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Core-Periphery Detection of Health Message Campaign on Social Media During COVID-19

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***Abstract*—Health communication is an essential factor to control pandemics and outbreaks. Social media is one of the prominently used channels for health communication during the recent pandemic, COVID-19. The identification of the key players of a communication network can play a crucial role in the success of health communication. Different studies identify the key players using social network analysis methods. However, most of them focused on trending hashtags generated by the users, not on a hashtag launched officially by a health organization. This research aims to conduct a social network analysis on an organized health awareness campaign launched on Twitter by the Saudi Ministry of Health called "Natawan ma Natahawan", meaning cooperating not neglecting, that is, this health message campaign aims at encouraging people to cooperate and not relax in implementing preventive measures. 40108 tweets from the hashtag were collected using Twitter API. Two types of analysis were conducted: network property analysis and core-periphery detection. As a result, we found that the users of the network are closely connected but have much fewer connections than expected. Moreover, only four users were identified as key players on the network. All four nodes are trusted parties, as two of them are the campaign launchers, and the other two are official accounts that support them. This structure, i.e., the leadership of the network by trusted parties, enabled the control of the health message communication and limited the spread of the misinformation within social media users during the campaign.**

***Index Terms*— centrality, hashtags, influencers, social network analysis, Saudi Arabia, Twitter.**

I. Introduction

In late 2019, a new coronavirus has emerged in China, called the novel coronavirus (COVID-19) [1]. Since that time, COVID-19 spreads around the world to reach almost all countries and became a global pandemic [1]. Local and global health organizations keep fighting this pandemic by providing fast and effective communication to aware the public and help them protect themselves. In fact, effective communication is an essential factor to control pandemic and outbreaks [2]. One prominent used channel for delivering health messages during COVID-19 is social media, particularly Twitter. It was used by different health organizations to maintain direct and updated communication with the public. One of the advantages of using social media for health communication is the ability to track and analyze that communication [3].

Different studies focused on analyzing the health communication on Twitter during COVID-19. Social Network Analysis (SNA) is one of the methods used for this purpose. SNA is based on graph theory and represents social networks in terms of nodes and edges. [4]. SNA could be used to determine the impact of health communication on a network [5]. One of the prominent applications of SNA during COVID-19 is the identification of key players of a network. The key players could play a crucial role in the dissemination of the health message on social media due to their strong positions in the communication network. In fact, the absence of the key players in the communication network may hinder the success of the message spread [5]. The importance of identifying the key players during campaigns lies in the potential of employing them to maximize the reach of the health message. Previous studies in this field, analyzed the network of different types of hashtags. For example, hashtags related to misinformation [6], health events [5] or general COVID-19 hashtags [7]. While most of these studies focused on analyzing trending COVID-19 hashtags created by the users, in our study we focused on a hashtag created by an official health organization to characterize the effectiveness of official hashtags in spreading awareness messages in such a critical situation.

Therefore, the main aim of this research is to analyze the network of an organized health message campaign launched officially by a health organization using a core-periphery structure, which measures the importance of nodes by classifying each node either as a core or peripheral node [8]. This structure is a common method to identify the key players in social media campaigns [9]. By analyzing the network using a core-periphery structure this research aims to answer the following research questions:

RQ1. What are the social network properties of an organized health message?

RQ2. Who are the key players of the campaign?

II. Literature Review

A. Core-Periphery Structure

Social network analysis involves several detection algorithms for local, intermediate (meso-scale), and global structures (e.g., summary statistics) [8]. Meso-scale structure focuses on understanding the group features of nodes by classifying them based on their distinctive interaction patterns [10]. There are two types of meso-scale structures that are widely used which are community and core-periphery structures [10]. The former is used to detect various communities in the network, in which each community contains densely connected nodes. The latter, which is the focus of this work, measures the importance of a component or a single node in the network [8]. It split the network into two different categories known as core and periphery, where:

- Core: refers to a set of nodes that are well-connected together and tend to have more centrality in the network.
- Periphery: refers to sparsely connected nodes that are usually connected only to core nodes [8].

The difference between community and core-periphery structures lies in the interaction between nodes [10]. In community structure, there are interactions between nodes within the same community, while no interactions should exist between those in different communities. In contrast, interactions exist between core-core nodes and core-peripheral nodes in core-periphery structure, while no interactions are expected between two peripheral nodes.

