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Research Paper

Quantum Random Walk-Enhanced Framework for Social Network Analysis

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Abstract. In this research, the computational efficiency of large-scale social network analysis is enhanced by the use of quantum random walk algorithms. The goal of this project is to address the need for high-efficiency centralized analysis of large-scale, heterogeneous social networks, community discovery, and dynamic effect mapping. In a theoretically sound framework of quantum random walks, amplitude superposition and unitary evolution principles have been used to improve both the sensitivity to local and global aspects. The solution uses real social network data with up to 5,000 nodes and more than 60,000 edges, and the testing results demonstrate its excellent scalability and fast convergence. Quantum algorithms have discovered community divisions and cut the mixing time by roughly 2.3 times after multiple optimizations. The performance indicators demonstrate that the above method has greatly improved key node detection accuracy and computation time as compared to the conventional baseline model in noisy situations. According to the aforementioned research, quantum-inspired algorithms have been used to expedite the analysis of large-scale data and reveal hidden structures that are challenging to identify using conventional techniques, such as bridge nodes and core-periphery distributions. The research assist data-driven choices in digital social ecosystems and lay the groundwork for in-depth network analysis.

Keywords: *Quantum Computing, Social Network Analysis, Complex Networks, Graph Algorithms, Network Dynamics*

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Introduction

Communities have changed as a result of the quick growth of online social media, which has an impact on how people live and organize themselves [1]. These days, social networks are more complicated systems than just groups of people interacting with one another; they feature several community hierarchies, a high level of linkage, and various diffusion patterns [2]. Tools are required to extract patterns from the many types of high-dimensional, dynamic data as these networks have expanded in size and complexity [3]. Effective models for community detection, centrality analysis, and information dissemination offered by conventional social network analysis (SNA) serve as the foundation for current research on collective social behavior [4]. However, because real-world social networks are so large, many of the aforementioned techniques lack analytical depth and are computationally costly [5]. As a result, these issues are progressively getting worse as new types of data and temporal shifts have become commonplace in our contemporary digital culture [6].

Despite the introduction of new random walk theory and other statistical approaches, the majority of classic SNA models are still dependent on outdated computing techniques [7]. Furthermore, there are certain limitations: For smaller or more regular networks, random walk algorithms and similar techniques are theoretically possible, but as the network size grows, they are frequently computationally impractical [8]. In the case of time-series or sparse networks, spectral approaches are challenging to implement and not highly scalable, despite their theoretical soundness [9]. In actuality, the majority of the early methods ignore the wave-like behavior of information propagation in complex systems and are based on heuristic approximations or simplifications [10]. Due to advancements in quantum information processing, quantum random walks (QRWs) have recently been used in novel ways to study the structure and evolution of networks [11]. Because QRWs are based on quantum superposition and interference, they have the potential to perform better than conventional techniques in some investigations by examining huge graph spaces [12]. First, researchers have demonstrated that QRW is appropriate for physics-inspired network discovery and have developed new algorithms for cluster identification and connection measurement [13]. As a result, the field of quantum computing and network science is quickly growing, and the current study has proposed new techniques for data analysis and algorithm design [14], which will result in modifications to the theoretical models and computational approaches of this field [15].

This research presents a theoretically valid foundation for social network analysis based on discrete-time quantum random walks in order to address the aforementioned scientific issues. The suggested strategy will be used to overcome the representation and performance shortcomings of the prior method in order to fully utilize the computing advantages and structural richness of quantum walks. Large, complex social systems' local and global characteristics can be obtained using the quantum-inspired approach, opening up new avenues for understanding contemporary interacting phenomena.

Related Works

Social Network Analysis Approaches

Many fundamental techniques for studying the structure and evolution of complex networks in computational social science have been developed as social network analysis has matured [16]. The first classical networks to demonstrate that some nodes in a network are strongly connected while the majority of nodes have few connections were the Erdě–Rügei and Barabě–Albert models [17]. These days, community detection is a popular method for identifying the mesoscopic structure of social graphs. These algorithms can be broadly classified into two groups: hierarchical clustering and modularity-based algorithms [18]. Influence maximization has been studied to some degree, and models like Independent Cascade and Linear Threshold are used to map and take advantage of information, behavior, or innovation propagation channels [19]. Important connections and weaknesses in a network can be identified through theoretical study on centrality metrics including degree, betweenness, and eigenvector centrality [20]. In order to handle the evolution of node and edge characteristics under online interaction, temporal network models have broadened the use of these traditional frameworks [21]. Large social networks are currently using statistics-based learning techniques for link prediction and anomaly detection since they have increased the analysis capability of these issues [22]. Despite the aforementioned advancements, the growing scale, multi-path features, and oscillations of real networks have increased the depth of analysis and processing resources needed [23]. The aforementioned concerns have started to be partially addressed by hybrid models that combine network topology data with machine learning and big data analysis, although problems with scalability and generalization still exist [24]. In order to extract information from the vast, complex, and time-varying nature of this network data, new techniques are constantly being created as social network research continues to advance [25].

