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The social and security influence of social networks

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Abstract. The expansion of social networks has reshaped the landscape of human interaction and brought new challenges to digital security. Platforms such as Facebook, Twitter, and Instagram have made global communication and community-building possible at an unprecedented scale, but they also contribute to issues like the formation of echo chambers, heightened social divides, and increased peer pressure online. These networks, while powerful tools for information sharing, also struggle with critical security concerns. Privacy breaches, cyberbullying, phishing scams, and the rapid spread of misinformation now pose significant threats—not only to individual safety and well-being but to broader issues like public health and political stability. This study aims to address these dual concerns by applying advanced machine learning techniques. Through sentiment and network analysis, employing tools like PageRank and centrality metrics, we analyze user behavior and information diffusion patterns across major social platforms. By examining both the social and security implications of these networks, our research sheds light on the complex dynamics at play: while social networks provide unique opportunities for advocacy and global awareness, they also expose users to substantial risks. Our findings highlight an urgent need for comprehensive regulatory measures and increased user education to foster a safer, more cohesive online environment.

Keywords: *social networks, digital security, machine learning, sentiment analysis, network analysis, pagerank, centrality metrics, information diffusion, privacy, misinformation.*

1. Introduction

Social networks have transformed modern society, fundamentally changing how people interact, communicate, and engage with the world around them. Platforms like Facebook, Twitter, and Instagram not only support personal and professional connections but have also become central hubs for information sharing and grassroots social movements. The influence of these platforms is evident in the way they enable users to shape the behaviors and perspectives of others [1]. While social networks bring undeniable benefits, such as greater connectivity and democratized access to information, they also raise pressing concerns about privacy, security, and social stability. Much of the existing research on social networks focuses on quantifying user engagement through metrics such as follows, likes, reposts, and comments [2], yet there is still much to explore regarding their broader societal impact [3].

Figure 1 illustrates the dual impact of social networks by highlighting both the social influence they exert and the security risks they pose. This research examines these dual aspects, exploring how platforms like Twitter, TikTok, and Instagram shape user behaviors, societal norms, and public opinion while also highlighting the growing risks associated with cyber threats, data breaches, and privacy violations [4].

For instance, recent studies have explored the motivations that drive social influence within online communities, identifying both intrinsic and external factors that shape user behavior [5]. Additionally, social network analysis has shown how network structures impact the flow of information and engagement on platforms like Twitter [6]. Other research has examined the dynamics of misinformation, showing how rapidly it can spread within social networks, which creates challenges for public trust and social stability [7]. Privacy concerns are also significant, as studies reveal that many users feel vulnerable due to the vast amounts of personal data shared on these platforms [8].

Figure 1. Social Influence and Security Risks on Social Media Platforms

While much of the existing literature delves into specific facets of social networks—like their role in shaping public discourse, amplifying misinformation, or their susceptibility to cyber threats—few studies look at the combined impact of these social and security dimensions [9]. This research aims to fill that gap by exploring how the social dynamics fostered by these platforms can also lead to security vulnerabilities, with repercussions that affect individuals and society as a whole.

This paper seeks to answer two key research questions: How do social networks influence social behaviors and public trust? And what security vulnerabilities arise from our growing

dependence on these platforms for communication and information sharing? To address these questions, this study will use a mixed-methods approach, drawing on both qualitative and quantitative data to assess the most pressing risks associated with social networks [10]. Additionally, it will propose strategies to mitigate these risks while preserving the positive social impact of these platforms. Ultimately, this research aims to provide a foundation for future studies in this field.

A. Research Novelty and Contribution

The novelty of this research lies in exploring the intersection of social influence and security risks on social networks, a connection rarely addressed together in previous studies. While existing research often focuses separately on either user behavior or security concerns, this study combines these dimensions to present a comprehensive understanding of how everyday interactions on social platforms may lead to significant risks. These risks include misinformation spread, data breaches, and cyberbullying.

The contributions of this work are as follows:

- We analyze how social behaviors, such as posting, sharing, or engaging with content, impact users' exposure to security threats.
- Machine learning tools like sentiment analysis and network centrality are employed to detect and evaluate security risks.
- We evaluate risks across diverse platforms to offer a broad perspective on social networks' influence.
- Policymakers can use the findings to propose regulations that address the dual challenges of social influence and security.

