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FEATURES AND DIFFERENCES OF USING GRAPH THEORY FOR ANALYSIS AND VISUALIZATION OF CONNECTIONS IN SOCIAL NETWORKS

This article explores the potential for adapting classical graph theory to the analysis of social networks through key criteria such as node types, edge types and weights, graph directionality, temporal variability, centrality metrics, community structures, analytical algorithms, big data processing, visualization, prediction capabilities, and the role of content. The aim of the research is to enhance the effectiveness of analyzing the structure and dynamics of social networks by applying graph theory methods and visualization tools to identify interaction patterns between users.

The paper provides a comparative analysis of how graph theory is applied to study the structure and user interactions in four of the most popular social networks: ***Facebook****,* ***Instagram****,* ***TikTok****, and* ***LinkedIn****. It discusses differences in graph structure (nodes, edges, edge weights, directionality), connection types and their evolution over time, the nature of user interactions, analytical approaches (methods and forecasting), big data handling, and visualization techniques.*

The key analytical methods used to examine connections within each of the selected networks are outlined, and visualizations of graphs representing these connections are presented. The study demonstrates that the defined graph-theoretical features for analyzing the structure of leading social networks can significantly improve the use of these tools in the areas of: ensuring ***cybersecurity****, supporting* ***political interest analysis*** *through public opinion monitoring, enhancing* ***customer relationship management****, and optimizing* ***social media algorithms****.*

Data sources for this type of analysis may include: direct platform data; data from electronic communication systems (e.g., email, chats, forums); internal organizational records; results of surveys conducted to map social ties and user interactions; and publicly available datasets.

The scientific novelty of the study lies in the development of a methodology for selecting appropriate types of graph models and visualization strategies for analyzing the structure and dynamics of multilevel social connections with maximum efficiency. The results obtained may be applied by government institutions, business entities, and civil society organizations to gain deeper insights into digital social interactions – not only at the level of basic connections (“friendship”, “subscription”), but also in more complex informational and behavioral contexts.

Key words: *social networks, graph theory, analysis, modeling, information technology, information system, data analysis, visualization of connections.*

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АНАЛІЗ І ВІЗУАЛІЗАЦІЯ СКЛАДНИХ БАГАТОРІВНЕВИХ ЗВ'ЯЗКІВ У СОЦІАЛЬНИХ МЕРЕЖАХ ТА ЇХ ДИНАМІКИ НА ОСНОВІ ВИКОРИСТАННЯ ТЕОРІЇ ГРАФІВ

У статті розглянуті можливості адаптації класичної теорії графів до аналізу соціальних мереж у розрізі таких критеріїв як: пити вузлів, типи і ваги ребер, напрямленість графа, змінність у часі, метрики центральності, типи спільнот, алгоритми аналізу, оброблення великих даних, візуалізація, прогнозування, роль контенту. Метою проведення даного дослідження є підвищення ефективності аналізу структури та динаміки соціальних мереж на основі використання методів теорії графів і засобів їх візуалізації для виявлення закономірностей взаємодії між користувачами. У роботі здійснено порівняльний аналіз особливостей застосування теорії графів для вивчення структури та дослідження взаємодій між користувачами чотирьох таких найпопулярніших соціальних мереж як Facebook, Instagram, TikTok і LinkedIn. Розглянуто відмінності у структурі графів (вузли, ребра, ваги ребер, напрямленість), типах зв'язків та їх змінності у часі, характері взаємодій у соціальній мережі, особливостях аналізу (методи, прогноз), обробці великих даних і візуалізації. Наведено основні методи якими здійснюють аналіз зв'язків у кожній із розглянутих соціальних мереж. Здійснено візуалізацію графів, що відображають ці зв'язки. Доведено, що окреслені особливості застосування теорії графів для аналізу структури найпопулярніших соціальних мереж дозволять ефективніше використовувати даний інструментарій для забезпечення кібербезпеки; реалізації політичних інтересів із врахуванням тенденцій громадської думки; побудови якісної взаємодії із клієнтами; удосконалення алгоритмів соціальних мереж. Джерелами даних для такого аналізу можуть бути: дані безпосередньо із самих платформ; дані з платформ електронних комунікацій; внутрішні дані компаній та організацій; результати проведених опитувань про соціальні зв'язки та взаємодії через спеціально створені анкети; дані з публічних баз даних. Наукова новизна дослідження полягає у розробленні методики вибору видів графових моделей соціальних мереж та їх візуалізіцій для забезпечення максимальної ефективності проведення аналізу їх структури і динаміки багаторівневих зв'язків. Отримані результати можуть бути використані органами влади, представниками бізнесу та громадянського суспільства для глибшого аналізу цифрових взаємозв'язків – не тільки на рівні базових зв'язків («дружба», «підписка»), а й у складніших інформаційних і поведінкових контекстах.