1) Core-periphery types

There are two types of core-periphery detection models, discrete model, and continuous model, such that:

- Discrete Model: this type assumes that the nodes in a network can be divided into two types only core or periphery [11]. This means, the discrete model classifies each node either as a core node or periphery node. This can be done using a partitioning algorithm to identify the two types of nodes. For example, [11] proposed a method in which only the nodes that are highly connected to each other are classified as core nodes. While other nodes are classified as periphery nodes.
- Continues Model: unlike the discrete model, this model assumes that the nodes in a core-periphery network may have more than three classes [11]. For example, the nodes can be divided into core, semi-periphery, and periphery nodes. Borgatti and Evererett [11], suggested a "coreness" measure; a continuous value assigned to a node that represents its strength or connectivity, where coreness score is identified by a certain threshold.

2) Coreness measures

Different types of centrality measures are used in the literature to determine the coreness score [12][13], such as the following:

- Degree centrality: this represented by the number of edges that connected to a node [14]. For directed networks, two types of centralities exist: (1) in-degree, which represents the number of edges directed to a node; (2) out-degree, represents the number of edges directed from a node toward other nodes.
- Betweenness centrality: this represents the extent in which a node lies in the shortest path between other nodes [14].
- Closeness centrality: this represents the average shortest path distance from a node to other nodes [14].

3) Core-periphery application

The detection of core-periphery structure has been studied in several domains. In election campaigns, [9] analyzed the engagement between Victorian politicians and citizens in social media (Twitter and Facebook). Using core-periphery structure, they found that people who engaged in the campaign's hashtag are grouped into three clusters: core users who had a high number of mentions and re-tweets; semi-periphery; and periphery users who had a limited number of replies. Core users are usually political journalists, news organizations, etc. In the health field, a more recent study [15] investigated the spread of COVID-19 in human mobility networks by applying core-periphery structure on data of more than 200 countries. The study found that six countries acted as core nodes in the COVID19 network, indicating that these countries may be considered as hubs in COVID-19 transmission. Other domains that applied core-periphery structure are environmental policies [16], research groups [17], and smoking prevalence [13].

B. Related Work

Social network analysis is used to identify the key players or influencers of a network in different fields. This also attracted researchers' attention in the public health field during COVID-19. As the key players could play an important role to the success of the communication. Therefore, several studies detect the key players and influencers of a specific network on Twitter during COVID-19. Some of them focused on misinformation networks by analyzing the communication of a specific fake information hashtag. For example, a study conducted by [6] analyzed the hashtag related to the Film Your Hospital conspiracy theory. The key players were identified based on the betweenness centrality of users who have at least 100 followers. They found that the key players of the network were ordinary citizens. Another study conducted by [18] analyzed a different conspiracy theory of linking 5G with COVID-19 in the United Kingdom. They also used the betweenness centrality to rank the users and found that the top three key players were citizens. On the other hand, some studies targeted general COVID-19 hashtags. For example, a study [7] analyzed general hashtags and keywords related to COVID-19 to understand the communication network in the United States. They measured the influence of the public key players in the network using in-degree centrality. This means, their study was limited to the public key players only. However, they found different types of key players are influencers also in the network such as presidents and health organizations. Another study [5] used also similar general hashtags, but targeting the period of different health events, for instance, when COVID-19 was declared as a pandemic. They used the degree centrality to indicate the key players. The study found that the WHO organization and different government figures were the most key players in the network. Moreover, a study conducted by [19], analyzed the network of the hashtag "mask", which is also a general hashtag related to COVID-19. They used the betweenness centrality to detect the key players of the network. They found that the most influencers were citizens.

Overall, the mentioned studies emphasized the importance of identifying the key players in social media networks during COVID-19. However, all of them analyzed the network of trending hashtags generated by the Twitter users. Most of these studies found that most of the key players were citizens. In this study, we aim to identify the key players of an organized health message campaign launched by an official account; the Saudi Ministry of Health, which none of the previous studies discussed. Moreover, previous studies used only centrality measures to identify the key players such as betweenness and degree centrality. While in our study, we focus on identifying the key players using the core-periphery structure.

III. Method

In this research article social network analysis was used to analyze the collected data. SNA is a method that understand and analyze the social structure of a network by means of a graph [14]. A graph is composed of a set of nodes, and edges, the relationship between those nodes. In this work, undirected graph was built in which the node represents twitter users, and the edges shows the re-tweets that those users did or received. In this research, we used SNA to conduct two types of analysis: (1) network properties analysis, which aims to answer RQ1; (2) core-periphery detection, which aims to answer RQ2. For the social network analysis, we used Python version 3 [20]. While for the network visualization we used NodeXL [21]. The subsections below describe each of these analyses in detail.

