INTERNATIONAL SCIENTIFIC JOURNAL **ISSN 2710-0766**
«COMPUTER SYSTEMS AND INFORMATION TECHNOLOGIES»

https://doi.org/10.31891/csit-2025-1-8
UDC 004.94

Olha KOVALCHUK
West Ukrainian National University

CHAT GPT FOR NETWORK ANALYSIS CRIMINAL CO-OFFENDERS

In the complex structure of global society, crime remains a persistent problem. It significantly threatens community foundations and hinders social and economic progress. Today, artificial intelligence (AI) technologies are actively being developed to predict possible offenses and detect and analyze criminal network structures through criminal data analysis. The article presents a new approach to studying social connections in criminal networks using GPT-4 tools. A methodology for visualizing criminal data in graphs has been developed to identify criminal group structures. Visual models of criminal co-offender networks were created using data from 2,113 criminal proceedings involving vehicle theft, robberies, and armed robberies committed in the Ternopil region between 2013 and 2024. Using the GPT-4 multimodal model, data processing was performed and graphs were constructed that reflect the structure of social connections between criminals. The analysis revealed significant differences in the structure of criminal interactions for different types of crimes: vehicle theft shows complex interconnected networks with a high degree of centralization and the presence of key coordinator figures; robberies are dominated by small stable groups of 2-3 people, which is explained by the specifics of executing these crimes; armed robberies are characterized by the formation of larger (4-6 people) and structured criminal groups with defined role distribution, due to the need for violence and ensuring control over victims. The proposed methodology effectively allows law enforcement agencies to counter organized crime in modern conditions. The obtained results have practical value for law enforcement agencies in making operational and strategic decisions, as they allow for the identification of key participants in criminal networks and the prediction of their potential criminal activities.

Keywords: criminal network analysis, artificial intelligence, GPT-4, visual model, graph, organized crime, social network analysis, criminal co-offending.

Ольга КОВАЛЬЧУК
Західноукраїнський національний університет

ЧАТ GPT ДЛЯ АНАЛІЗУ МЕРЕЖІ СПІВУЧАСНИКІВ ЗЛОЧИНІВ

У складній структурі глобального суспільства злочинність залишається стійкою проблемою. Вона суттєво загрожує національній безпеці та перешкоджає соціальному й економічному прогресу. Сьогодні активно розвиваються технології штучного інтелекту (ШІ) для прогнозування можливих правопорушень та дослідження структур кримінальних мереж шляхом аналізу кримінальних даних. У статті представлено новий підхід до вивчення соціальних зв'язків у злочинних мережах за допомогою інструментів GPT-4. Розроблено методологію візуалізації кримінальних даних за допомогою графів для виявлення структур злочинних груп. Створено візуальні моделі мереж співучасників злочинів з використанням даних 2 113 кримінальних проваджень щодо незаконного заволодіння транспортними засобами, грабежів та розбійних нападів, скоєних у Тернопільській області протягом 2013-2024 років. За допомогою мультимодальної моделі GPT-4 було проведено обробку даних та побудовано графи, що відображають структуру соціальних зв'язків між злочинцями. Аналіз виявив суттєві відмінності у структурі кримінальних взаємодій для різних видів злочинів: викрадення транспортних засобів демонструє складні взаємопов'язані мережі з високим ступенем централізації та наявністю ключових фігур-координаторів; у грабежах домінують малі стійкі групи з 2-3 осіб, що пояснюється специфікою виконання цих злочинів; розбійні напади характеризуються формуванням більших (4-6 осіб) та структурованих злочинних груп з визначеним розподілом ролей, що обумовлено необхідністю застосування насильства та забезпечення контролю над жертвами. Запропонована методологія може надати правоохоронним органам інформаційну підтримку для ефективної протидії організованій злочинності у сучасних умовах. Отримані результати мають практичну цінність для прийняття оперативних та стратегічних рішень правоохоронними органами, оскільки дозволяють ідентифікувати ключових учасників злочинних мереж та прогнозувати їхню потенційну злочинну діяльність.

