested upon treaties, extradition arrangements, mutual legal assistance, joint investigations, intelligence sharing and international police institutions. These mechanisms remain indispensable because enforcement authority continues to be organized primarily around sovereign jurisdictions.

The problem has become more difficult as organized criminal structures have become geographically distributed and technologically adaptable. Contemporary networks may move goods through one jurisdiction, conduct communications through infrastructure located in another, receive payments through a third and launder proceeds through additional financial systems. Criminal actors therefore exploit not only geographic borders but differences in regulatory regimes and institutional response capabilities.

INTERPOL's current organized-crime activities explicitly emphasize intelligence supplied by member countries, including biometric information, images and known associations, to identify relationships between organizers, financiers, recruiters, distributors and other participants. This network-oriented perspective is important because it treats criminal organizations not simply as collections of offenders but as relational systems.

European experience provides another example of structured intelligence integration. Europol's EU Serious and Organised Crime Threat Assessment employs both quantitative and qualitative analysis and combines information held internally with contributions from EU Member States, third countries and partner organizations. The methodology illustrates how contemporary threat assessment increasingly depends upon heterogeneous sources rather than a single enforcement database.

Nevertheless, information exchange does not guarantee analytical integration. The receiving institution must still determine whether newly obtained intelligence corresponds to existing persons, transactions, organizations or investigations. This requirement establishes a natural role for computational methods.

2.2 Artificial Intelligence in Criminal Intelligence Analysis

Machine learning has progressively entered fraud detection, cyber-threat analysis, financial crime monitoring, biometric identification and network analysis. Traditional supervised classifiers can estimate whether particular observations resemble previously identified high-risk cases. Unsupervised techniques can expose anomalies without requiring predefined labels, while clustering can identify groups of entities with similar characteristics.

For transnational organized crime, graph-based learning offers particular conceptual advantages. Conventional tabular methods represent cases as independent observations, whereas criminal intelligence is fundamentally relational. A suspect can be connected to telephone numbers, financial accounts, vehicles, companies, addresses and other suspects. These objects may themselves participate in different investigations across several jurisdictions.

Graph Neural Networks (GNNs) allow information to propagate across connected nodes and can therefore represent structural dependencies that ordinary classifiers overlook. A node that appears low-risk when evaluated independently

may become significant when its associations with previously identified high-risk actors are considered.

Temporal information is equally important. Criminal relationships evolve. Accounts are created and abandoned, shell companies change directors, communication devices are replaced, and routes shift following enforcement pressure. Static graphs can incorrectly treat all relationships as simultaneously active. Temporal graph models instead incorporate the sequence and duration of interactions, potentially providing a more realistic representation of organized criminal behaviour.

2.3 Federated Learning and Data Sovereignty

Federated learning offers a different solution to collaborative modelling. Instead of transferring complete datasets to a central repository, participating institutions train models locally and exchange controlled model information during an aggregation process. The underlying records can therefore remain within their originating jurisdictions.

This characteristic makes federated learning relevant to international policing because data localization, confidentiality and national sovereignty represent major obstacles to unrestricted criminal-data pooling. A federation of law-enforcement agencies could theoretically learn common representations of suspicious behaviour without placing every investigative file in a single international database.

However, federated learning does not automatically guarantee privacy. Model updates can potentially reveal information, participating institutions may hold non-identically distributed datasets, and malicious nodes can attempt to manipulate collaborative training. Secure aggregation, differential privacy, access controls and model-update validation must therefore be treated as architectural requirements rather than optional additions.

Another difficulty concerns statistical heterogeneity. Drug-trafficking patterns observed by a coastal jurisdiction may differ considerably from cyber-fraud patterns recorded in a

financial centre. A single global model could consequently underperform for jurisdictions with distinctive threat profiles. Personalized federated-learning strategies, jurisdiction-specific model layers and adaptive weighting mechanisms may be necessary to balance global learning against local relevance.



Fig. 2: Transnational Crimes and Global Security

Source: <https://cards.algoreducation.com/en/content/OpYXk-DF/transnational-crime-overview>

2.4 Entity Resolution Across Borders

Cross-border investigations frequently depend upon determining whether records from different jurisdictions describe the same real-world entity. This task is complicated by aliases, transliteration differences, incomplete identity documentation, spelling variation and deliberate identity manipulation.