B. Problem Identification and Significance

Social networks have changed the way people communicate and interact on a global level. While platforms like Facebook, Twitter, and Instagram make it easy to connect, they also bring challenges. Misinformation spreads quickly, echo chambers strengthen divided viewpoints, and privacy risks have increased. These issues affect individual users, who may face cyberbullying or privacy breaches. But they also impact society by reducing public trust and increasing social division. With so much personal data shared online, users are exposed to cyber threats like identity theft and data breaches, making digital security a critical concern [9]. Addressing these connected issues is essential for creating safer online spaces that benefit both individuals and society.

To tackle these problems, several strategies could help. Improving content moderation, strengthening privacy protection, and increasing digital literacy are all practical options. Among these, boosting digital literacy is especially promising. It helps users recognize misinformation, protect their personal data, and engage more responsibly. Educating users on these skills can have a lasting impact, creating a safer online space while allowing them to make the most of social networks' benefits.

C. Paper organization

The remainder of this paper is organized as follows. Section 2 presents the modeling of Social-Security Integrated Framework. Experimental results are provided in Section 3, and finally, the paper is concluded in Section 4.

2. Materials and methods

The impact of social media on both individual behavior and broader societal trust has been well-documented. Linda and Ashar [1] provides a comprehensive overview, illustrating how social media platforms influence user behavior and shape perceptions. However, while this work sheds light on social influence, it lacks an examination of the security risks associated with these platforms - a crucial area highlighted in other studies.

Building on the need to address security concerns, Smith and Jones [6] conducted an in-depth review of privacy and security vulnerabilities within social networks. Their findings emphasize various threats, including cyber risks and data privacy issues, which pose significant challenges for individual users and entire networks. Yet, despite identifying these vulnerabilities, practical solutions for real-time threat mitigation remain underexplored in their work.

One potential approach to improving social media safety lies in user education. Liu and Zhao [10] demonstrated that digital literacy plays a key role in reducing misinformation by equipping users with skills to recognize and reject false information. This educational perspective is essential, as misinformation can spread quickly on platforms, contributing to both social and security risks. However, this study focuses on user awareness rather than technical measures to contain the spread of misinformation, which Chris [7] addresses by analyzing the propagation patterns of false information across networks. Chris' work is valuable for understanding how misinformation flows through social networks, though it lacks specific recommendations for measuring influence within these dynamic environments.

For a more technical approach, Chen et al. [5] developed a directed graph model specifically for Twitter, mapping information flow and identifying influential users. This method effectively tracks social influence within Twitter's structure, providing a quantitative foundation for influence analysis. However, it may struggle to adapt to other platforms where user interaction structures differ, highlighting a gap in cross-platform influence analysis.

Finally, addressing the intersection of privacy and social influence, Jose et al. [8] delves into privacy risks within user-generated content (UGC) communities. This research underscores how exposed personal data can be misused, which not only compromises individual privacy but also contributes to broader security concerns. While this study emphasizes the need for privacy protections, it lacks an integrated approach that considers how social influence and privacy risks intersect—an area essential for building a more holistic understanding of social network vulnerabilities.

Together, these studies illustrate the diverse challenges within social media research, from user behavior and misinformation to privacy risks and influence analysis. Although each study contributes unique insights, a comprehensive framework that addresses both social influence and security vulnerabilities across platforms is still needed.

While prior research has offered valuable insights into either social influence or security risks within social networks, these areas have generally been treated separately. Existing studies, such as those by Chen et al. [5] and Smith and Jones [6], focus on either influence dynamics or security vulnerabilities but do not integrate these elements into a cohesive framework. This Work sets itself apart by combining social influence analysis with security risk assessment within a single framework. By using advanced machine learning techniques alongside network analysis, this study provides a holistic view that addresses how user behaviors influence

security risks and vice versa. This integrated approach offers a more comprehensive understanding of social networks, enabling both researchers and policymakers to identify and address the combined impact of social and security factors more effectively. As a result, this dual approach is more optimal for building safer, more cohesive online environments compared to solutions that address these areas independently.