A. Data collection and preparation

In this study, we focused on a specific health awareness campaign launched on Twitter by the Saudi Ministry of Health called "Natawan ma Natahawan" [22]. Natawan ma Natahawan means to cooperate not relax in implementing preventive measures. The campaign was launched on 06 February 2021 and aims to urge the public about the importance of preventive measures (e.g., social distance and wearing the face mask) in preventing the spread of COVID-19. The data is collected from Twitter API [23]. We collected tweets from the official campaign Arabic hashtag "نتعاون ما نتهاون", between 07 February 2021 (second day of the campaign) and 3 March 2021. As a result, we got 40108 tweets. After removing duplicated tweets, it became 39556 tweets.

B. Network properties analysis

In this phase, we conducted a general descriptive analysis. The goal from this preliminary analysis is to characterize our network dataset. Six network measures [14] were used for this analysis: average distance; average clustering coefficient; diameter; radius; and density. The average distance calculates the average distance of shortest paths between every pair of twitter users. The average clustering coefficient measures the extent in which twitter users in a network cluster together, e.g., if the nodes are fully connected, the value of the clustering coefficient will be 1. The diameter measures the longest shortest path between any two pairs of users. Radius measures the shortest distance between any two nodes in the graph. Finally, the network density measures the ratio of the existing connections between nodes to the possible connections that could occur.

C. The usage of core-periphery detection

This phase aims at identifying the network key players using core-periphery detection. In this research, we applied a discrete core-periphery detection algorithm that was proposed in [11]. The proposed algorithm follows a partition-based approach. It assumes that there is an ideal adjacency matrix in which the core nodes are adjacent to each other and to some periphery nodes, while the periphery nodes are not adjacent to each other. Then, it examined the extent to which the adjacency matrix of the real network approximates the ideal one by using an equation based on the Pearson correlation coefficient (see equation 1).

$$p = \sum_{i,j} \alpha_{ij}\, \delta_{ij} \tag{1}$$

Where:

- α_{ij} represents the presence or absence of a tie in the real data matrix.
- δ_{ij} represents the presence or absence of a tie in the ideal matrix.

The value of the equation ranges from 0 to 1. Where 1 means the two matrices are the same, and the real network follows a perfect core-periphery structure. Therefore, the bigger the value the better the fit of the algorithm. To detect core-periphery structure, the study uses a genetic algorithm as an optimization technique. The algorithm aims to find a partition in which the correlation between the real data and the ideal matrix is the highest (best). Moreover, to understand the core users more, we analyzed their centrality measures.

IV. Results

As mentioned before the total number of collected tweets is 40108. After removing duplications, the final dataset includes 39556 tweets and 24574 users. Table I shows a general descriptive statistic of the dataset for different attributes including number of favourites, retweets, followers, and the verified accounts.

TABLE I. Dataset Descriptive Analysis

Attribute	Min	Mean	Max	SD
Favorite Count	978	0.97	0	16.07
Retweet Count	8768	517.43	0	1718.06
Followers Count	13M	13K	0	176887.42
Verified Account			1434	

Table II shows the top 10 users who tweeted the most in the hashtag. The tweets include original tweets and retweets. However, as shown in the table, 9 out of 10 top users are citizens. While only one account belongs to a Saudi province. After converting the dataset into an edge list, we got a network that consists of 20227 nodes and 30045 unique edges. The resulted network was not connected, i.e., it contained 1176 disconnected components, 78 of them contains a single node only. For this research, a connected component is needed, as most of the distance measures cannot be calculated for disconnected networks.

TABLE II. TOP 10 USERS WHO TWEETED THE MOST

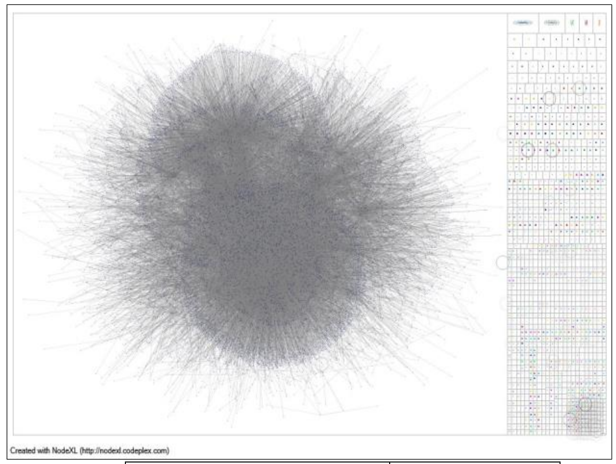
User Type	No. of Tweets
Citizen	108
Citizen	93
Citizen	80
Citizen	69
Official Province Account	66
Citizen	66
Citizen	66
Citizen	56
Citizen	52
Citizen	45