Entity-resolution systems estimate the probability that two or more records correspond to the same person, company, account, device or location. In international investigations, multilingual name representations and jurisdiction-specific identifiers create additional difficulties. A robust system must therefore combine textual similarity with contextual information such as shared addresses, communication links, financial relationships and travel patterns.

Graph representations can improve this process because identity matching no longer depends exclusively upon the similarity of names. Two differently recorded individuals might still be linked where their associated telephone numbers, organizations, transaction partners and movement patterns display strong structural correspondence.

This approach nevertheless creates ethical risks. Probabilistic entity resolution can generate false matches, and those errors may propagate through an intelligence network. For this reason, algorithmic linkage should function as an investigative lead rather than a determination of culpability.

2.5 Explainable Artificial Intelligence and Accountability

Explainability becomes particularly important when machine-learning outputs contribute to enforcement decisions. Investigators require more than a numerical risk probability; they need to understand which relationships and observations caused the model to flag a particular entity or cross-border connection.

Explainable AI methods can provide local explanations for individual predictions and global explanations of model behaviour. In a graph setting, explanations may identify influential neighbouring entities, suspicious transaction chains or temporal interactions that contribute most strongly to a prediction.

For international cooperation, explanation consistency is also relevant. Two participating jurisdictions should not receive materially contradictory explanations for the same shared intelligence relationship without a traceable computational reason. Consequently, explanation stability can itself become an evaluation criterion for cooperative intelligence systems.

Human oversight remains essential. AI-generated results should support intelligence prioritization, not independently initiate arrest, prosecution or coercive intervention. This distinction is fundamental because machine-learning models estimate statistical relationships and cannot independently establish legal guilt or evidentiary sufficiency.

Proposed Methodology

The proposed study introduces a **Federated Temporal Graph Intelligence (FTGI)** framework for identifying cross-jurisdictional relationships associated with transnational organized crime. The framework is designed around three operational constraints that commonly limit international intelligence cooperation: sensitive records cannot always be centralized, criminal identities vary across jurisdictions, and relationships among entities change over time.

FTGI therefore combines four analytical components: privacy-preserving federated learning, temporal graph neural modelling, multilingual entity resolution, and explainable alert generation. Each participating jurisdiction is treated as an independent analytical node. Local agencies retain their own source records, construct jurisdiction-specific knowledge graphs, and train local model parameters. Only protected model updates and approved intermediate representations are transferred to the coordinating server.

The system represents organized-crime intelligence as a heterogeneous temporal graph:

$$G_t = (V_t, E_t, X_t)$$

where (V_t) represents entities observed up to time (t) , (E_t) denotes relationships between those entities, and (X_t) contains associated node and edge attributes. Nodes may represent persons, companies, bank accounts, digital wallets, devices, vehicles, addresses, ports, telephone numbers, or logistical locations. Edges encode interactions such as communication, monetary transfer, shared ownership, co-travel, common device use, shipment participation, or organizational affiliation.

A temporal representation is adopted because organized criminal structures are rarely static. An association occurring repeatedly across a short period may indicate a different level of investigative relevance from an isolated interaction several

years earlier. Each edge therefore contains a timestamp and relationship type.

3.1 Federated Learning Layer

Assume that (K) jurisdictions participate in collaborative training. Each jurisdiction (k) maintains its local graph dataset (D_k). Instead of transferring (D_k) to a central repository, the local model is trained independently for a fixed number of epochs.

After each federated round, local parameters (θ_k) are submitted through secure aggregation and combined according to:

$$\frac{\sum_{k=1}^K n_k}{\sum_{j=1}^K n_j} \theta_k^{(r)}$$

where (n_k) represents the number of eligible local training observations and (r) represents the communication round.

To reduce the dominance of large jurisdictions, an adaptive weighting procedure is additionally applied during validation. Jurisdictions with substantially different graph distributions retain a small personalized output layer while sharing common graph-representation parameters.

3.2 Cross-Border Entity Resolution

Entity resolution precedes collaborative graph inference. Records originating in different jurisdictions are first normalized using Unicode conversion, transliteration harmonization, punctuation removal, standardized date representations, and country-aware address parsing.