Ключові слова: *соціальні мережі, теорія графів, аналіз, моделювання, інформаційна технологія, інформаційна система, аналіз даних, візуалізація зв'язків.*

Statement of the problem

Social networks have long since evolved from being mere platforms for sharing information, content, and communication on the Internet into tools actively used in politics, sociology, economics, and other spheres of human activity. Therefore, the need to analyze user interactions within social networks is becoming increasingly relevant in order to use these platforms more effectively to achieve specific goals.

Such interactions can be analyzed using social graphs and various network analytics methods. The key technologies applied here include:

- Graph databases for identifying opinion leaders, influencers, bots, and fake accounts, as well as analyzing social connections in large communities;
- Machine learning for predicting interactions and user behavior, which serves as the foundation for improving recommendation systems (e.g., Facebook, TikTok, Instagram), detecting anomalies (e.g., phishing, fraud), and forecasting viral content spread;
- Natural Language Processing (NLP) for analyzing user content and sentiment to detect hate speech, fake news, disinformation, emotion in comments and reviews, and for automating content moderation;
- Social Network Analysis (SNA) based on graph theory to explore user influence, detect communities, and evaluate user engagement within the network.

Social networks are constantly evolving, so even the use of graph theory for analyzing and visualizing user relationships requires new approaches that:

- account for fundamental differences in the functioning of various social networks and their user interaction models;
- cover not only general social connections (e.g., "friendship", "subscription") but also more complex and specific interactions (e.g., interpersonal relationships, group dynamics, influence networks, parallel engagements);
- incorporate temporal analysis of connections, including the emergence of new users or events;
- enable interactive and adaptive visualization, including large-scale data;
- support deeper analysis of specific influence types (psychological, economic, political) through corresponding graph types and multi-aspect user relationships (ranging from professional to friendly or romantic ties).

Such comprehensive research would extend current social network models and improve the analytical tools available to researchers, entrepreneurs, and developers.

Analysis of Recent Research and Publications

Various aspects of social network analysis and research have been more extensively covered in the works of foreign scholars.

For example, Albert-László Barabási developed the theory of scale-free networks [1]. Duncan J. Watts focused on the study of network structures and behaviors, the phenomenon of small-world networks, and the collective dynamics of human systems. He revealed fundamental rules governing the networks of people, machines, companies, economies, and the mechanisms of information diffusion in social networks [3–4].

Stanley Milgram introduced the concept of "six degrees of separation", which postulates that any person can be connected to any other through a chain of acquaintances or relationships involving no more than six intermediate steps. This idea helps explain user connections in large networks through intermediary contacts [5, pp. 60–67].

Among Ukrainian scholars, notable contributions include the works of A. Hizun and V. Hriha [8, p. 412], who analyzed the most common models of information dissemination in social networks within the context of information warfare. V. Mazurenko and S. Shtovba [13, pp. 62–74] focused on applying graph theory models for social network analysis.

A. Snarskyi, D. Lande, and I. Subach [12; 15] provided practical recommendations for mathematical and computational modeling, analysis, and visualization of complex networks. L. Didyk [10, pp. 95–105] examined the fundamental mechanisms of social network functioning. O. Shushura and B. Kokidko [16, pp. 12–17] developed approaches for analyzing and modeling social networks using graph databases and fuzzy logic.

Given that social networks are constantly evolving and differ significantly in their functioning principles, data structures, and user interaction models, and that most existing studies focus on general principles of analysis, it is advisable to expand these studies. This includes investigating the specific features and distinctions in the use of graph theory to analyze user interactions across different platforms. Such research would help fully understand not only general social connections (e.g., "friendship" or "subscription") but also specific types of relationships that reflect more complex interactions – such as interpersonal relationships, group dynamics, or influence networks.

This deeper understanding would enhance the analysis of social interactions, various types of influence (psychological, economic, political), allow adaptation to the unique features of different platforms, facilitate behavioral forecasting, reveal hidden patterns, and improve the algorithms used for analyzing social processes.

Research Objective

The aim of this article is to increase the efficiency of analyzing the structure and *dynamics of multilevel interactions* in social networks through the rational selection of their graph models and visualization tools, taking into account the specific features of their application, using the example of social networks such as Facebook, Instagram, TikTok, and LinkedIn.