Ключові слова: підтримка прийняття рішень, машинне навчання, кримінальне профілювання, кластеризація k-середніх, рецидивізм, інформаційно-аналітичне забезпечення

Introduction

Crime as a global threat is becoming an increasingly urgent problem for the world community. The sharp deterioration of economic conditions and political instability, amplified by armed conflicts in various parts of the world, creates a favorable environment for the growth of crime. Wars not only destroy the established social order but also lead to the emergence of new forms of criminal activity. Organized criminal groups often form in conflict zones, spreading their influence to neighboring regions, and creating transnational criminal networks. Such economic and social upheavals become powerful catalysts for the criminal environment.

The impact of criminal activity permeates all levels of society - from individual to national. Victims face not only material losses but also psychological trauma and loss of security. At the local community level, it is property devaluation, increased anxiety, and general deterioration of living conditions. On a society-wide scale, crime destroys social bonds and undermines citizens' trust in state institutions. The nature of this phenomenon is extremely diverse - it manifests in numerous forms: from minor offenses to serious crimes, including violent acts and activities of organized criminal groups.

In 2024, there was an observed increase in the global crime rate. According to global statistics, over the past two years, one in twenty people experienced a violent crime [1]. Analysts predict a further annual increase in crime by 4% until 2026, caused by deepening social inequality and general destabilization of social structures. In regions with political instability and war zones, such as Ukraine, the level of violent crime is expected to remain high [2].

Crime is a multifaceted social problem that significantly impacts individual lives and communities and society's functioning. To develop effective methods of prevention and response, it is necessary to employ effective mechanisms of counteraction and prevention. One such mechanism is detecting and analyzing social connections and networks formed in the criminal environment.

Criminal Network Analysis is an effective tool for understanding the structure and dynamics of organized crime. Modern artificial intelligence technologies open new possibilities for detecting hidden connections and patterns in large volumes of criminal data. AI systems can process huge amounts of unstructured data from various sources – from police reports to phone records and social networks. They can detect hidden connections between crime accomplices, even when these connections are not obvious in traditional investigations. AI tools effectively predict potential criminal conspiracies, identify key players in criminal networks, etc. They are used to create visual representations of criminal networks that help investigators better understand the structure of criminal organizations. Graph Neural Networks are used to analyze complex relationships between members of criminal groups. These models can detect non-obvious patterns in the structure of criminal networks and predict potential new connections. Developing effective methods for analyzing criminal networks requires an interdisciplinary approach that combines the expertise of law enforcement and data analysts. Only such a comprehensive approach will allow for the creation of truly effective tools for detecting and counteracting organized crime in the modern world.

This article proposes an innovative approach to analyzing social connections between participants in group crimes, based on using GPTChart for modeling criminal networks.

Related works

AI can detect patterns and templates in large datasets that are difficult to identify through manual processing [3]. Artificial Intelligence has become an essential element of forensic investigations [4–5]. Scientists use this capability to study heterogeneous datasets about criminals [6–7], particularly for criminal network analysis [8]. E. Cekic examined how AI is used in creating psychological profiles of offenders, specifically looking at its capabilities to reveal intricate patterns of criminal conduct and underlying motivations [9]. J. Adkins et al. developed a digital forensics approach combining multiple Natural Language Processing tools to generate a list of potential suspects based on text analysis. Their proposed technique functions to narrow down suspects, reducing a large pool of individuals to a smaller set of candidates who show stronger connections to the crime under investigation [10]. N. Shoeibi et al. used various AI methods to detect crimes on Twitter. They applied Graph network analysis to visualize relationships between users [11]. H.V. Ribeiro et al. investigated how graph convolutional networks could be utilized to identify patterns between connected criminals and forecast different characteristics of criminal networks [12]. Salcedo et al. studied the capabilities of Machine Learning Models when applied to Criminal Networks, examining both the potential and challenges of implementing advanced AI methods in Criminal Network Analysis [13].

Despite the existence of individual works, scientific research on using AI methods to study criminal networks is rare. This paper presents an innovative approach to analyzing networks of crime accomplices, based on the application of graph theory and Chart GPT tools.

