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RESEARCH ARTICLE

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The dream team: combining social network analysis and expert insights to disrupt Irish criminal networks

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ABSTRACT

Local criminal networks recruit young people and can impact their criminal trajectories, making effective prevention an emerging policy concern. Social network analysis reveals insights and structural reasoning through depiction of networks as well as measurements to describe them. The goal is using social network analysis to provide evidence-based knowledge that informs a decision-making approach for network interventions. Our analysis examines five local crime networks in Ireland. The data was gathered through interviews with local police force from five sub-districts. We utilise network measures, including betweenness centrality, to identify recruiters of young people in networks. To account for noisy, incomplete data, we provide a tool that informs the robustness of our results and supports the decision-making for interventions. We combine the quantitative results with qualitative, expert knowledge to form a 'dream team', capable of identifying overall patterns at the network level but also examining individual narratives of key actors and relationships.

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Social network analysis; network intervention; local crime networks; incomplete data

Introduction

The European Commissioner for Home Affairs highlighted the recruitment of young people into organised crime as an emerging policy concern (Johansson, 2024). For most young people, their involvement in crime declines as they mature (Farrington et al., 2012). Nevertheless, recent research suggests that in Ireland some young people are embedded within local crime networks that actively recruit and seek to exploit marginalised local children for criminal gain (O'Meara Daly et al., 2020; Naughton et al., 2020; Redmond, 2016). Involvement in these crime networks has a negative impact on the young people's crime trajectories (C. M. Naughton et al., 2022).

Local crime networks can be influenced by disruptions, which involve targeting and intervening in their functionality through various strategies (Ficara et al., 2023; Harvey et al., 2025). Tools like social network analysis can identify strategic positions of key actors within crime networks to inform intervention strategies, e.g. by disrupting the network

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through the removal of those key actors (see Bright & Whelan, 2020). Therefore, disruptions can be seen as strategically targeted interventions implemented by law enforcement. For instance, in the context of the Italian mafia, Calderoni et al. (2021) focus on the effects of intervention strategies targeting recruiters. They assess various types of disruption in criminal networks with the help of an empirically calibrated agent-based model that can be utilised by law enforcement. Targeted, effective intervention programmes can disrupt or reduce the functionality of criminal networks, such as targeting recruiters to limit the networks' growth and sustainability. In addition to a variety of intervention types, the influential or central actors in the network must be addressed (see, e.g. Cavallaro et al., 2020; Taha et al., 2024).

In this study, we pinpoint where to implement interventions to disrupt local crime networks by providing supportive evidence and revealing structural reasoning through social network analysis. Networks are frameworks for analysing complex systems, such as relations and interactions within criminally active groups (Sparrow, 1991). They reveal the organisational structures of local crime networks by defining the links between the network's actors (Redmond, 2016). Network analysis provides a systematic approach to identifying patterns in a range of local crime networks and determining common characteristics (see, e.g. C. M. Naughton et al., 2022). Our work will show how evidence-based knowledge on criminal networks through social network analysis informs decisions on which actors to remove. Moreover, pairing network analysis with expert knowledge leads to an improved understanding, which, in turn, provides the basis for possible network disruption strategies. For those strategies, it is essential to consider the overall context, risks, costs, and consequences along with insights from network analysis (Everton, 2012).

Our analysis examines five local crime networks in Ireland. Networks, derived from national crime and intelligence data on relationships between adults and juveniles in police sub-districts, were used as a methodological tool in interviews with local Gardaí (officers of An Garda Síochána, the National Irish Police Force). Interviews aimed to confidentially elicit detailed narratives about the individual actors and the links/relationships between them. This provides in-depth knowledge of individual actors and an overview of the structure and functionality of the criminal network as a whole.

To strengthen the evidence, the Twinsight method[1] used for the Greentown study was replicated in two additional Garda sub-districts; Bluetown and Redtown (for a detailed description of three trial sites, see Greentown project reports: O'Meara Daly et al., 2020; Naughton et al., 2020; Redmond, 2016). Findings from the three case studies were used to inform an intervention programme[2] (C. M. Naughton et al., 2022). The Greentown programme was funded by the Irish Department of Justice and is being trialled in two locations in Ireland (2021–2026). Prior to the start of the intervention programme, the Twinsight method was replicated in two trial sites (Yellowtown, Whitetown). The authors aimed to: (1) Provide an understanding of the structure and functionality of crime networks; (2) Identify young people involved in the crime network for a referral to the programme; and (3) Identify the actors involved in the recruitment and retention of young people in the crime network (recruiters). In this study, we focus exclusively on identifying the relevant recruiters.

As the data collection from the five case studies shares boundary conditions (e.g. topic, actors, environment, data sources), we explore similarities and differences between those networks and uncover common patterns. One of the pillars of the Greentown Programme

is intervention, focusing on the disruption of crime networks. By applying social network analysis, we aim to detect recruiters who groom, mobilise and manage young people. Hence, we identify relevant actors for interventions, i.e. network disruption, by considering their position in the network, including network centrality measures. For instance, betweenness centrality is used to identify important actors in a linking position, e.g. occupied by recruiters (Morselli, 2009). Given that the collected data on crime networks is often noisy or incomplete (Berlusconi et al., 2016), the resulting metrics must be interpreted critically (Rostami & Mondani, 2015). To account for this, we introduce a combination of social network analysis and Monte-Carlo simulations to assess the robustness of our results and to support the decision-making in case of the target selection for interventions.

By selecting one of the five Greentown projects, called *Yellowtown*,[3] we present an in-depth analysis of the approaches mentioned above. Parallel to the quantitative approach, our involvement in the data collection and analysis process of Yellowtown allows us to assess those findings qualitatively with expert knowledge. Thus, we juxtapose the quantitative and qualitative approaches. While expert knowledge is crucial for interventions in such a complex environment, our combined results provide a decision support tool, complementing intuition and identifying structural properties and actors that may have been overlooked. Finally, our approach to analysing local crime networks can be transferred to other locations and networks.

