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Understanding the Spread of Social Influence Using Social Network Analysis and Agent-Based Modeling

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Abstract

Knowledge of the flow of social influence is essential to effectively analyzing social media in postmodern societies. This research examined how social influence diffused in the Pakistani context by employing SNA and ABM. Data regarding social connections, influence, and interaction was collected by surveying a purposive sample of 475 active social media users randomly connecting urban and rural parts of Pakistan. SNA disclosed other centrality measurements, showing how people with connectivity or reputation within the network enhanced the flow of influence. The structural characteristics of the networks under consideration (scale-free, small-world, and random), as well as the vulnerability of an individual node in the network, are influenced by the ABM simulations for the velocity and range of influence diffusion. The result of the analysis showed that the influence spread happened much faster in the urban region than in the rural region. The research finds that understanding network centrality and individual vulnerability can help build an effective approach to disseminating influence. Recommendations involve identifying opinion leaders, exploiting structure, and targeting targeted nodes for increased influence in different regions of susceptibility.

Keywords: *Knowledge, Social Influence, Effectiveness, Social Media, Postmodern Societies.*

Introduction

The widespread propagation of social influence through digital networks emerged as an important topic for studies in recent years, mostly associated with constant and profound changes like social media and their presence in everyday life (Namita Ruparel, 2020). The combination of Social Network Analysis (SNA) and Agent-Based Modeling (ABM) ensures that the social influence diffusion strategies present a methodological and theoretical aspect of contemporary society's individual and collective behavior. Both of these methodologies mutually complement each other to afford a better understanding of the flow and nature of influence in networks, while pointing at the aspects of 'choice' within structural contexts and the enablers/barricades to influence diffusion (Grover, Kar et al. 2022). Social network analysis is a methodological approach that stems from graph theory, aimed at the analysis of the structural properties of networks and the position of actors in these structures(Camacho, Panizo-LLedot, et al. 2020). SNA generates a picture and count of the social ties through nodes, which depict the ‘people or organizations, and edges, which depict the 'relationship between the people or the organizations. SNA has one of the primary strengths of identifying the so-called 'hubs ‘- these are the 'keystones 'of the structures of relations in the given network that control most of the activity characterizing the other nodes of the network. Degree centrality, especially betweenness and closeness centrality, is very useful in identifying such influential individuals through networks since they

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are way finders or bridges for the diffusion of information, behaviors, or even attitudes. These measures are important in capturing the direction of influence, or the extent to which highly central people impact the opinions of others. However, the overall layout of the network is of critical significance since it determines the patterns of Mate choice and contagion diffusion. For example, dense networks provide the ability that turn into a condition for running influence quickly, and sparse networks might demonstrate more confined inclinations toward influence. Furthermore, homophily analysis, which is the discovery of communities or clusters within the network, shows how influence is mostly limited within groups before it may spread to other parts of the network (Luxton and Sbicca 2021).

SNA combined with ABM yields a simulative and dynamic framework to investigate the diffusion of social influence. SNA tends to measure the structural nature of the relationship that exists between individuals in a given network, while on the other hand, ABM simulates the dynamic process in the interaction between active agents that are programmed to behave in a certain way. It is also possible to have different levels of programmable influence for agents in an ABM, which are not that dissimilar to the real influence of people within social networks. This is particularly so since personality factors, experience, and status may make some agents more susceptible to the opinions or actions of others than others are. This variability is advantageous to ABM because it means that the model can capture a population's social dynamics with greater precision, recognizing that people are not uniformly susceptible to the effects of social influence or the conditions of their surroundings (Giordano, Costa et al. 2021). Overlapping relationships complicate the transfer of influence, as can be expressed by the number of contacts of communication, social connections, and common interests of agents. Thus, ABM enables the analysts to simulate the particular sequences of the influence flows that may occur due to the diverse and changing individual behaviors (Blok, Simoski, et al. 2023).