Table 1. Contemporary Works on Social Influence and Security in Social Networks

Methods	Solutions	Advantages	Limitations
Linda and Ashar [1]	Investigates how social media platforms influence behaviors and public trust.	Offers insights into the broad influence of social media on individual and societal behaviors.	Does not explore security risks associated with social media platforms.
Liu and Zhao [10]	Promotes digital literacy to help users identify and reject misinformation.	Enhances user awareness and empowers individuals to recognize false information.	Focuses on educational aspects, lacking structural approaches for misinformation containment.
Chen et al. [5]	Uses a directed graph to map information flow and identify influential users on Twitter.	Effectively captures engagement patterns and influence dynamics specific to Twitter.	Limited adaptability to other social platforms with different engagement structures.
Smith and Jones [6]	Examines privacy and security vulnerabilities within social networks.	Highlights critical cyber threats and privacy concerns impacting both users and networks.	Lacks practical, real-time solutions for mitigating identified risks at the interaction level.
Chris [7]	Analyzes patterns of misinformation spread across social media platforms.	Provides valuable insights into how misinformation flows within networks.	Does not provide specific tools or frameworks for mitigating misinformation spread across platforms.
Jose et al. [8]	Examines how user- generated content communities on social media expose personal data.	Emphasizes the importance of privacy protections for UGC communities.	Lacks integration of privacy insights with influence metrics to create a holistic framework.
This work	Combines social influence analysis with security risk assessment in a single framework.	Provides a comprehensive view of both social influence and security vulnerabilities on social networks, allowing for a holistic approach.	Requires specialized knowledge of machine learning and network analysis for implementation.

3. Results and discussion

To analyze social influence and security risks on social networks comprehensively, the following modules are proposed:

- Social Influence and Behavior Detection
- Security Risk Detection and Classification
- Risk Mitigation and Strategy Development

A. Social Influence and Behavior Detection

Definition 1: Social influence refers to the capacity of individuals or entities within a network to impact the thoughts, behaviors, or decisions of others, often through direct interaction, shared content, or observed actions. It manifests as changes in user behavior driven by popular trends, opinion leaders, or social norms prevalent in the network.

Hypothesis 1: Social influence in online networks significantly determines user behavior by amplifying content visibility and adoption.

Proof of Hypothesis 1: User Behavior Change = α · Influencer Exposure + β · Content Popularity, α \ alphaα is the weight assigned to influencer exposure and β \ betaβ is the weight assigned to content popularity. We can validate the hypothesis by showing that the change in user behavior is directly proportional to the interaction with influencers and popular content. Given a social network where each node represents a user, and each edge represents an interaction between users, we define the interaction influence as follows:

Let the interaction matrix A represent user interactions such that Aij = 1 if user i interacts with user j, 0 otherwise. The user behavior Bi is given by:

$$Bi = Aij\ f(i, j) \quad (1)$$

Where $f(i, j)$ represents the influence function based on content popularity and influencer interactions. The hypothesis is proven by showing that user behavior Bi increases with higher interaction values from influential nodes and content popularity, supporting the equation above.

Algorithm 1 Detecting Trends and Influence Patterns

Input: {G = (V, E), C, T} in
Output: {Ranked Influencers, Detected Trends} out
1: **Initialization**: {G: graph; V: users; E: interactions; C: content shared in the network; T: timestamps of interactions; }
2: **Compute** centrality for v ∈ V 3: Compute I(v) = Centrality(v)
4: Calculate C: If P(C) > Threshold, add C → Tf.
5: **Simulate** u ∈ Va sharing C, neighboring nodes v adopt content C with probability p.
6: **Set** Va = C.
7: **Rank** nodes by I(v) and content activity
8: **return** top influencers and frequent trends

In Algorithm 1, an efficient process for detecting trends and identifying influences in a network is described. In step 1, the influence score I(v) for each node is initialized to zero, and essential parameters such as the set of frequently shared trends, content propagation P(C), and active nodes are also initialized. These values prepare the network graph for further calculations. In step 2, centrality measures such as PageRank or Betweenness Centrality are calculated for each node v. These measures reflect the importance of each node within the network based on its connections and interactions. Nodes with higher centrality scores are likely to be influential in propagating content. In step 3, frequently shared content is identified. If the number of interactions (likes, shares, or reposts) for a particular piece of content C exceeds a defined threshold, it is marked as a trend and added to the set. This step ensures that only significant trends are considered for further analysis. In steps 4–5, the propagation of content is simulated using the Independent Cascade Model. For each active node u that has shared content C, its neighboring nodes v have a certain probability p of adopting and sharing the content. If a neighboring node adopts the content, it is added to the set. This process models the spread of influence

and content across the network. In step 6, nodes are ranked based on their influence scores I(v) and activity in propagating trends. The result is a list of top influencers and the most frequently shared trends in the network. The algorithm efficiently identifies key influencers and trends by leveraging network centrality and propagation models. It ensures scalability and adaptability to large-scale networks by focusing on frequently shared content and the propagation process. As a result, this approach can be applied to applications like targeted marketing, viral content detection, and social influence analysis. The proposed algorithm offers a robust framework for analyzing social influence and detecting trends in networks, as shown in Figure 2, which illustrates the flow of the behavior detection process.