We extracted the largest connected component which consists of 16,873 nodes and 27,555 edges; thus, the result of the analysis is based on this largest component. Figure 1 presents the original network grouped by connected components. Where the largest component is at the center of the figure, and other components are listed in at the right side. As shown in Figure 1, this component contains most of the nodes and edges of the original network, specifically, it contains 83.4% and 92% of total nodes and edges respectively. While the second largest component consist of only 51 nodes and 50 edges, which is much less than the largest component.

The result of descriptive analysis is presented in Table III. The diameter is 16, i.e., the largest distance between two pair of nodes is only 16. Considering that the network consists of 16873 nodes, the diameter indicates that users in the network are closely connected. The average shortest path of the network is 5, which means a large number of nodes will take less than 16 steps to reach other nodes. On the other hand, the radius of the network is 8. This means, some users need to take at most 8 steps to reach all other users in the network, which called the center nodes.

Fig. 1 Original network grouped by connected components

TABLE III. DESCRIPTIVE STATISTICS



Metrics	Value
Diameter	16
Average shortest path	5
Radius	8
Density	0.000014
Clustering coefficient	0
Metrics	Value

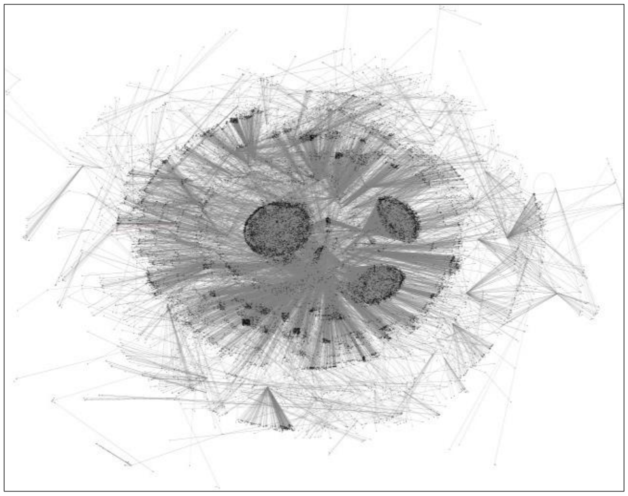
In this network, only one user is considered a center node, who is a citizen has around 200 followers only. Although the network is closely connected based on the diameter, it has almost zero density (0.000014) and a clustering coefficient equal to 0. The density value indicates that the nodes have actual connections much less than the "possible connections". The possible connections are the potentially existing connections between two nodes (regardless of whether they exist or not). While the actual connections are the connections that already exist between two nodes in the network. This value is reflected by the clustering coefficient, as it indicates that the neighbors are not connected. In other words, no two connected users have a common friend.

Overall, the result of this analysis indicates that this health message campaign network is closely connected, as any user can reach all other users by taking a small number of steps (around 16). Regardless of the small distance between the users, they have very few connections between them which could slow the spread of the health message.

A. Core-periphery detection

As shown in Figure 2, the network follows core-periphery structures where there are densely connected nodes in the core of the network, and the remaining nodes are distributed in the network periphery. However, by applying the core-periphery detection algorithm, each user in the data was classified either as a core or peripheral user. As a result, only four users were classified as core, while the majority are peripheral users. The following sections discusses each type of users.

Fig. 2 The health message campaign network



2) Periphery users

Periphery users are connected to the core users, and they have limited connections together. However, all the remaining users in the health message campaign are periphery users. A great diversity of periphery users is found including journalists, news organizations, Saudi provinces principality, health practitioners, football clubs, official spokesman for Saudi MOH, social activists, and citizens.

3) Centrality measures of core users

Centrality measures shows the different types of importance a user has in the network. Therefore, the core users have been investigated in terms of centrality measures. Three centrality measures were applied: degree, betweenness, and closeness centrality. The result of centrality analysis is shown in Table IV.

