Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-025-09613-x

ORIGINAL PAPER

Opportunistic Organization of Illicit Supply Chains

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Accepted: 16 May 2025

Abstract

Objective This article aims to propose and utilize an agent-based model to understand how opportunistic behavior in criminal groups contributes to the adaptive capacity of illicit supply chains. These efforts aim to better understand empirical studies, such as drug trafficking networks, that exhibit patterns of resilience and replacement after enforcement actions.

Methods Strategic decisions are modeled dyadic and group contexts using an agent-based approach. To differentiate social relationships, transactions, and activities. Various simulations with different parameters were conducted to analyze the structural, functional, and temporal dependencies of the network.

Results Simulation results point group interactions significantly boost the adaptive capacity of illicit supply chains only when interaction frequency is high, whereas dyadic interactions are more effective for decentralized optimization. Risk-tolerant agents enhance network effectiveness, and low-visibility brokers are crucial for resilience. Lead-based interventions targeting connections of removed agents are more disruptive in low-interaction order networks, while random interventions are less effective in highly connected networks.

Conclusion The emergence of low-visibility brokers urges to better understand the behavior of the illicit organization before deploying specific law enforcement interventions. Simulation offers further insight in how to consider both structural properties and temporal dynamics when designing effective intervention strategies.

Keywords Simulation · Game theory · Criminal networks · Illicit supply chains · Organised crime

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Published online: 06 June 2025

Introduction

Illicit markets accommodate the trade of illicit commodities such as drugs and weapons or facilitate illicit services like assassination. These markets are populated not only by long-standing criminal enterprises but also by a wide array of smaller, flexible groups that operate in a more decentralized and adaptive fashion. In this paper, we focus on these opportunistic groups, to describe ad hoc, self-organizing collectives that emerge in response to specific opportunities in illicit markets, without a durable hierarchical structure or institutional continuity. These groups often lack the organizational history or deeply entrenched reputations characteristic of mafia-style syndicates, yet they still function effectively by leveraging local trust networks, situational reputation, and mutual contacts to facilitate transactions and reduce uncertainty (Bouchard and Morselli 2014). While reputation and long-term relationships are indeed central to many forms of illicit enterprise, empirical research has also documented the rise of more fluid, cell-like structures within illicit networks, particularly in environments where enforcement pressures, digital communicatConclusionion, and market volatility favor agility over permanence (Kenney 2007). These "opportunistic" actors do not operate in isolation; instead, they are embedded in broader social and transactional networks that enable the coordination of complex activities like trafficking and distribution. Their ability to form temporary collaborations and adapt to changing conditions contributes significantly to the resilience and regenerative capacity of illicit supply chains (Grund and Morselli 2017; van Elteren et al. 2024).

These dynamics creates an overlap of different types of markets (Grund and Morselli 2017; Vermeulen et al. 2021). The opportunistic character of illicit markets is visible in the manner that criminal organizations tend to work together when supply chains overlap (Coutinho et al. 2020). Prior empirical work, such as Bright and Delaney (2013), has shown that drug trafficking networks evolve dynamically in response to enforcement pressure, often reconfiguring roles and links to maintain operational capacity. These findings support the conceptualization of illicit markets as complex adaptive systems. Further, Bright et al. (2019) demonstrate that networks adapt structurally through triadic closure and strategic recruitment, reinforcing the importance of modeling replacement and adaptation mechanisms.

The network analysis approach has led to a plethora of new insights into illicit markets (Catanese et al. 2016), for example, by analyzing them as illicit supply chain networks. However, analyzing complex phenomena requires incorporating the different types of dependencies that originate from the interactions of the observed system (Torres et al. 2021; Battiston et al. 2021). These dependencies can be considered on a temporal or spatial dimension. Additionally, interaction can occur at various levels of the system. Whereas interactions between individuals are described as dyadic interactions, interactions between groups of individuals are described as higher-order interactions (Battiston et al. 2021).

In this study, we aim to understand how opportunistic behavior yields the adaptive capacity of collective organization in illicit supply chains. We propose a model that incorporates the necessary dimensions to represent a generalization of the dependencies in illicit supply chains and models different organizational dynamics that enable individuals to share information and subsequently make strategic decisions. With this model, we aim to grasp how opportunistic behavior is affected by the intertwining of social, financial, and functional relationships over time, and why specific intervention strategies are more effective in certain scenarios. For this purpose, our model includes relationships between individuals, distinguishing individual interactions from group interactions, and incorporates temporal and structural dependencies that affect the behavior of the system as a whole. This is specifically of interest when testing prevailing hypotheses that focus on the importance of individual characteristics such as social capital (relationships and networks) or human capital (knowledge and skills). Additionally, it enables the formalization of new hypotheses on the resilience of illicit supply chains, such as the impact of agents with different behavior types or the impact of group interaction compared to dyadic interaction on the whole system's behavior. Second, our model enables scenario testing. Scenarios allow the analysis of variations in network characteristics (Vázquez 2003), behavioral theories (Schlüter et al. 2017), or specific characteristics of illicit supply chains and their effect on the adaptive capacity of the system. This enables us to compare the emergent behavior of the model with prevailing knowledge on the emerging structures of illicit supply chains, such as the importance of low-visibility brokers or resource brokers. Lastly, we specifically aim to model the behavior of the system from the perspective of the individual, as we focus on the opportunistic behavior of agents. This means that individuals are only able to communicate and interact with their neighbors and are not able to optimize their behavior based on information beyond these interactions. With this approach, we incorporate the context of secrecy in illicit supply chain networks.

This paper makes several contributions to the field. We propose a new approach to analyze the embeddedness of illicit organizations in a social context, extending the work on multiplex networks (Calderoni et al. 2022; Grund and Morselli 2017), by distinguishing both individuals and groups. Our model addresses several aspects that characterize the emergent behavior of illicit organizations, such as functional and structural adaptation, resource flows, and social and human capital in organizations (van der Zwet et al. 2022). We provide a framework to describe temporal, spatial, and other dependencies that describe the development of illicit organizations of supply chains over time. In our approach, similar to other network-based approaches (Manzi and Calderoni 2024), we make the common distinction between different roles in illicit organizations. Finally, in contrast to most network-based approaches, it provides the ability to analyze different types of individual behavior, such as differences in risk perception between individuals related to their actions. It also supports the evaluation of the agents' positions in the market, enables the analysis of differences in adaptation behavior, such as imitation, optimization, or reputation-based behavior changes, or group dynamics.

The remainder of the paper is structured as follows. The next section provides an overview of related literature. Section "An Agent-based Model of Opportunistic Organisation of Illicit Supply Chains" describes the proposed modeling approach. Section "Simulation Analysis" provides the design of the simulations and systematic analysis. In Section "Results", computational results are presented, and concluding remarks are drawn in Section "Conclusion".

Network Theory for Illicit Supply Chains

Network analysis has emerged as the focal quantitative method for analyzing illicit supply chains quite naturally, as these supply chains are organized through communication interactions and transactions (Anzoom et al. 2021). This approach has been adopted extensively to analyze different forms of illicit organization (Bichler et al. 2017; Zech and Gabbay 2016). Research focuses predominantly on identifying key persons and network vulnerabilities to improve intervention and disruption strategies. However, illicit organizations have proven to be rather resilient to interventions (Agreste et al. 2016). For example, disruption through the elimination of leaders or the random removal of individuals has proven to be rather inefficient, as illicit networks have effective adaptation strategies (Duijn et al. 2014). The adaptations of illicit networks can be differentiated between structural and functional changes (O'Reilly et al. 2020). Structural changes occur as networks change their organizational structure of communication. These changes impact the efficiency of the illicit supply chain in terms of planning and transaction possibilities, consequently affecting their robustness. Functional changes are facilitated by dynamics such as introducing individuals with new roles or a fundamental operational shift to another illicit supply chain. The functional adaptation capacity in illicit organizations is closely related to the theory of specialists and generalists (Grund and Morselli 2017; Spapens 2017). Recently, various modeling perspectives have emerged to analyze the structure, vulnerability, and dynamics of illicit supply chains (Anzoom et al. 2021).