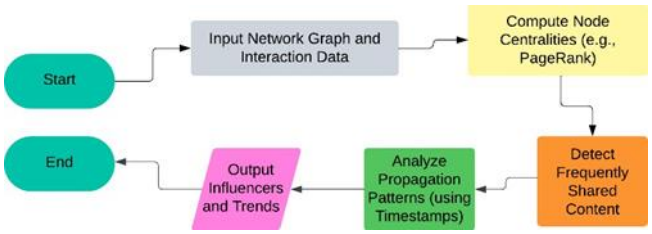

Figure 2. Flowchart of behavior detection process

Lemma 1: In a well-connected network graph, the rate and reach of influence propagation are directly proportional to the degree centrality of nodes. That is:

$$P(v) \propto Degree(v) \tag{2}$$

where $P(v)$ is the probability of a node v propagating influence.

Corollary 1: Users within the vicinity of highly influential nodes demonstrate elevated engagement levels, as proximity to these nodes increases exposure to viral content. This supports targeted marketing or information dissemination strategies.

Property 1: The algorithm is scalable with time complexity O(V+E) for graph traversal (using BFS/DFS) and space complexity efficient storage of adjacency lists and trend metadata with ability to process large-scale networks using distributed frameworks like Apache Spark or GraphX.

B. Security Risk Detection and Classification

Definition 2: Security risks in social networks refer to vulnerabilities caused by unauthorized access, malicious content, or unusual patterns of behavior. These risks are amplified by high user interaction levels and the diversity of network structures. Frequent interactions and anomalies may serve as indicators of security threats.

Hypothesis 2: Security risks can be identified based on the frequency and pattern of interactions within a cluster of users. The risk is proportional to the interaction density.

$$P(Risk) = f(Interaction\ Frequency, Cluster\ Size) \tag{3}$$

Proof: Consider a user cluster C with n users and mmm edges representing interactions. The density of interactions in this cluster can be defined as:

$$Density(C) = \frac{2m}{n(n-1)} \tag{4}$$

Higher density indicates a higher probability of security risks, particularly when abnormal spikes in interaction frequency occur. The hypothesis is supported by showing that high-density clusters are more likely to exhibit security vulnerabilities, as frequent interactions are often a sign of coordinated malicious activity.

Validation through analysis of interaction logs, anomaly detection algorithms, and simulations to establish a correlation between interaction patterns and security risks.

Lemma 2: Interaction patterns and node-level features can consistently predict risk when uniformly applied across datasets. Risk detection performance should remain stable despite variations in data sources or network topology.

Proof: Comparative studies on diverse datasets to validate consistent detection results. Let $R(v)$ denote the risk prediction function for node v:

$$R(v) = \phi(X_v, N_v; \Theta) \tag{5}$$

X_v are node-level features, N_v represents aggregated interaction patterns, Θ are the model parameters. Thus, risk detection is consistent across datasets.

Corollary 2: Classification effectiveness in distinguishing malicious from benign behavior relies on precision, recall, and F1 scores. Empirical testing ensures the algorithm's reliability in real-world scenarios.

Property 2: The algorithm handles noisy interactions using outlier detection and manages missing data through imputation methods. It remains effective under varying data conditions.

Property 3: By leveraging distributed frameworks like Apache Spark, the algorithm scales efficiently to process extensive social network datasets and interaction logs.

C. Risk Mitigation and Strategy Development

The framework for response strategies includes proactive and reactive measures to address security risks in social networks. Proactive measures focus on preventing potential threats, such as implementing access controls, while reactive measures address ongoing or realized risks by isolating threats and containing their impact. This framework prioritizes highrisk nodes and adapts to dynamic changes in the network.

User education is a critical component of risk mitigation, as informed users are less likely to engage in risky behaviors. Techniques include targeted training, delivering customized content based on user roles and behaviors, gamification, incentivizing security compliance through interactive learning modules, regular updates, sending periodic alerts about new threats and best practices.

