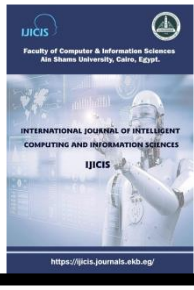
IJICIS, Vol.25, No.1, 18-28
DOI: 10.21608/ijicis.2025.359952.1376

International Journal of Intelligent Computing and Information Sciences

https://ijicis.journals.ekb.eg/



THE DYNAMIC USER'S INFLUENCE IN SPREADING INFORMATION ON TWITTER

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Received 2025-02-11; Revised 2025-03-24; Accepted 2025-03-24

Abstract: *Social media became a significant channel for spreading information and linking common interests' users. Therefore, the users of social media have direct/indirect influence on others, which provides spreading information. This supports the marketers on directing their campaigns through the most influential users. Since, the social influence has a level of uncertainty; this paper focuses on analysing the different criteria that may be helpful in measuring a user's influence across topics and time. It applied study on 1.5 million tweeters that have been crawled to measure the influential users category and their impact in spreading information on social networks. Mainly, the paper focuses on ranking the influential users based on analysing the correlation between four essential measures; the user's tweets visibility, participation, retransmission, and reply. Then, the impact of the different user's category in spreading information has been investigated by topic. The findings emphasized that top ranked influential users have a high percentage of retransmission, participation, and visibility. It found out that popular users (who have high activity and big number of followers) have the highest spreading ratio in the first hour of posting compared to unpopular users. The ratio increased incrementally over the first few hours for 60% up to 100% of influencers. Moreover, the influential user's experience, and specialty in a specific field is an essential influencing factor in spreading information, where 70% of their tweets are spread in the first hour of posting and increasing incrementally.*

Keywords: *Spreading information, dynamic influence, user influence*

1. Introduction

Nowadays, social network became an important interactive communication community, which is full of common interests and similar experience. This made it as an efficient tool for exchanging information and sharing different experience among people over the world. Social media users often discuss common topics, share emotions, and establish an interpersonal relationship through the virtual social community

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[1, 23]. The interaction among users through sharing emotions and information has a great influence on developing and changing the user's experience.

This influence has long been studied in the fields of sociology, communication, marketing, and political science. Knowing the influence of users and being able to predict it can help to detect viral markets, improve searches, obtain recommendations from experts, more efficiently disseminate information or better manage social relationships with customers of a given company [3, 7, 10].

Since 1960's, many theoretical studies focused on the impact of word of mouth on others [7, 13]. They studied the influence by analysing the interpersonal relationships among small limited network of people and attempted to read the society to adopt innovation [2, 4, 5]. These theories have different forms of operational format by social network revolution, where people have different levels of expertise and repaid expansion of information. The user's influence can be transferred from area to another and the marketing service became more active. Therefore, the social networks permit researchers to validate the influence theories [7, 12].

The social influence is defined as "a relationship established between two entities for a specific action" [6, 9, 11]. The one who influences others is called 'influencer' and the entity who takes the action is 'influential'.

Actually, the social influence has level of uncertainty, where influential could not make sure what is the user's action toward his word? [2, 8, 10]. Moreover, the influence is dynamic, since it could be increased or decreased depending on new experience, topic, and by time.

This paper concerns with analysing the direct and indirect influence of influential and its impact on spreading information. It focuses on influence behaviour toward influential word of mouth. Additionally, the dynamic influence was investigated by topic over a period of time. This paper is arranged as follows: section 2 demonstrates the related work, section 3 presents the proposed methodology and findings, and section 4 includes the conclusion.

2. Related Work

The social network studies almost focused on the user's characteristics, such as behaviour or community formation of positive/negative users [10]. Only few focused on the reaction and influence caused by emotion expression. Many studies discussed the impact of users' relationships on social networks, they concerned with the impact of word of mouth on others.

I.Stamenković, et al 2022 [22] present an empirical analysis on text and influential users identification problem in Twitter. The proposed approach considers that the influential level of users can be detected by considering its communication patterns, by means of particular writing style features as well as behavioural features. Performed experiments on more that 7000 users profiles, indicate that it is possible to automatically identify influential users among the members of a social networking community, and also it obtains competitive results against several state-of-the-art methods.

Kiichi. T, et al. 2018 [10] analysed the influence of emotional behaviours to user's relationships based on Twitter data using emotional dictionaries. The findings emphasized that the positive users were the most interacted users, and the negative users with aggressive words were lazy and had less interactions. This expected to be helpful in the certain of a rich relationship on social media, and recommending users with similar interests or topic is generally common. Accordingly, the study results improve the user's quality experience.