TABLE IV. CENTRALITY MESURES OF CORE USERS

Core user	Description	Degree centrality (rank)	Betweenness centrality (rank)	Closeness centrality (rank)
Saudi MOH	The Saudi Ministry of Health	3416 (1)	0.591 (1)	0.349 (1)
MOD	The Ministry of Defense in Saudi Arabia	1620 (2)	0.207 (2)	0.298 (4)
Minister of health	The official account of the minister of health	1591 (3)	0.189 (3)	0.290 (12)
SPA	The official Saudi Press Agency	550 (4)	0.071 (4)	0.280 (49)

1) Core users

Core users usually are well-connected with each other and have more centrality in the network. However, four users act as core users in the campaign network. Those users played a key role in the spread of the health message campaign. All of them are official accounts related to the Saudi government as follows: (1) Saudi Ministry of Health (Saudi MOH); (2) minister of health; (3) the official Saudi Press Agency (SPA); and (4) the Ministry of Defense in Saudi Arabia (MOD). Moreover, all of them are verified twitter accounts with a very large number of followers: 4.8M; 3.9M; 1.5M; and 628K respectively. Figure 3 shows the positions of key players in core of the network.

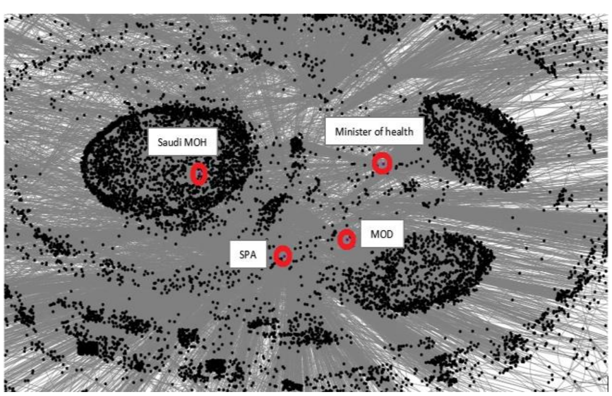


Fig. 3 The positions of key players in core of the network

The top four users who have the highest degree and betweenness are the same four core users. High degree centrality indicates to what extent a user had strong social connections. In this health message campaign, having core users with the highest degree means that people trust the information posted by those core users and consider them as the main source of information. Moreover, core users also have high betweenness, this means that they control the flow of information in the health message campaign. While in terms of closeness, only two core users (Saudi MOH and MOD) are from the top ten users with the highest closeness. Saudi MOH have the highest closeness centrality. This means that Saudi MOH can spread an information efficiently and faster than others. Also, there are several citizens who have high closeness centrality in the health messages campaign, these could help in spreading the information faster than other nodes in the network.

V. DISCUSSION

This study answered two research questions related to the social network of a health message campaign on social media during COVID-19. The first question investigated the social network properties of an organized health message. We found that the network has closely connected users, where each user is far away from other users at most 16 steps, which indicates that this health messages campaign network is closely connected, as any user can reach all other users by taking a small number of steps. Moreover, the users themselves have much fewer connections than possible connections that they could have, as there are no connections between the neighbors.

The second question aimed at finding core nodes in the network. The results showed that four users are the core nodes, and considered as key players of the campaign network, indicating that these players can spread information efficiently, correctly, and faster than other nodes.

Two of the key players are the campaign launchers, and the other two are official government accounts. Although there are a few key players in the network, all of them are trusted information sources. However, some of the periphery users are influencers with millions of followers, but none of them considered a core node. This indicates that the users tend to share the messages posted by the original source of information. As a result, the network is controlled and lead solely by the primary trusted sources. The trust of the periphery users in the campaign launchers may occur because it is an awareness hashtag dedicated to a campaign. Unlike other general COVID-19 related hashtag where other studies found the citizens were the key players of the network [6][18]. In fact, this can hinder the success of the communication [5], as it is not led by a trusted party.

The network leadership by few key players affects some of the network properties, particularly the clustering coefficient. In other words, most of the users preferred to contact the four core users not with each other, thus the clustering coefficient became zero. However, if the users have more connections between them, the message will spread faster, and the number of core nodes may increase. Although this could be helpful for faster information dissemination, new core nodes may emerge. If the new core users are untrusted ones and had a strong position as the trusted parties in the network, it may be hard to control the communication by health agencies. Therefore, the zero-clustering coefficient might slow the spread of information, but it would enable the trusted key players to lead and control the network.

Misinformation during pandemic spreads rapidly on social media [24]. In fact, misinformation is being fought alongside COVID-19 by health organizations, as it could erode public trust in health organizations [25]. One of the main factors that help health organizations to control the spread of misinformation on social media is to lead the network of communication [5]. The network of this study is led only by the Saudi MOH and other trusted parties, this will minimize the spread of misinformation. Moreover, the Saudi MOH and other core nodes have a strong position in the network, so they can reach a large group of people to correct the misinformation and bring the public to the right track.