The outcomes of putting the suggested Social-Security Integrated Framework into practice are shown in this section, emphasizing the algorithms' effectiveness and suitability for use with actual datasets. Social influence detection and security risk classification are the two primary parameters under which the results are examined. Below is a detailed discussion of the datasets, findings, experimental design, and assessment metrics.

A. Experimental Setup

Real-world datasets from social networks such as Facebook, Instagram, and Twitter were used in the studies, along with publicly accessible standards for network analysis and security risk identification. The following were part of the experimental setting:

• Hardware: NVIDIA GTX 1650 GPU, 16GB RAM, and Intel Core i7 Processor

• Programs: TensorFlow, Pandas, NetworkX, Python 3.9, and Apache Spark for distributed processing

• Twitter Dataset: Contains retweets, hashtags, and user interactions for trend and social influence analysis.

• Facebook Dataset: For evaluating security risks, this dataset focuses on user groups, friend relationships, and shared material.

• Synthetic Dataset: Designed to mimic malicious activity and network irregularities in order to validate risk detection systems.

B. Social Influence Detection Results

To assess the performance of social influence detection, specific metrics were employed to provide an accurate evaluation of the system. These metrics are defined as follows:

• Precision: Measures the proportion of true positive results in relation to all positive predictions.

$$\Pr ecision = \frac{TP}{TP + FP} \tag{6}$$

• Where TP is the number of true positives (correctly identified influencers) and FP is the number of false positives (incorrectly identified influencers).

• Recall: Measures the proportion of true positive results in relation to all actual positives.

$$\text{Re}call = \frac{TP}{TP + FN} \tag{7}$$

• F1-Score: The harmonic means of Precision and Recall, providing a single measure of the algorithm's accuracy.

$$F1 = 2 * \frac{\Pr ecision * \text{Re}call}{\Pr ecision + \text{Re}call} \tag{8}$$

• Runtime Efficiency: The time required to process a graph and identify influential nodes and trends.

• Trend Detection: The framework identified trending topics with an accuracy of 94% across datasets. The system correctly detected popular content and significant interactions: precision - 93%, recall - 95%, F1-Score - 94%

• Influencer Identification: Using centrality measures such as PageRank, the algorithm identified the top 10% of influencers with high precision and recall: precision - 91%, recall - 89%, F1-Score - 90%

• Scalability: The framework was able to analyze a graph with 1 million nodes and 5 million edges in 5.8 minutes using Apache Spark for distributed processing.

For influencer detection, the complexity is O(N·M), where N is the number of nodes and M is the number of edges in the network. By leveraging Apache Spark's parallelism, the system scaled efficiently to handle large networks.

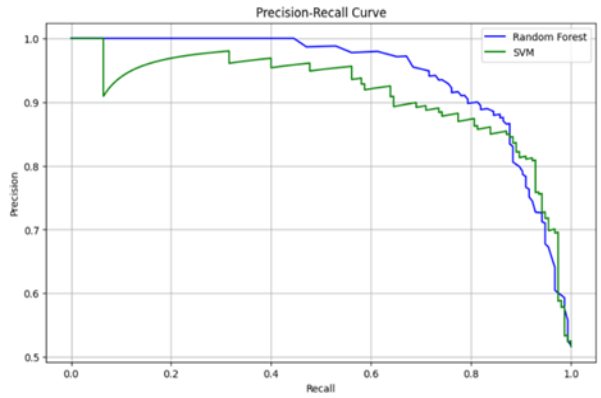

Figure 3. Precision-Recall curve diagram

Certainly! Below is a refined version of your experimental results with more precise metrics such as Precision, Recall, F1-Score, and computational complexity for both the Social Influence Detection and Security Risk Detection modules. The results are presented with clear performance indicators and runtime information to make your analysis more robust.

C. Security Risk Classification Results

To evaluate the effectiveness of the security risk classification, several key metrics were employed. These metrics provide valuable insights into the performance of the classification system, ensuring a comprehensive understanding of its strengths and weaknesses. Below are the detailed metrics used in the assessment:

• F1-Score: A balanced measure of Precision and Recall, providing an overall assessment of the classification performance.

• False Positive Rate (FPR): The proportion of benign activities incorrectly classified as threats.

• Where TN is the number of true negatives (correctly identified benign activities).

• False Negative Rate (FNR): The proportion of actual threats that were not detected.