Social Network Analysis

One application of social network analysis is the reconstruction of the structure of illicit organizations and the connections among individuals based on empirical data (Duijn and Klerks 2014). In these networks, vertices and edges represent, respectively, the individuals and their relationships. Metrics such as degree centrality, mean degree, and degree centralization are used to analyze these relationships (Armstrong et al. 2013).

Social network analysis metrics are predominantly used to identify leaders or key individuals, explain clustering patterns based on similar roles, background, and ideology (Agreste et al. 2016). The role of individuals in an illicit supply chain provides a link between social networks and the illicit supply chain activities, which can be described by the associated crime-scripting (Bright and Delaney 2013). Morselli and Roy (2008) applied crime script analysis to study the transactions in the criminal market of stolen cars. This resulted in a described process of theft, concealment, disguise, marketing, and finally disposal to the customer, which are the sequential steps of criminal activity. They combined this analysis with social network analysis to assess how criminals organize themselves to align these activities. With this methodology, they aimed to detect key brokers in the criminal network using centrality metrics. The removal of these key players would have the highest disruptive effect on the organizational efficiency of the criminal groups. Bright and Delaney (2013) applied a similar methodology to analyze the evolution of a criminal drug network with a temporal dataset. They analyzed the structure and function of the network and found evidence for the flexibility and adaptivity through organizational mechanisms. As the illicit supply chain network grew and increased their production, they were able to cope with police actions by shifting their manufacturing operations to secure places. Additionally, the flexible nature of the organizational structure was demonstrated as new recruits were introduced to support the logistical activities, or people changed their roles to accommodate a shortage in manufacturing capacity.

Dynamic Network Analysis

To analyze the dynamics of illicit organizations specifically, Carley et al. (2003) introduced dynamic network analysis. Dynamic network analysis can be used to study replacement mechanisms in criminal networks (Duijn 2016). In the case of Dutch cannabis production, distribution, and selling processes, it was demonstrated that individuals with specific skills are more pivotal than individuals with a central position in ensuring the resilience capacity of the network. As the criminal network can replace central leaders subject to disruption efforts, the network secures an even more efficient coordination structure. The illicit supply chain was described as a “value chain” as each individual and transaction adds value by adding information, goods, or quality to the final product. Other approaches focus more specifically on the flow of illicit goods through the illicit organizational structure. These studies aim to identify strategies that minimize the potential flow of illicit goods from origin to destination (Jabarzare et al. 2020; Mirzaei et al. 2021).

Agent-based Modelling

Modeling the activities, interactions, and adaptations from the perspective of individual criminal actors has provided a new dimension of analysis. In this context, agent-based modeling has been introduced as a new method to analyze how illicit organizational structures emerge from bottom-up dynamics (van der Zwet et al. 2022). This approach enables the analysis of adaptive dynamics that facilitate the flow of illicit goods from a source to a sink (Magliocca et al. 2019). Additionally, agent-based modeling allows for combining computational methods with complex illicit behavior modeling (McBride et al. 2016) and network analysis methods such as multilevel networks (Calderoni et al. 2022).

An Agent-based Model of Opportunistic Organisation of Illicit Supply Chains

In this section, we develop a theoretical model for analyzing the opportunistic organization of illicit supply chains. The model builds on existing social network theory and rational choice theory, linking various micro-level processes to illicit organizations. It combines different modeling approaches in a novel manner to better address the challenges of grasping the dynamics of the opportunistic organization of illicit supply chains. The model illustrates how the emergence of illicit organization can be explained by a combination of individual and group-level interactions. The model is described using the overview, design concepts, and details (ODD) protocol for documenting social simulation models (Grimm et al. 2017). First, we explain the purpose, entities, and processes in the model. Second, we explain the concepts of the model at a system level. Finally, we document the initialization and inputs for the experiments.

Model Purpose

The model's purpose is to study the resilience illicit supply chain when random or specific actions taken against the network by law enforcement. The idea behind the model is that individuals act in self-interest and create value by rationally optimizing their activities and transactions within illicit supply chains. For this optimization, individuals interact with each other to share information about their potential to carry out transactions based on the activities of their neighbors. Under the assumption of rationality and self-interest, we model the interactions as a network formation game. The decentralized, adaptive, and self-interest-focused behavior of the agents assumes opportunistic-oriented behavior in illicit environments. As law enforcement agencies focus on intercepting communication and transactions and can design their interventions based on these intercepted interactions, individuals in our model can limit the number of interactions to reduce the chance of being intercepted. This characterizes the necessity for efficiency and secrecy in illicit environments, which forces individuals to only establish the most effective transactions or limit the entire number of transactions.

Entities, State Variables, and Scales

The model includes two types of entities: individuals and activities. Individuals are the agents that update their status at each time step. We consider a population of N agents. These agents are characterized by a risk parameter R_i that influences their risk-averse behavior, which is explained in Section "Risk Averse Behavior". The agents are connected into a set of groups G. Each group $g \in G$ is a subset of two or more agents and represents a stable relationship between the agents that enables (group) interaction (e.g., an encrypted group chat). We assume that interactions are undirected, which means the connection matrix is symmetric.

Next, we consider a set of X activities that form a set of S illicit supply chains. The activities and supply chain objects in the model are described using a number of attributes. The activities are linked by E edges to form a sequential chain of activities. Therefore, supply chains are modeled as directed acyclic networks H of activities and edges, such that $H_s = (X_s, E_s)$. It follows that each supply chain edge e_{ij} represents a connection between an activity x_i to a successor activity $x_j \mid x_i \preceq x_j$. As a result, each x_i activity has a set of predecessor actions $X_s^-(i)$ and successor actions $X_s^+(i)$ in each supply chain. The beginning of the supply chain is represented by the activity at the source node, which has an empty predecessor set. Similarly, the sink node at the end of the supply chain has an empty successor set.

Finally, we consider transactions D as a third link type next to the group connections G and supply chain edges E. We assume the agents can choose one activity to generate value. An agent n_i choosing activity x_i can generate value in a supply chain as they create a transaction link d_{ij} with another agent x_j who has chosen either a predecessor or successor activity. The transaction links have an attribute γ that accounts for the intensity of transactions between the two agents d_{ij}^{γ}. The activities have a synergy factor Y_x that boosts the generated value from transactions and enables to account for external effects (e.g. higher demand for a specific illicit commodity).

Production supply chains assemble resources into half-fabricates, which in turn will be used to produce a final product in a sequential manner. In illicit supply chains, the same sequencing is observed, and thus agents in our model require half-fabricates from a predecessor activity. Therefore, the possible transaction intensity that an agent n_i can establish with other agents conducting a successor activity is limited by the transaction intensity the agent n_i currently has with predecessor activities. To establish a supply transaction intensity with agents conducting the successor activities $X_s^+(i)$ for an agent that chooses activity x_i, this agent should have at least a transaction intensity $d_i^{\gamma} n$ with agents conducting each of the predecessor activities $X_s^-(i)$ to establish a similar transaction intensity. This dependency between predecessor and successor activities is expressed by Eqs. 1 and 2. Equation 1 and 2 express that the maximum transaction intensity d_{ij}^{γ} an agent n_i with action x_i can have with an agent n_j who conducts a successor action in $X_s^+(i)$ is determined by the transaction intensity the agent n_i has with agents N_i that conduct the predecessor activities $X_s^-(i)$ (and vice versa):

$$\forall x \in X_s : \max d_{ij}^{\gamma}(x_j \in X_s^+(i)) = \min \sum_{n(x_n=x)}^{N_i} d_{in}^{\gamma} \forall x \in X_s^-(i) \tag{1}$$

$$\forall x \in X_s : \max d_{ij}^{\gamma}(x_j \in X_s^-(i)) = \min \sum_{n(x_n=x)}^{N_i} d_{in}^{\gamma} \forall x \in X_s^+(i) \tag{2}$$

An exception is made for the source and sink activities, which are given an arbitrary value (default value 1 in our model) for the transaction intensity that the agents (choosing these activities) are able to establish with successor and predecessor activities, respectively. Therefore, the formation of the supply chains always starts with agents that choose sink and source activities. The arbitrary value that determines the possible transaction intensity enables heterogeneities to exist in the agents' ability (human capital) to produce a specific commodity in the case of a source activity or to sell a specific commodity in the case of a sink activity. The model allows for extensions that increase the number of activities per agent or the inclusion of other activity-related attributes for agents, such as skill requirements that impact or limit the ability of agents to choose specific activities or that limit the transaction intensity an agent is able to establish.