Teng, X, et al. 2016 [8] examined the Collective Influence (CI) efficacy in realistic information spreading. They examined real-world information flow in various social and scientific platforms including American Physical Society, Facebook, Twitter and LiveJournal. The study utilizes data to extract behavioural patterns of users to construct "virtual" information spreading processes. The results demonstrate that the set of spreaders selected by CI can induce larger scale of information propagation. Furthermore, local measures as the number of connections or citations are not necessarily the deterministic factors of nodes' importance in realistic information spreading. This result has significance for rankings scientists in scientific networks like the APS, where the commonly used number of citations can be a poor indicator of the collective influence of authors in the community.

Y. Y. Ahn, et al 2007 [5] presented an observation of the microblogging phenomena by studying the topological and geographical properties of Twitter's social network. They have analysed a large social network in a new form of social media known as microblogging. Such networks were found to have a high degree of correlation and reciprocity, indicating close mutual acquaintances among users. Moreover, they focused on individual user's intention by analysing the aggregate behaviour across communities of users, and describing the community intention. Understanding these intentions and learning how and why people use such tools can be helpful in improving them and adding new features that would retain more users. They have identified different types of user's intentions and studied the community structures. Finally, they analysed the user's intentions associated at a community level and demonstrated how users with similar intentions connect with each other.

The current study builds upon previous research in social media influence analysis but introduces a more dynamic and topic-sensitive approach to measuring user influence. Accordingly, it measures the effect of that on spreading information. Table (1) represents a comparison between this study and the key related works mentioned in the paper.

Finally, we can contribute the main motivation of the proposed study in four point as follow:

1. Dynamic Influence Analysis: Unlike previous studies that treat influence as static, this work examines how influence changes over time and across topics.

2. Multi-Metric Evaluation: This study integrates visibility, participation, and retransmission as core influence measures, providing a more holistic approach compared to single-metric studies (e.g., Cha et al., 2010).

3. Topic-Specific Influence: Previous research mainly considered general influence, whereas this study categorizes influencers by topic and analyses how their impact varies across different domains.

4. Temporal Influence Measurement: Unlike traditional methods focusing on total influence, this study highlights how the timing of a tweet affects its spread and reception, which is crucial for marketing and crisis communication.

Table1: Comparison between the proposed study and the previous related works

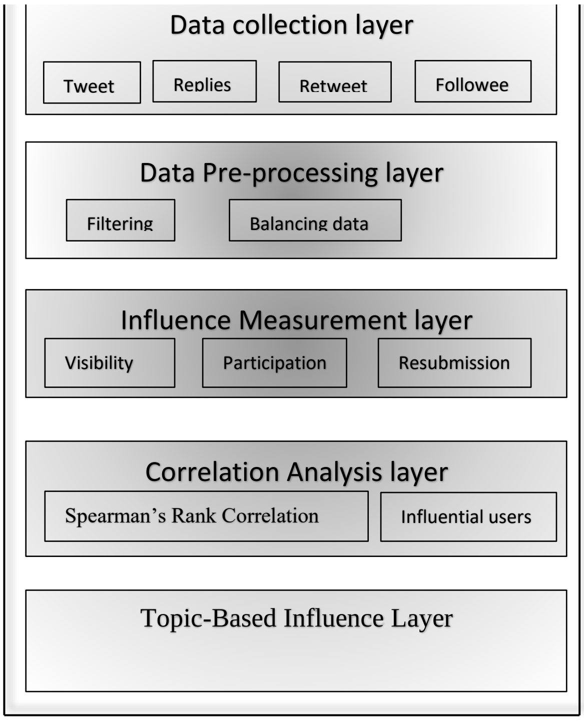
Study	Methodology	Findings	Comparison with This Study
Stamenković et al. (2022)	Used text-based and behavioural features to detect influencers	Demonstrated that it is possible to classify influential users automatically	Our work extends this by incorporating topic-based influence variations and analysing the role of user interaction rather than text alone.
Kiichi et al. (2018)	Used emotional dictionaries to analyse user sentiment	Positive users had higher engagement, while negative users had lower interaction	Our study focuses on behavioural metrics beyond sentiment, such as participation and retransmission, providing a broader measure of influence.
Teng et al. (2016)	Analysed large-scale networks using behavioural patterns	Found that spreaders selected by CI have greater influence than those selected by traditional methods	While "Teng et al." focused on network-wide diffusion, our study focuses on individual user influence dynamics over time and by topic.
Cha et al. (2010)	Analysed the "Million Follower Fallacy"	Found that follower count alone is not a reliable measure of influence	Our study supports this conclusion but adds participation and retransmission as additional indicators of true influence.
Ahn et al. (2007)	Network analysis of user intentions and interactions	Found that social networks have high reciprocity and mutual acquaintanceship	While "Ahn et al." examined network structures, our study quantifies the impact of user behaviour on spreading information dynamically.