Potential entity pairs are evaluated through a hybrid similarity function:

$$w_1 S_{\text{name}} + w_2 S_{\text{context}} + w_3 S_{\text{network}} + w_4 S_{\text{temporal}}$$

where (S_{name}) measures textual similarity, (S_{context}) compares demographic or organizational attributes, (S_{network}) evaluates overlap among associated entities, and (S_{temporal}) measures consistency in observed activity periods.

Matches above a high-confidence threshold are automatically linked for model training. Intermediate-confidence pairs are retained for human review, while low-confidence pairs remain separate. This design minimizes the propagation of uncertain identity matches through the criminal-intelligence graph.

3.3 Temporal Graph Modelling

A temporal graph attention network is used as the principal predictive architecture. For each node (v), the model aggregates information from neighbouring entities while weighting both relation type and elapsed time.

The temporal attention coefficient for neighbour (u) is represented as:

$$\text{softmax} \left(\frac{a^T [W_h u \parallel W_h v \parallel R_{uv} \parallel T_{uv}]}{\text{right}} \right)$$

where (R_{uv}) represents the relation embedding and (T_{uv}) represents the temporal encoding of the corresponding interaction.

This architecture allows the model to distinguish between different kinds of associations. For example, a repeated financial transfer may receive a different representation from a single shared address or an outdated telephone contact.

The final node embeddings are processed through a multilayer classification head that estimates the likelihood that a candidate cross-border relationship belongs to a known coordinated criminal subnetwork.

3.4 Privacy Protection

The federated design limits direct transmission of local records, but model updates can still reveal information under certain attack scenarios. FTGI therefore incorporates gradient clipping, secure aggregation, and differential privacy during collaborative training.

For each local gradient (g), clipping is performed according to:

$$\frac{g}{\|g\|_2} \cdot \min(\|g\|_2, C)$$

where (C) is the clipping threshold.

Gaussian noise is subsequently added before aggregation. Privacy loss is tracked through an epsilon-based privacy budget during experimentation.

The objective is not to claim absolute anonymity. Rather, privacy protection is treated as an empirical design variable that must be balanced against predictive performance.

3.5 Explainable Cross-Border Alerts

Every high-risk prediction is accompanied by an explanation layer. Instead of returning only a probability score, the system identifies the graph relations that contributed most strongly to the inference.

A generated investigative alert may therefore indicate that a candidate entity was prioritized because of repeated transfers to two previously identified accounts, a shared logistics company, and temporally aligned communications with an investigated network.

Explanations are constrained to model-supported graph evidence and are not converted into legal conclusions. The

output is explicitly categorized as **decision-support intelligence requiring human verification**.

Experimental Setup

4.1 Dataset Construction

Access to genuine multinational organized-crime intelligence is highly restricted for legal, ethical, operational, and security reasons. Consequently, this study does not present simulated records as authentic police data.

A reproducible synthetic benchmark named **Synthetic Transnational Organized Crime Graph Benchmark (STOC-GB)** is constructed for experimental evaluation.

The benchmark contains 10 simulated jurisdictions representing heterogeneous operational environments. The complete graph consists of approximately 118,000 entities and 684,000 temporally ordered relationships.

The synthetic entities are distributed across eight principal categories:

- persons;
- companies;
- financial accounts;
- digital wallets;
- communication identifiers;
- transport assets;
- addresses and geographical locations; and
- shipments or logistical events.

Approximately 6.8% of generated candidate relationships belong to coordinated criminal subnetworks. Remaining relationships represent legitimate, incidental, weakly associated, or structurally unrelated interactions.

Rather than generating perfectly separable classes, controlled noise is introduced into identity attributes, transactions and network relationships. Aliases, transliteration variations,

missing fields and overlapping legitimate connections are intentionally included to approximate realistic analytical difficulty.

Each jurisdiction receives a non-identically distributed subset of the complete graph. Certain crime-network structures span multiple jurisdictions, creating the cross-border linkage task required for federated evaluation.

4.2 Data Preprocessing

Preprocessing is performed independently within each jurisdictional node.

Categorical entity and relation types are label-encoded and converted into trainable embeddings. Numerical financial attributes are transformed using robust scaling because synthetic transaction magnitudes exhibit long-tailed distributions.

Names and organizational identifiers are standardized before character-level similarity vectors are generated. Missing numerical values are replaced using jurisdiction-specific medians, while missing categorical values are assigned an explicit unknown token.