The analysis of the local crime networks starts by describing the data source and the transformation from data to a network structure. Then, after presenting the network methods and the variants for the link prediction simulation to account for missing data, we compare the networks from the trial sites and focus on the Yellowtown project as our exemplary project. We present a detailed network analysis to spot recruiters. The results are then linked and evaluated by using expert knowledge regarding the Yellowtown project, highlighting the advantages and disadvantages of both the quantitative and the qualitative approach.

Data

The analysis of local crime networks reveals the underlying social structures that expose the actors' positions and their mutual relationships. The networks from the Greentown projects are based on a unique set of expert interviews with the local Gardaí (Irish national police), describing criminal activities that involve young people in a specific area (see Greentown project reports O'Meara Daly et al., 2020; Naughton et al., 2020; Redmond, 2016). To ensure anonymity, each actor is given a unique identifier number. For instance, in the Yellowtown project, all adult actors' IDs are coded with a 'Y' for Yellowtown, and children are coded 'U' followed by a unique number. The anonymity of the network actors allows the data to be used for investigation and facilitates detailed discussions about the network as well as individual actors.

The building of the networks requires defining the links between the network actors (participants in criminal activities). The networks are formed based on two approaches: First, actors share a link if they were detected for involvement in a criminal activity, e.g. burglary, drug sale, and drug supply, as observed by the Gardaí. Second, the transcripts of the expert interviews[4] hold information about the activities and relations between the

actors. Through the automated processing of expert interview transcripts, actors are identified and linked in the network if they are mentioned in the same sentence, tracked by their unique codes. Furthermore, the importance of a link augments with each recurrence in the interviews. The co-occurrence of actors within the same sentence signals a form of association and assumes that they share certain characteristics or a common history (see, e.g. Motilla-Chávez et al., 2024). The process of building the networks as a representation of the local crime networks is the same for all five case studies.

Additionally, we leverage qualitative analyses that were previously conducted for the Yellowtown project. The Yellowtown transcripts of the expert interviews were imported into NVivo software, coded, and analysed using thematic analysis (Braun & Clarke, 2006). Patterns identified provided an understanding of the size and shape of the networks. Case profiles were also created for each individual (node) by synthesising data across the transcripts (C. M. Naughton et al., 2022). Relative findings from the Yellowtown study (C. Naughton et al., 2022)[5] are referred to in the discussion section.

Methods

We examine the local crime networks with a combination of social network analysis and a repeated simulation of adding links to the network (Monte-Carlo simulation). The variation of the number of links in the local crime networks can affect the networks structural properties. In case of using the structural information to identify recruiters, simulating missing information, such as links, makes our results more robust if they persist. This leads to improved decision-making in the target-selection process. The proposed method aims to take into account the common challenge of incomplete networks due to missing links, which is especially prevalent in the analysis of illicit networks (Calderoni et al., 2020; Ficara et al., 2022; Yeung et al., 2025).

To describe the five networks, we compute several general network metrics. Nevertheless, our primary focus lies on actor-specific metrics that can be used to evaluate the actors' structural roles within the network. Centrality measures assess how central an actor is positioned in the network with respect to a specific aspect. They can facilitate to uncover actors who occupy strategically relevant positions in the network (Freeman, 1977). In social networks, a central position can have individual advantages, for example, perceived leadership or increased access to information (Freeman, 1978). In illicit networks, centrality can take a different angle than in legitimate environments. Centrality can indicate vulnerability, where more central actors are more likely to be visible to law enforcement; thus, occupying a more peripheral position may serve as a strategic advantage (Diviák et al., 2019; König, 2019; Morselli, 2010). Furthermore, the network may be explicitly designed to obscure central or key actors (Bright et al., 2017) – this contrasts with structures typically found in legitimate organisations.

Here, three prominent centrality measures are applied to assess the actors' network position within the network. First, a high number of links positions the actor in a more central role within the network. The number of links an actor has, i.e. its number of network neighbours, is known as the *degree*. Degree centrality, especially in illicit network, indicates visibility of an actor (Morselli, 2009). Second, *closeness centrality* determines the actors' centrality by identifying the average shortest path[6] from an actor to all other actors

in the network. This metric uncovers strategic positions to influence the network. Third, the influence on the communication or connectedness of the actor on the network can be addressed by another centrality measure: *betweenness centrality*. This measure takes into account how often each actor is part of the shortest paths between the actors. It is especially relevant for the linkage in the network and the information flow, as if information propagates through the network, this will likely flow through actors with a high betweenness centrality (Newman, 2003). We expect recruiters to have high betweenness when playing a connecting role between groups, such as a broker position. Therefore, the fact that the recruiters would link new, unattached actors (young people) to the network supports positioning themselves in such a strategic position.

The network data from the Greentown projects are highly dependent on offence relations recorded on the PULSE system and perceptions from the Gardaí. Missing links in criminal networks are common (Berlusconi et al., 2016) and can impact global as well as local network metrics, including centrality. This limitation in data must be accounted for, particularly if networks interventions are rolled out and the decisions on where these interventions will be implemented are based on these network characteristics. If there is a lack of information regarding network links, centrality measures can be biased and less reliable. Therefore, by simulating several link prediction processes, the robustness of actors' positions in the network (i.e. Yellowtown) is assessed.

The randomised simulation of adding links to the network helps to monitor possible structural changes. However, in order to make statements about the simulated networks, simulations of the link prediction are repeated, and the final assessment is based on the mean and possible deviation. We use Monte-Carlo simulations as an experimental setting with 1000 simulation runs to approximate the possible network structures. Our simulations for link prediction incorporate three strategies: random selection, common neighbour and preferential attachment score.

(1) **Random selection**: The simplest way of adding links to the network without additional information is at random. A pair of actors who are not already linked to each other is selected randomly, and a link is added.
(2) **Common neighbour**: This strategy is based on the idea of homophily, which describes the tendency that similar actors (e.g. attributes, common friends) are connected to each other – notably in social networks (Liben-Nowell & Kleinberg, 2007). In an analysis of a criminal network, Berlusconi et al. (2016) propose the structural proximity in networks as a successful strategy to predict the link formation process. Here, the probability that two actors are connected depends on the number of neighbours they have in common. To form a link, an actor is selected randomly. Consecutively, the number of common neighbours for the selected actor and the set of actors that share mutual actors are computed. A link is formed with one of these indirect neighbours. The probability of linking is proportional to the number of common neighbours: the more neighbours two actors share, the more likely they are to be linked.
(3) **Preferential attachment score**: The third strategy relates to the growth of networks where actors with higher degrees (number of links) have a higher probability to build new links. Hence, these networks of *preferential attachment* are based on many actors that have a low number of links and on a few actors with many links

(aligns with the idea of network growth in (Barabasi & Albert, 1999)). To incorporate this mechanism in the link prediction of the networks, a preferential attachment score is used (Liben-Nowell & Kleinberg, 2007). The probability of a link being formed is based on the product of the degrees of the possible actor pair. Thus, the most likely links being formed are between actors with the highest degrees.