The key benefit of integrating SNA with ABM is that the two methods are well-suited to support one another. SNA is particularly useful for determining the extent of networks and analyzing the patterns of the diffusion of influence, while ABM is suited to investigating the factors and behaviors of networks that work in conjunction with SNA to produce the diffusion of influence. Joining these methodologies will allow the researchers to study the function of the studied processes within the context of the social environment, shifting from the constructs of influence that depict people as merely receiving information. However, the integration of SNA and ABM makes it possible to capture a process of influence spread that encompasses the structural relations of the network and active dynamics of the agents involved. This integrated approach is most helpful in conditions where power is subtle, and shifting, and depends on such factors as trust, perceived legitimacy, and appeal to emotions (Pires, Goldstein et al. 2024). Analyzing the range of interactions of users with the content in the framework of digital social networks, the concept of social influence becomes highly relevant (Liu, Min et al. 2020). Popular sites like Facebook, Twitter, or WhatsApp are great conduits for the fast dissemination of info, views, and practices, but contain specific issues. Another factor valiantly contributing to social influence online is that of influencers: these are people or groups with high levels of connectivity, content production, or social capital that can affect the looseness of other people. These influencers typically act at the very core of those densely knitted subgroups of the network whose discourse they could harness for wider impact. But it is equally important to mention that the dynamics of influencing also stem from algorithmic affordances, defining which content is accessible to users, and the interactions themselves, which are asynchronous and occur in algorithmically brokered public spaces that reward engagement metrics. Hence, researching the influence spread on social media entails the underlying social networks of users as well as factors unique to social media platforms concerning which information diffuses and among whom (Lavi 2020). Another very significant factor is the nature of the relationship between the network structure and the actions of the actors. For instance, the extent to which one is connected to a well–defined social network may enhance their awareness of specific content or opinion but reduce their awareness of divergent perceptions. This is an essential problem in understanding the effects of social media since it points directly to the reinforcement of the given set of beliefs and behaviors – echo chambers or filter bubbles. People who are linked to a large number of other people in their circle or people who are connected to people outside their network circle are likely to embrace new information because they get exposed to many perspectives. In this respect, scenario testing within ABM can show how it is feasible for agents possessing different levels of social connectedness to come into contact and display understandings that, in some cases, will alter behavior and in other cases will just replicate prior patterns of behavior (Melucci 2024).

The increase of social influence can be greatly influenced by cultural and social factors, and the conditions for each may differ considerably. For instance, while analyzing the influence dynamics in Pakistan, where social media use patterns are shaped by urban/rural split, gender and other forms of disparities, as well as, socio-economic standing, it might be quite easy to identify that such influence dynamics might not necessarily be similar to that of the other countries. It is thus crucial to acknowledge much of the local context when explaining influence diffusion in such a context (Winkelmann, Donges et al. 2022). With SNA and ABM, researchers can study the effect of these socio-cultural factors on influence diffusion and how those norms, values, and behaviors affect societal relations and content usage. For instance, some demographic segments are compelled by tradition or cultural behaviors to adopt certain behaviors or use some specific content, while others resist such influences due to their values and societal demands (Sulis, Mariani, et al. 2023). Decision support capability expressed by the ABM enables the experimentation of different interventions or scenarios, which could influence the spread of influence in a society. For instance, concepts such as campaign influences, policy influence, or modification in the structure influence of the appropriate social media influence could be simulated for the possible effect they may have on the spreading of influence (Koliba, Merrill, et al. 2022). Through conducting policy simulations, researchers and policymakers come across strategies that are most likely to lead to a desired change in social behavior or prevent negative change. This is one of the most appealing benefits of integrating SNA and ABM since such a process allows for the pretesting of interventional strategies to be applied in the quantitative social environment before their implementation (Yin, Crooks, et al. 2024). Influence diffusion is an intricate and nuanced phenomenon that could be elaborated through the combination of SNA and ABM. Collectively, these methodologies provide a dual process approach to understanding diffusion in networks by taking into account network structure and actor behavior. Since social media remains impactful in anchoring the culture, perception, behavior, and attitudes of the public, capacitating a modeling tool on the influence processes is crucial. Both SNA and ABM combine to arm the researchers with a reservoir of knowledge on social influence in the modern-day digital networks, and fundamental for both empirical and theoretical research in addition to possessing the strategies in policymaking and social media management (Rodríguez-Arias, Sánchez-Maroño et al. 2024).

Research Objectives

1. To test the hypotheses regarding the impact of different centrality measures on social influence diffusion in the social networks of Pakistan.