Process Overview and Scheduling

The focus of the model is that agents aim to establish effective transaction connections and, in such a way, optimize the illicit supply chains in a decentralized manner. The agents have two types of revision opportunities to strategically improve their situation. First, agents can update their activity status x_i. Second, agents can change their transaction status D_i. These adaptation possibilities model the action-oriented strategy of 'organizing by doing' by illicit organizations, which is closely related to a vast number of noncriminal organizations specialized in trade (Levi and Van Duyne 2005). Agents evaluate their revision opportunities based on information obtained through interactions with neighbors. Agents interact either pairwise or in groups, which impacts the amount of information available to the agents. For this purpose, we describe a dyadic game and a group game. The following described events impact the opportunities of the agents at each time step.

Network Generation

The social relationships in the model are described by a hypergraph. Hypergraphs are the natural network representation to account for group interactions (Battiston et al. 2021). In our model, a hypergraph consists of nodes that represent agents N and hyperedges that represent groups G, in which each hyperedge accounts for an interaction between two or more nodes. The hyperdegree of a node is the number of groups in which a node interacts. The order m of the interaction is the number of possible interactions by a node in the hyperedge. If the hypergraph only contains hyperedges of order 1, the hypergraph is an ordinary graph. To generate hypergraphs for our model, we apply the algorithm for growing uniform random hypergraphs by Kovalenko et al. (2021). This algorithm generates scale-free random hypergraphs in which all hyperedges have a specified similar order and which allows for adding nodes to the graph. Figure 1 gives an example of a random m-uniform hypergraph of order 3. The network generator works as follows. The initialization starts with a group of m+1 agents. In each step, m-1 agents are added to the network that form a group with a randomly selected agent in the network and a randomly selected neighbour of this agent.

Opportunistic Behavior

The agents evaluate and opportunistically change their activity status and transaction status, aiming to maximize their utility u. For each possible activity, the agent can determine the expected utility $u(x_i)$, which is a combination of the expected transaction intensity of the agent and the synergy factor of the activity. To determine which activity has the highest utility, agents update a potential function $F(X_i)$ that maps every strategy u_i to a real value,

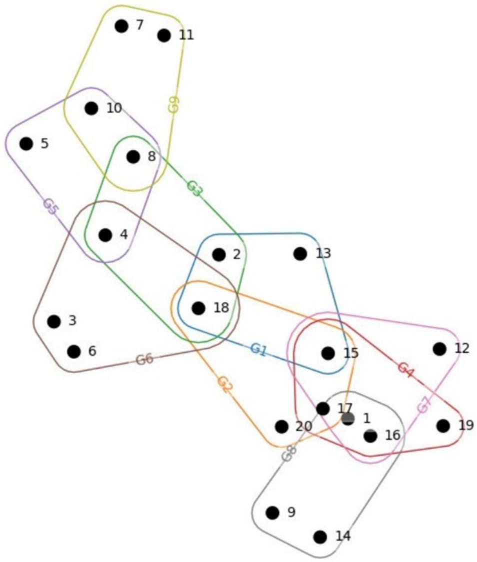

Fig. 1 Generation of a hypergraph with interaction order $m = 3$. In this example, agent 8 can interact with agents in groups G3, G5, and G9. This enables interaction with agents 2, 4 & 18, agents 4, 5 & 10, and agents 7, 10 & 11 respectively. As agent 8 interacts with agent 4, agent 4 and 8 will both determine potential transaction opportunities based on the status of their neighbours and mutually share this information. This indirectly provides agent 8 with information of agents 3 and 6, who share group G6 with agent 4

such that $u_i(x_i')$ is an alternative for $u_i(x_i)$. In this manner we introduce a stylized form of opportunistic behavior. As value in supply chains is created by transactions, the value for an agent that conducts an activity is determined by the transaction intensity the agent has with agents that conduct the successor activity. For the sink activity, the value is determined by the transaction intensity the agents have with agents that conduct the predecessor activity, to equally compare the contribution of all activities to the supply chain. We assume linearity in the value of transactions, such that an increase in transaction intensity between agent i and j increases the payoff (u) generated by an agent i choosing activity (x_i) with the amount of the increase of transaction. Thus, the utility function for a non-sink activity x_i over all supply chains is:

$$u(x_i) = \sum_{s}^{S} \sum_{n_j(x_j \in X_i^+)}^{N_i} d_{ij}^{\gamma} \times Y_x \tag{3}$$

And the utility function for a sink activity x_i over all supply chains is:

$$u(x_i) = \sum_{s}^{S} \sum_{n_j(x_j \in X_i^-)}^{N_i} d_{ij}^{\gamma} \times Y_x \tag{4}$$

With these functions, the agents calculate the utility for the current activity in the supply chains based on current transaction intensities. However, evaluating the potential of other activities requires information about the potential transaction intensity of each activity. Therefore, to update the potential function, the agents need to calculate the potential transactions $d^{'y}(x)$ the agents can have with other agents when choosing activity x, such that the potential function is:

$$F(X_i) = u(X_i') \tag{5}$$

With the alternate utility function for non-sink activity being:

$$u(x_i') = \sum_{s}^{S} \sum_{n_j(x_j \in X_i^+)}^{N_i} d_{ij}^{'\gamma} \times Y_x \tag{6}$$

And for sink activity being:

$$u(x_i') = \sum_{s}^{S} \sum_{n_j(x_j \in X_i^-)}^{N_i} d_{ij}^{'\gamma} \times Y_x \tag{7}$$

Using function 1 and 2 an agent n_i can determine the potential transactions with another agents N_j based on the other agents' current activity x_j and the other agents' current transaction intensities d_j^{γ}. An agent sharing this information with its neighbors enables the ability to anticipate opportunities and threats that follow from changes in the local environment. After updating the potential function, the agent can evaluate each of the possible strategies and determine which activity minimizes the difference between the optimal and current situation. Therefore, best response dynamics always converge to a Nash equilibrium in which no player can improve their payoff (Tardos and Wexler 2007).

Risk Averse Behavior

Furthermore, we assume that agents are risk-averse and thus not purely opportunistic, as they account for the risks of adding more transactions than they assume necessary (Bouchard and Morselli 2014). Increasing the transaction intensity poses both a risk to the agent, as transactions are at risk of being intercepted, and an opportunity to increase the (potential) utility from illicit activities. This demonstrates the characteristic trade-off between secrecy and effectiveness presented to individuals in illicit supply chains. As agents are risk-averse, they tend to prioritize the most profitable transactions. The introduction of the agent-specific risk parameter (R_i) models the risk-averse behavior. A higher value for the risk parameter assumes the agent is tempted to take more risks. The risk parameter is assigned to the agents R_i and uniformly distributed on the interval 1 and the system risk parameter R. This creates behavioral heterogeneity among agents. The game-theoretic approach assures agents rationally add or deduct transactions to increase the payoff, such that the transaction intensity does not overshoot the risk aversion parameter:

$$R_i \geq \frac{D_i^{\gamma}}{u_i} \tag{8}$$

Dyadic Game

The dyadic game describes a game played by two agents in one step. The player agent randomly chooses another agent from the groups in which the player agent participates. The games are played sequentially, and the agents are selected in a random order. At each time step, each agent is selected probabilistically, determined by the game frequency factor GF, which is equal for all agents.