Results

Comparing criminal local networks in Ireland

The Yellowtown project is part of a larger set of networks from the Greentown projects. Social networks, such as local criminal networks, reveal structural characteristics that emerge from the links between the actors (see, e.g. Calderoni, 2014). Our local criminal networks describe social networks in a very specific context (illicit activities) with a selected set of actors. Moreover, research on illicit networks faces a range of additional challenges, e.g. regarding the data collection (Bright et al., 2022).

Due to applying network analysis across various operation areas, the resulting networks may show similarities in their structures and reveal prototypical characteristics. To compare those networks, we refer to network metrics that describe their structural properties. We find that the Yellowtown project is similar to the other networks. Therefore, the following social network analysis is potentially relevant for those networks and similar projects in the future.

We determine the corresponding network metrics for the project areas and outline their composition (see Appendix B for description of these network metrics). The networks are defined by a set of actors (active actors of the Greentown projects) and links (relations between actors) based on both co-offence and interview data. Although the interview data is highly entangled with the co-offence data, we outline a comparison of the relative contributions to the number of ties in Appendix C (Table A1). Table 1 summarises the network metrics for the project towns. The networks are representations of a criminal network in specific, geographically bounded limited areas, and, consequently, are similar in their size. The information on the networks was collected in a similar manner with limited access to data. All networks are small, but vary in the density of links between the actors. This is also reflected in the lower average degree of Whitetown and Yellowtown, which are 3.67 and 3.3, respectively. These project sites also have the two largest networks.

Table 1. Comparison of networks metrics for the five project sites: Redtown, Bluetown, Greentown, Whitetown and Yellowtown.

	Red	Blue	Green	White	Yellow
Actors	49	60	44	112	109
Links	282	340	221	411	362
Density	0.24	0.19	0.23	0.07	0.06
Average degree	5.76	5.67	5.02	3.67	3.3
Assortativity	0.12	0.27	0.15	0.11	0.19
Clustering coefficient	0.57	0.52	0.56	0.47	0.42
Average shortest path length	2.05	2.20	2.17	2.83	3.25
Diameter	4	5	4	6	8

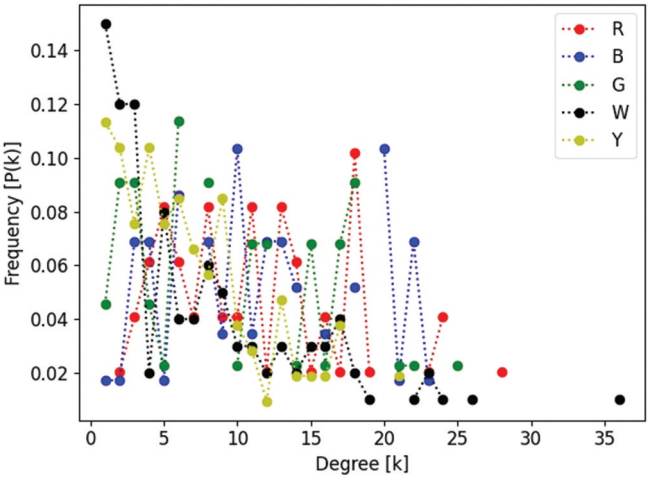


Figure 1. Degree probability distribution of the project networks – the probabilities of the degrees within the networks of the five project towns (Redtown (R), Bluetown (B), Greentown (G), Whitetown (W) and Yellowtown (Y)).

The degree assortativity ranges from fully dissortative (−1) to fully assortative (+1). Social networks tend to be assortative (see Newman et al., 2003). In the present networks, all networks are positively assortative, with two networks being moderately assortative. High-assortative networks are more resilient to disturbances than low-assortative networks (Newman, 2003). Resilient networks regain their functionality despite disturbances (Manzi & Calderoni, 2024); this becomes also evident in criminal networks being, which are not or less effected by detentions of key players and continue operating (Ficara et al., 2023). In addition, these networks are more centralised, as actors with high degrees are connected to other high-degree actors.

The clustering coefficient is similar in all networks (0.4 to 0.6), determining the networks as clustered. As a consequence, the probability that the actors' neighbours are also connected with each other is high. The average shortest path length ranges from two to three. This means that every actor is only a few steps away from all the other actors in the networks. Therefore, these criminal networks exhibit characteristics of small-world networks – networks that have a high clustering coefficient and a low average path length (Watts & Strogatz, 1998).

The diameter of the networks varies and ranges from four to eight. Both the diameter and the average shortest path length scale with network size, generally increasing as the networks grow larger. Consequently, larger networks tend to have higher values for both metrics.

To capture the differences between the actors in the networks, the probability distribution of the actors' degrees is computed (see Figure 1). The degree probability distribution of the project networks describes the likelihood of an actor having a certain number of links. The project networks show very heterogeneous degrees, especially the networks of Redtown, Bluetown, and Greentown. In contrast, the Yellowtown and Whitetown networks have a higher number of actors with fewer links.

The Greentown project networks are similar to each other, regarding their average degree, their degree distribution and their clustering coefficient. The comparison of the criminal networks shows that they have the characteristics of small-world networks. Assortativity varies across different networks and can inform on which networks are more susceptible to a disruption through an intervention. Structural similarities could indicate that those networks face comparable challenges due to disruption but without allowing indications for the network dynamics. Therefore, we will use the Yellowtown network as a representative for our Irish local criminal networks. Before providing a detailed analysis of the Yellowtown network, we evaluate the link prediction processes for the Greentown projects.