Research Methodology

The research employed a comprehensive methodological framework that integrated multiple approaches, including literature overview, critical analysis, and case study, along with the proposed application of Graph Network Analysis and ChatGPT tools for detecting and analyzing social connections in networks of criminals who committed crimes.

Organized crime consists of groups that operate secretly and unlawfully, with the potential to impact both social and economic systems [14] severely. Criminal relationships can be analyzed using network theory principles, where they are classified as covert or dark networks [15]. These networks, including those of terrorists and criminals, can be expressed mathematically as graphs. The graph theoretical framework enables us to examine the structure of covert networks and draw conclusions about criminal group behavior [16].

Proposed Crime Data Model

Criminal data can be represented as a finite attributed bipartite hypergraph G containing X and U, which represent the vertices and edges of G. The vertex set X is divided into two mutually exclusive sets, $O = \{o_1, o_2, ..., o_p\}$, $E = \{e_1, e_2, ..., e_q\}$, reflecting offenders and events referring to crime incidents of a certain type.

The set U consists of hyperedges such that each e $u \in U$ is a subset of vertices $\{u_1, u_2, ..., u_r\} \subseteq U$ with $|u \cap E| = 1$ (each edge is connected to exactly one incident) and with $|u \cap O| \geq 1$ (at least one offender).

For any $u, u' \in U$ with $u \cap E = u' \cap E$ it follows that $u = u'$. It means that every edge u of G identifies a subset of offenders $o_{e_1}, o_{e_2}, ..., o_{e_j}$ with any crime event $e_k \in E$, that is $u = \{e_k, o_{e_1}, o_{e_2}, ..., o_{e_j}\}$. An example is shown in Fig. 1.

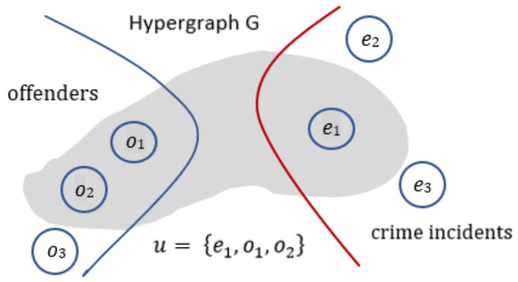

Fig. 1. Crime data model hyperedge

The proposed model does not take into account the number of repeat crimes committed by the same pair of accomplices. Under martial law conditions, criminal connections are extremely unstable. Our goal is to establish the existence of social connections between perpetrators and identify the scale of criminal groups.

Chat GPT for Graph Network Analysis

GPT-4 has built-in capabilities for creating and visualizing graphic elements, including the construction of graphs of varying complexity. The system can generate structured graph representations where nodes, edges, and their attributes can be defined. An important feature is the ability to customize the visual appearance of graph elements - their size, color, shape, and connecting line styles.

When working with graphs, GPT-4 allows the creation of both simple tree structures and complex network diagrams with different types of connections between nodes. The system supports various visualization formats, including directed and undirected graphs, weighted graphs, and hierarchical structures. Additionally, you can customize element placement, and add labels and legends for a better understanding of the presented data. These capabilities make GPT-4 a powerful tool for visualizing complex relationships in various domains, from social network analysis to representing organizational structures and business processes.

We used GPT-4 tools to visualize complex network structures to simplify the analysis of criminal groups. Our task was to generate structured graph representations with the following elements:

- nodes (or vertices) represent individual participants in criminal activity;
- edges (or links) of a graph (or network) show connections between the offenders (nodes).

Proposed Approach

This study presents a novel methodology for detecting and analyzing criminal networks using Graph Network Analysis by the ChatGPT tool (Fig. 2).