3. The Proposed Methodology

The proposed methodology is developed based on investigating the influence measures correlation, user's influence varied by topic, and the spreading information. One of the essential questions we are interested in is how trends and innovations get adopted and spread. Most traditional views assume individuals' relationships have an important impact on spreading information. Nowadays, social media permits individuals to make a wide friendship network, where they could create it based on the common interest and like-minded users. Accordingly, information flows freely between users and innovations are not only spread by the author publishing them but also by the interaction of their followers.

As shown in figure (1), the system architecture of this study consists of multiple stages, from data collection to influence measurement and topic-based analysis.

Figure 1: The proposed system architecture



3.1. Data Collection and Pre-processing

In this study, Twitter API was used that permits us to build our dataset. The collected data has been gained from November 2023 to February 2024. After pre-processing, the dataset consisted of 1.5 million tweets, from 300 profiles during that time. By the end of this step, the data were balanced to guarantee that it is not biased.

The dataset concentrated on reading users' profile and followers' data. It includes tweet's text, time spam, URL, retweets, and reply. In addition, it contains data about user's profile such as profile creation date, user ID, and message ID. Hence, it was possible to collect users' activities and create network of followers, and retweets. Information was gathered about 345118 accounts, and ignored the private user's accounts. In addition, users who have suitable level of activity were focused, and thus users who have less than 10 posted tweets were eliminated.

Some challenges were faced during the process of collecting data which lead to pre-processing the crawled data. First, some of crawled data lacked of some features such as retweet time, and screen name of user. This kind of tweets has been filtered for eliminating uncompleted data. Second, the tweets that have no retweets and unclear profile have been removed from dataset to make the dataset more balanced.

Finally, based on the Twitter mechanism on spreading information, the message may be spread not only between followers and followees, but the indirect followee may share it. for example, user A shares a message, user B retweets it, then user C retweets from user B. Therefore, this case was considered for determining the source of tweet and source of retweet.

3.2. Influence Measurement

The notion of influence is investigated through analysing three criteria: visibility, participation, and modularity. This provides better understanding of the user's role and impact on social media.

3.2.1. Visibility and Participation

The visibility of user (Uv) represents the number of followers of the user. It is considered as one of the important measures in many recent social network research [2, 7]. It directly indicates the size of audience for the user. In addition, the participation (out-degree) of user (Up) on social network indicates the amount of user's activity. This determines the interactive user, where some users may have large number of followers with weak amount of interactivity.

For distinguishing the popular and unpopular users, the average of how much attention can user get is measured through user visibility (Uv), and user participation (Up); where the user who has popularity degree average greater than 1 is popular and otherwise classified as unpopular.

$$\text{Popularity Degree} = U_v / U_p \qquad (1)$$

3.2.2. Modularity (Retransmission)

Once user shares a message, another can retransmit it either follower or follower's friends. The amount of retransmission (Ri) reflects the influence of others. It calculated from the dataset for indicating the user's ability to spread information. For distinguishing the user's influence, users are classified into ordinary and extraordinary users. The ordinary user is the user who gains low/mid retransmission with high activity. On the other hand, the extraordinary user is the user who has low number of outdegree (activity) and high number of retransmissions.