During the dyadic game, both agents update the possible interaction intensities for each of the possible activities (based on functions 1, 2, and 7) and their potential function (function 5) based on the current activities and transactions of agents in their local environment. The other agents share the potential interaction with the player agent. Based on this information, the player agent can determine the potential value for each activity.

First, the player agent evaluates its activity status and potentially switches to a more profitable activity. If an agent switches to another activity, the transactions that are no longer possible are deactivated. Second, the agent can add a transaction with a specific intensity to the other agent, with consent, if this agent conducts either a predecessor or successor activity in an illicit supply chain (Fig. 2). With this transaction, the agents improve their actual utility while compromising on risk aversion. Additionally, agents might alter their activity if an opportunity arises from changes in their environment (e.g., another neighbor is involved in a more profitable supply chain). As other agents change their activity, existing activities and transactions might become more or less profitable. Therefore, agents reevaluate their current chosen transactions after each game that is played. As the game focuses on creating efficient networks, the game is best described as a network formation game (Tardos and Wexler 2007) in which the behavior of the agents is characterized as opportunistic (Zhang et al. 2014).

Group Game

In comparison to the dyadic game, the group game describes a game in which an agent compares its payoff with multiple other agents. In this way, agents profit from the resource-sharing ability of group operations (Bouchard and Morselli 2014). Similar to the dyadic game, each agent is selected sequentially and randomly. In contrast to the dyadic game, the player agent selects at random one of the groups the player agent is involved in. In the group, every agent updates their potential transactions. The player agent receives this information and opportunistically selects the activity that has the highest potential. Next, the player agent selects the agent in the group that has the highest potential transaction intensity with the activity of the agent and consequently reevaluates its transaction status and attempts to cooperate with the other agent. In this setting, the player agent receives more information for revising the activity and transaction status. This is of particular interest when the action revision possibilities of the player agent are limited, and the group is able to provide necessary transaction opportunities.

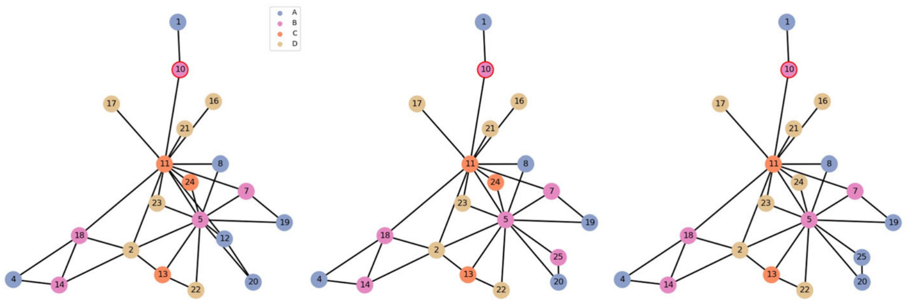

Fig. 2 In chronological order, three snapshots of a agent network that aims to process an illicit supply chain of 4 sequential actions (A → B → C → D) and underwent an intervention and an adaptation. An intervention removes agent 12 with activity state ‘A’ from the network. Consequently agent 5 loses a supply transaction. In the following time step agent 25 enters the network. Consequently group games are being played by all agents in the network. After these games, agent 25 changes his activity state to ‘A’ which enables to replace the supply transaction with agent 5. Additionally, agent 24 changes his activity state to ‘D’ which enables to agent 11 to transfer more illicit commodities to agent 24, which the agent receives from agent 25 via agent 5

Intervention Dynamics

Intervention tactics aim to disrupt the flow of the illicit supply chain by removing agents from the model. As agents are removed from the model, organizing the necessary illicit transactions becomes more difficult and becomes impossible with a limited number of agents. As in reality, the demand for the illicit commodity is not influenced by the intervention (demand modeling is out of scope), we assume that for each agent that is taken out of the model, a new agent enters the illicit network according to the network generation algorithm (introduced in Section "Network Generation"). The assumption of agent replacement is supported by empirical observations from drug trafficking networks. Bright et al. (2019) document rapid reorganization and actor replacement following enforcement disruptions, especially in decentralized structures. Similarly, it is observed that removed actors were often quickly replaced, preserving network functionality. These findings reinforce the relevance of modeling replacement dynamics, even if the exact timing of entry may vary across market contexts. With the introduced replacement dynamic, the number of agents remains stable during the simulation, while the intervention actions only impact the structural and functional character of the illicit network. This enables to analyze these specific dimensions of the system.

Similar to the agent model, the strategies to intervene in the illicit supply chains are decentralized. Completeness of records and the time span of data collection are challenges for law enforcement agencies (Campana and Varese 2020). Therefore, the interventions modeled are not based on network characteristics, as these would imply knowledge of the whole network or complete information of an agent and their surroundings. Instead, we compare two different intervention strategies. First, we model a random intervention in which an agent is selected at random and removed from the model. Second, we implement a lead-based approach that focuses on the relations of the agent removed by an intervention. This approach first performs a random intervention action, after which the following intervention action selects a neighbor of the removed agent, and a neighbor of the second action during the third action, and so forth. This procedure continues until no neighbors exist for the removed agent, and again a random agent has to be selected. This iterating strategy complies with the need to restrict the information requirements about possible suspects of illicit activities to a minimum. With this strategy, agents that have more relationships or transactions are more at risk of being removed as they are more likely to be selected as a neighbor.

The interventions have two different variations. In the first variation, the interventions can be targeted at agents based on the transaction or social level. The transaction level is more obvious, as agents that actually conduct illicit transactions are more likely to be detected. The interventions in the social layer can be explained as successful preventive measures that aim to withhold individuals from attraction to the illicit market. The second variation focuses on different intervention intensities, which are modeled by the number of interventions at each time step. The intensity could imply that one or more agents are removed at each time step (intensity ≥ 1) or one agent is only removed every number of steps (intensity < 1). The intervention intensity allows testing the temporal aspect of the adaptive capacity of the network to deal with the structural and functional changes caused by the intervention strategy. A low intervention intensity provides the network with more time to readjust, redistribute activities, and reestablish transactions through dyadic or group game interactions.

Model Concepts

This model extends earlier dynamic network models on the organization of illicit supply chains, which either assumed a static activity status for agents or only accounted for dyadic interactions. Two network approaches are applied to observe the core concepts of interaction, adaptation, and emergence in the system. First, a hypergraph approach is used to account for the group interactions. Second, a multilayer network approach is applied to distinguish the different types of relationships, which enables modeling both the enduring relationships of the agents and the fluid transaction relationships.

Hypergraph Model: Group Interactions

To account for the higher-order interactions, the model initializes connected groups of agents based on a hypergraph generation algorithm. The groups enable interaction to share information and establish transactions. In the context of illicit supply chains, two network measures are particularly of interest to analyze the characteristics of the network. First, the degree centrality identifies the potential impact of an individual on the network. Individuals with high degree centrality are potentially more effective in establishing transactions as more neighbors are available for cooperation. Second, the betweenness centrality aims to assess the importance of individuals for information passing through the network. Individuals with high betweenness centrality values have a higher probability of receiving information about transaction opportunities.