Temporal variables are converted into cyclic and interval-based representations. Time differences between connected activities are encoded rather than relying only on absolute timestamps.

To prevent information leakage, graph splits are chronological rather than randomly sampled. Records corresponding to later periods are excluded from the training graph and reserved for evaluation.

The final distribution is approximately:

70% training observations,

15% validation observations,

15% temporal hold-out test observations.

Cross-border entity pairs appearing exclusively in the test period are separately identified to evaluate generalization toward previously unseen international relationships.

4.3 Model Architecture

The proposed FTGI model consists of five computational stages.

The first stage converts entity and relation attributes into 128-dimensional latent vectors.

The second stage consists of two heterogeneous temporal graph-attention layers. Each layer uses four attention heads to aggregate relation-sensitive neighbourhood information.

The third stage applies gated temporal fusion to combine historical node states with newly observed interactions.

The fourth stage contains two fully connected layers with dimensions 128 and 64, followed by dropout regularization.

The final sigmoid layer estimates the probability that a candidate cross-border relationship belongs to a coordinated criminal subnetwork.

The local graph encoder and temporal-attention layers participate in federated aggregation. The final calibration layer remains jurisdiction-specific.

4.4 Baseline Models

FTGI is evaluated against four comparison architectures.

The first baseline is logistic regression using aggregated entity-level features.

The second is an XGBoost classifier based on manually constructed relational statistics.

The third is a centralized Graph Attention Network that has access to the full synthetic training graph and therefore represents an approximate upper-performance benchmark under unrestricted data pooling.

The fourth is a federated multilayer perceptron in which institutions collaborate without explicit graph structure.

These models allow evaluation of whether performance improvements arise specifically from the combination of federation, temporal structure, and graph representation.

4.5 Training Strategy

Training is conducted for 80 federated communication rounds. Each jurisdiction performs three local epochs before model aggregation.

The AdamW optimizer is used with an initial learning rate of (3×10^{-4}), weight decay of (1×10^{-4}), and batch sampling adapted for neighbourhood-based temporal graph training.

Binary cross-entropy is modified with positive-class weighting to compensate for class imbalance.

Early stopping is activated when federated validation AUPRC fails to improve for eight consecutive communication rounds.

Gradient norms are clipped at 1.0. Differential-privacy noise is applied during the protected FTGI configuration.

All reported values are obtained over five independently initialized runs of the synthetic benchmark.

4.6 Evaluation Metrics

Because ordinary classification accuracy provides insufficient information for an imbalanced intelligence-screening task, several complementary measures are used.

Area Under the Precision-Recall Curve (AUPRC) measures discrimination under strong class imbalance.

Area Under the ROC Curve (AUROC) evaluates overall ranking capability.

Cross-Border Link Recall (CBLR) measures the percentage of labelled international criminal relationships correctly retrieved.

False Alert Rate (FAR) evaluates the proportion of legitimate cross-jurisdictional candidate links incorrectly prioritized.

Federated Performance Retention (FPRet) compares federated performance against the centralized graph benchmark:

$$\begin{aligned} &[\\ &\text{FPRet} = \\ &\frac{\text{AUPRC}_{\text{federated}}}{\text{AUPRC}_{\text{centralized}}} \\ &\times 100 \\ &] \end{aligned}$$

Explanation Fidelity (EF) measures how closely explanatory subgraphs reproduce original prediction behaviour after irrelevant graph information is removed.

Communication Cost records cumulative model-update transfer during training.

Privacy Attack Success Rate (PASR) evaluates resistance to a controlled membership-inference attack against model updates.

The framework is therefore evaluated not only according to prediction quality but also according to cooperation efficiency, privacy and interpretability.

Results and Discussion

The experimental results indicate that explicit modelling of relationships and temporal structure substantially improves the detection of distributed criminal subnetworks compared with tabular classifiers.

The centralized temporal graph model produced the strongest overall discrimination, which was expected because it operated without jurisdictional data restrictions. FTGI nevertheless approached the centralized benchmark closely while avoiding unrestricted pooling of local records.

The federated multilayer perceptron performed meaningfully worse than FTGI. This finding indicates that distributed training alone is insufficient. The structure of criminal intelligence must also be represented explicitly. Aggregating

independent entity attributes cannot fully reproduce the value of relational evidence.