Presentation of the Main Research Material

Various information technologies are used to study the structure of social networks, with graph theory, machine learning, and interaction analysis algorithms being among the most common. Their combined application enables the identification of key users, determination of behavioral patterns, measurement of influence, and detection of community structures within social networks. This facilitates a deeper understanding of human interaction and allows for predicting behavior in order to more effectively manage information flows.

Based on the analysis of classical applications of graph theory [2; 11] to social network analysis [14, p. 19–13], a graph-based schema has been developed (see Fig. 2). At the same time, it should be noted that the rapid development and widespread use of social networks create a pressing need for more in-depth research into the mechanisms of using this toolkit to analyze and visualize connections in the most popular platforms, such as Facebook, Instagram, TikTok, and LinkedIn [9].

It is evident that there are substantial differences between these platforms, as each of them operates on different principles and has distinct models of user interaction. These differences directly affect the structure of graphs and the methods used for their analysis.

Any social network can be formalized as a graph:

$$G = (V, E), \tag{1}$$

where $V = \{v1, v2, \ldots, vn\}$ is the set of vertices (users) of the network, $E = \{eij\}$ is the set of edges representing interactions between them.

The weight of an edge $w(eij)$ can be defined by the formula:

$$w(eij) = \alpha f_{like}(i, j) + \beta f_{comment}(i, j) + \gamma f_{share}(i, j), \tag{2}$$

where f_{like}, $f_{comment}$, f_{share} – are functions that determine the number of likes, comments, and shares between users i and j, α, β, γ – are weight coefficients.

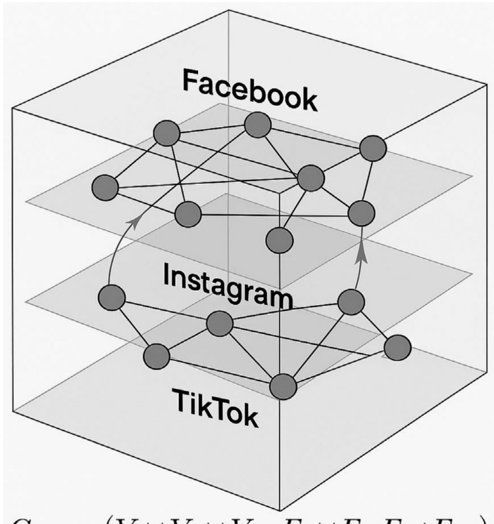
To analyze such a network, the adjacency matrix is used, which captures the presence and weights of connections between users.

For a multilayer network (e.g., Facebook, Instagram, TikTok, LinkedIn), the model can be formalized as:

$$G = \{G_{Facebook}, G_{Instagram}, G_{TikTok}\} \cup E_{cross}, \tag{3}$$

where E_{cross} – is the set of inter-network edges that define users active across multiple platforms simultaneously.

$$G_{multi} = (V_1 \cup V_2 \cup V_3, E_1 \cup E_2 \cup E_3 \cup E_{inter}) \tag{4}$$



$$G_{\mathrm{multi}} = (V_1 \cup V_2 \cup V_3,\ E_1 \cup E_2\ E_3 \lrcorner E_{int})$$

Fig. 1. Visualization of a multilayer model of social networks

Source: compiled by the authors. Each plane represents a separate network (Facebook, Instagram, TikTok), while the transparent arrows show cross-platform connections between the same users.

Social network Facebook, for example, is characterized by a well-defined structure of social groups (such as family, friends, or professional relationships). In this network, group interactions, including comments and reposts, are especially important. As a result, the analysis typically focuses on node clustering and centrality.

A traditional social graph (directed, often bidirectional to represent mutual friendship) is best suited for this purpose. Using graph models, it is possible to analyze not only friendship connections between users (e.g., to identify influential individuals or friend clusters), but also additional interactions (such as likes, comments, or shared group memberships), which allows researchers to determine key influencers and the structure of social ties.

Examples of such interaction graphs are presented in Fig. 3. Visualization tools such as Gephi, NetworkX (Python), and Pajek are commonly used for further analysis of Facebook network interactions.

Зазначимо, It should be noted that the primary goal of analyzing the structure of the Facebook network using graph models is to identify social groups, determine key users, and study communication patterns. To achieve this, several groups of methods are commonly applied:

Centrality analysis methods, which help identify the most important nodes in the Facebook social graph and understand which users have the greatest influence on communication and information dissemination;

Clustering and community detection methods [7, pp. 508–530], used to reveal tightly-knit groups of users most closely connected to each other;

Information diffusion analysis methods, which make it possible to understand how informational or viral content spreads across the network [6].