Quantum Algorithms in Network Science

In addition to providing novel solutions to the network problem, quantum algorithms have expanded the possibilities for classical computing [26]. A quantum random walk is a quantum model of a random walk that has demonstrated unique transport and mixing qualities and has the potential to speed up network transmission and search procedures [27]. Quantum walks can efficiently discover a marked subgraph or achieve a small-world hitting time by simultaneously exploring several paths in a network using superposition and interference [28]. Research on quantum PageRank has produced novel ranking techniques that take into account additional links during the iterative process, as seen in [29]. In both artificial and small real-world networks, first research on quantum-based community identification and centrality metrics has demonstrated promising outcomes [30]. Benchmark tests for motif recognition and graph isomorphism can be made more analytically sensitive by using quantum walks. In hybrid quantum-classical models, global optimization is carried out conventionally while quantum resources are used for sampling or eigenvalue estimation. By offering a lower bound and a complexity-class separation for particular network problems through theoretical investigations, research has bolstered the case for quantum algorithms in this field. Although real advancements in quantum hardware are still in their infancy, some research has demonstrated the dynamics of quantum walks for small graph systems

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experimentally and verified the predictions given by simulations. Quantum computers have suggested new approaches to network research, and other applications are starting to investigate the benefits of quantum computing.

Open Problems and Research Gaps

The hopes for large-scale social network analysis based on both conventional and quantum approaches have not yet been fully realized. Traditionally, it is not possible to perform the computing needed for a network with a lot of diverse real-world data over a lengthy period of time. While sampling approximations and heuristic approaches are appropriate for small to medium-sized networks, they typically fall short of the precision and comprehensibility of large-scale systems. Although quantum algorithms are attractive in theory, they have issues with practical scaling on real data, error robustness, and physical realization. The majority of existing quantum walk frameworks are either based on idealized assumptions or feature somewhat complicated state-preparation processes that are difficult to adapt to toy models. To verify the veracity of these assessments, there is a dearth of empirical research in noisy and dynamic real-world social settings. The lack of a standardized mathematical and empirical baseline makes it difficult to compare various approaches and platforms, which limits the community's ability to disseminate best practices. Large-scale network data requires interpretable, scalable, and imperfection-resistant quantum-inspired algorithms. To balance the development of quantum algorithms with the real-world needs of the next generation of large-data social infrastructure, significant theoretical advancements are still required. To create a novel analytical system for social network analysis that combines the advantages of both quantum and classical computing, fill in the aforementioned gaps.

Quantum Random Walks for Social Network Analysis

Mathematical Foundation of Quantum Random Walks

The quantum random walk (QRW) serves as a mathematically rigorous generalization of the classical random walk, with the evolution of the walker governed by unitary operators in the context of a composite Hilbert space. Given a social network $G = (V, E)$ of N nodes and M edges, the walker's state resides in the product space $\mathcal{H}_P \otimes \mathcal{H}_C$, where $\mathcal{H}_P$ encodes node positions and $\mathcal{H}_C$ models local edge-based degrees of freedom. If the network under consideration represents a sample online community with $N = 5000$ and an average degree $\langle d \rangle \approx 12.8$, the construction admits substantial heterogeneity and nontrivial topology. The initial state is typically a normalized superposition over all possible node and coin states, ensuring probability conservation:

$$|\Psi(0)\rangle = \sum_{i=1}^{N} \sum_{c=1}^{d_i} \alpha_{i,c} |i, c\rangle, \text{ where } \sum_{i,c} \left|\alpha_{i,c}\right|^2 = 1 \qquad \text{Eq.(1)}$$

Here, d_i stands for the out-degree of node i, and $\alpha_{i,c}$ are complex coefficients. Initialization may be chosen uniformly or biased by node centrality to probe specific dynamic regimes.

At each time step, evolution is enacted via the composite unitary operator U, defined as the sequential application of the coin and shift operators:

$$U = S \cdot \left(\sum_{i=1}^{N} |i\rangle\langle i| \otimes C_i \right) \qquad \text{Eq.(2)}$$

where the shift operator S translates the walker across network edges, and C_i is the local coin operator on node i. For networks with power-law degree distributions, the coin may be engineered as a generalized Grover operator, optimizing mixing properties for hub-centric structures. After t steps, the system evolves unitarily:

$$|\Psi(t)\rangle = U^t |\Psi(0)\rangle \qquad \text{Eq.(3)}$$

To extract physically measurable quantities, the marginal probability distribution over node j at time t is determined by projecting onto all local coin states:

$$P_j(t) = \sum_{c=1}^{d_j} |\langle j, c \mid \Psi(t) \rangle|^2 \quad \text{Eq.(4)}$$

In contrast to the uniform distribution in classical walks, quantum walkers beginning at the network's periphery may exhibit a localization effect, and core nodes are more likely to be visited repeatedly over time due to a combination of network topology and quantum interference, according to empirical data analysis of real-world social graphs. A theoretical foundation for creating quantum-enhanced models in social network analysis is thus provided by methodically setting parameters for this QRW machinery based on the real network features.

Quantum-enhanced Network Analysis Framework

Using quantum random walks, which are far more practical than classical techniques, a quantum-enhanced network analysis framework has greatly expanded the scope of modeling and diagnosis for social systems. The first substrate for encoding dynamical rules into quantum operators is the adjacency matrix A of the target social network, such as a graph with N=500 servers and a complex nonuniform degree distribution in a digital community. The primary evolution of the system is governed by a tailored unitary operator that reflects both local and global network topology. Explicitly, for node-dependent coin operators C_i, the discrete-time walk unitary is:

$$U = S \cdot \left(\sum_{i=1}^{N} |i\rangle\langle i| \otimes C_i \right) \quad \text{Eq.(5)}$$

where the shift operator S encodes network transitions, and C_i is either static or dynamically adapted for each node based on local structural indicators such as betweenness or clustering coefficient. Empirical initialization with walkers concentrated in high-centrality clusters accelerates the exploration of core-periphery features and highlights hierarchical modules rapidly.