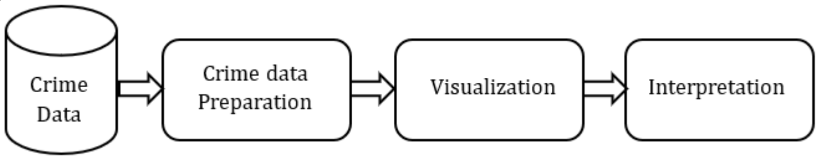

Fig. 2. Flow chart of the proposed approach for analysis of social connections within criminal co-offenders

Our data set is generated from crime data by natural language generation using GPT-4 [17]. Using this AI tool, based on facts of criminal cases, a new table was created containing relevant information for constructing the criminal network graph: data about persons who committed crimes; data about types of crimes committed; and information about accomplices [18].

We used the large multimodal model GPT-4 to construct a graph that is a visual representation of social connections between criminals who participated in joint crimes [19].

Data selection and description

To detect and analyze criminal networks, we used information about actual crimes committed between 2013 and 2024 in the Ternopil region of Ukraine. Using ChatGPT-4, we generated Data Sets from 2,113 criminal proceedings involving Illegal appropriation of a vehicle, thefts, and robbery. The datasets include information about offenders and their criminal incidents for these types of offenses. Based on the formed Data Sets, we created graphs representing the structures of social connections in criminal networks, using GPT-4. The graph's edges represent connections between criminals who committed crimes as part of the same group. The graph edges represent connections between offenders who committed crimes together. The stages of generating Data Sets and creating a graph network are shown in Fig. 3.

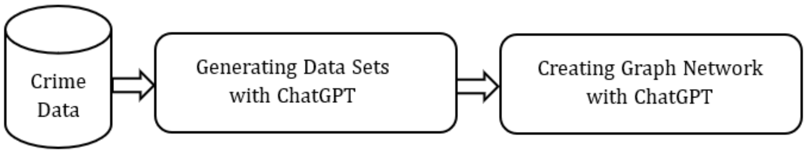

Fig. 3. Generating data sets and creating graph network process

Fig. 4 illustrates the workflow beginning with raw crime data, the formation of a new data table containing the necessary attributes for a graphical representation of the criminal network, and the creation of a co-offender graph. Its vertices represent criminals from the dataset; edges visualize social connections between them (indicating the presence of crimes committed jointly by the corresponding pair of offenders).

Results and Discussion

Visualization can facilitate the analysis of social connections in criminal networks. It can enable the detection of patterns in interactions between offenders, identification of criminal groups, identification of offenders who are crime organizers, and their roles, as well as recognition of communication patterns between offenders [20–21]. The process of visualization of social connections in offender networks goes beyond simple image generation. It creates opportunities for deeper study and analysis of criminal connections.

Based on information from real data of 2,113 criminal proceedings, which includes details about perpetrators and their committed crimes, graphs of criminal accomplice networks were constructed using ChartGPT tools. We created visual models separately for three types of crimes (illegal appropriation of a vehicle, thefts, and robbery) committed in the Ternopil region, Ukraine, between 2013 and 2024. Using the multimodal GPT-4 model, based on input data containing detailed information about committed crimes, a data table was created that included attributes necessary for further visualization of social relationships between criminals [18]. The newly created data were used as a basis for creating graphs representing a visual model of criminal interactions in the network of criminals by GPT-4 [19].

Fig. 4 presents a graph that is a visual representation of interactions in the network of criminals who committed illegal appropriation of a vehicle. The vertices of the graph represent criminals, while the edges reflect the complicity of the respective pair of criminals in crimes. We aimed to identify the structure of interactions in the criminal network. When constructing the graph, the fact of complicity itself was taken into account, while the number of repeated crimes within the same group was not considered. The visual model of co-offenders for illegal appropriation of a vehicle demonstrates the presence of multiple interconnections between criminals. The instability of criminal groups is evident, as indicated by the presence of many criminal interactions between different participants in the criminal network.