Testing link prediction for missing information

The performance of the three link prediction methods is evaluated by reconstructing the networks after deliberately reducing the information on the links. Hence, we simulate missing data and allow for a comparison of how effectively each method predicts and restores the original network structure. We argue that, regarding the results from all five networks, the *common neighbour* approach gives the best results for the link prediction when comparing it to the data it is based on. We summarise the results of all networks by estimating the quality of the three link prediction methods and showing which of those are the closest to our five resulting local crime networks.

First, we generate the networks for the trial sites based on the method described above. Second, we delete 10–50% of the given information on the links between the actors. Third, we run the three link prediction processes to recover the eliminated links. Finally, we compare the original networks with those that contain parts of the original information as well as predicted links by using the Jaccard index.

The *Jaccard Index* quantifies the similarity between two given sets A and B as a ratio of overlap. It measures the ratio of intersection of the two sets to their union. In other words, it takes into account the number of elements present in both sets and the number of unique elements in both sets:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}. \tag{1}$$

This index provides an estimate for which of the three link prediction processes have the best fit over all five networks. For each parameter setting (i.e. percentage of missing information), we run the link prediction process 10,000 times. For every resulting network with reduced information, all three link prediction methods are applied.

The common neighbour approach provides more efficient link prediction than random methods (see Figure 2). Although there is some overlap in the resulting indices of the recovered links, the common neighbour approach also exceeds the preferential attachment. For instance, for the 40% missing information scenario, the common neighbour approach has a Jaccard index (between eliminated and predicted links), on average, of 0.104, while preferential attachment reaches 0.076 and random only 0.040. Additional simulations, varying the percentage of eliminated information, are provided in the Appendix (Figure A1).

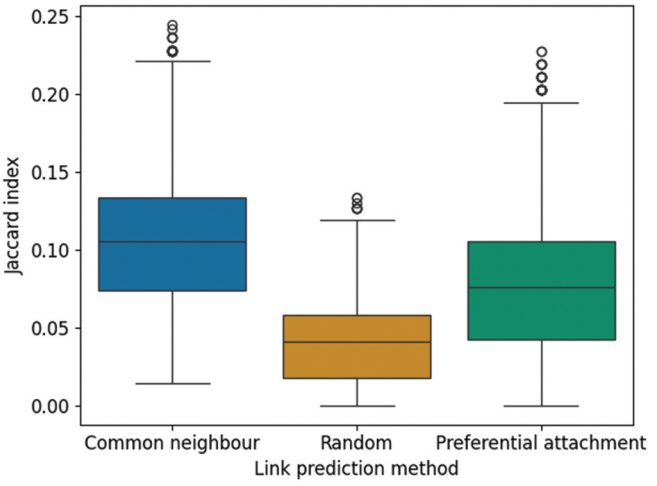


Figure 2. Jaccard index of the predicted links and the eliminated links – the Jaccard index is computed for the three link prediction methods: common neighbour, preferential attachment and random. The networks are based on 40% reduced information. The number of eliminated links defines how many links needed to be predicted. Common neighbour approach tend to have higher Jaccard-indices than the random or preferential attachment approach. The whiskers are within the 1.5 times interquartile range, starting from the 25th or 75th percentile.

In summary, these findings support using the common neighbour method for the analysis of the Greentown projects, based on its superior performance compared to the other two methods. The link prediction can be tailored to a specific data set. If necessary, additional and more complex methods could be introduced for link prediction. Additionally, Berlusconi et al. (2016) demonstrated that the common neighbour approach is a valuable approach to provide a solution for missing data in criminal networks. Therefore, for our case, using the common neighbour approach as the link prediction for a robustness test of the central actors is sufficient.

Yellowtown

The Yellowtown network is the primary case study of our analysis. We focus on identifying the actors' centralities and assessing their robustness. This is achieved through multiple link prediction simulations on the Yellowtown network to account for missing data. Additionally, we draw a relationship between the centrality metrics of actors and the information on their age. This approach facilitates assessing the potential structural importance of actors within the network by using centrality measures. It provides insights into the network's resilience and the factors that influence central positions.

The Yellowtown network spreads over 109 actors with 362 mutual links. Those connections are determined through the Gardaí experts and by shared crime history. We note that the Yellowtown network may be subject to bias, such as missing actors or links, as it relies on a single source (law enforcement), which, most likely, does not capture the entire network (see also Yeung et al., 2025). Relevant recruiters for the Yellowtown network are uncovered by computing the actors' betweenness centrality. Our analysis encompasses the top 10 actors with the highest betweenness centrality to provide a sufficiently high

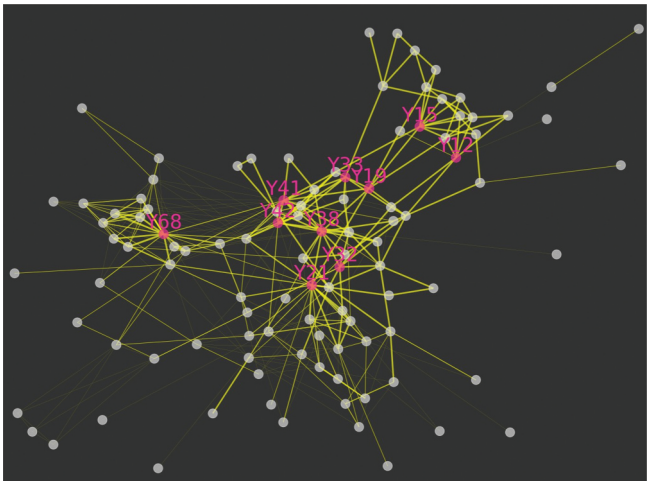


Figure 3. Central actors in Yellowtown network (betweenness centrality) – network of the Yellowtown project where the actors with the highest betweenness centrality are marked (in pink).

threshold to detect all recruiters identified the qualitative analysis. Our robustness simulations indicate that these actors inhibit consistently central positions; however, the threshold may underestimate the total number of relevant actors. In Figure 3, the 10 actors with the highest betweenness centrality are marked. It is visible that the majority of those actors are situated around the core of the network.