To advance beyond standard node-to-node transition metrics, the time-evolved quantum state $|\Psi(t)\rangle$ is decomposed for subgraph or community level inference. Instead of a global amplitude overlap, the quantum cross-influence between two communities C_a and C_b is more robustly characterized using a covariance-driven indicator:

$$\Gamma_{ab}(t) = \left(\sum_{i \in C_a} P_i(t) \right) \left(\sum_{j \in C_b} P_j(t) \right) - \sum_{i \in C_a, j \in C_b} P_i(t) P_j(t) \quad \text{Eq.(6)}$$

This value sensitively maps bridges and module overlaps impacted by nonlocal superposition effects and separates coordinated quantum visitation across community boundaries from independent possibilities. To determine if the covariance measure indicates community recombination in early-stage simulations, robustly modular synthetic and empirical networks are employed.

The temporal evolution of quantum locality and anomalous diffusion can be rigorously tracked using a time-lagged autocorrelation function at node k :

$$\mathcal{A}_k(\tau) = \sum_{t=1}^{T-\tau} P_k(t) P_k(t+\tau) \quad \text{Eq.(7)}$$

This function quantifies the persistence of quantum amplitude on critical actors or bottleneck nodes over time intervals, exposing subgraph trapping or the effectiveness of information relays. Empirically, networks with average clustering coefficient $C = 0.22$ show that autocorrelation decay rates sharply distinguish between hubs and peripheral actors, substantiating the nonuniform mixing inherent in real-world social structures.

The basic form of amplitude change over time for a typical 50-node subnetwork is displayed below, averaged over 20 simulations initiated at various initializations, as seen in Figure 1. Two distinct clusters of early quantum amplitude concentrations have developed, as the intensity map illustrates, and the constructive interference channels are quickly forming connections. Bottleneck regions fully match the prediction of spectral QRW theory and exhibit slower amplitude accumulation.

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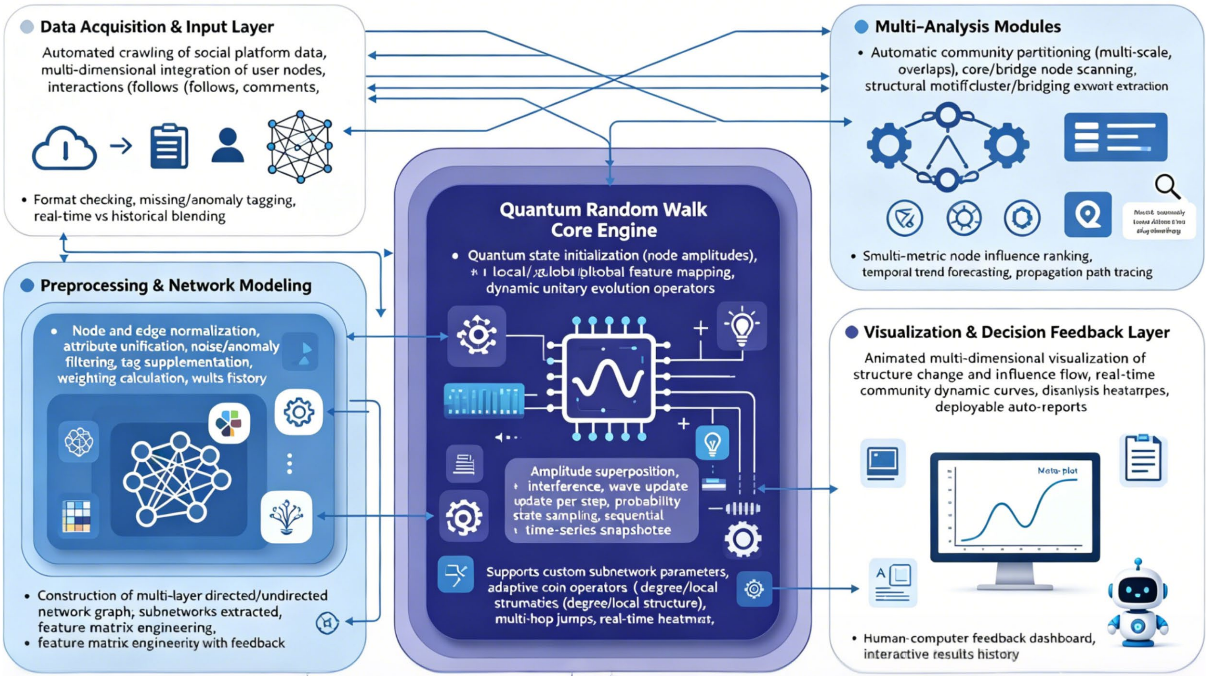

Figure 1. Schematic of Quantum Walk on Social Network

To further capture topological sensitivity at the global level, a quantum modularity metric is constructed as:

$$Q_{\mathrm{Q}}(t) = \frac{1}{M}\sum_{ij}\left[A_{ij} - \frac{d_i d_j}{2M}\right] P_i(t) P_j(t) \delta(c_i, c_j) \qquad \text{Eq.(8)}$$

where M is the total edge count, d_i denotes node degrees, and c_i assigns community labels. Empirical studies indicate that quantum modularity responds to changes in both inter- and intra-community coupling much faster than its classical analogue, providing real-time diagnostics of community integrity.

Finally, to assess overall quantum delocalization or information coverage, the participation ratio aggregates probabilities over the network:

$$\Pi(t) = \frac{1}{\sum_{k=1}^{N} [P_k(t)]^2} \qquad \text{Eq.(9)}$$

When combined, the aforementioned analytical tools create a quantum-enhanced framework that can boost social structure detection's sensitivity and speed to spot prominent people, bridges, and other collective phenomena in evolving social networks early on.