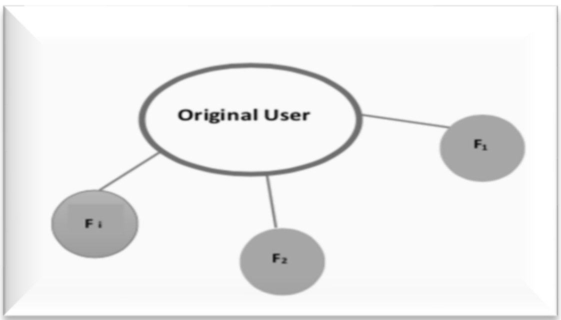


Figure 2(a): The direct retransmission between original users message & flowee

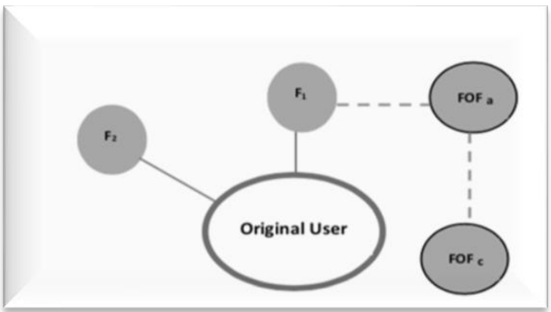


Figure 2(b): The indirect retransmission between original users message & friends of

According to twitter retransmission methodology, the user's message could be spread directly and indirectly. Figure (2a) presents the direct relationship between nodes, where user(U1) message is spread through the direct links, which represents the implicit user's followers. However, figure (2b) demonstrates an indirect retransmission where the original message could have indirect path from the user's followers to the follower's friends and so on.

3.3. The Correlation Analysis

For investigating the user's influence, the three measures are applied to 300 users, then users have been sorted and ranked. The Spearman's Rank Correlation is used for measuring the strength of association between each two ranked sets (equation 2).

$$P = 1 - \frac{\partial \sum (xi - yi)^2}{N^3 - N} \qquad (2)$$

The strength coefficient and xi, yi are the ranks of users based on two different measures. The P has values between +1 and -1, where +1 represents the positive and strong correlation and -1 is the negative and weak correlation. As displayed in table (1), the correlation between each pair of measures was investigated. For all pairs, they realized high correlation more than 0.6. The analysis process focused on the users who have high visibility for investigating the retransmission and participation impact effectively.

Table (2): The correlation between influence measures

Correlation	All users	Top Users
Visibility VS Retransmission	0.612	0.313
Visibility VS Participation	0.737	0.465
Retransmission VS Participation	0.650	0.711

First, the above results emphasize the high importance of visibility and participation as an efficient pair represents influencers. Where the user who has many followers and low activity has probably weak effect on others. Second, the retransmission is coordinated to the active user who has many activities to spread information. Third, the lowest pairs without ignoring their effect are visibility and retransmission, this may be because of their little activity (participation) over time.

To conclude the analysis results, the number of users' followers only could not make his/her influencer. It is based on his activity and interaction with others which may support information transmission through his followers and others who do not have direct link. Accordingly, the users have been normalized by filtering the strongest two pairs of measures (visibility & participation) and (retransmission & participation). Therefore, users have been ranked and the top influencers are extracted for preparing data to next phase (measuring the impact of topic on spreading information).

3.4. Topic Based Influence and Spreading Information

The influencers may have different impact based on topic which they share. The impact of top influencers in spreading different topics is investigated. Although they have high rates based on the measures in (3.3); they do not have the same ability to affect people in all fields. Probably, the followees may put their trust in influencers partly (not all topics are trusted), or totally (shared information are trusted regardless the topic).

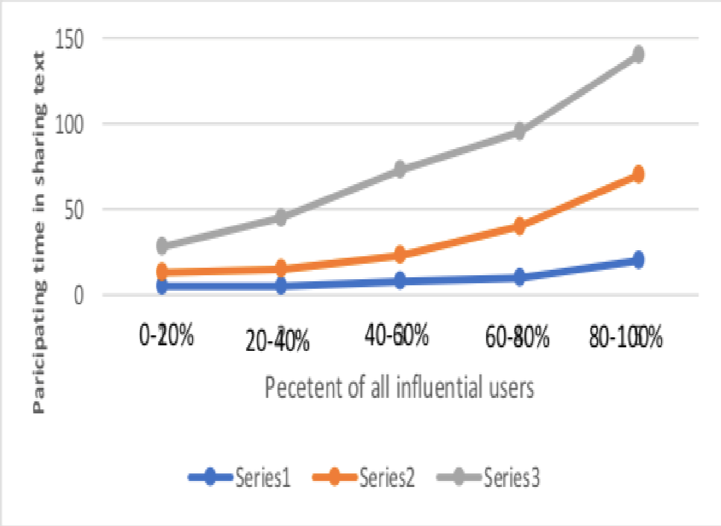


Figure (3): the participating time in sharing tweets for

The influence of user on spreading information may vary based on the topic type (political news media, sport,.. and so on). In this regard, the top 100 users' posts were analysed depending on a group of keywords for determining the type of topics that they interested in the majority. The result is 20% of users are categorized as political users, 30% are news media, and 50% are general purpose users (did not have specific specialty). The findings indicate that the specialty is one of the influencing factors that contributes to spreading information (share, reply, retweet). The political and news media are more attractive for high portion of users. This reflects the importance of experience and specialty in gaining users' trust.