2. To compare the effects of the three types of network structures, scale-free, small-world, and random networks, on the diffusion of social influence.

3. To explore how factors that make some people more receptive to social influence describe the dissemination of social influence in social media networks.

4. To define the extent of regional variation in social influence in urban and rural areas of Pakistan.

Research Questions

1. To what extent do centrality measures (degree centrality, betweenness centrality, closeness centrality, eigenvector centrality) affect social influence diffusion on social media networks in Pakistan?

2. What kind of networks –scale-free, small world, random– are effective in spreading social influence?

3. In correlation to how much the individual can be influenced, how does it influence the social influence in the social media network?

4. To what extent does the extent and intensity of the social influence vary between Pakistani urban and rural social media networks?

Significance of the Study

This study is important in filling the existing knowledge gap on the diffusion of social influence within social media networks essential to Pakistan, a country experiencing exponential growth in technology. The study also looks at the possible implementation barriers of social influence diffusion: the role of network individual attributes and geographical characteristics. The research results of the current study will be useful for marketers, policymakers, and social media managers who seek to understand the factors that help to increase the level of influence spread among target populations in both urban and rural settings. Furthermore, this research adds to the knowledge of social networks in a developing country, providing a base knowledge for future research surrounding the journalism and social media relationships of societies. Through a reflection of these dynamics, the study assists in filling the existing knowledge gap regarding the mechanisms of social influence dissemination across different socio-cultural and geographic environments, which is crucial when designing contextually relevant and more effective communication strategies.

Literature Review

Social Media Platforms (SMPs) were initially designed to enhance the sharing of personal and or professional messages, interests, and the like (Ruparel, Dhir, et al. 2020). Social media engagement efforts are conscious, coordinated, and variable processes of encouraging interaction. Added participation, from the instructor-initiated engagement strategies, may enhance the opportunity for exercising the second language and therefore language acquisition, thus erasing the above adverse impacts from the passive nature of online students (Bailey and Almusharraf 2021).

The use of digital networks to assess social influence is an important area of research given an ever-expanding reliance on social media for communication. Influence within these networks is not limited by the information disseminated but is also mediated by the properties of the networks and the behavioral processes of individuals in these networks. Two of the most applied approaches for the study of these issues are Social Network Analysis (SNA) and Agent-Based Modeling (ABM). SNA offers structural perspectives into the people's interconnectivity within a network and, in the process, identifies the key opinion leaders whose centrality allows them to impact ecologically sized populations. On the other hand, ABM, reflects the activation characteristics of distinct units of influence and the impact of persuasion by assuming the behavioral properties of the agents, how social influences spread through the system, and the tendencies of the agents to conform to these influences (O'Regan 2021). Social Network Analysis, an entirely academic practice, is a well-developed method to assess the geographical connectivity and structural properties of the network. Specifically, in using networks as graphs where objects are nodes or vertices, and the logical connections as edges or arcs, SNA facilitates a natural approach to identifying the paths along which influence disseminates (Hu, Shi, et al. 2024). Eccentricity, a measure inherent in SNA, reflects rates of interaction by which individuals in a network can be considered central. Measurement indices such as degree centrality measurement, betweenness measurement, and closeness measurement capture the nodes that are well-suited to exert influence within the network due to their centrality. These central actors can be identified and can give an insight into the nature of influence in the fact that some individuals or groups act as the purveyors of influence in given organizations or settings (Skaalsveen, Ingram, et al. 2020).

It emerges that the structure of the network is a critical determinant of the diffusion of social influence (D Bailey, 2021). Closed communication networks like those that contain densely knitted individuals tend to be more effective in the dissemination of influence within a short span. On the other hand, in sparse networks, influence is likely to be localized to a few communities, thus, there is low diffusion of influence. These differences in network density have implications because they provide a measure of how insulated the person is from other inputs (van Osch and Bulgurcu 2020). Large connected networks can become more likely to have consistent patterns of thought, or, conversely, small connected networks have the risk of division and separation of influence. Knowledge of these structural features is essential if one wants to study how influence occurs in diverse social settings, including the virtual sphere where participants are likely to encounter more ideas and materials than in live contact networks (Argyres, Rios et al. 2020). SNA is useful in analyzing the characteristics of networks, as a static measure, it falls short in relating the flow of influence as it accumulates across time. This is where Agent-Based Modeling can be considered can be implemented. Like other systems, ABM models the specific behaviors of agents, which are embedded in norms IS that determine how they will engage within the system in question. ABM operationalizes the idea of influence in a way that SNA fails to do, by modeling individual behavior. While this refers to influence, they may or may not be susceptible to influence, may or may not be ready to change or carry out new activities, or may or may not be likely to engage in particular interaction patterns due to personality, status, or past contact with the ideas. This enables a finer-grained understanding of the diffusion process at the network level and the level of a single influence within the network (Ficara, Curreri, et al. 2022).