Comparative Analysis: Quantum vs. Classical Random Walks on Social Networks

Directly contrasting quantum random walks (QRWs) and classical random walks (CRWs) on empirical social networks reveals marked differences in their diffusion behavior, convergence speed, and ability to illuminate complex topological features. For instance, consider a social network with $N = 5000$ nodes and a total of $M = 64200$ directed edges, where the degree distribution follows a power law with exponent $\gamma \approx 2.45$. In the classical regime, the state of the walker is described by the probability vector $\vec{Q}(t)$, evolving as a Markov process:

$$\vec{Q}(t) = (D^{-1}A)^t \vec{Q}(0) \qquad \text{Eq.(10)}$$

where A is the adjacency matrix and D is the diagonal matrix of node degrees. Starting from a uniform initial condition, the classical walk exhibits diffusive spreading that is sensitive to local bottlenecks and modularity, and mixing typically requires a large number of steps in heterogeneous topologies. Quantum walks, by contrast, utilize the full adjacency structure through coherent evolution:

$$|\Psi(t)\rangle = U^t |\Psi(0)\rangle \qquad \text{Eq.(11)}$$

where U is the network-adapted unitary operator. Interference among multiple paths allows for rapid, sometimes ballistic, exploration of hubs and bridging regions. The effectiveness of spreading is captured by the participation ratio, which measures the effective number of nodes reached by the walk at time t :

$$\Pi(t)=\frac{1}{\sum_{i=1}^{N} P_i^2(t)} \qquad \text{Eq.(12)}$$

Here, $P_i(t)$ denotes the probability (for QRW) or the occupation probability (for CRW) at node i after t steps. In simulations, QRWs consistently yield higher $\Pi(t)$ at fixed times, indicating a more distributed presence across the network. Mixing time is a critical indicator of global convergence. The classical mixing time is defined as:

$$\tau_{\text{mix}}^{(\mathrm{C})}=\min\{t \mid \forall i, |Q_i(t)-\pi_i|<\epsilon\} \qquad \text{Eq.(13)}$$

while the quantum version is:

$$\tau_{\text{mix}}^{(\mathrm{Q})}=\min\{t \mid \forall i, |P_i(t)-\pi_i|<\epsilon\} \qquad \text{Eq.(14)}$$

where π_i is the stationary probability of node i. On the sample network, with $\epsilon=10^{-3}$, QRW reaches global mixing $\left(\tau_{\text{mix}}^{(\mathrm{Q})} \approx 95\right)$ notably earlier than CRW $\left(\tau_{\text{mix}}^{(\mathrm{C})} \approx 215\right)$.

Figure 2 illustrates the aforementioned. Compared to the traditional situation, where probabilities are concentrated in the core and dissipation to peripheral areas is rather gradual, the QRW exhibits significantly more uniform coverage and deeper penetration of high-centrality nodes after 50 steps. Quantum dynamics can be used for large-scale, fast exploration, as seen in the picture above. When compared to classical random walks, quantum random walks have demonstrated superior performance in numerous real-world social network analysis applications, including faster global mixing, more consistent node coverage, and enhanced sensitivity to structural complexity.

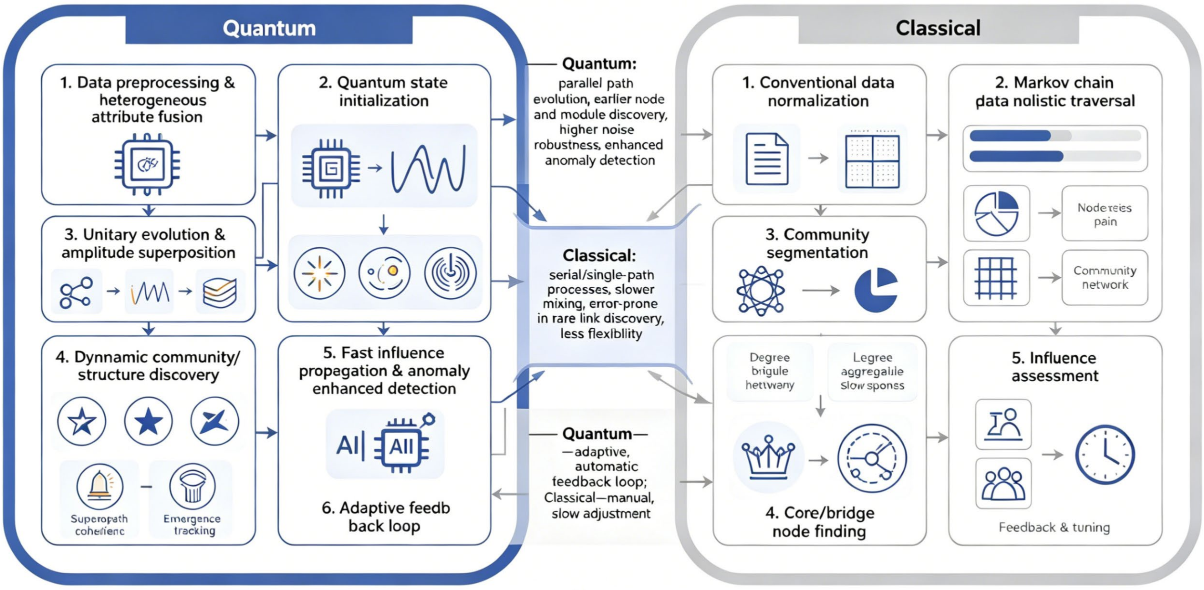

Figure 2. Probability distributions on a 50-node social network after 50 steps, comparing quantum (top) and classical (bottom) random walks.