The normalized average degree centrality and normalized average betweenness centrality distributions of the nodes for hypergraphs with different interaction orders are displayed in Fig. 3. The normalized average centrality scores measure how the degree centrality and betweenness centrality are distributed over the network, as a higher value indicates a more distributed degree and betweenness centrality over the individuals in the network. Notably, in networks with a higher order interaction degree centrality is relatively more distributed among agents and the betweenness centrality is relatively less distributed. Due to the existence of larger groups, the higher order networks are better connected and the number of connections is more distributed. Therefore, it can be hypothesized that higher order graphs offer a higher potential for establishing transactions, as on average, agents are able to interact with a larger diversity of agents. However, as the betweenness centrality is less distributed in higher order graphs, a few individuals have a relatively higher impact on the information flow in the network. This results from the fact that the network generation algorithm connects (in this case relatively larger groups) only to two other individuals in the network. These are the individuals that have a high possibility of connecting agents that are otherwise disconnected, which are often present in illicit networks such as jihadist cells (Bright et al. 2020). For lower order networks, the degree centrality is less distributed, indicating that a few individuals are relatively more connected. Therefore, these networks are more centralized than higher order graphs. Finally, as lower order graphs have a more distributed betweenness centrality, it can be expected that a random removal based intervention strategy has a lower potential to disrupt the information flow of the network.

Multilayer Network: Analysing Illicit Supply Chains

The different relationships and entities can be modeled and analyzed as a multilayer network that represents the connections and activities of illicit supply chains, the relationships and

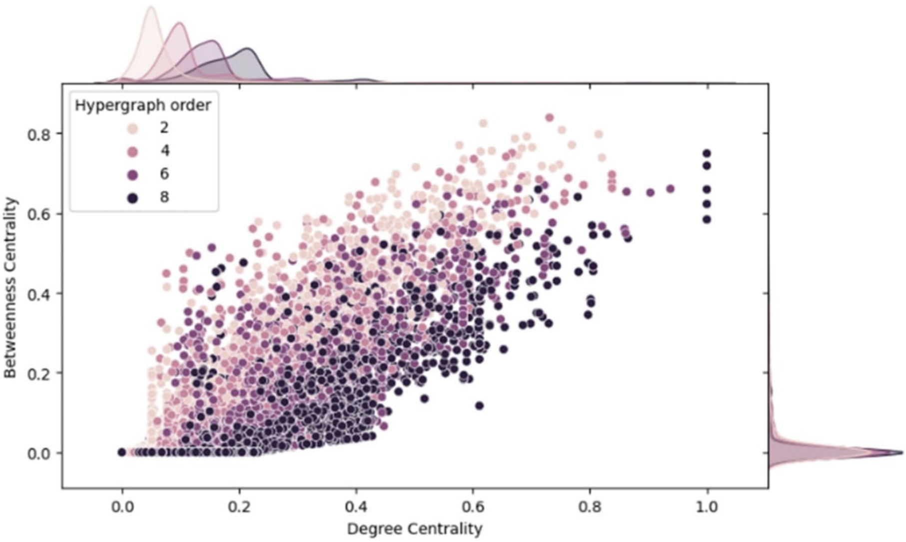

Fig. 3 The normalised average degree centrality (x-axis) and normalised average betweenness centrality (y-axis) and their distribution for networks with different interaction orders. A higher normalised average centrality value implies that the centrality is more distributed among nodes in the network. As the degree centrality in networks with interaction order 2 are less distributed, a randomly selected node in the network has a high probability to have a relatively low degree centrality. The networks are generated using the algorithm of Kovalenko et al. (2021), for growing uniform hypergraphs. For this data, 270 networks are generated for each interaction order (1080 total realisations) with 40 nodes each

individuals that facilitate interaction, and the illicit transactions. With this approach, we can model, identify, and evaluate dynamics and dependencies between various layers of the system (see Fig. 4).

In the social network layer, the agents are adaptive as they can strategically change their activity status and transaction status. The adaptation is based on the information obtained from interactions defined at this level. The model allows extensions to model more complex organizational dynamics that include hierarchical relationships. The transaction layer is emergent as transactions develop through interactions between agents and their adaptation process. As explained in Section "Entities, State Variables, and Scales", it is assumed the illicit activities have a specific sequential order. Therefore, the illicit transactions can be modeled as a directed graph, which has weighted edges based on the transaction intensity of the transaction links. The agents performing activities at the beginning of the supply chains are the sources, and the agents that perform activities at the end of the supply chains are the sinks. This allows measuring the effectiveness of the emergent supply chain by calculating the maximum flow using a multi-source multi-sink maximum flow problem. Analyzing network design and flow problems using maximum flow are common in supply chain management (Anand Jayakumar et al. 2017) The resulting maximum flow of the network is a measure of the collective effectiveness of the individuals to organize the supply of illicit commodities. Also, the different layers enable distinguishing different metrics for intervention tactics. For example, interventions based on degree centrality of the social layer would target different agents compared to the centrality metrics of the transaction layer.

Finally, the model has various sources of stochasticity. First, for introducing and connecting a new group of agents to the network, the network generation algorithm randomly

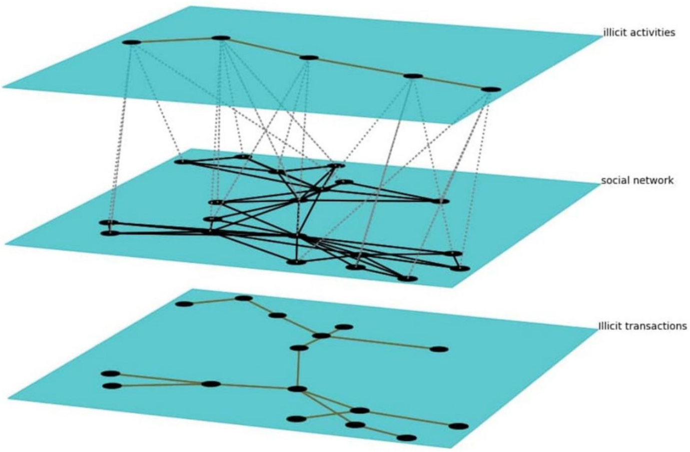

Fig. 4 Multilayer network representation of the model. The illicit activities layer models the sequencing of the illicit supply chain. The social network layer includes the possible interactions between agents. The dotted lines between the first and second layer represent the activities chosen by the agents. The illicit transactions layer includes the illicit transactions established between agents and facilitate the handover of activities in the supply chain

selects two existing agents. Second, the risk parameter is uniformly distributed over the agents. Therefore, some agents are more risk-averse and establish fewer transaction intensities. Third, a game frequency parameter value below 1 causes some agents not to play a game at each time step. Lastly, one of the law enforcement intervention strategies relies on a random selection of agents.

Simulation Analysis

The proposed model is too complex to allow for a closed-form analytical solution. Therefore, the dynamics of the model are analyzed using a simulation-based approach. This approach allows for comparing the behavior of the model under various parameter settings. We run the model for 20 iterations for each parameter combination provided in Table 1, resulting in

Table 1 Parametrisation of the simulation experiment

Parameter	Values	Interpretation
N	40	Number of agents in the model
m	{2, 4, 6}	Interaction order of the hypergraph
H_s	{3,4,5,5 compete, 5 complete}	Supply networks
GT	{dyadic, group}	Game type
GF	{0.33, 0.66, 1}	Game frequency
R	{10, 20, 40}	System risk parameter
IS	{random, lead}	Intervention strategy
IL	{social, transactions}	Intervention level
IP	{0, 0.25, 0.5}	Intervention intensity

a total of 64,800 runs. Each iteration runs for 40 steps. At each time step, the model collects both system and agent-level information.

At the system level, the model collects data on average degree centrality and average betweenness centrality to monitor the structural characteristics of the underlying illicit social network. Furthermore, the max-flow through the transaction network and average agent payoff are monitored to analyze the functioning of the illicit supply chain. Finally, the number of low visibility brokers is tracked during the simulation. These brokers are agents with higher-than-average betweenness centrality and lower-than-average degree centrality (an example, agent 10, is circled in red in Fig. 2) and potentially play an important role in the resilience of illicit markets (O'Reilly et al. 2020). On an agent-level the model analyses the individual degree and betweenness centrality of the agent in the social layer. Additionally the agent utility is monitored, and it is analysed whether an agent is a low visibility broker.