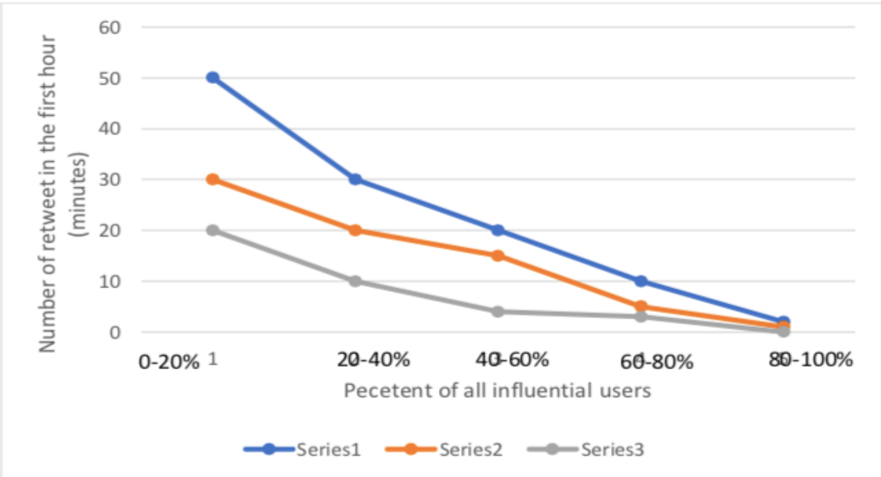


Figure (4): the number of retweet in the first hour which created by influential user

Another factor that may affect spreading information is ratio of sharing, replying activities time against time of posting. The findings indicate that the popular users (who have high activity and big number of followers) have the highest ratio in the first hour of posting compared to unpopular user. The ratio increased incrementally over the first few hours for 60% up to 100% of influencers. (as shown in figure 3 & 4).

The last considered factor is trusted resources. The extraordinary users have their own trusted information resources that made them considered as sources of information for others. While analysing the interaction between influencers through following their retweet actions, the researcher dedicated 26% of top users with neighbourhood which represented in sharing posts action (retweet). Therefore, the tweets were analysed using quantitively measures (co-occurrence number) to determine how many different kinds of users rely and trust others in spreading information. This reflects the force of each one as a trusted source of information.

Moreover, the finding emphasized that the extraordinary users' posts got high retweet rate by ordinary user. However, more than 60% of extraordinary users are retweeted by ordinary users, and 70% of extraordinary users' retweets were from posted spread by other extraordinary ones. In addition, the retweet interaction between ordinary users were 2% of posts. Thus, ordinary users may increase their rate by following extraordinary and retweeting their posts. The findings reported that specialty and experience are essential factors to build trust between users and to spread trusted information

4. Conclusion an Future Work

This study analysed the dynamics of user influence in spreading information on Twitter, focusing on three key influence metrics: visibility, participation, and retransmission. The findings emphasize that follower count alone is not a sufficient indicator of influence; rather, active participation and content retransmission play a more significant role in determining an influencer's impact.

The correlation analysis revealed that the strongest relationships exist between visibility & participation (0.737) and retransmission & participation (0.711), indicating that highly active users with strong engagement levels are more likely to spread information effectively. Additionally, the study found that the nature of influence varies by topic, with users specializing in politics and news media demonstrating higher engagement rates compared to general-purpose users.

A key insight from the study is the temporal aspect of influence, where highly active and popular users achieve the highest engagement rates within the first hour of posting, while ordinary users experience a slower diffusion process. Furthermore, the findings suggest that trusted sources and expertise significantly enhance information credibility, as extraordinary users tend to rely on and amplify each other's content, reinforcing their position as key opinion leaders.

Overall, this research contributes to a more nuanced understanding of influence measurement, moving beyond static metrics to a dynamic, topic-sensitive model. These insights can be valuable for marketers, political strategists, and social media analysts looking to optimize information dissemination strategies. Future research can extend this work by incorporating deep learning models to predict influencer behaviour, analysing cross-platform influence patterns, and investigating the ethical implications of social media influence in shaping public opinion.

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