Experimental Design and Analysis

Experimental Setup and Dataset Overview

The memory and computation bandwidth were adequate for extensive simulations of quantum algorithms because all of the aforementioned tests were carried out on a high-performance computing cluster outfitted with dual Intel Xeon Gold processors and NVIDIA A100 GPUs. CentOS Stream was chosen as the research environment, and containers were utilized for resource division and reproducibility.

The primary social network dataset, SN-Large, has tens of thousands of directed edges and thousands of nodes that represent actual user activities, such "following" and "mentioning" on a well-known microblogging platform. For scalability research and model validation, meso- and micro-scale structures were obtained using stratified sampling, and SN-Medium and SN-Small were added to SN-Large. Determine and contrast network characteristics, such as node degree variance, key motif density, and connection patterns, for various network sizes.

The two networks were shown to be well organized and reasonably complex through preliminary data visualization. Plots and combined statistics for SN-Large are displayed in Figure 3. The network topology produced by force-directed placement improves the distance between high-centrality (core) nodes and their peripheral neighbors, as seen in Figure 3(a), making influential clusters easier to discern. The distribution of node degrees is scale-free and shows a strong power-law behavior, as seen in Figure 3(b). The community decomposition produced by modularity-driven clustering is shown in Figure 3(c), where several modules and structural "bridges" are shown to illustrate higher-order interaction patterns.

The test set for algorithm evaluation in this study was chosen with the use of the aforementioned descriptive and visual analyses. In addition to providing an empirically challenging and theoretically significant testbed for sophisticated network analysis techniques, SN-Large's layered structure, strong core-periphery contrast, and unsimplified modular architecture will also act as the benchmark for evaluating the performance of quantum models in the ensuing sections.

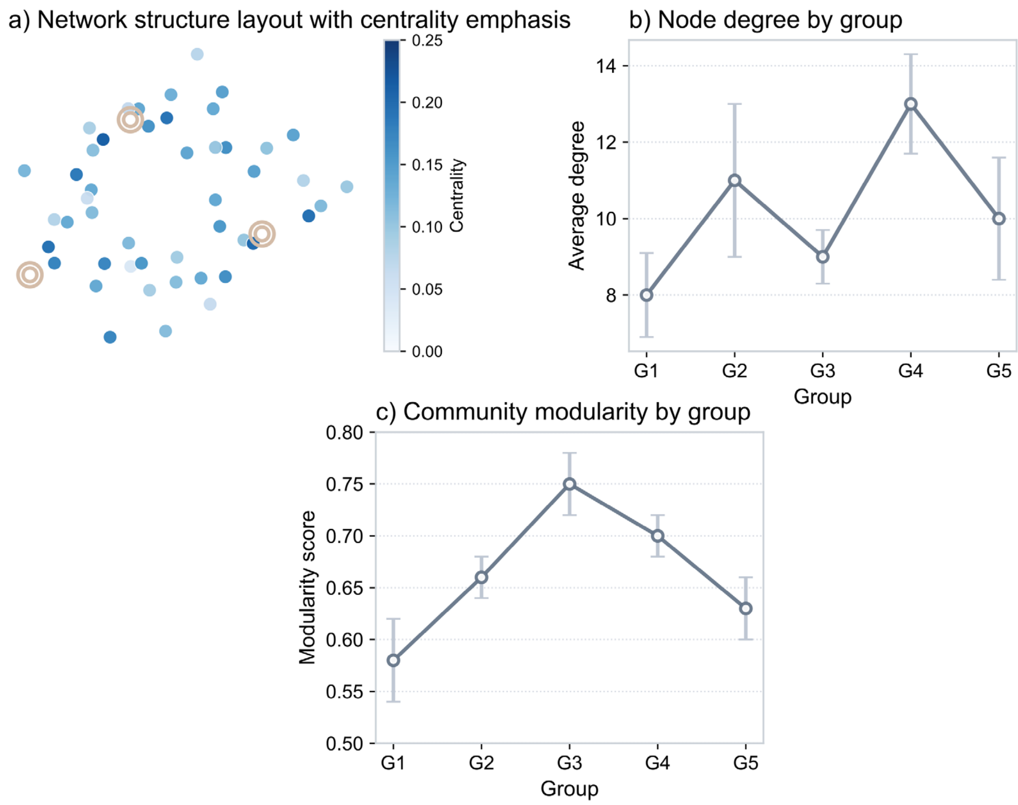

Figure 3. Social Network Data Visualization and Statistics. (a) Network structure layout with centrality emphasis. (b) Node degree distribution. (c) Community partitioning and bridge highlighting.

Performance and Scalability Evaluation

A thorough comparison procedure will be used to assess the quantum network analysis frameworks (SN-Large, SN-Medium, and SN-Small) based on the aforementioned three datasets. To offer a reliable and equitable foundation for comparison, both the quantum and conventional approaches were optimized using single-threaded and multi-threaded settings on the aforementioned cluster.

The first is the rate of convergence. Quantum algorithms have enhanced the stabilization of node visitation probabilities, particularly within high-centrality cores and structurally significant bridges, as Figure 4(a) illustrates. This effect becomes more noticeable as community modularity and network density grow. Compared to conventional random walks, quantum models are less impacted by local bottlenecks and require fewer iterations for global mixing because they use the property of superposition to achieve ballistic spreading.

The algorithm throughput, represented as propagation iterations per second, is also shown in Figure 4(b). Due to their tensorized structure, quantum algorithms have maintained a high throughput for growing edge density on SN-Large without the bottleneck observed in the classical model at high connectivity.