We extend the analysis of the actors with the highest betweenness centrality and account for missing data in the networks. Based on the initial structure of the Yellowtown network (see Figure 3), we evaluate the robustness of these actors through simulating link predictions. By using a high number of simulations ($n = 1000$), we redefine the structure of the Yellowtown network by adding a fixed number of links (100). These links are added by employing the common neighbour approach to reassess the actors' centrality measures.

To quantify the similarity between the sets of actors with the highest betweenness centrality before and after adding a certain number of links, we use the Jaccard index. This index measures the similarity between two sets by dividing the number of actors common to both sets by the total number of actors in either sets. Figure 4 illustrates the development of the Jaccard index for the actor with the highest betweenness centrality, as well as for the sets consisting of the top five and ten actors by highest betweenness centrality, relative to the number of links added. These figures show the stability of the most central actors in the networks and highlight that this stability varies depending on the link prediction strategy used. A Jaccard index closer to 1 indicates lower variability in the new set of the most central actors, thus, implying greater stability.

Successively adding links to the Yellowtown networks affects the set of the central actors that we obtain. The common neighbour approach in Figure 4 shows a high variability in the most central actor and a low variability for the set of top five and top ten central actors, indicating a high overall stability of the central actors.

As mentioned previously, the centrality measures can be essential regarding the planned interventions for the networks. If the interventions address singular actors, the robustness for each of the most central actors is relevant. In Figure 5, the relative

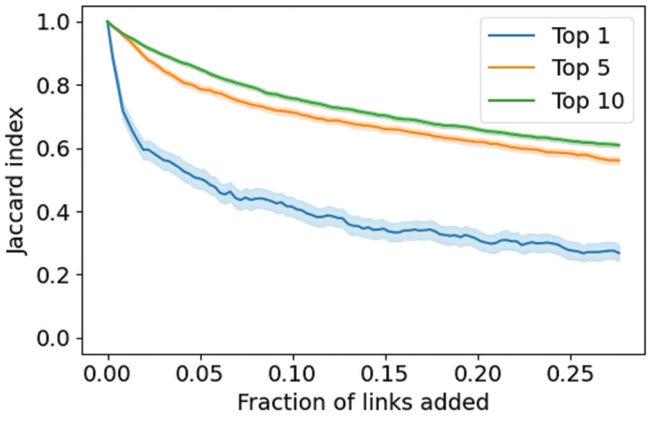


Figure 4. Development of Jaccard index for the actors with the highest betweenness centrality (Yellowtown) – the simulations on the link prediction are based on the common neighbour strategy. The curves are based on the mean Jaccard index for 1000 simulations and a confidence interval is given. The higher the Jaccard index is the higher the robustness towards adding links to the networks. A slower decrease in the index points out a higher degree of robustness.

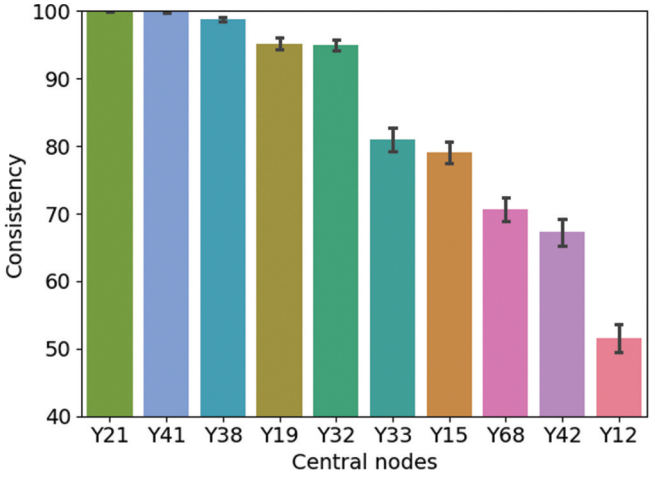


Figure 5. Consistency of the ten most central actors (Yellowtown) – the bar plot shows how often the ten most central actors appear in the simulations to be one of the ten most central actors. As in the previous figure, the simulations on the link prediction are based on the common neighbour strategy. The results are based on the actors' occurrences for 1000 simulations and a confidence interval is given as well.

frequencies of the actors are given, which occur in the set of the most central actors after adding links to the network.

The three actors, Y21, Y41 and Y38, have the highest consistency in the link prediction scenario. As the most central actor (highest betweenness centrality) and also with the highest consistency, the robustness test confirms actor Y21's central position. Actor Y12 has the lowest consistency of the 10 most central actors in Yellowtown. Actors Y33, Y15, Y68 and

Y42 play a less important role, given their consistencies. The provided information on the most central actors and the robustness of the most central actors informs about an ideal target actor for intervention. A complementary analysis for all three link prediction processes as well as a stability analysis of the ten most central actors can be found in the Appendix (see Figure A2 and A3).

Network position and participants' age

The structure of a network can be influenced by the actors' attributes. After evaluating the betweenness centrality and robustness of the central actors, we examine whether centrality measures align with additional information, specifically age.

In the Yellowtown project, the information on age is available for the majority of actors in the network. The correlation between centrality measures and actors' age reveals whether there is a relation and how strong it is. To test this, we apply the Quadratic Assignment Procedure (QAP) permutation test[7] for the variable age (a quantitative variable) and the three centrality measures from above (also quantitative). Subsequently, the significance of this relation is determined by the permutation-based p-value ($p < 0.05$). As depicted in Table 2, the results indicate a significant moderate correlation between age and degree centrality. This draws the conclusion that influential actors tend to be older and occupy positions at the core of the network, while the younger people tend to be situated in the periphery of the network. There is no significant relation between the closeness or the betweenness centrality in regard to range.

Comparison between quantitative and qualitative approaches

Here, we link our results of the social network analysis with insights derived from the qualitative methods. Therefore, we contextualise the quantitative findings through expert knowledge grounded in prior qualitative understanding of the Yellowtown trial site. We discuss the centrality metrics and the robustness analysis by taking into account the roles of relevant single actors in the network. These results are then compared to existing studies and interviews findings, in which experts identified the most important actors in the trial site. Both approaches are examined for their contributions to understanding the network's hierarchical structure.