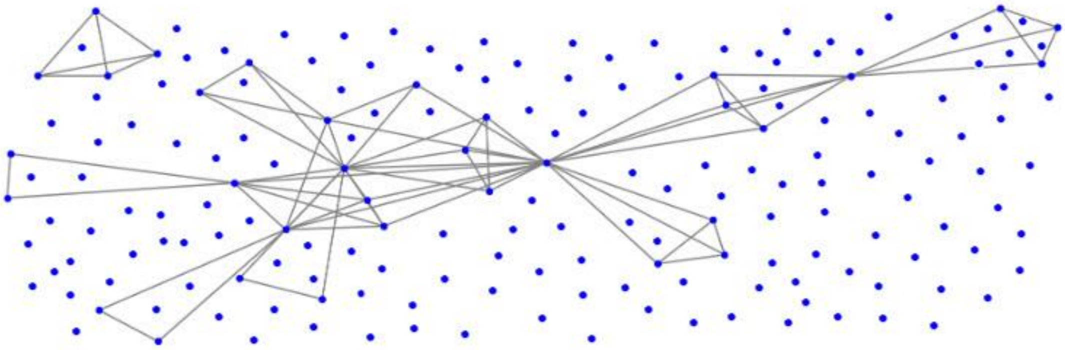

Fig. 4. Visual model of co-offenders of illegal appropriation of a vehicle

Of particular note are nodes with high centrality, indicating the presence of key figures in the network who have numerous connections with other participants. Such individuals could potentially be organizers or coordinators of criminal activity. There are also clusters of more densely connected criminals, which may indicate the existence of established criminal groups specializing in vehicle theft. This result can be explained by the fact that most professional car thefts are carried out by organized criminal groups of 2–3 to 5–6 people, where each person performs a specialized role (thief, driver, reseller, etc.). This is due to modern vehicles having complex security systems, and the need for logistics for quick concealment of stolen vehicles [22].

Criminals who committed illegal appropriation of a vehicle alone are represented by isolated vertices on the graph. Such cases more commonly occur in spontaneous thefts (for example, when the owner left keys in the ignition); theft of older models with simple security systems; or joy-riding (“car rides”). The large number of isolated vertices indicates many criminals who steal vehicles without co-offenders. This fact can be explained by our study's Data Set covering 3 years of martial law in Ukraine. During this time, the structural composition of crime has changed significantly, with many connections being lost. Social vulnerability and mass population displacement have also become significant factors. At the same time, the created visual model of social interactions between participants in the illegal appropriation of a vehicle indicates the presence of large-scale criminal networks of vehicle thieves. However, accurate statistics on the ratio of group versus solo vehicle thefts are difficult to establish, as many crimes remain unsolved.

Fig. 5 shows a visual model of criminal interactions between participants in thefts. The number of criminals who committed crimes of this type is significantly lower than in the case of illegal appropriation of a vehicle. Robberies are carried out by groups of 2–3 people in cases of attacks on pedestrians at night, robberies in public places, attacks on cash collectors or banks, and store robberies. This is because in a group attack, it is easier to control the situation and the victim, there is a better chance of overcoming resistance, and there is an opportunity to divide roles (one threatens, the other takes valuables) [23]. Such groups are relatively stable since successful robberies require coordinated actions of participants, mutual trust, and a clear understanding of each accomplice's role. Analysis of the graph shows that a significant proportion of vertices are connected by edges into stable components of 2–3 vertices, which confirms the tendency to form small but stable criminal groups when carrying out robberies.

Single robberies more frequently occur during attacks on elderly people, spontaneous unplanned robberies, robberies under the influence of alcohol or drugs, and minor street robberies (snatching bags, and phones). The presence of a large number of isolated vertices in the graph representing interactions between theft participants indicates a significant proportion of situational, unorganized crimes in the overall structure of robberies. This may indicate that a significant portion of such crimes occur spontaneously, without prior planning, and are not connected to the activities of organized criminal groups.