We first explore the behavior of the model by varying the order of interaction in the initial generated hypergraph. This impacts the structural dimension of the market as described in Fig. 4. Secondly, the impact of different supply chain types is evaluated. We assess the length of the supply chain for 3 to 5 connected activities. Additionally, two scenarios are evaluated in which different illicit supply chains of 5 activities either overlap halfway (in action 'C') or are sequential but overlap in the final activity of the first supply chain and the first of the second (in action 'E'). These illicit supply chains can be regarded as "compete" and "complete" respectively, as they either compete for agents (who will have to choose between supply chains) or in which agents can participate in both. An example of competing supply chains would be two chains where a trafficker must choose between smuggling different goods. An example of completing supply chains would be a scenario where an agent has two roles: selling an illicit product and providing the (illicitly obtained) money for starting the process of money laundering.

The analysis of the order of interaction and the temporal dependency of the adaptation is conducted as follows. First, different game types are considered. A game type determines whether the agent optimization process is based on dyadic information sharing or information sharing among group members. Also, the game frequency (the number of evaluations each agent executes each time step) is varied. The risk parameter is assigned to agents individually and uniformly distributed between 1 and R. This creates heterogeneity among agents, which potentially impacts the functioning of the illicit market. An agent with high degree centrality might receive more opportunities from neighbors. However, establishing many transaction connections might make the agent more vulnerable to intervention actions. In contrast, an agent with a similar central position and a risk-averse profile would receive a similar number of opportunities but would potentially remain longer in the system. Lastly, the intervention strategy, level, and intensity are implemented as the discussed intervention variations (Section "Intervention Dynamics").

Results

The results reported in this section capture the impact of changes in the parameters on the behavior of the model at three levels. First, the structural and functional characteristics of the illicit supply chain are analyzed. Second, the temporal dependencies between the model dynamics are analyzed. Third, we evaluate the impact of intervention strategies on the structural and temporal dependencies. The impact of the changes is examined in two different ways. At the system level, the analysis of the maximum flow through the transactions allows us to analyze the effectiveness of the illicit supply chain under various conditions. At the individual level, the payoff function enables the evaluation of the effectiveness of individual agents.

Structural and Functional Dependencies

We use the model to analyze the impact of the structure of the social network and the size of the supply chain network on the agents' capacity to organize different types of illicit supply chains. Logically, supply chain networks with fewer activities are easier to organize and therefore have a higher maximum flow. Additionally, social networks in which agents have more connections are more capable of organizing and conducting the activities of the supply chain, creating a higher maximum flow when no law enforcement interventions take place.

The effect of dynamics of opportunistic behavior on the structural dependencies of illicit organization becomes more interesting when we look at the emergence of low visibility brokers. Figure 5 displays the average maximum flow and centrality measures of model runs, distinguishing runs with and without low visibility brokers. These low visibility brokers emerge specifically in runs with social networks of interaction order 6 and a low average degree (upper right), and runs with social networks with interaction order 2 and a high average betweenness (lower left). In these scenarios, illicit supply chains have a higher average maximum flow than in supply chains without low visibility brokers, especially in the case of interaction order 6. This suggests that supply chains with a high interaction order and thus larger groups depend more specifically on these brokers to connect one end of the social network with the other and maintain a relatively high effectiveness.

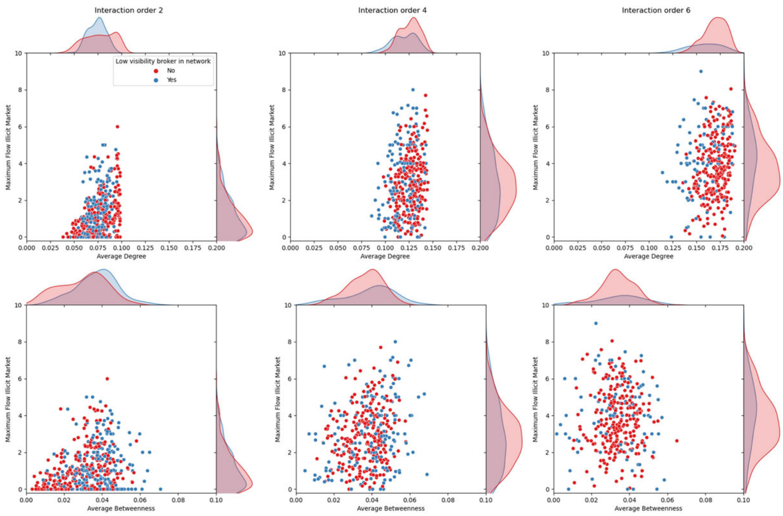

Fig. 5 Emergence of low visibility brokers in model runs for networks with different interaction orders. In this figure, the interaction order of the networks changes from left to right. The plots at the top describe the average degree centrality in the networks on the x-axis, the plots at bottom describe the average betweenness centrality. Blue dots are networks in which a low visibility broker (as defined in Section "Simulation Analysis") is present, and red dots are networks that have no low visibility broker. The y-axis displays the maximum-flow for each of the networks (as defined in Section "Multilayer Network: Analysing Illicit Supply Chains"). Most notable, low visibility brokers emerge in networks with a low interaction order and high average betweenness centrality (lower left) and networks with a high interaction order and low average degree centrality (upper right) and have a relative high maximum flow compared to networks without low visibility brokers

Next, we evaluate the impact of the risk-averse behavior of the agents on the maximum flow of emergent illicit supply chains (see Fig. 6). We expect the risk parameter to positively affect the maximum flow, as agents with less risk-averse behavior organize more transactions. Secondly, we expect agents with less risk-averse behavior to have an important effect in keeping the illicit supply chain operational. As expected, in scenarios with less risk-averse behavior (higher value for the risk parameter), we observe more effective illicit supply chains. As agents reject fewer cooperation opportunities, cooperation games result in more transactions. In the current model, the intervention intensity does not increase with the number of transactions. Therefore, risk-taking agents do not decrease the effectiveness of the illicit supply chain as a whole since the number of intervention actions remains equal compared to simulations with less risk-taking agents.

Next, we observe increasing variance in scenarios with a higher risk parameter, especially in low interaction order networks (see Fig. 6). Risk-taking agents that have an important position as a broker between multiple sources and sinks may have a high impact on the effectiveness of the supply chain. However, if these agents are in a less important position, the risk-taking character of the agent might be significantly less important. This points to a dependency between individual characteristics and group sizes in illicit supply chains. While smaller, more flexible decentralized organizations might benefit from better security, it implies that risk-taking individuals become more important for the market as a whole to maintain operational capacity.

Temporal Dependencies

The differences between the dyadic game and the group game impact both the structural and temporal dimensions of opportunistic illicit organization, as the order of interaction (based on the group size) impacts the number of opportunities for transactions received by the agent per time step. Furthermore, the number of games played by agents at each time step impacts the adaptive capacity of the agents, and thus the system over time. Figure 7 distinguishes the effects by different interaction orders (horizontally), different game frequencies (vertically), and different game types on the maximum flow of the resulting transaction network over time. Most interestingly, it is noticeable that the group game only allows faster optimization by the network (marked by a faster increase of maximum flow) if the game frequency is high. This can be explained by the effect that in scenarios with fewer adaptation opportunities per time step, the sparse number of games are all focused on central agents with high cooperation potential. Therefore, in these scenarios, group games result in less decentralized decision-making on new transaction links, which limits the number of new connections. More frequent