The qualitative analysis was time-consuming but provided in-depth context. It enabled us to zoom in to understand individual contexts and relationships and zoom out to understand the dynamics and structure of criminal networks. Similar

Table 2. Age vs. centrality measures in Yellowtown – the relation between the age and the centrality measures is tested, using a quadratic assignment procedure (QAP) permutation test with 10,000 permutations. For an $\alpha = 0.05$, the degree centrality is correlated with age with a moderate effect size. However, the closeness centrality and the betweenness centrality are not statistically significant and both show low effect sizes.

Centrality measure	Effect size (Pearson correlation)	P-value
Degree centrality	0.197	0.042
Closeness centrality	0.120	0.222
Betweenness centrality	0.036	0.720

to the Bluetown case study (O'Meara Daly et al., 2020), the qualitative analysis of the Yellowtown data identified four interrelated but distinct networks; these were not evident from the social network analysis. On a relationship level, the qualitative analysis identified people who may groom children for crime. Betweenness centrality is proposed as a quantitative metric that can identify people who may groom children for the crime. This holds for the two most central actors, Y21 and Y41; they also have the highest stability across the three scenarios.

From the qualitative analysis, Y21, a juvenile, was linked to high-status adults by family; he was also linked to younger children and described as bringing them to commit random acts of violence and engaging in drug-related initiation. Actor Y41 (in his 40s and Y42's father (within the top 10 most central actors)) was specifically linked to grooming children for crime; Garda described how he befriended a young boy, giving him small tasks (for example, walking the dogs), and these escalated to criminal tasks (delivering packages) to acts of violent intimidation. Actor Y68 was described as the leader of the most established network. Throughout the qualitative data set, there were many descriptions of how he had groomed several children (many of whom are young adults on the current map) on the network map. Actor Y38 (among the three most central actors) was described as mid-level, unpredictable and involved in serious crime, including armed burglary and drug-related violence. While he was well connected, and one Garda described how he made introductions between young people and adult criminals, both within and outside the area, he was not linked in terms of grooming to any specific child in the qualitative analysis (he was, however, not living in Yellowtown at the time of interviews). Actor Y32 (18 years old) had the fourth highest betweenness centrality. He had older siblings in the network and was linked, through friendships, to the young people on the map (who lived in the same neighbourhood). While his family were described as problematic, he was not portrayed as a criminal influence on other young people in the area.

Actors Y57, Y31, and Y30 were described as mid-high status in the qualitative data and as having a significant negative criminal influence on the children in the network; however, these were not identified as having a high betweenness centrality (outside the 10 most central actors) in the social network analysis. There was no evidence from the qualitative analysis that the remaining actors with top 10 betweenness centralities, Y12, Y15, Y19, and Y33, had a negative criminal influence on children in the area. In the quantitive analysis, these actors were substantially less consistent then other actors; especially, Y12 having the lowest consistency of the 10 central actors. The inclusion of Y21 (16 years) and Y32 (18 years) as top betweenness centralities (1st and 4th) may explain why the correlation between betweenness centrality and age was not significant.

While the social network analysis may yield timely insights, the qualitative analysis may offer nuanced contextual understanding.

While the social network analysis may provide timely analysis, the qualitative analysis may offer a more nuanced understanding. Future social network analysis may benefit from giving a higher weighting to the links between older and younger actors.

Conclusion

Through collaboration between law enforcement and researchers, the Greentown projects revealed the structures of local crime networks across various trial sites. Building on these insights, we compare both quantitative and qualitative approaches to identify recruiters in local crime networks, aiming to provide methodological guidance for disrupting their functionality through social network analysis.

The quantitative approach processes information about local crime areas to build network from interview data and crime history. The five networks show similar network features, such as high clustering, a short average path length, and being same order of magnitude. In the case of the Yellowtown network, we apply a simulation-based robustness method for analysing the network actor's hierarchy that is used for identifying recruiters through the local betweenness centrality. We robustly identified key recruiters. Furthermore, a prominent network position (i.e. a high number of links) correlates with the actor's age. Influential network actors tend to be older.

The qualitative approach, incorporating expert knowledge from researchers and Gardaí, outlines the roles of the 10 most central network actors. The most relevant recruiters identified through the qualitative approach were also detected through the social network analysis. As both approaches share the same data base, a partial overlap is expected. However, the network analysis focuses on potential structural features of recruiters by measuring the betweenness centrality, while the qualitative approach might capture a different aspect of recruiters and does not necessarily overlap with these findings. Additionally, the robustness simulation for missing information directs to misclassified network actors as recruiters.

Simulating missing information and testing the robustness of network actors in central positions assumes a specific underlying network mechanism for link formation. Here, we utilise link prediction as an approach for simulating additional information and to inform about robust network positions. Nevertheless, alternative mechanisms and approaches are possible and might enhance the accuracy of the results further. Despite the strength of the quantitative analysis, such as effectiveness and a more objective angle, the quantitative approach may be necessary but not sufficient on its own.

The Twinsight methodology provides the unique opportunity for researchers and Gardaí to work together on the same local crime networks without disclosing sensitive information. Hence, it allows combining the conducted quantitative analysis and the information on individual narratives of the local crime networks. The combination of expert knowledge with insights from the social network analysis highlights both potential pitfalls and strengths of these approaches. Integrating elements of network analysis into the work of the law enforcement can reveal overlooked actors and highlight structural weak point of the local crime networks. The presented quantitative approach introduces a more reliant tool to uncover key recruiters in the network, even under uncertainty due to missing information. The combined approach provides strategic advantages for disrupting criminal structures. This work contributes to action-orientated research to shorten young people's criminal trajectories and limit their entry into local crime networks.

Notes

1. The Twinsight method enables an in-depth analysis of local crime networks by combining qualitative and quantitive network analysis. It provides a common ground for researchers and law enforcement to collaborate on sensitive data.
2. The Greentown Intervention Programme includes four integrated pillars: Intensive Family Support, Pro-social opportunities, Community efficiency, and Network disruption.
3. Yellowtown was selected due to the fact that new data will be collected on this trial site and the analysis will be repeated.
4. The interviews were conducted with a selected set of people from the Gardaí with prior knowledge of network actors of the trial site.
5. This detailed report was produced as a confidential report for the Interagency Referral Committee, Yellowtown trial site, and An Garda Síochána. It will not be published in its current format as deductive disclosure of the location and specific individuals are possible from the detailed content. Further details can be obtained by contacting PI Sean Redmond.
6. The shortest path is the minimum number of links an actor is separated from another actor in the network.
7. This measure provides the possibility to test correlations, such as the Pearson correlation, but takes the interdependencies of actors into account.