The social network Instagram is centered around visual content, which largely defines the dynamics of user interaction. Its users can follow others without mutual consent, and interactions (likes, saves, comments) matter more than the mere act of following.

Therefore, the graph that represents user interactions in Instagram is typically directed, one-sided (following ≠ mutual connection), and less dense than that of Facebook. An example of such a graph is shown in Fig. 4.

This type of visualization allows for: identifying influential users, especially those with a large number of followers; detailed analysis of the intensity of interactions; determining which accounts to recommend for following.

Software tools commonly used to build follow graphs in Instagram include Neo4j, Tableau, and Python libraries such as Scikit-learn and NetworkX.

Among the most effective methods for analyzing Instagram are popularity analysis, used to identify the most influential accounts in the network, the most active users, and how audience engagement is formed, graph clustering, used to divide users into groups based on common interests, behavior, and interaction, content and hashtag analysis [6], used to examine post texts to identify the most discussed topics among users.

The key characteristic of the TikTok social network is algorithmic virality. User interactions occur according to specific recommendation algorithms, which causes content to spread faster than in Facebook or Instagram. Moreover, direct connections between users are not required – viral content often reaches audiences beyond a user's follower base.

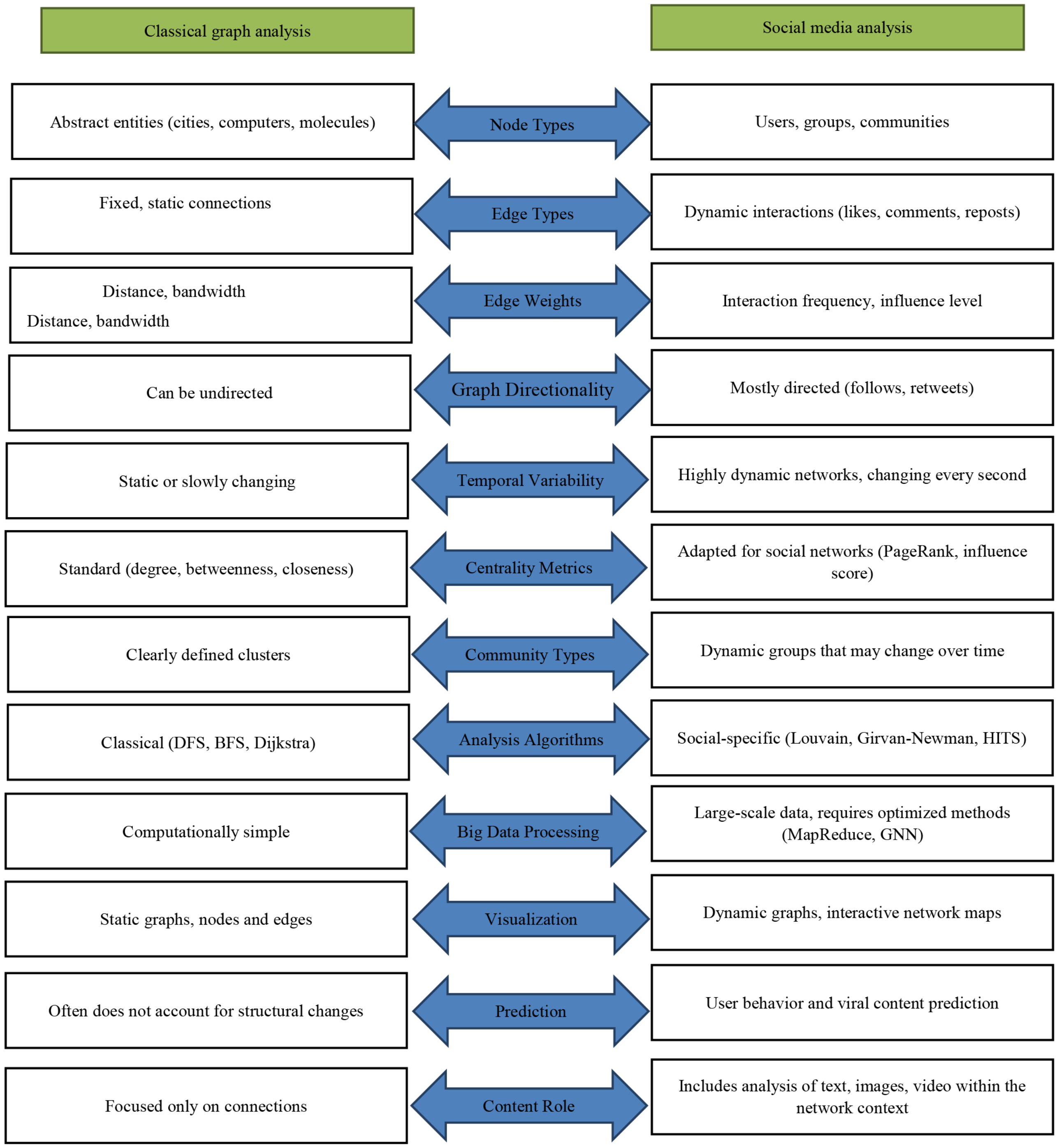


Fig. 2. Adaptation of graph theory to social network analysis

Source: compiled by the authors based on [6].

To represent user interactions on this platform, a dynamic directed graph is used. Such a model makes it possible to identify the originator of viral content, study the cascade of dissemination (how videos travel from one user to another), improve clustering algorithms for recommending videos to similar audiences.

An example of a viral content dissemination graph for TikTok is shown in Fig. 5. Tools used for its construction include TensorFlow, PyTorch, D3.js, and NetworkX.

For broader analysis of this network, the following methods are commonly applied [6]: (1) virality analysis – tracking chain reactions to see how videos go viral and through which users, (2) anomaly and bot detection – identifying suspicious activities, such as the use of bots or artificially inflated views/likes, (3) recommendation system analysis – determining which videos receive more reach and why.