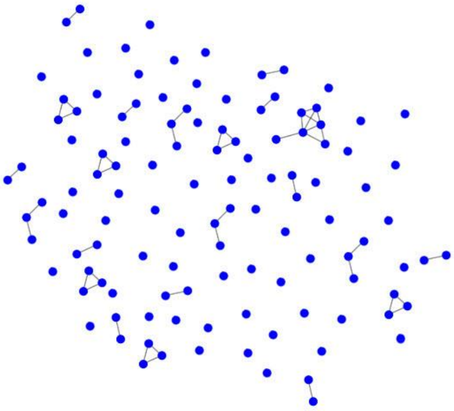

Fig. 5. Visual model of co-offenders of thefts

Fig. 6 presents a visual model of criminal interactions between offenders who committed robbery. The graph representing the visual model of co-offenders of this type of crime shows clearly defined criminal groups. However, compared to thefts, these groups are more numerous. This is explained by the fact that robberies are most often committed by groups, which is related to the nature of the crime itself. Group robberies predominate in attacks on private residences, robberies of businesses or stores, attacks on cash collectors, and highway robberies. The reasons for the dominance of group robberies include the need to use violence or threats of violence, the need to control multiple people simultaneously, a higher likelihood of overcoming resistance, and the necessity to quickly ensure escape and transportation of stolen goods.

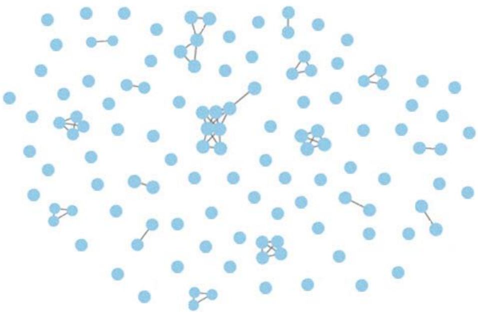

Fig. 6. Visual model of co-offenders of robbery

In the graph presented in Fig. 6, a significant number of vertices are isolated. These vertices represent offenders who committed single robberies. Such cases occur during attacks on lone pedestrians, spontaneous unplanned crimes, attacks in sparsely populated places, and robberies committed by repeat offenders.

Unlike thefts, robberies show more clearly structured criminal groups and a higher intensity of criminal connections between co-offenders [24–25]. The visual model demonstrates the presence of both large organized groups and a significant number of individual criminals. Under martial law, the structure of robbery crime has undergone substantial changes: there is an increase in the number of armed robberies, especially with weapons removed from the combat zone. There is also a trend toward an increase in the number of robberies targeting homes of internally displaced persons and temporarily abandoned houses in areas close to the combat zone. The formation of criminal groups involving former military personnel who use skills and knowledge gained during service has become characteristic.

The analysis of visual models of criminal networks for three types of crimes (illegal appropriation of vehicles, thefts, and robberies) demonstrates significant differences in the structure of criminal interactions and patterns of criminal group formation. The visual representation of network data made it possible to identify characteristic patterns of criminal activity organization: from complex interconnected networks in vehicle theft to more structured group formations in robberies. Of particular value is the ability to identify key figures and stable criminal groups, which is critically important for law enforcement agencies. Martial law has significantly impacted the structure of crime, which is reflected in a significant number of isolated subjects and the emergence of new forms of group criminal activity. Quality visualization and interpretation of the obtained data create a bridge between theoretical analysis of criminal networks and practical law enforcement activities, providing them with an effective tool for understanding and countering organized crime in modern conditions.

Conclusions

The article proposes an innovative approach to analyzing social connections in criminal networks using GPT-4 tools for data visualization and interpretation. A methodology was developed for representing criminal data as a finite attributive bipartite hypergraph and creating visual models of criminal interactions based on it. Based on information from 2,113 criminal proceedings regarding illegal appropriation of vehicles, thefts, and robberies committed in the Ternopil region during 2013–2024, graphs of co-offender networks for these types of crimes were created and analyzed. Using the GPT-4 multimodal model, unstructured data from criminal proceedings was processed and a structured table with attributes necessary for visualization was created. Based on this data, using ChartGPT tools, graphs were constructed that reflect the structure of social connections between criminals, where vertices represent individual offenders and edges represent instances of their criminal cooperation.

The conducted research demonstrates the effectiveness of using GPT-4 tools for analyzing and visualizing social connections in criminal networks. Applying the proposed methodology to analyze real crime data revealed significant differences in the structure of criminal interactions across different types of crimes.