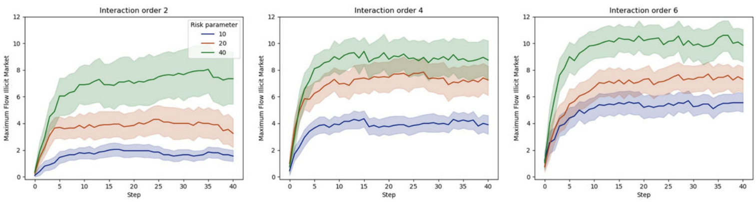

Fig. 6 The effect of the system risk parameter on the maximum-flow in the illicit supply chain (as defined in Section "Multilayer Network: Analysing Illicit Supply Chains"). A higher value for the agent' risk parameter, allows the agents to take more risks and notably establish more effective illicit supply chains. The error bars are the 95% confidence intervals

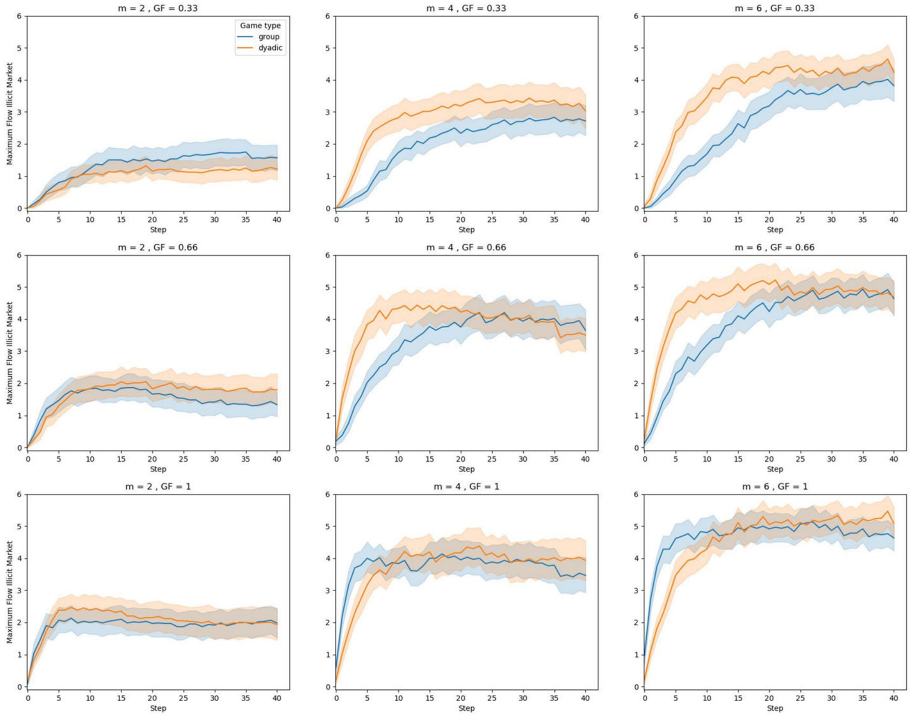

Fig. 7 The effect of interaction order, game frequency, and game type upon the maximum-flow of the illicit market. The blue line displays the maximum flow of the illicit supply chains over time for simulations with group games, the orange line displays similar for simulations with dyadic games. The effect of the interaction order is differentiated horizontally, the effect of the game frequency is differentiated vertically. Notably, the maximum flow converges to a similar equilibrium for both game types. The group game allows faster optimisation by the network (marked by a faster increase of maximum flow to the equilibrium) only when the game frequency is high. The error bars display the 95% confidence intervals

games, however, allow the agents to detect more opportunities and saturate the agents with the most opportunities more quickly, which enables less profitable agents to also establish connections (see lower middle and lower right). This dynamic might explain that not only do larger groups appear to seek less security in illicit supply chains, but they also appear to require a high degree of organizational sophistication or interaction frequency to distribute their opportunities.

Intervention Effects

The model was used to design and analyze the effect of different types of interventions aimed at disrupting the illicit supply chains. These interventions focus on the supply chain dynamics in different layers, as discussed in Section "Intervention Dynamics". The intervention strategies have different effects on the structural dependencies of the illicit supply chains (see Fig. 8). While the lead strategy has a higher impact on both the average betweenness and average degree, it affects the betweenness centrality more strongly. To assess the effectiveness of different intervention strategies, we compare the effect of the strategies on the maximum flow of the supply chains (Fig. 8). Additionally, we simulated different interven-

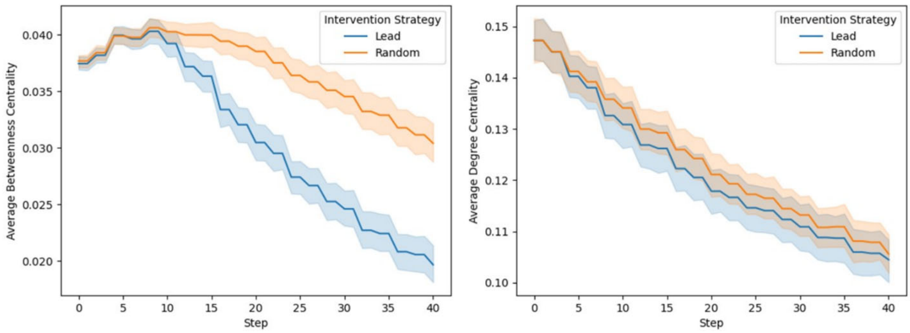

Fig. 8 The different effects of intervention strategies on the structural dependencies between agents in simulation (average betweenness centrality on the left, and average degree centrality on the right) at the social network layer over time. The lead-based intervention strategy more quickly and severely decreases the average betweenness centrality which implies that a few agents become relatively more important for the information sharing in the network

tion intensities (Figs. 9 & 10). First, we observe that, in general, increasing the intensity of intervention leads to a reduction in the network's maximum flow Fig. 9. However, the network's adaptive capacity allows it to gradually replace removed agents. Therefore, to cause lasting structural disruption, interventions must outpace the network's ability to adapt. Through analyzing replacement strategies, this work extends existing literature that focuses on identifying vulnerabilities in criminal networks (Duijn et al. 2014; Bright et al. 2024)

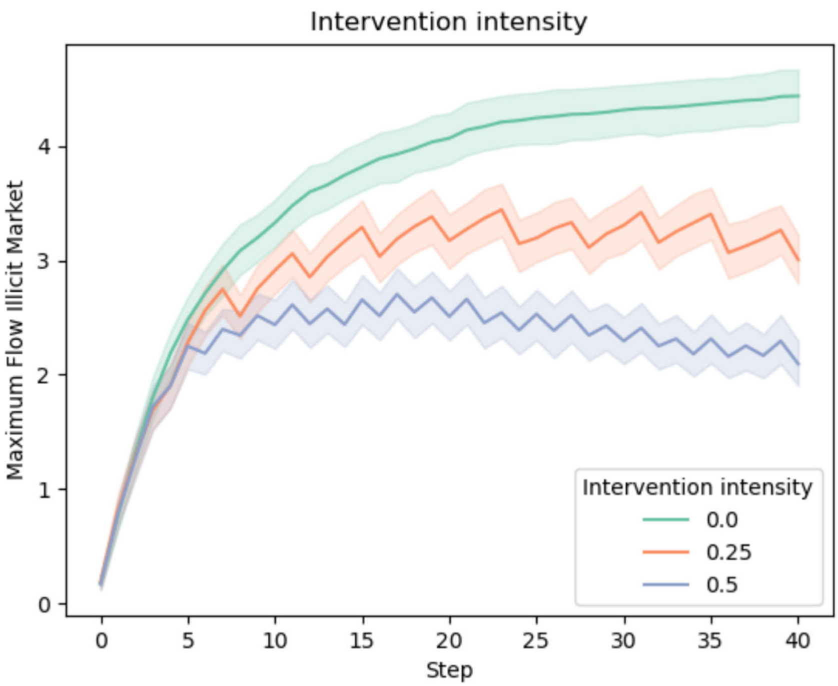

Fig. 9 The general effect of intervention intensity over time. The error bars are the 95% confidence intervals