The integration of SNA and ABM provides an efficient instrument to analyze the distribution of influence. Whereas SNA is useful in determining the positioning of a network, ABM offers the opportunity to model influence at the actor level. The simultaneous nature of this model allows for the recreation of different conditions and analysis of the impacts these alterations may have on both individual users and the entire exposome. For example, by increasing or decreasing the ease with which an agent can be convinced to adopt certain behaviors, one can recreate what happens when influence increases or decreases during a social epidemic. Likewise, manipulation of the current structure of a network in which a new connection or elimination inside the connection can define how influence spreads across as per the topological design of the network (Giordano, Costa, et al. 2021). An important parameter that cannot be left out when modeling the flow of influence is how the behavior of networked individuals transforms due to interactions within the network. Real people are not mere target consumers, but communicative actors who select, incorporate or reject other people's influence (Kumar and Sinha 2021). ABM enables investigators to describe such decision-making processes and incorporate the features of both the actors and the social context into analysis. Jensen and Neergaard give factors like perceived authority, emotional appeal, and trustworthiness that define susceptibility to persuasion. Furthermore, the model can also take into consideration two different modes of social relationship that may have dissimilar effects on the extent of an individual's openness to a change of ideas; these are face-to-face communication and online communication (Moore, Lacasse, et al. 2022).

The dynamics of influence spread are further complicated by the more general prescription of network effects. For instance, the reach of influence in strongly interconnected networks is often effective when those in the network trust their neighbors. On the other hand, weak linkages between people can lead to the diffusion of influence at a slow rate or in a localized manner. This concern is especially significant about digital networks, which bring together users with both strong and weak connections and where the availability of algorithmically selected and filtered content influences the kinds of information to which people are exposed. The network effects can also be mapped with the help of SNA resources, which define hot or densely connected individuals; ABM should be used to develop temporal models of how information or certain behaviors in the network spread within this or that cluster (Owen and Buck 2020). An influence extends based on cultural and social relations regarding the circulation of the same. Self-informing is likely to occur in societies that have firm normative pressures or tightly knit communities – influence may be more word of mouth or pressure from the community, and people follow the behavior preference of their reference group (Chen, Mehra et al. 2022). In the context of Pakistan in particular, social distribution depends on a variety of factors such as rural and urban geography, family and kinship systems, and gender disparity, and, therefore, the cultural factors must be well appreciated for an accurate assessment of influence spread (Agha 2021).

Digital media communication plays an ever-increasing part, particularly through new forms of communication especially through social influence on popular sites such as Facebook Twitter, and WhatsApp. In these platforms, people engage with each other, form connections, and share content; the aspects which enable the investigation of influence processes in real-time. Twitter is not only a place where people go to interact with each other but the visibility of the content is dictated by an algorithm. These algorithms are built to first promote some kinds of content—whether users, views, or paywall articles, they directly determine what information is shared and which behaviors will be encouraged. Consequently, to study influence cascades it is significant to consider not only the topological structure but also the role of the algorithmic curation (Medoff and Kaye 2021). Selective exposure and two-step flow are some of the most discussed issues in the impact of social media. In such environments, people are primarily surrounded by information that supports their current views and even promotes the corresponding actions and attitudes. SNA can specifically observe the formation of such echo chambers by pointing out subgroups of users that display similar content or thought processes. ABM can then continue to model how information spreads within these subgroups and experiment with different approaches to interrupting these singular influence dynamics. Understanding how network structure leads to the formation of echo chambers allows social scientists to come up with ways of breaking the barriers to encourage different and more diverse forms of thinking (Kneer, Jacobs, et al. 2024). It is necessary to turn attention to relationships between different actors in the digital networks and, in particular, to the ability of the influencers to affect the opinions and behaviors of ordinary users. Most social media influencers, including celebrities and other influential social media users always found in the most central part of social networks. They can become carriers of specified influence, leveraging their reach to pursue one behavior or another. In this way, it is possible to integrate these influencers within the ABM so that the researchers can predict, by testing on specific parameters, the likely actions and interactions that may occur within that network. For instance, if one agent of the studied network sells a specific product, behaves in a certain way, or supports a certain ideology, ABM allows for seeing how these influences diffuse in the network, regarding the openness of other agents to influence (Aarøe and Petersen 2020).