Visual models showed that vehicle theft is characterized by complex interconnected networks and key figures with a high degree of centralization. Robberies involve more compact, established groups of 2–3 people, while armed robberies are marked by the formation of larger and more structured criminal groups. Of particular note is the significant number of isolated subjects across all types of crimes, which may be related to the destabilization of the criminal environment under martial law conditions.

Visual representation of network data can provide investigators with new insights into the structural characteristics of criminal groups, particularly under martial law conditions. The proposed methodology, which combines GPT-4's capabilities for data processing and visualization, creates a powerful tool for analyzing criminal networks. Quality visualization and detailed interpretation of the obtained results help bridge the gap between theoretical analysis and practical law enforcement activities, providing them with effective means for understanding and countering organized crime in modern conditions. Future research will focus on improving algorithms for detecting hidden connections and predicting potential criminal conspiracies using more sophisticated methods of graph analysis and machine learning. In particular, the problem of repeat offenses by established criminal groups will be examined.

References

1. The Global Safety Report. Gallup. 2024. URL: https://insightcrime.org/wp-content/uploads/2024/10/Gallup_Global-Safety-Report-2024.pdf (Last accessed: 10.01.2025).
2. Joshi K. Crime Statistics by Country Crime Index and Facts. 2024. URL: https://www.coolest-gadgets.com/crime-statistics/ (Last accessed: 07.01.2025).
3. Yagunov D. The Ukrainian Prison and Probation Policy (1991 – 2024): Modulations and Key Indicators. *Evropský časopis ekonomiky a management*. 2024. Vol. 10(4). Pp. 17–86. https://doi:10.46340/eujem.2024.10.4.2.
4. Bharadiya J. P. Machine learning and AI in business intelligence: Trends and opportunities. *Int. J. Comput*. 2023. Vol. 48(1). Pp. 123–134.
5. Jarrett A., Choo K.K.R. The impact of automation and artificial intelligence on digital forensics. *Wiley Interdiscip. Rev. Forensic Sci*. 2021. Vol. 3(6):e1418. https://doi:10.1002/wfs2.1418.
6. Sarzaeim P., Mahmoud Q. H., Azim A., Bauer G., Bowles I. A Systematic Review of Using Machine Learning and Natural Language Processing in Smart Policing. *Computers*. 2023. Vol. 12(12):255. https://doi:10.3390/computers12120255.
7. Rigano C. Using Artificial Intelligence to Address Criminal Justice Needs. *NIJ Journal*. 2019. Vol. 280. Pp. 1–10.
8. Ficara A., Curreri F., Fiumara G., De Meo P., Liotta A. Covert Network Construction, Disruption, and Resilience: A Survey. *Mathematics*. 2022. Vol. 10(16):2929. https://doi:10.3390/math10162929.
9. Cekic E. The Impact of Artificial Intelligence Tools on Criminal Psychological Profiling. *International Journal of Academic Research in Psychology*. 2024. Vol. 11(1). Pp. 1–13. https://doi:10.46886/IJARP/v11-i1/7405.
10. Adkins J., Bataineh A. A., Khalaf M. Identifying Persons of Interest in Digital Forensics Using NLP-Based AI. *Future Internet.* Vol. 16(11):426 (2024). https://doi:10.3390/fi16110426.

11. Shoeibi N., Shoeibi N., Hernández G., Chamoso P., Corchado J.M. AI-Crime Hunter: An AI Mixture of Experts for Crime Discovery on Twitter. *Electronics*. 2021. Vol. 10(24):3081. https://doi:10.3390/electronics10243081.

12. Ribeiro H. V., Lopes D.D., Pessa A. A. B., Martins A. F., da Cunha B. R., Gonçalves S., Lenzi E. K., Hanley Q. S., Perc M. Deep learning criminal networks. *Chaos, Solitons & Fractals*. 2023. Vol. 172:113579. https://doi:10.1016/j.chaos.2023.113579.

13. Salcedo-Albarán E., Salamanca L.J.G., Cano-Melani J. A. Machine Learning Models on Criminal Networks (MLMoCN): Artificial Intelligence to Disentangle Crime. *Vortex Working Paper*. 2023. Vol. 65. https://doi:10.2139/ssrn.4651714.