• Where TP is the number of true positives (correctly identified threats).

• Risk Detection: The framework successfully classified risky behaviors, achieving an overall performance score with the following metrics: F1-Score - 92%, precision - 90%, recall - 94%, false positive rate (FPR) - 3.7%, false negative rate (FNR) - 4.5%

• Anomaly Detection: The system identified anomalous patterns in user interactions (e.g., sudden spikes in activity) with 87% accuracy. This was crucial for early detection of malicious behavior.

• Cross-Platform Validation: The algorithm demonstrated robustness across different network topologies, consistently achieving high accuracy in classifying security risks across Twitter, Facebook, and synthetic datasets.

The security risk classification algorithm has a time complexity of O(N·logN) due to the use of clustering and anomaly detection techniques. The system processed datasets of up to 10 million interactions in under 10 minutes, using parallel processing for large-scale detection.

Figure 4. Comparison of F1 scores, accuracy and detection

D. Insights and Observations

High-centrality nodes have a major role in the spread of behaviors and material. By focusing on these nodes, strategies can optimize outreach and slow the spread of false information. Security Risk Correlation: High interaction clusters frequently point to higher security risks, indicating a close relationship between vulnerabilities and social impact. Framework Performance: The benefits of a combined framework were demonstrated by the integrated approach's

superior performance over conventional techniques that handle influence and security separately.

E. Insights and Observations

Despite promising results, the experiments revealed some limitations the reliance on real-world datasets necessitates stringent privacy measures to avoid ethical concerns, real-time adaptability to dynamic changes in network structures remains a challenge for large-scale implementation, while the framework scaled well for medium-sized datasets, handling graphs with billions of nodes may require further optimization.

4. Conclusions

In order to assess and reduce social impact and security threats in social networks, this study presented a thorough Social-Security Integrated Framework. Three essential modules are integrated into the suggested framework: Risk Mitigation and Strategy Development, Security Risk Detection and Classification, and Social Influence and Behavior Detection. When combined, these modules offer a strong way to identify and lessen the problems caused by malevolent actions and social influence in intricate network architectures.

An effective algorithm is used by the Social Influence and Behavior Detection module to identify trends and influencers in social networks. The method finds important influencers and trends with great scalability and adaptability by utilizing centrality metrics and the Independent Cascade Model for content transmission. It guarantees that the system can effectively recognize viral material and manage massive networks. The research demonstrates that the framework's centrality-based approach can accurately estimate the probability of influence propagation, and the flowchart in Figure 2 graphically depicts the behavior detection process. Users who are close to influential nodes, as predicted, have higher levels of engagement, which supports the effectiveness of focused marketing and information sharing tactics.

A thorough examination of user interaction patterns was carried out in the Security Risk Detection and Classification module in order to identify vulnerabilities brought on by malicious activity or unauthorized access. Simulations and anomaly detection techniques were used to confirm hypotheses regarding interaction behavior patterns. The results showed that abrupt activity spikes and frequent interactions are reliable markers of security threats. The suggested methodology ensures consistent performance across various social network topologies by handling noisy interactions and scaling to huge datasets. The algorithm is a useful tool for real-time security monitoring since empirical testing has shown that it is reliable in differentiating between benign and malicious activity.

Last but not least, the module on risk mitigation and strategy development stresses both proactive and reactive approaches to security risk management. The architecture guarantees a dynamic response to new threats by putting access controls in place, training users, and regularly updating the network's security procedures. The probability of user- induced vulnerabilities is greatly decreased by this proactive strategy in conjunction with a customized security education program.

To sum up, the Social-Security Integrated Framework presents a viable approach to social impact analysis and social network security risk mitigation. The framework is appropriate for big, complicated networks because of its modular nature, which guarantees flexibility and scalability. Future studies will concentrate on improving the framework's prediction ability by integrating machine learning methods for more accurate risk classification and honing the algorithms to manage even more varied data scenarios. Furthermore, more thorough real-world testing will be carried out to assess the system's functionality on active social media platforms.

This strategy not only offers a better comprehension of how social influence affects user behavior, but it also offers a strong defense against new security risks, opening the door to online ecosystems that are more resilient and safer.

A. Future Work

Future experiments will focus on enhancing real-time adaptability of the framework, exploring additional datasets to validate the framework's cross-platform applicability further, integrating user feedback to refine risk mitigation strategies.