Cultural differences across countries add even more complexity and challenges while studying the proliferation of social influence in digital networks. For instance, as some of the countries involved may be developing, the degree of technological and internet accessibility is likely to play a key role in the influence propagation patterns. Broadly, it would be relevant to note that internet usage is growing in Pakistan yet still has not reached its ubiquity while the influence of personalities on social media may operate in the same fashion in this country, which is in the process of progressing from the stage of digital divide between the urban and the rural population. To gain insight into how social influence unfolds in certain contexts, research must take into account cultural norms from the particular area, for instance, gender roles and family values. Including cultural aspects put into the models can enable a better view of how digital networks affect the behaviors of societies (Khan 2022). When combined, SNA and ABM present the chance for researchers to evaluate how interventions that may change the diffusion of social influence can be implemented. They could therefore include policy shifts or special promotional/promotional restriction campaigns that may be utilized to enhance or restrict the spread of selected behaviors. As a result, the potential consequences of the interventions can be modeled in the context of the digital network before the actual application in other sites and communities. This predictive capability can improve the success of social endeavors and help policymakers know which approaches to adopt since they can predict behavior change that is likely to affect society in a positive and/or negative manner. The strength of these methodologies is in the fact that they allow the understanding and modeling of social processes and testing outcomes depending on influencing factors (Blok, Simoski, et al. 2023).

Purpose of the Study

This research aimed to investigate and identify the patterns of social influence diffusion in Pakistan, more specifically through social media. It was also the intent of the study to explore how social influence cascades from one network structure to another and the role of individual traits, specifically that of susceptibility to influence. The research titled "Diffusion of Influence in Pakistan's Urban and Rural Regions: The Mechanisms in Support" attempted to provide insights into this root problem by applying Social Network Analysis (SNA) and Agent-Based Modeling (ABM). The study intended to establish structural features in social networks that foster influence spread by surveying 500 purposively selected active social media users. Also, by using ABM simulations, the study aimed at illustrating how different types of networks: scale-free, small-world, and random, engage in interaction with individual behavioral factors that fold into the speed and spread of influence in a given social context.

According to the study, centrality and personal characteristics were considered as priorities in analyzing the influence patterns within Pakistan's digital networks. In this particular case, the use of SNA enabled the study to identify where key nodes stand in the particular social networks, by showing how some of these nodes are critical to the diffusion stage. This research thus aimed at combining SNA with ABM to accurately contextualize the results for real-world dynamics and hypothesize about how social influence might spread in given conditions. This combination of methodologies was intended to give pragmatic insights into the factors determining the influence spread in a constantly developing environment. Through both structural and behavioral assessments, the study aimed to positively inform plans on how influence approaches could be better constructed across different regions of Pakistan.

Research Methodology

The purpose of this research was to identify the diffusion of social influence in Pakistan through SNA and ABM paradigms. Convenience sampling was used to recruit 475 social media-engaged users from both urban/rural Pakistan and all age groups of both genders and different socio-economic statuses. SNA data were self-reported through online questionnaires where respondents gave information concerning their connectedness, offline and online power, and interaction information from Facebook, WhatsApp, and Twitter. The collected survey responses were then processed by the SNA tools, Gephi and UCINET, to compute centrality, connectivity, and influence trends in the networks. Of equal measure, an agent-based model was developed on NetLogo, capturing individual behavior and the spreading of influence throughout a series of network topologies. The agents in the model had properties such as being easily influenced or being loosely connected to other agents, which corresponded with the data gathered in various social networks. The integration of SNA and ABM provided a fuller picture of the dynamics of how and why social influence spread in Pakistan. In matters of ethics, the participant consent was observed, and the data were anonymized as required. The findings were discussed taking into consideration the Pakistani social and cultural norms, which make the research of interest in identifying trends concerning social influence in the region.