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Appendices

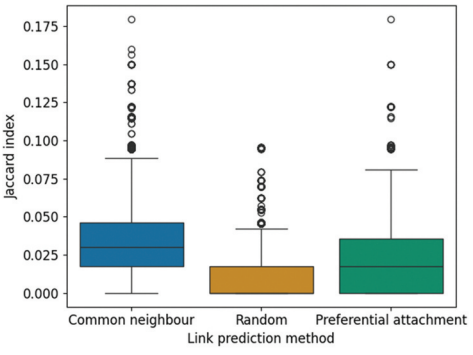
Appendix A. Figures for additional analysis

The figures in this section cover the supplementary results from our analysis from several simulation runs that were performed in this study. Although these figures have not been included in the main part, they provide additional insights in line with the primary findings.

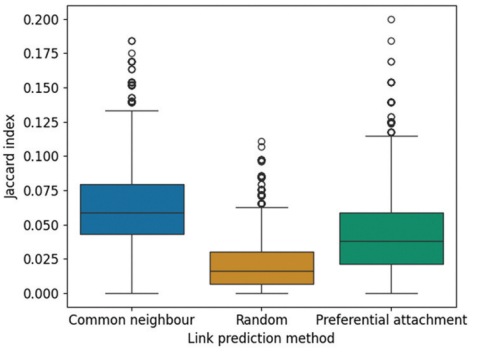
In Figure A1, we evaluate three link prediction methods, common neighbour, preferential attachment and random, by comparing how many links can be recovered by each method. To simulate incomplete network data, we delete a certain amount of information on the links between the actors in the five local criminal networks (i.e. 10%, 20%, 30%, 40%, and 50% of the links). We now compare the links recreated by the three link prediction method to our set of deleted links, using the Jaccard index (see Appendix B). To ensure the statistical robustness, we run each simulation 10,000 times with a random deletion of link information. Across all scenarios, the common neighbour approach consistently shows a more efficient link prediction than the random method. Further, despite some overlap with and less significant than the preferential attachment, the common neighbour shows a better performance. In Results Section, we present the 40% missing information scenario as a representative example of the pattern that we see observe here.

In Figure A2, we illustrate how the composition of the set of actors with the highest betweenness centrality evolves while adding links to the network. At each step, the newly calculated set of central actors are compared to the most central actors in the original networks via the Jaccard index. The results reflect the variability in the central actors' positions, depending on additional information (links) for given networks. For the main analysis presented in this work, we focus exclusively on the common neighbour approach as the selected link prediction method.

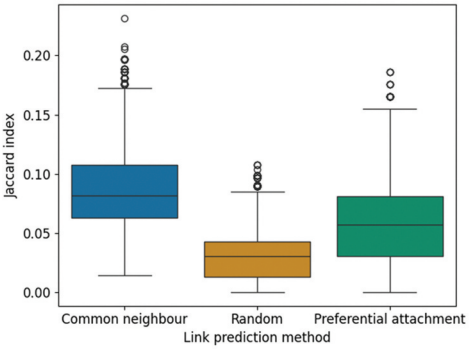
In Figure A3, we assess the stability of individual central actors by steadily adding new links to the networks, using one of the three link prediction methods: common neighbour, preferential attachment and random. We monitor the number of times each of the central actors was present in the newly calculated set of central actors. The bar plots show their overall appearances, including their variability within the 1000 simulations. This gives us insights on how robust each central actor is to missing or inferred network data. Similar to the results from Figure A3, for the main analysis presented in this work, we focus exclusively on the results of the common neighbour approach.



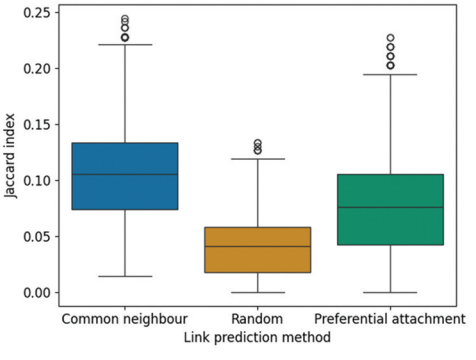
(a) 10%



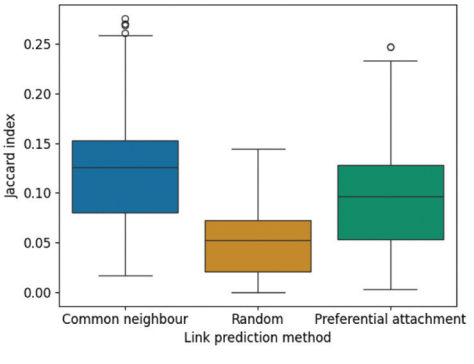
(b) 20%



(c) 30%

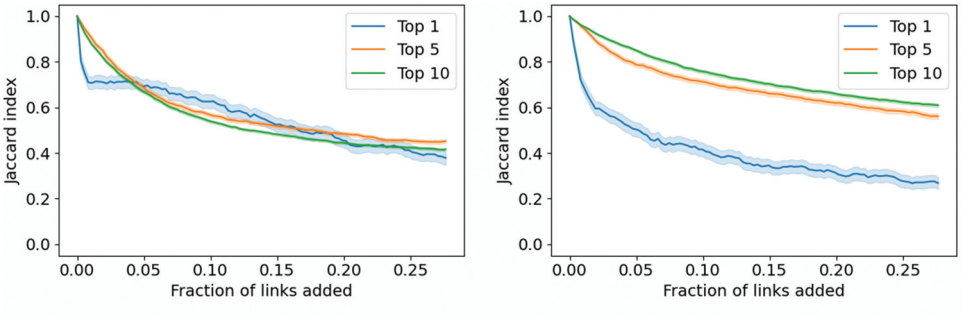


(d) 40%



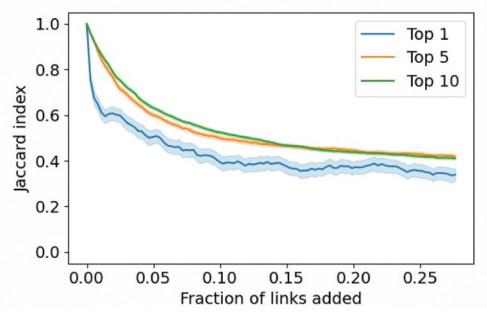
(e) 50%

Figure A1. Jaccard index of the predicted links and the eliminated links – the Jaccard index is computed for the three link prediction methods: common neighbour, preferential attachment and random. The networks are based on information from which varying percentages have been eliminated: (a) 10%, (b) 20%, (c) 30%, (d) 40% and (e) 50%. The number of eliminated links defines how many links needed to be predicted. The whiskers are within 1.5 times the one-and-a-half interquartile range, starting from the 25th or 75th percentile.