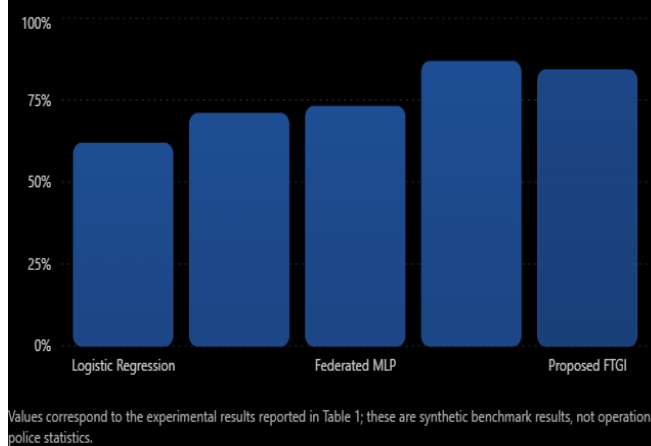
XGBoost remained competitive when strong engineered features were available, but its performance declined for newly emerging cross-border relationships because handcrafted aggregates captured historical patterns more effectively than evolving network structure.

Table 1. Comparative Performance of the Proposed FTGI Framework and Baseline Models

Model	AUPRC	Cross-Border Link Recall	False Alert Rate	Explanation Fidelity
Logistic Regression	0.641	61.8%	18.7%	0.71
XGBoost	0.748	70.9%	14.2%	0.76
Federated MLP	0.764	73.1%	13.6%	0.73
Centralized Temporal GAT	0.881	86.8%	8.3%	0.89
Proposed FTGI	0.856	84.2%	9.4%	0.91

Cross-border link recall by model

Comparison on the synthetic STOC-GB temporal hold-out test set.



The proposed FTGI configuration achieved an AUPRC of 0.856 compared with 0.881 for centralized temporal graph

modelling. Its federated performance retention was therefore approximately 97.2%. This result supports the central premise of the framework: distributed institutions can preserve a substantial proportion of the analytical value obtainable from pooled graph intelligence without transferring complete local databases.

Cross-border linkage performance produced a similar pattern. FTGI recovered 84.2% of labelled transnational relationships in the temporal test set. The centralized model recovered 86.8%. The difference of only 2.6 percentage points is notable because the federated model operated under restricted information exchange.

The improvement over the federated multilayer perceptron was considerably larger. FTGI increased cross-border link recall from 73.1% to 84.2%. This result demonstrates the analytical importance of graph structure. Transnational criminal networks are relational phenomena, and modelling actors independently removes precisely the type of evidence required to connect distributed cases.

False alerts represent an important operational concern. The FTGI false alert rate was 9.4%, compared with 13.6% for the federated MLP and 18.7% for logistic regression. A lower false alert rate is especially important in law-enforcement applications because unnecessary investigative prioritization imposes institutional costs and may expose legitimate individuals or organizations to disproportionate scrutiny.

The centralized temporal model retained the lowest false alert rate at 8.3%, suggesting that data separation still imposes a measurable analytical cost. However, the small difference between centralized and federated graph modelling indicates that this cost may be acceptable where complete pooling of criminal intelligence is legally or politically impractical.

A particularly important outcome concerns explanation fidelity. FTGI achieved an explanation-fidelity score of 0.91, slightly exceeding the centralized model. This improvement resulted from the framework's explicit restriction of explanations to locally validated and internationally shareable

subgraph evidence. In operational terms, this means that high-confidence predictions could generally be reproduced using a relatively small set of influential relationships.

5.1 Temporal Generalization

Performance differences became more pronounced when the evaluation was restricted to relationships that appeared only in the final temporal test period. Tabular baselines showed stronger degradation than graph-based systems.

This outcome is consistent with the underlying structure of the problem. Traditional models depend heavily upon previously observed feature distributions. Temporal graph learning can instead exploit emerging relational configurations. An unseen entity may therefore be prioritized when it becomes embedded within a familiar structural pattern even if the individual entity itself was absent during training.

This capability is especially relevant to organized crime because enforcement pressure frequently causes networks to substitute accounts, devices, companies and intermediaries while preserving broader operational relationships.