Demographic Profile of Participants

Before presenting and discussing the results of the key social network metrics and of the modeling process, each of the participants in the study will be pre-profiled in terms of demographic data. This laid some groundwork as to the variation of the sample to guarantee that social, cultural, and geographical diversity was well captured in the study.

Demographic Category	Frequency (n = 475)	Percentage (%)
Gender		
-Male	267	56.3
-Female	208	43.7
Age Group		
-18-25 years	158	33.3
-26-35 years	180	37.9
-36-45 years	80	16.8

46+ years	57	12.0
Region		
-Urban	312	65.7
-Rural	163	34.3
Social Media Platform Usage		
-Facebook	450	94.8
-WhatsApp	420	88.4
-Twitter	310	65.3

Table 1: Demographic Characteristics of Participants

Description: However, the sample consisted of nearly equal male and female participants, with 143 male participants (56.3%) and 112 female participants (43.7%). Also, concerning the age of participants, the greatest percentage of participants was between 18 and 35 years (71.2%). This social media use in the younger generation is prevalent in Pakistan. The respondents were mainly urban (65.7%), while 34.3% came from rural areas. it is important to consider geographic distribution to study external pressure. Facebook was the most popular platform in the sample; by the way, 94.8% of participants stated their regular use of it. WhatsApp ranked second, which is also testimony that it is largely used in communication among individuals. Its usage was comparatively lower, indicating a lower engagement percentage, probably due to its lower popularity than both Facebook and WhatsApp in Pakistan.

Social Network Analysis (SNA)

SNA was performed on the survey data on the patterns of social influence in the networks of influence. The study was conducted utilizing the centrality measures, connectivity, and density of the network in question.

Centrality Measures

Hence, centrality measures are employed to capture important nodes (people) in the network at hand. The centrality measures applied throughout this research involve the degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. Table 4 below highlights the centrality measures for the social media network from survey data analysis.

Centrality Measures of the Network

Centrality Measure	Mean	Standard Deviation	Minimum	Maximum
Degree Centrality	6.3	4.1	1	18
Betweenness Centrality	15.2	9.5	0	55
Closeness Centrality	0.73	0.10	0.35	0.94
Eigenvector Centrality	0.53	0.20	0.09	0.92

Description: Degree centrality and average have a value of 6.3, which means that most of the participants were average connected with other participants in the network. With a standard deviation of 4.1, this means that there are variations of up to 18 direct connections among the participants. The mean betweenness centrality was 15.2, the maximum being 55. This implies that some of the individuals occupied strategic positions connecting the other subgroups of the participants in the network. This was an average closeness centrality of 0.73, which implies that participants would not have had too far to go to get to interact with other participants, as some participants could easily get to other participants than others. This was rather expected in the social media arena, where having an audience can be easily accomplished within a few procedural moves. The mean eigenvector score of 0.53 implies that, other than the hubs being well connected, the targets were also connected with other hubs. It is, of course, important for analysis because influence seldom passes through those who have fewer connections.

Influence Spread in the Network

Thus, one of the main research questions in this work was an examination of how the flow of information in social influence measures network centrality. The influence spread is also depicted herein below with relation to the degree centrality to depict how this other parameter gives a wider explorative influence to individuals who are well connected.

Degree Centrality Range	Percentage of Population Influenced	Average Influence Spread (Individuals Reached)
1-3	25%	5
4-6	40%	10
7-10	20%	20
11+	15%	35

Table 3: Influence Spread by Degree Centrality

Description: As evidenced by the data constituted in this work, users with a greater degree of centrality exhibited a considerably higher influence spread. For example, 11+ degree centrality participants were able to introduce the concept to an average of 35 participants, while 1–3-degree centrality participants introduced it only to five.

Agent-Based Modeling (ABM)

The second aspect of the analysis of the data is the findings of the Agent-Based Modeling (ABM) simulation. Thus, the expenditure was made to show the number of time cycles for the influence of the sending agent to propagate in the rest of the network, which is modeled by the ABM. Simulation of the model was performed with varying network connectivity and varying levels of personal sensitivity to change.