14. Kovalchuk O., Shynkaryk M., Masonkova M. Econometric Models for Estimating the Financial Effect of Cybercrimes, in: Proceedings of the 11th International Conference on Advanced Computer Information Technologies, Deggendorf, Germany, 2021, pp. 381–384. https://doi:10.1109/ACIT52158.2021.9548490.

15. Kovalchuk O., Masonkova M., Banakh S. The Dark Web Worldwide 2020: Anonymous vs Safety. *In Proceedings of the 11th International Conference on Advanced Computer Information Technologies (ACIT-2022). IEEE,* Deggendorf, Germany, 2021. Pp. 526–530. https://doi:10.1109/ACIT52158.2021.9548578.

16. Ficara A., Saitta R., Fiumara G., de Meo P., Liotta A. A. Game of Thieves and WERW-Kpath: Two Novel Measures of Node and Edge Centrality for Mafia Networks. *In Complex Networks XII. Springer International Publishing*, Cham, Switzerland, 2021, Pp. 12–23. https://doi:10.1007/978-3-030-81854-8_2

17. Kovalchuk O., Shevchuk R., Masonkova M., Banakh A. Content Analysis of Court Decisions: A GPT-4 Based Sentence-by-Sentence Data Generation and Association Rules Mining. *In Proceedings of the I International Workshop of Young Scientists on Artificial Intelligence for Sustainable Development*. 2024. Pp. 56–70. URL: https://ceur-ws.org/Vol-3716/paper5.pdf.

18. Gewirtz D. How to use ChatGPT's Advanced Data Analysis to create quality charts and tables. URL: https://www.zdnet.com/article/how-to-use-chatgpt-to-make-charts-and-tables-with-advanced-data-analysis/ (Last accessed: 17.12.2024).

19. Lanoue S. How to Use ChatGPT to Make Charts and Graphs. URL: https://www.thebricks.com/resources/how-to-use-chatgpt-to-make-charts-and-graphs (Last accessed: 07.12.2024).

20. Anastasiadis E. K., Antoniou I. Directed Criminal Networks: Temporal Analysis and Disruption. *Information*. 2024. Vol. 15(2):84. https://doi:10.3390/info15020084.

21. Zhao K., Zhang H., Li J., Pan Q., Lai L., Nie Y., Zhang Z. Social Network Forensics Analysis Model Based on Network Representation Learning. *Entropy*. 2024. Vol. 26(7):579. https://doi:10.3390/e26070579.

22. Quinn A. Vehicle Crime, CPTED, and Offending under the Influence: A Qualitative Investigation of Offender Perceptions. *Social Sciences*. 2019. Vol. 8(3):88. https://doi:10.3390/socsci8030088.

23. Kwon E., Jung S., LeeJ. Artificial Neural Network Model Development to Predict Theft Types in Consideration of Environmental Factors. *ISPRS International Journal of Geo-Information*. 2021. Vol. 10(2):99. https://doi:10.3390/ijgi10020099.

24. Zhang H., Gao Y., Yao D., Zhang J. Interaction of Crime Risk across Crime Types in Hotspot Areas. *ISPRS International Journal of Geo-Information*. 2023. Vol. 12(4):176. https://doi:10.3390/ijgi12040176.

25. Rasmusson M., Helbich V. The Relationship between Near-Repeat Street Robbery and the Environment: Evidence from Malmö, Sweden. *SPRS International Journal of Geo-Information*. 2020. Vol. 9(4):188. https://doi10.3390/ijgi9040188.

Olha Kovalchuk **Ольга Ковальчук**	PhD, Associate Professor of the Law Theory and Constitutionalism Department, West Ukrainian National University, Ternopil, Ukraine, e-mail: olhakov@gmail.com. https://orcid.org/0000-0001-6490-9633 Scopus Author ID: 57782473100, Researcher ID: H-3889-2017	кандидат фізико-математичних наук, доцент кафедри теорії права та конституціоналізму, Західноукраїнський національний університет, Тернопіль, Україна