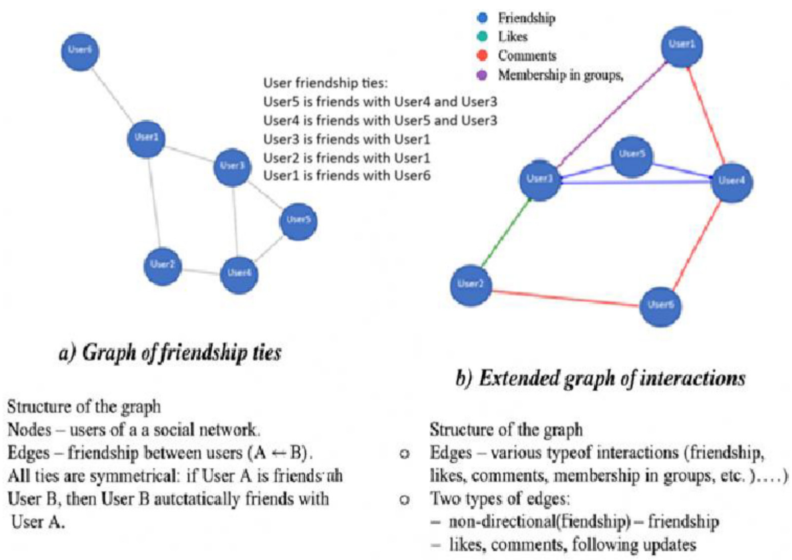


Fig. 3. Examples of interaction graphs for the Facebook social network

Source: compiled by the authors

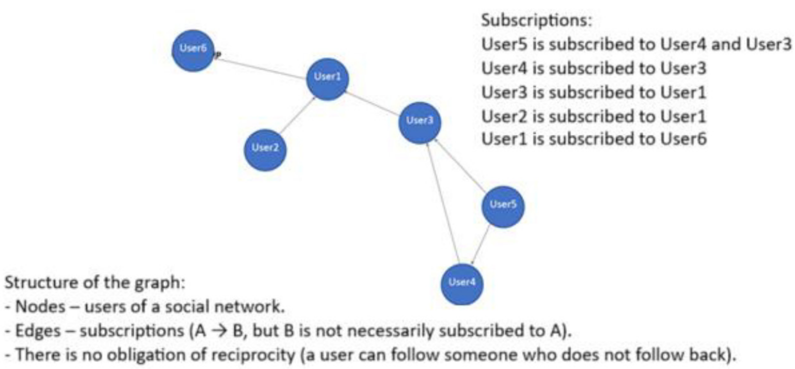


Fig. 4. Example of a follow graph for the Instagram social network

Source: compiled by the authors

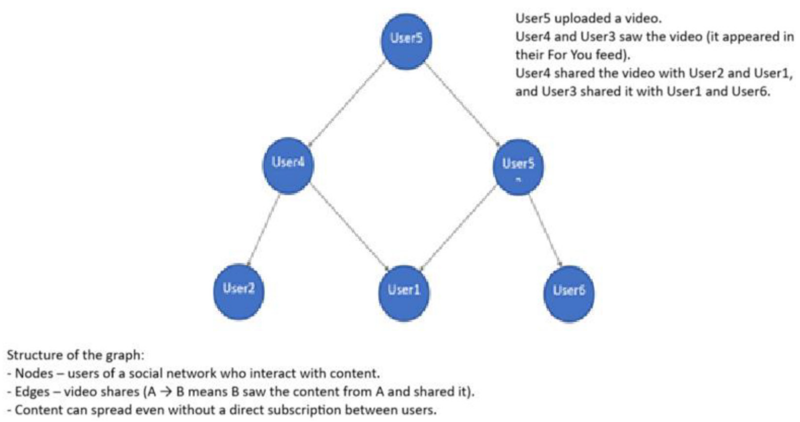


Fig. 5. Example of a viral content dissemination graph for the TikTok social network

Source: compiled by the authors

The structure and functioning of LinkedIn can be represented by a professional social graph, which is directed, hierarchical, and often one-way (subscriptions, corporate connections). This is because the platform reflects professional contacts, corporate networks, and career-related interactions.