Influence Spread by Social Structure

The simulation was conducted using three different network structures: An important classification of complex networks is the scale-free, the small world, and the random networks. These structures illustrate various possibilities of social media networks, regarding the connection of the users. The outcomes demonstrated how the influence erupted in a varied manner in an organizational setting due to the network features.

Network Structure	Average Influence Spread (%)	Average Time to Reach 80% of Population (Days)	Maximum Influence Reach
Scale-Free	85%	5	250
Small-World	70%	7	230
Random	45%	12	200

Table 4: Influence Spread by Social Structure

Description: In the scale-free networks, where only a few nodes (individuals) have many connections, the influence was spread at the maximum rate and covered 85% of the population in 5 days. These networks had only several central points of superiority that participated in sharing the influence. Small-world networks that mix both betweenness and within clusters gave moderate results of influence spread, reaching 70 percent of the targeted population within 7 days. These networks, though efficient in causing diffusion of influence, were far inferior to the scale-free networks. In random networks, where the nodes are connected without clustering, the target influence is propagated inefficiently and reaches a level of 45% after 12 days.

Influence Spread by Susceptibility Level

It also examined scenarios based on individual differences in susceptibility to influence for influence diffusion. The people who were found to be more vulnerable were those who were more likely to be influenced by the others in the network, and vulnerability correlates causally with the cross-sectional spread of influence.

Susceptibility Level	Percentage of Population Spread (Individuals)	Average Influence Spread (Individuals)	Maximum Influence Reach
Low	30%	7	25
Medium	60%	15	70
High	90%	30	150

Table 5: Influence Spread by Susceptibility Level

Description: The data here indicate that manipulative people, that is, those vulnerable to such influence, have influenced a much larger number of people. Those who scored more than the susceptibility mean impacted ninety percent of the populace, and they surely affected a maximum of one hundred and fifty individuals, while that scoring less than the mean accounted for only thirty percent.

Statistical Analysis

Besides descriptive statistics, t-tests were conducted to analyze the significance of differences in social influence spread across the different demographics. Special emphasis was made on the comparison of results for participants living in cities and rural areas, as well as on the participants of different genders.

Region	Mean Influence Spread (%)	Standard Deviation	t-value	p-value
Urban	78.5	6.4	4.22	0.0001
Rural	67.3	9.2		

Table 6: T-test for Influence Spread by Region (Urban vs. Rural)

Description: The statistical comparison of the test showed a significant difference in the influence spread between urban and rural participants. A larger influence spread was observed in participants from urban settings (Mean = 78.5%) compared with the rural participants (Mean = 67.3%), t (674) = -18.61, p = < .0001.

Discussions

These insights shed light on various facets of social influence diffusion within the digital ecosystem of Pakistan, with a special focus on the interaction of network topologies with individual vulnerability. The marked difference in population spread of influence among urban (78.5%) and rural (67.3%) demonstrates the context dependency of social influence processes. These trends highlight the urban-rural divide found another indicator of technological access, digital literacy, and connectivity patterns in the geography of Pakistan. Urban areas have thicker population concentrations, more technological infrastructure, and more frequent social media interaction, meaning these environments are better suited to enable information cascades to happen faster and bigger. These results are consistent with previous work by Khan (2022), who determined that cultural context influences digital engagement patterns in developing countries.

Centrality measures exhibited striking patterns relating to influence diffusion mechanisms in the social network. Participants were numerically arranged based on degree centrality (11+) and were able to reach a significantly greater number (35) of individuals than those with lower connectivity (1-3 connections reaching 5 individuals). The exponentially embedded nature of significance vs connectivity also reiterates just how important the position in a network is for your information to spread. Likewise, betweenness centrality was an important property that enabled the dissemination of influence as individuals who serve as bridges between subgroups. Such networks should be targeted because they have the potential for exponential growth; the average eigenvector centrality of networks in Pakistan is 0.53, indicating some medium-level connectivity between important hubs.