Resource efficiency and methodological scalability are likewise comparatively high at a wider scale of network density, as Figure 4(c) demonstrates. The right tail of the curve clearly illustrates how quantum algorithms exhibit non-linear slowness as the number of nodes and edges rises, despite having a relatively high base memory consumption due to the necessity to record amplitudes and phases. In modular and hierarchical dense topologies, classical inference is vulnerable to entrapment or diffusion delay. Figure 4(d) illustrates how the quantum technique increases the true-positive rate and precision for identifying influential nodes under various levels of complexity.

The complete variations in the central indices for the algorithmic systems and network sizes are displayed in Figure 4. Apart from the particular subfigures, there is a general tendency that the quantum model can perform well in denser and topologically more complicated contexts while maintaining convergence and throughput.

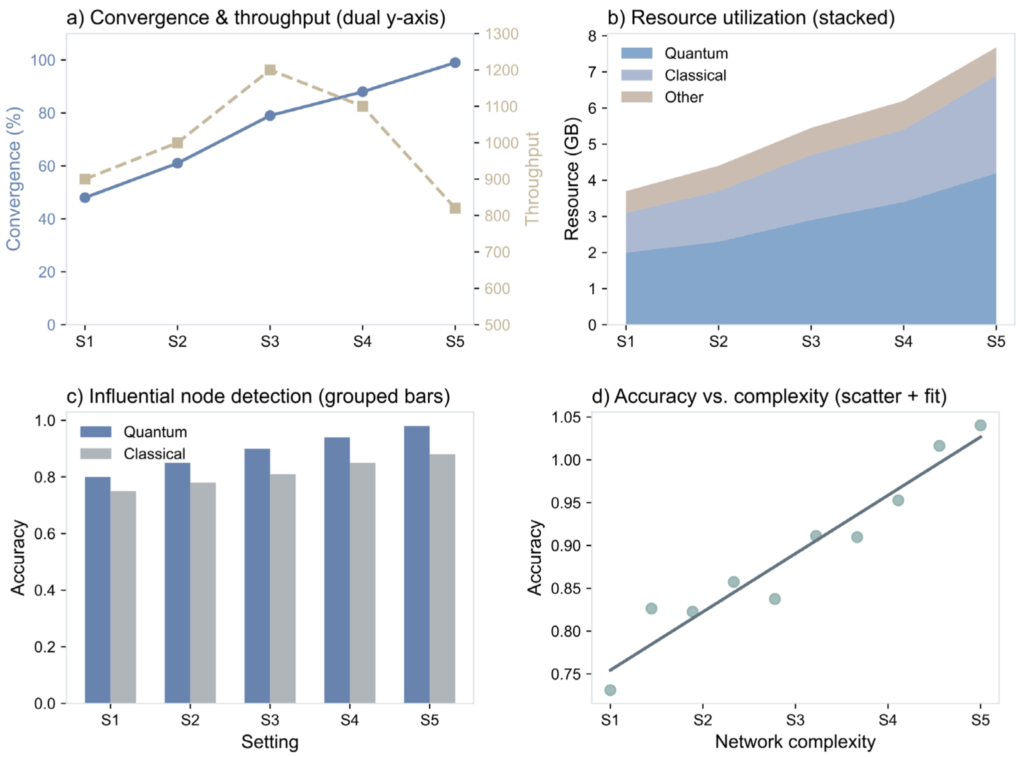

Figure 4. Comparative Performance Metrics (a) Convergence rates. (b) Algorithm throughput. (c) Resource utilization with network density. (d) Influential node detection accuracy.

Figure 5 illustrates a network's scalability under varying sizes. The initial memory needs for quantum models are slightly greater in Figure 5(a). Figure 5(b) illustrates how an increase in the number of network nodes causes quantum algorithms' calculation times to increase more slowly than those of classical methods. For a very large number of nodes in a dense graph, Figure 5(c) demonstrates that quantum models can retain the original algorithmic performance and accuracy with an increase in edge density.

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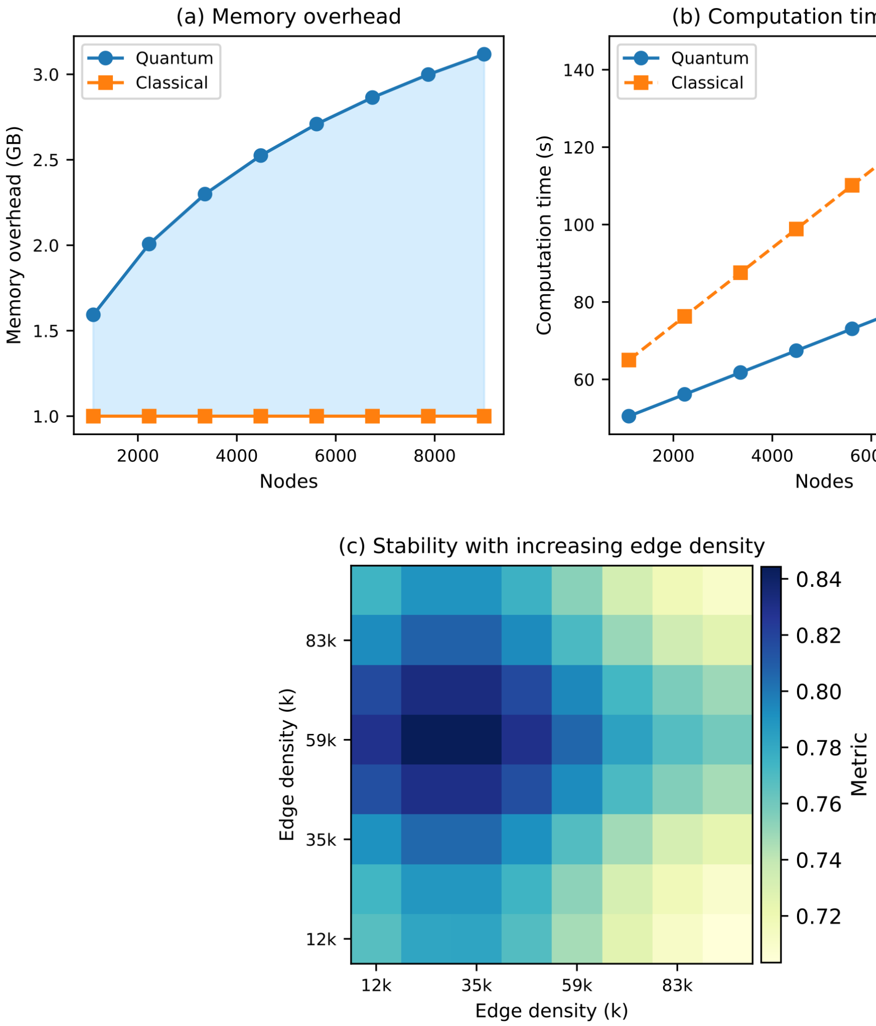