In this network, the weights of connections (such as endorsements, recommendations, or interaction levels) are crucial. The following types of graphs can be used to analyze the structure of LinkedIn – directed graph – modeling friend requests or subscriptions, undirected graph – showing mutual professional contacts, centrality graph – identifying the most influential users in the network, community graph – helping to detect professional groups through clustering. Examples of such graphs are presented in Fig. 6.

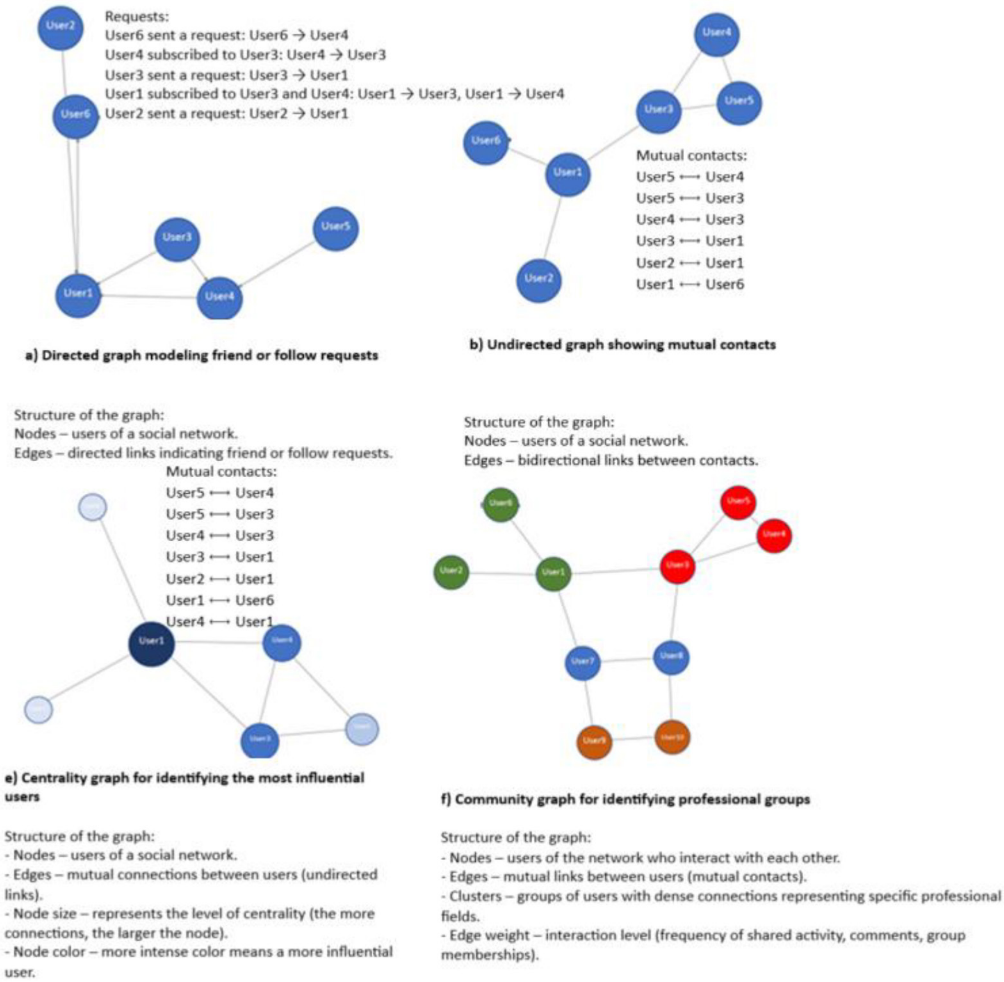


Fig. 6. Examples of interaction graphs for the LinkedIn social network

Source: compiled by the authors

The LinkedIn social network is analyzed using graph-based models of career growth and influence, including:

- Identification of authoritative users and hubs using the HITS algorithm;
- Evaluation of influence levels within the professional network using the Prestige Score method;
- Detection of professional communities and corporate groups using Graph Clustering techniques [6].

As we can see, graph theory can be applied to the structural analysis of any social network, but the structure of the graph itself and the methods of analysis will depend on the nature of user interactions within that network:

- In Facebook, the focus is on community detection and identifying influential users through mutual friendship ties;
- In Instagram, the emphasis is on analyzing visual content and user engagement through follows and likes;
- In TikTok, the primary concern is modeling the real-time viral spread of content;
- In LinkedIn, the analysis centers around professional connections, career opportunities, and corporate networks.

The proposed methodology for selecting graph models of social networks, taking into account the dynamics of their multilevel connections and the nature of user interactions, is presented in Table 1.

The outlined features of applying graph theory to the analysis of the structure of the most popular social networks enable more efficient use of this toolkit for: 1) ensuring cybersecurity by detecting fraudulent accounts, disinformation campaigns, and bot networks based on analyzing user connections; 2) serving political interests by incorporating trends in public opinion (political analytics); 3) enhancing customer interaction through behavioral analysis and personalized marketing strategies; 4) improving social network algorithms. Clearly, the primary stakeholders in such analysis are government authorities, local municipalities, businesses (both public and private sector), and society at large (political parties, individual users, etc.).

Table 1

Features of Social Network Analysis Through the Lens of Graph Theory

Graph Structure	Types of Connections and Temporal Variability	Nature of Interactions	Analysis Features	Big Data Processing
Facebook				
Directed graph, often bidirectional. Nodes: users, pages, groups. Edges: mutual friendships, one-way subscriptions, group memberships. Edge weights: interaction frequency, number of mutual friends. Directionality: mixed (friendship – undirected, subscriptions – directed)	Friendships (two-way), reactions, comments, group activity. **Variability**: moderate (connections change gradually)	Detection of communities and influential users through friendship ties	Analysis of clearly structured communities and user influence. **Methods**: Louvain, Girvan-Newman (group clustering). **Prediction**: long-term connections, user influence	Large volume but structured data. **Visualization**: static and dynamic community graphs
Instagram				
Directed, one-way graph. Nodes: users, business accounts. Edges: follows, comments, likes, hashtags. Edge weights: interaction frequency (likes, comments, DMs). Directionality: present (follows, interactions)	One-way follows, likes, comments, stories. **Variability**: dynamic (users frequently follow/ unfollow)	Analysis of visual content and engagement via likes and follows	Awareness of interaction value (likes, saves), analysis of content-based communities. **Methods**: community detection, engagement graphs. **Prediction**: content popularity, changes in follows	High activity, many interactions. **Visualization**: dynamic interaction networks
TikTok				
Dynamic directed graph. Nodes: users, content creators, trends. Edges: follows, comments, likes, shares. Edge weights: algorithmic recommendations, engagement level. Directionality: present (recommendation system, follows)	Follows, reactions, shares, views. **Variability**: very dynamic (connections update every second)	Real-time analysis of viral content dissemination	Analysis of recommendation algorithm impact, viral spread tracking. **Methods**: Graph Neural Networks, Temporal Graphs. **Prediction**: virality of content, trend dynamics	Extremely large volume, requires fast data processing. **Visualization**: trending graphs, content impact heatmaps
LinkedIn				
Directed, hierarchical graph. Nodes: users, companies, job posts, groups. Edges: mutual connections, one-way follows, endorsements, corporate links. Edge weights: communication frequency, strength of professional ties, endorsements. Directionality: present (user-company-job relationships)	Professional contacts (one- or two-way), endorsements, recommendations, corporate connections. **Variability**: slow (connections are long-term but can evolve)	Modeling professional connections, analyzing career paths and corporate networks	Study of professional ties, career development evaluation **Methods**: Graph clustering, HITS, authority scoring. **Prediction**: career growth, job recommendations, professional influence	High structural consistency, text data analysis (resumes, job descriptions). **Visualization**: professional network maps, career path graphs

Source: compiled by the authors

Data sources for this analysis may include: platform data from the social networks themselves; data from electronic communication platforms (email, forums, chats); internal organizational data (meeting logs, communication records); survey results (social ties and interactions gathered through custom questionnaires); public open data repositories..