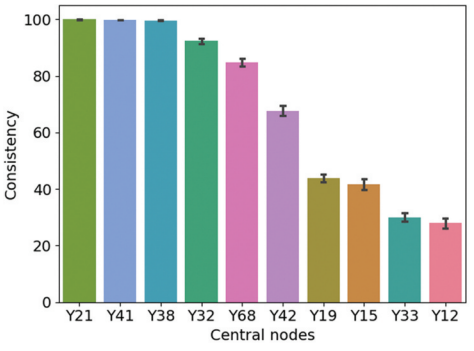
(a) Random

(b) Common neighbour

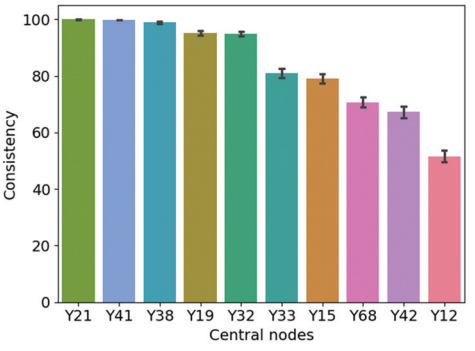


(c) Preferential attachment

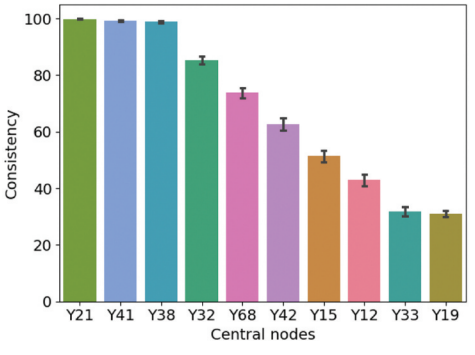
Figure A2. Development of Jaccard index for the actors with the highest betweenness centrality (Yellowtown) – the simulations on the link prediction are based on three strategies: random (a), common neighbour (b) and preferential attachment score (c). The curves are based on the mean Jaccard index for 1000 simulations and a confidence interval is given. The higher the Jaccard index is the higher the robustness towards adding links to the networks. A slower decrease in the index points out a higher degree of robustness.



(a) Random



(b) Common neighbour



(c) Preferential attachment

Figure A3. Consistency of the ten most central actors (Yellowtown) – the bar plot shows how often the ten most central actors appear in the simulations to be one of the ten most central actors. As in the previous figure, the simulations on the link prediction are based on three strategies: (a) random, (b) common neighbour and (c) preferential attachment score. The results are based on the actors' occurrences for 1000 simulations and a confidence interval is given as well. In all three scenarios of the link prediction, the first three actors (Y21, Y41 and Y38) have the highest consistency. As the most central actor (highest betweenness centrality) and also with the highest consistency, the robustness test confirms actor Y21's central position. In contrast to that, the actors on positions four to ten vary. While, in the random scenario (a) and in the preferential attachment scenario (c), the orders are similar and as well the lower levels of consistency, the common neighbour scenario shows a much higher consistency and a different order. For instance, actor Y68 has a much less consistent role in common neighbour scenario then in the other two scenarios. Moreover, actor Y19 role and consistency differs the most in all three scenarios (7th, 4th and 10th).

Appendix B. *Description of network metrics*

We provide here a brief overview of a selection of network metrics. These were also used in Table 1. For further information on network metrics, see Barabási (2016) or Newman (2018).

Network size: The size of the network is defined by the number of actors (n) and the number of links.

Node degree: The degree describes the average number of links for each actor, whereas the density defines the number of links in comparison to the maximum possible number of links.

Network structures: The network structure is further described by the assortativity, the clustering coefficient, the diameter and the average shortest path length.

Network assortativity: The assortativity of the network describes the similarity of the actor pairs in relation to their degree. Thus, a network is assortative by degree if there is a tendency to connect to those actors that have a similar number of links (see Newman, 2003).

Clustering coefficient: The clustering coefficient of a network indicates whether most of the actors' neighbours are also linked between themselves. It measures the fraction of possible triangles in the network.

Path: A path describes a sequence of links between two actors in a network.

Average shortest path length: The shortest path is the minimum number of links that connect two actors. Therefore, the average shortest path length is the average length of all shortest paths between all actors in a given network.

Diameter: The diameter describes the expansion of the network by describing the length of the longest path between two actors in the network, considering only all shortest paths.

Appendix C. *Edges in trial-site networks*

The Greentown project network include co-offence data (co-off.) and interview data (int.). Table A1 presents the composition of the type of nodes and edges across the five trail sites. The first two columns describe the network size based on the co-offence data alone and on all data combined. Furthermore, we show the quantities of two edge types and estimate the overlap of edges that appear in the co-offence data and are mentioned during the interviews. As the interview data builds on the co-offence data, we expect a certain degree of overlap. Separate co-offence data was unavailable for Redtown and Whitetown.

Table A1. Comparison of Co-offence and interview data across towns.

Town	Nodes (co-off.)	Nodes (co-off. & int.)	Edges (co-off.)	Edges (co-off. & int.)	Edge (co-off. & not int.)	Edge overlap (in int.)
Yellowtown	54	156	114	417	90	0.21
Bluetown	56	58	173	339	47	0.73
Greentown	40	45	51	222	9	0.82
Redtown	—	49	—	282	—	—
Whitetown	—	109	—	396	—	—