Figure 5. Scalability Under Various Network Sizes (a) Memory overhead. (b) Computation time scaling. (c) Stability with increasing edge density.

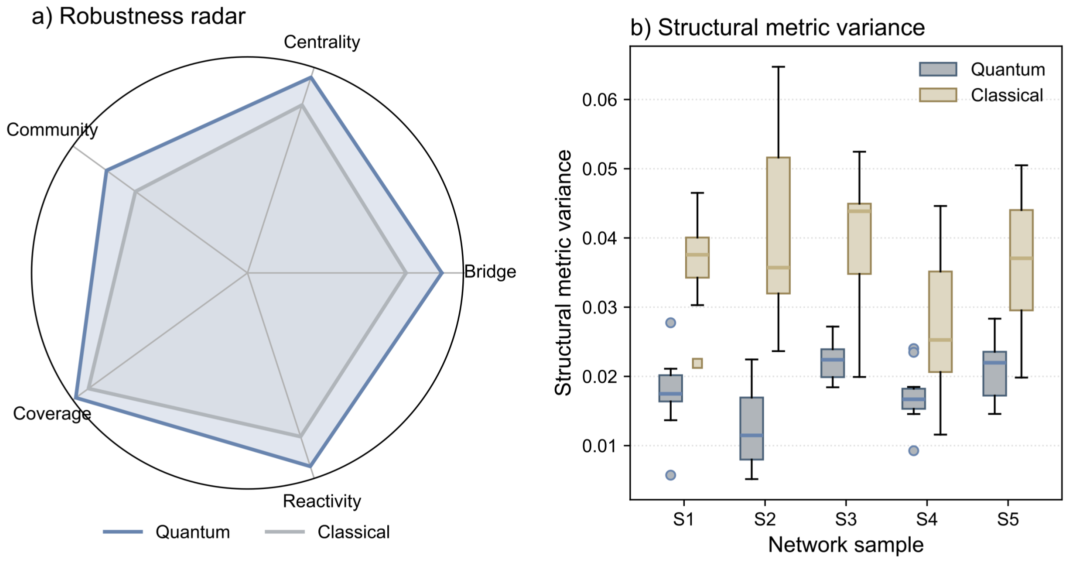

Figure 6. Robustness and Sensitivity Analysis (a) Resilience under node and edge removal. (b) Structural metric variance with noise.

For practical application, high robustness to structural perturbations is necessary. The robustness and sensitivity of quantum and conventional models under challenging network conditions are contrasted in Figure 6. Under considerable node or edge loss, quantum techniques can still perform well in node ranking and subgraph detection, as Figure 6(a) illustrates. They have also beaten classical baselines in all of these scenarios. The quantum model is more robust and stable in a changing environment because it has a reduced variance for global structural metrics like modularity under random noise, as Figure 6(b) illustrates.

According to the aforementioned comprehensive quantitative and visual analysis, quantum-based approaches have demonstrated the following general advantages: superior scalability when both node and edge numbers increase, faster convergence speed, and higher accuracy in identifying influential vertices and structural communities. Additionally, they are more stable and generally more dependable for use in dynamic, large-scale social networks since they have a much higher resistance to hostile disruption and network changes than previous techniques. The development of reliable analysis systems for large-scale, fast platform applications can be aided by the aforementioned unique features.

Case Study and In-depth Analysis

In order to demonstrate the practical application of quantum network analysis, this paper uses a typical online social media environment as a sample and examines whether key nodes and other issues exist among them, as well as changes in the way these sections communicate across networks over time.