The methodology described above can also be effectively applied to track the activity of a single user across different social networks. For instance, in cybersecurity systems, this would make it possible to detect fake accounts, monitor coordinated information campaigns, and study how a single user influences audiences across multiple platforms. This requires building a multigraph or multilayer network model, where each layer represents a separate platform (e.g., Facebook, Twitter, Instagram). Each instance of a person on a platform is represented as a separate node within that layer. Interlayer edges indicate the user's presence across multiple platforms.

A user's activity across platforms can then be analyzed and compared by examining: the number and type of connections formed; frequency of appearances in content streams; the intended audience; time intervals of activity.

Together, these metrics enable behavioral comparison across networks, where the user may behave differently on each platform (sometimes under different usernames or pseudonyms).

Even if usernames differ, user identity can still be established using: 1) profile similarity algorithms – matching based on content style, posting time, and formatting patterns; 2) graph matching algorithms – identifying nodes across graphs likely representing the same person; 3) shared environment analysis – comparing structural similarities of user connections across networks.

Stages of Tracking Multi-Platform User Activity Using Graph Theory.

Stage I: Structured Data Collection from Each Platform

Via social network APIs (e.g., Twitter API, Facebook Graph API, Instagram Graph API), gather:
- user profiles (ID, name, username, email/phone);
- friends/followers list;
- posts, likes, reposts, comments, activity timestamps. If APIs are restricted, web scraping tools (e.g., BeautifulSoup, Selenium, Scrapy) can be used.

Stage II: Multilayer Graph Construction

Build a multilayer graph model where:
- Each layer = one platform;
- Nodes = user profiles;
- Interlayer edges = hypothesized matches of the same user across layers. Tools: networkx, igraph, graph-tool, Neo4j.

Stage III: User Matching

Apply algorithms to determine if profiles from different layers belong to the same user:
1. Heuristic matching (similar names, emails, posting style, image hashes);
2. Graph matching techniques: Node similarity, Label Propagation, Entity resolution;
3. Machine learning approaches for comparing vectorized profile representations.

Stage IV: Visualization and Analysis

Visualize the graphs with tools like Gephi, Cytoscape, Plotly, or networkx + matplotlib. Analyze for centrality, clustering, engagement level, activity dynamics, and influential nodes.

The outcome is a multi-platform user activity map, applicable in:
- behavioral and influence analysis;
- personalized recommendations or cybersecurity protocols;
- sociological, marketing, and information-analytical research..

The use of graph theory in analyzing social network structures has significant practical value in the context of cybersecurity. It enables the identification of anomalous interaction structures that may indicate botnets or coordinated disinformation campaigns. By building and analyzing user interaction graphs (reposts, comments, mentions), it becomes possible to detect clusters of accounts with high-intensity, uniform activity – a potential sign of manipulation.

In the political context, such an analytical approach allows for optimizing communication channels and forecasting public reactions to events. For instance, analyzing hashtag propagation (e.g., #elections2025, #reforms) via information graphs helps identify influence hubs and the users shaping public opinion.

In the business context, constructing interaction graphs in Instagram or TikTok helps identify users with small but highly engaged audiences – crucial for targeting advertising campaigns, improving marketing performance, and optimizing spending.

Conclusions

As a result of the conducted research, a formalized methodology for graph-based analysis of social networks was proposed, accounting for multilevel user interactions and their dynamic characteristics. The introduction of adjacency matrices and interaction weighting made it possible to describe the connection structure among users across platforms more precisely.

The proposed multilayer network model effectively addresses the task of identifying a user across multiple platforms simultaneously. This enables analysis of multi-platform activity, detection of hidden interconnections, and formation of a comprehensive activity profile.

The use of clustering and centrality algorithms (Louvain, Girvan-Newman, HITS) within this framework has proven effective in detecting influential user groups, bot networks, and disinformation campaigns. The study showed that combining structural and temporal parameters enhances the accuracy of predicting social phenomena and user behavior.

Thus, adapting graph models to the specifics of different social platforms significantly extends the analytical capabilities for researchers, businesses, government institutions, and civil society organizations in cybersecurity, marketing, sociology, and information policy.

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