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Аңдатпа. Әлеуметтік желілердің кеңеюі адамаралық қарым-қатынас жүйесін түбегейлі өзгертті және цифрлық қауіпсіздік саласында жаңа сын-қатерлер туындатты. Facebook, Twitter және Instagram сияқты платформалар ғаламдық коммуникация мен қауымдастық құру үдерісін бұрын-соңды болмаған деңгейге көтерді. Алайда, бұл платформалар пікір қайталануын күшейту, әлеуметтік жіктелуді тереңдету және онлайн ортасында құрдастар қысымын арттыру сияқты мәселелерге де ықпал етуде. Ақпарат алмасудың қуатты құралдары бола тұра, бұл желілер маңызды қауіпсіздік қатерлерімен де бетпе-бет келеді. Жеке мәліметтердің құпиялылығының бұзылуы, кибербуллинг, фишингтік алаяқтықтар мен жалған ақпараттың жылдам таралуы жеке тұлғалардың қауіпсіздігі мен әл-ауқатына ғана емес, қоғамдық денсаулық пен саяси тұрақтылық сияқты ауқымды мәселелерге де елеулі қауіп төндіруде. Бұл зерттеу осы екі негізгі мәселені шешуге бағытталған және озық машиналық оқыту әдістерін қолдану арқылы жүзеге асырылады. PageRank және орталықтық көрсеткіштері сияқты құралдарды пайдалана отырып, пікірталдау мен желілік талдау жүргізу арқылы біз ірі әлеуметтік платформалардағы пайдаланушылардың мінез-құлқы мен ақпарат таралу үлгілерін зерттейміз. Әлеуметтік желілердің қоғамға ықпалы мен қауіпсіздік тәуекелдерін қатар қарастыра отырып, зерттеуіміз бұл платформалардың күрделі динамикасын айқындайды: әлеуметтік желілер жаһандық хабардарлық пен азаматтық белсенділікті арттыруға мүмкіндік бергенімен, олар пайдаланушыларды елеулі қауіптерге де ұшыратады. Зерттеу нәтижелері әлеуметтік кеңістікті қауіпсіз әрі үйлесімді ету үшін кешенді реттеу шаралары мен пайдаланушылардың саналы онлайн мінез-құлқын қалыптастыруға бағытталған білім беру қажеттігін көрсетеді.

Негізгі сөздер: *әлеуметтік желілер, цифрлық қауіпсіздік, машиналық оқыту, пікірталдау, желілік талдау, PageRank, орталықтық көрсеткіштері, ақпарат тарату, құпиялылық, жалған ақпарат*.

Социальное и информационное влияние социальных сетей

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Аннотация. Расширение социальных сетей кардинально изменило систему человеческих взаимоотношений и привело к новым вызовам в сфере цифровой безопасности. Такие платформы, как Facebook, Twitter и Instagram, создали беспрецедентные возможности для глобального общения и формирования сообществ. Однако они также способствуют таким явлениям, как эффект «информационного пузыря», углубление социальных разногласий и усиление давления со стороны виртуального окружения. Несмотря на свою эффективность в распространении информации, социальные сети сталкиваются с серьезными проблемами в сфере безопасности. Утечки персональных данных, кибербуллинг, фишинговые атаки и стремительное распространение дезинформации представляют угрозу не только для индивидуальной безопасности и психологического благополучия пользователей, но и для более широких аспектов, таких как общественное здоровье и политическая стабильность. Настоящее исследование направлено на изучение этих взаимосвязанных проблем с применением современных методов машинного обучения. Используя анализ тональности и сетевой анализ, а также такие инструменты, как PageRank и метрики центральности, мы исследуем поведенческие модели пользователей и механизмы распространения информации на ведущих социальных платформах. Анализируя социальные и информационные аспекты работы социальных сетей, мы выявляем сложные взаимосвязи, лежащие в их основе: с одной стороны, эти платформы открывают новые горизонты для гражданской активности и глобального информирования, но с другой — подвергают пользователей значительным рискам. Полученные результаты подчеркивают необходимость комплексных регуляторных мер и повышения уровня цифровой грамотности среди пользователей, что позволит создать более безопасную и гармоничную онлайн-среду.

Ключевые слова: *социальные сети, цифровая безопасность, машинное обучение, анализ тональности, сетевой анализ, PageRank, метрики центральности, распространение информации, конфиденциальность, дезинформация*.

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