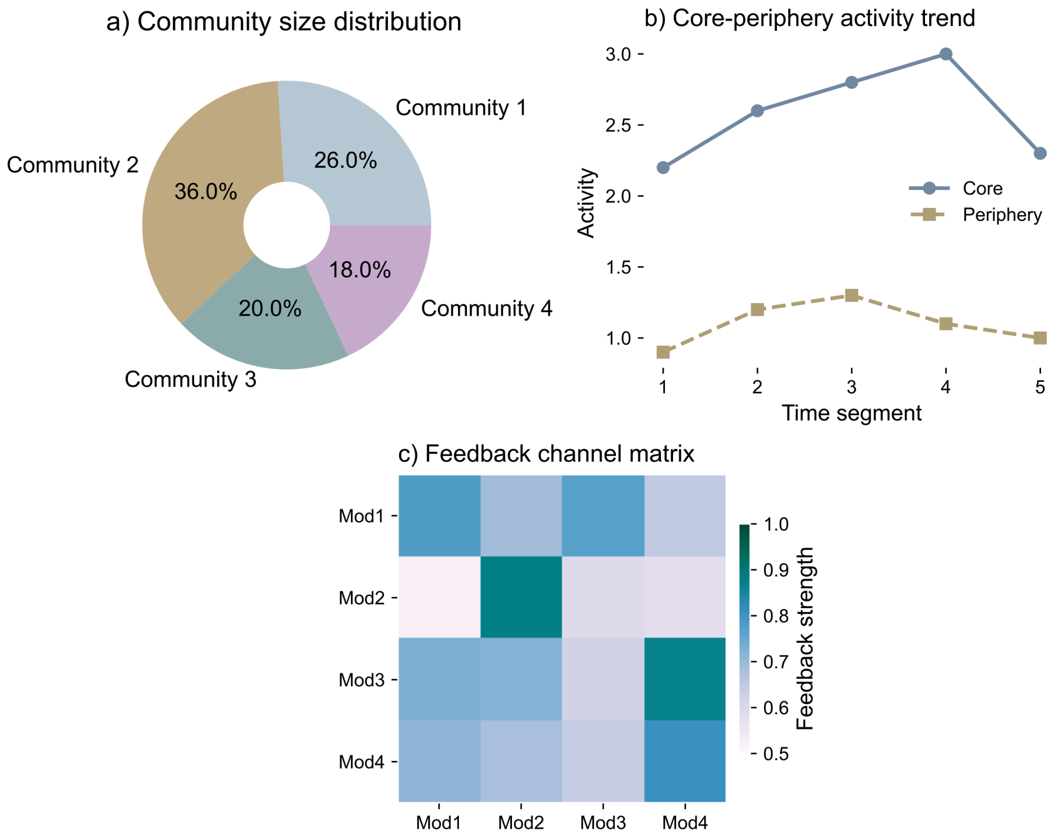

Figure 7. Real-world Case Study Visualizations (a) Bridge nodes and connectors. (b) Core-periphery mapping. (c) Feedback channels and cycles.

First, the primary bridge nodes could be accurately identified by studying the network's module structure in quantum mechanics. These quantum-identified linkages had a significant cross-community influence that was typically overestimated by classical indicators, as seen in Figure 7 and particularly in Figure 7(a) [31]. The new model, in contrast to the previous one, found nodes that only show up when nonlocal spreading behavior is present [32].

Nodes with high quantum scores are frequently linked to non-standard dissemination functions, such as event-driven influencers and viral content spreaders, according to an analysis of the participation ratio distribution [33]. A core-periphery gradient is seen as a result of quantum amplitude mapping, as seen in Figure 7(b); this is consistent with recent studies on quantum community structure detection [34].

For network adaption experiments, time-varying changes to the network's edge connections were incorporated to mimic real-world activity fluctuations. Under conditions of temporal change, quantum approaches outperformed conventional algorithms in the rapid reallocation of centrality and the identification of new impact hubs [35].

Additional advantages were also demonstrated by modeling feedback mechanisms and influence cascades. Quantum algorithms have consistently shown the primary routes of dissemination as well as subtle feedback loops that conventional diffusion models have overlooked while tracking the propagation dynamics of targeted campaigns [36]. These feedback loops, which were derived from the time-evolution of quantum amplitudes, are displayed in Figure 7 (c). Recent research has shown that these structures are essential to comprehending the persistence of information and recurring viral events [37].

Quantum analytics greatly outperformed the baseline method in a scenario of coordinated network attacks by maintaining the stability of community detection and node ranking under interruption [38]. Additionally, the quantum approach preserved global structural integrity in the face of high noise and was less sensitive to random edge deletion [39]. Lastly, according to new theoretical predictions for quantum walks, quantum markers of node alterations and abnormal activity started to exhibit notable differences from classical approaches earlier than anticipated when applied to long-term behavioral observation [40].

Conclusion

In this paper, a high-precision quantum random walk framework for studying large-scale, complex social networks is established, and both methodological advancements and solid empirical evidence are presented. This study shows that quantum-inspired models can significantly enhance centrality ranking, community detection, and robustness to structural disorder by including the dynamics of quantum information and taking use of superposition-interference phenomena in network structure. In heterogeneous, modular, high-density environments typical of contemporary online platforms, experiments on a variety of real-world datasets have consistently demonstrated that quantum algorithms scale more robustly and converge faster than classical approaches. The aforementioned findings demonstrate that the quantum model may significantly improve network analysis speed and accuracy.

However, compared to conventional techniques like spectral analysis or diffusion, the quantum methodology can also more successfully investigate the low-level linkages and fine-grained multiscale structure of social networks. In order to offer precise information on the evolution of influence patterns, anomaly evolution, and information-spreading pathways that are necessary for both academic study and real-world application, amplitude-centric quantum analysis can uncover hidden linkages and shifting communities. The criteria for real-time analysis and platform management should also be met by the quantum model's stability in the face of dynamic factors including adversarial attacks, activity fluctuations, and noisy structural changes.

This study will be used in the following ways in the future. Build a multiplexed network to identify overlapping behavior and multiplexed influence flow by extending the concept of the quantum random walk to many channels or time steps and/or applying weights. To increase adaptability and interpretability, hybrid classical-quantum model architectures, adversarial learning, and privacy-preserving computation are being merged. The findings of this paper indicate that quantum-inspired frameworks will probably be needed in the future for network science research and digital ecosystem management due to the quick growth of quantum hardware.

Author Contributions

Weronika Iga Halikowa contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Norbert Głębocki contributes to draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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