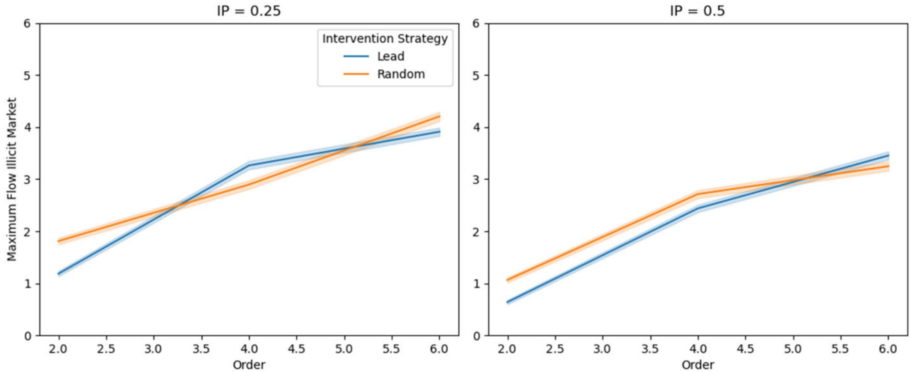

Fig. 10 The effect of intervention intensity (left 0.25, right 0.5) and strategy (blue line represents the lead-based strategy and the orange line represents the random strategy) on networks with different interaction orders (x-axis). The error bars are the 95% confidence intervals

and evaluating the effectiveness of intervention strategies (Calderoni et al. 2022), enabling a deeper examination of the sustainability and long-term effectiveness of such interventions. The proposed model also provides a framework for systematically investigating alternative replacement dynamics that typify distinct illicit supply chain configurations. The most interesting insight from this assessment is the observable relatively higher effectiveness of the lead strategy in disrupting networks with a low interaction order Fig. 10. An explanation for this effect is that the betweenness centrality of these networks is more distributed. Consequently, as the lead-based strategy reduces the average betweenness centrality, it is also able to more effectively find and remove the few important agents that keep the network together. Conversely, the lead-based strategy has mixed results for higher-order interaction networks. As these networks have a higher and more distributed degree centrality, they are less affected by the lead-based approach. Additionally, as the lead-based approach focuses on local disruption, it might be less effective on more distributed networks.

Finally, we compare and analyze the emergence of low visibility brokers for simulations with different intervention strategies (Fig. 10). We compute the average number of low visibility brokers in the illicit supply chains over time during the simulations. Notably, low visibility brokers emerge especially when applying the random removal strategy for lower

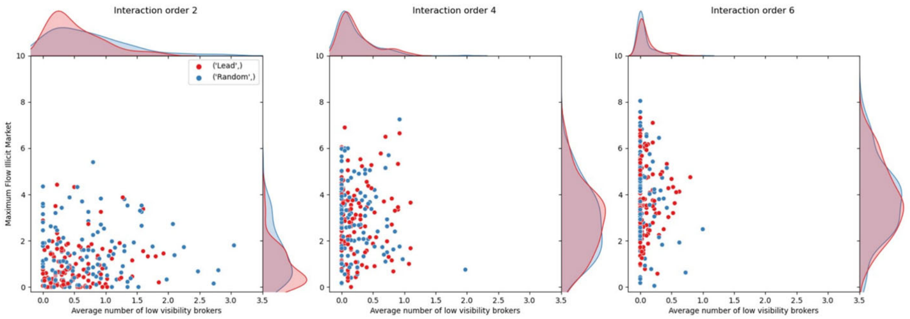

Fig. 11 The effect of the intervention strategies lead-based (red) and random (blue) on the maximum flow of the illicit supply chains and the average number of low visibility brokers in illicit supply chains for networks with different interaction orders

order interaction networks. Due to the lead-based strategy, the betweenness centrality is less distributed and therefore fewer agents have higher-than-average betweenness centrality. Networks without low visibility brokers have a higher potential to become disconnected and therefore have a lower average maximum flow. Removing one agent after another might have the desired effect of breaking illicit organizations, but it potentially provides individuals with specific characteristics, such as a central role in the supply chain or risk-averse behavior, to place themselves in a highly valuable position in the supply chain (Fig. 11).

Conclusion

This paper provides insights into several complex aspects of the adaptive capacity of opportunistic illicit supply chains. We have presented a generic computational model to analyze the dynamics of illicit supply chains, which enables the analysis of different intervention strategies. Our model incorporates a combination of different functional, structural, and temporal dependencies that characterize illicit supply chains. The opportunistic, decentralized behavior of the individuals characterizes the organization of these supply chains.

While this study is primarily theoretical, its assumptions and outcomes are grounded in empirical work. Our findings can therefore inform the design of intervention strategies by highlighting which structural properties (e.g., reliance on low-visibility brokers) make illicit networks more or less resilient. Most interestingly, our computational results demonstrate that group interactions only provide more adaptive capacity when the interaction frequency is high. The group game optimization is affected by both the structural and temporal dependencies of the illicit supply chains, as agents use this optimization strategy to obtain more information in scenarios with a higher-order interaction network and a higher game frequency. While higher-order interaction suggests that organization takes place more efficiently, this is only the case when the interactions are frequent. This dependency can be explained by the fact that group game optimization results in a more centralized organization. Furthermore, the model points out that the risk-averse character of agents has a significant impact on the functioning of the illicit supply chains. Heterogeneity in the risk-averse behavior results in some agents becoming important for the effectiveness and adaptive capacity of the illicit supply chains. Further exploration of these strategies and heterogeneities will enable us to assess the boundaries of the flexibility of illicit supply chain networks and will provide insights into the impact of different specific intervention strategies. It must be stated that the work presented in this paper is rather theoretical, and the practical usability for law enforcement organizations is to be further investigated. However, due to the highly confidential character of intervention strategies, it remains quite unlikely that researchers will be able to investigate the practical contributions to these law enforcement agencies.

This paper makes several contributions. We provide a generic model to analyze the dynamic behavior of illicit supply chains. To the best of our knowledge, our model includes higher-order interactions for these types of dynamics for the first time. Extending this generic model allows us to analyze specific scenarios or incorporate more sophisticated behavior models or dynamics. Furthermore, we analyzed the structural and temporal dependencies between interaction types and higher-order networks, specifically in the context of illicit supply chains. The findings in this paper emphasize the importance of analyzing these dependencies jointly as this yields a more complete understanding of the impact of interventions for different scenarios.

This paper provides insights into the complex dynamics underlying the adaptive capacity of opportunistic illicit supply chains. Our agent-based model integrates structural, functional, and temporal dependencies and captures how decentralized, self-interested actors contribute to network resilience. By modeling interactions at both individual and group levels, we reveal under what conditions different types of organization support effective coordination and adaptation.

To strengthen the model's practical relevance, we now explicitly highlight its potential applications. The model can be used to simulate and evaluate law enforcement strategies, such as the targeting of brokers or the timing of interventions, and can be compared against real-world outcomes. It also supports exploratory modeling, enabling policy scenario testing where empirical data is incomplete or sensitive. Finally, the model has potential value as a training tool for practitioners, offering simulation-based environments to improve understanding of the complexity and adaptivity of illicit networks (Barros et al. 2024).

Together, these contributions position the model as both a theoretical framework and a practical instrument for improving our understanding of illicit supply chains and informing more effective responses. Several extensions can be suggested for the proposed model. Introducing agents that join other groups allows for the analysis of mergers between organizations, a phenomenon that characterizes some of the illicit organizations (Bouchard and Morselli 2014). Currently, agents only evaluate their risk-averse behavior at the transaction layer, however, agents could also change the totality of their social interactions and decide to interact in larger or smaller groups. Additionally, this allows for the analysis of the impact of interventions, as smaller groups could merge. Another extension would be to include hierarchical coordination of organization as in Magliocca et al. (2019). This limits the opportunistic and flexible character of illicit markets, but allows for the analysis of the dependency between hierarchical relationships, different adaptation strategies, and how they are impacted by interventions.

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