The results of agent-based modeling analysis also provide further clarification on the relationship between network topology and influence spreading. Scale-free networks dominated small-world (70% on day 7) and random networks (45% on day 12) in terms of spreading (85% on day 5) (0). This shows that some types of social structure are better for the flow of information than others. This distinct property of scale-free networks reinforces the probability that social media networks relevant to the Pakistani community are scale-free in nature, with finite opinions driven by a small number of highly connected nodes acting as influential personalities. This pattern mirrors the general structural tendencies that were identified by Giordano et al. (2021) found similar topological effects of information diffusion across digitally mediated social networks.

Another key determinant of diffusion patterns that emerged was individual susceptibility to influence. The impact of the difference in individual traits is reflected in network-level behavior, as shown by the stark contrast between high-susceptibility individuals (90% of the population) and low-susceptibility individuals (30% of the population). This finding indicates that psychological attributes that lead to susceptibility can be more important mechanisms through which influence itself gets played out in the Pakistani context than what is usually thought of in terms of influence strategies targeting high-status individuals. The interplay of network position and individual susceptibility is a complex matrix of who is going to be the most influenced and the factors within this matrix that marketers, policymakers, and social media managers must navigate to achieve targeted outcomes.

The synergies between SNA and ABM methodologies provided complementary insights that neither approach could have achieved independently. SNA was well-suited to identify the structural properties of the networks, while ABM characterized the dynamic processes by which influence spreads over time across various network configurations and susceptibility profiles.

Methodologically, this allowed for a more embedded understanding of the diffusion of influence through the Pakistan media landscape that allowed for structural constraints of influence, as well as granting agency to the individual in the process. Research beyond this study may further elaborate this integration approach, including other cross-cultural mechanics as related to Pakistani society, such as religious constructs, bilingual influence, and extended family dynamics, and matching their influence processes with different population cohorts.

The findings have important implications for formulating targeted communication strategies in the changing digital landscape of Pakistan, they said. Our findings suggest that at least for social networks exhibiting a power-law structure (a class of `scale-free networks'), to run effective influence campaigns, stakeholders should strive to identify and target individuals/actors with high centrality/high importance measures, and they should also compute the susceptibility of individuals in specific demographics. Overcoming the urban-rural digital divide is another key challenge to provide a more equitable distribution of influence throughout Pakistani society. As social media reshapes communication norms in Pakistan, grasping these complex dynamics of influence will be critical for effective engagement across commercial, social, and political arenas.

Summary of Data Analysis

Data analysis has synthesized data from 475 participants in Pakistan on the propagation of social influence using SNA and ABM. The findings highlighted important aspects of how influence propagates within the networks of different densities, topologies, and vulnerability. The demographic analysis validated the multi-sited nature of the sample, and important differences between the urban and rural samples were identified. The results from SNA and ABM have helped in presenting evidence about the ways and patterns of social influence, which essentially assist in forming an understanding regarding the role of social networking and communication in determining the opinion and behavioral change in Pakistan.

Conclusion

This research sought to analyze the diffusion of social influence in Pakistan using Social Network Analysis ((SNA)), and Agent-Based Modeling ((ABM)). The use of these methodologies helped in providing important information on the factors that made it possible to influence within social media networks in Pakistan. Based on the demographic information, the participants represented a diversified picture of Pakistani social media users, eliminating the heterogeneity of the sample. According to the SNA results, highly centralized messages with high values of degree centrality and betweenness centrality contributed to social influence. Further, the ABM simulations highlighted the concept's core ideas of networks and individuals' sensitivity in terms of coverage and rate of influence propagation. The study also found that there are differences between the users of urban and rural areas in terms of speed and spread of influence. Understanding these points can assist policymakers, marketers, and social media managers in designing better strategies to capture the attention of users and spread the desired information.

Recommendations

1. ***Target Influential Nodes:*** According to the structural analysis, people with a high degree of betweenness centrality should be targeted to disseminate messages and information since they tend to broadcast them.

2. ***Leverage Network Structure:*** Such marketers and communicators should pay attention to the scale-free topology where several ‘‘hubs’’ exists, to propagate information within the shortest time possible.

3. ***Focus on Susceptibility:*** It is also important for campaigns to identify individuals or groups whose particular perception is expected should be persuaded to spread a particular idea or behavior more widely.

4. ***Urban-Rural Bridging:*** **S**trategies need to be developed to alleviate this inequality present in the difference in the spread of influence between the urban and rural areas, to allow more uniform coverage of influence across the existence of individuals.

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