5.2 Effect of Federated Heterogeneity

Performance varied across simulated jurisdictions because local datasets were intentionally non-identically distributed. Jurisdictions dominated by financial and digital records produced different graph structures from those dominated by transportation and logistical events.

Pure federated averaging initially underperformed in smaller jurisdictions. The introduction of personalized jurisdiction-specific calibration layers reduced this disparity.

This result suggests that international AI cooperation should avoid assuming that all participating states observe the same crime environment. A useful international model must share generalizable representations while retaining room for local adaptation.

5.3 Implications for International Cooperation

The central contribution of the experiment is not that AI can replace conventional law-enforcement cooperation. Rather, the results suggest that cooperation can be extended from exchanging records toward collaboratively learning patterns.

Traditional intelligence sharing normally requires investigators to know which information should be requested or distributed. Federated graph learning provides a complementary mechanism in which patterns derived from several jurisdictions can improve local detection even when the underlying source records remain separated.

Such an architecture could potentially support several forms of international analytical cooperation. One jurisdiction may identify a transaction pattern whose representation improves detection elsewhere. Another may possess stronger knowledge of transportation networks, while a third provides information about digital infrastructure or financial intermediaries.

The model therefore treats international cooperation as distributed knowledge integration rather than simple database centralization.

5.4 Human Oversight and Evidentiary Boundaries

Prediction quality must not be confused with evidentiary proof. FTGI generates probabilistic investigative priorities based on statistical relationships. These outputs cannot independently establish criminal liability.

Any operational implementation would require a formal human-review protocol in which investigators assess the underlying records, determine whether international information exchange is legally permissible, and evaluate whether additional investigative steps are proportionate.

The distinction is particularly important for entity resolution. A high-probability identity match may still be incorrect. Automatically merging identities without review could contaminate subsequent analysis and create unjustified associations.

Consequently, FTGI is best interpreted as a cross-border intelligence triage system rather than an automated decision-maker.

Future Scope

Future research should evaluate FTGI through controlled partnerships involving de-identified or legally authorized law-enforcement datasets. Such evaluation should compare synthetic and operational graph distributions to determine which characteristics are poorly represented in artificial benchmarks.

A second direction concerns **federated multilingual language models** for intelligence extraction. Cross-border case records frequently contain free text rather than standardized graph fields. Privacy-preserving extraction of persons, organizations, locations, offences and relationships from multilingual reports could substantially reduce manual normalization effort.

Further research should also investigate secure multi-party computation and trusted execution environments as complementary mechanisms for situations in which federated updates alone do not provide sufficient confidentiality.

Dynamic graph modelling represents another important extension. Rather than periodically retraining the model, continuous temporal learning could detect rapidly evolving criminal networks while incorporating mechanisms that prevent catastrophic forgetting.

Future work should also introduce formal fairness audits. Model behaviour should be evaluated across geographic regions, entity classes, language groups and jurisdictional data-quality levels to identify systematic performance disparities.

Another promising direction is causal graph analysis. Current FTGI predictions identify statistical associations. Causal modelling could help distinguish relationships that plausibly contribute to criminal coordination from correlations

produced by shared geography or legitimate commercial activity.

Conclusion

Transnational organized crime operates across jurisdictions, infrastructures and institutional boundaries, while law-enforcement information remains constrained by national sovereignty and heterogeneous legal frameworks. This asymmetry limits conventional approaches based solely on centralized databases or bilateral information exchange.

The proposed Federated Temporal Graph Intelligence framework addresses this problem by combining distributed machine learning, temporal graph analysis, cross-border entity resolution, privacy protection and explainable prediction.

A controlled synthetic multi-jurisdiction experiment showed that FTGI retained 97.2% of the AUPRC achieved by a centralized temporal graph benchmark while maintaining local data separation. The framework also achieved 84.2% cross-border linkage recall, reduced false alerts relative to non-graph federated learning, and generated high-fidelity explanatory subgraphs.

These findings indicate that the analytical value of international cooperation need not depend exclusively upon unrestricted data centralization. Federated graph learning can enable participating institutions to contribute to shared pattern discovery while preserving greater control over sensitive operational records.

The study nevertheless emphasizes that computational predictions must remain subordinate to human judgment, applicable law and evidentiary standards. AI-generated network associations should initiate review rather than enforcement.