As a recommendation, health organizations and governments should engage with citizens in social media during the pandemic to ensure the communication of reliable and correct information. As shown in the results, people try to exchange information from the original and reliable source of information. Therefore, the engagement of health organizations and other reliable sources will increase their chance to leads such communication. Leading a communication by a health organization has several benefits: First, the health organization will have a strong position in the network. This means it could spread the information faster and reach a large group of people. Second, as misinformation spreads rapidly during a pandemic, health organizations would be able to bring the public back to the right track and control the spread of misinformation.

VI. Conclusion and Future Work

Health communication is a key factor to control pandemics. Recently, social media became a prominent channel for health communication. Among different types of users, key players have a significant influence on the success of health communication. This research analyzed a specific health awareness campaign launched on Twitter by the Saudi Ministry of Health called "Natawan ma Natahawan". The results found that four users act as key players in the health message campaign. All of them are verified official accounts related to the government, and two of them are the campaign launchers. This indicates that the users tend to share the messages posted by the original source of information. However, as the campaign leaders are trusted users, this will able them to control the spread of misinformation.

Among the challenges faced in this work is the limited period of the data collection of campaign tweets, while the campaign would continue as long as the COVID-19 exists. However, although it is a limited period, but we covered an important event, which is the start of the campaign. Thus, in future, we will collect more data from Twitter by increasing the period of data collection phase. The second limitation is that we depended only on one Twitter relation, the "retweets", so in future we may consider other relations during the analysis. Finally, we did not analyze the campaign qualitatively to understand the public attitude and opinions towards the campaign and the key players. In this study, we only analyzed the campaign quantitatively in terms of the social network structure. Qualitative analysis can be a future work that can be applied to this research or similar works, after acquiring the necessary ethical approvals (IRB).

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تحديد مركز وأطراف شبكة تواصل اجتماعي لحملة صحية خلال أزمة كوفيد ١٩

غادة عامودي، بشرى الصاعدي، بشاير الصاعدي، هند بيطار
قسم نظم المعلومات ، كلية الحاسبات وتقنية المعلومات
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المستخلص. يعد التواصل الفعال خلال الأزمات الصحية ووقت انتشار الأوبئة من أهم العوامل المساعدة في احتواء المرض وتفادي الخسائر. تعد وسائل التواصل الاجتماعي من أهم القنوات لنشر الوعي الصحي خلال فترة جائحة كورونا. إيجاد أهم المؤثرين في شبكات التواصل يساهم في زيادة فعالية نشر الوعي الصحي وبالتالي احتواء الجائحة. هناك العديد من الدراسات التي تهدف إلى تحديد أبرز المؤثرين باستخدام طرق تحليل الشبكات الاجتماعية. ركزت معظم هذه الدراسات على الأوسام الشائعة (الهاشتاغ) التي ينشؤها المستخدمون، وليس على الأوسام التي تطلقها منظمات صحية رسمية. هذا البحث يهدف إلى إجراء دراسة عينة من المنشورات على شبكة التواصل الاجتماعي تويتر وتحليل ما يتعلق بحملة توعوية صحية منظمة أطلقتها وزارة الصحة السعودية بعنوان "نتعاون ما نتهاون". تهدف هذه الحملة الصحية إلى تشجيع الناس على التعاون وعدم التراخي في تنفيذ التدابير الوقائية. تم جمع 40108 تغريدة باستخدام الوسم عن طريق واجهة البرمجة من تويتر. بعد ذلك تم إجراء نوعين من التحليل: تحليل خصائص الشبكة وكشف مركز وأطراف الشبكة. أسفرت النتائج عن وجود روابط وثيقة بين مستخدمي الشبكة. أما التواصل أو الرسائل المتبادلة بينهم فقد كانت أقل بكثير من المتوقع. علاوة على ذلك، تم تحديد أربعة مستخدمين فقط كمؤثرين رئيسيين على الشبكة. جميع هؤلاء المؤثرين الأربعة هم جهات موثوقة، حيث إن اثنين منهم هم مطلقي الحملة، والاثنان الآخران هما حسابات رسمية تدعمها. كشف هذا البحث أن هذا النموذج، أي قيادة الشبكة من قبل جهات موثوقة، مكّن من التحكم في الرسائل الصحية والحد من انتشار المعلومات المضللة بين مستخدمي وسائل التواصل الاجتماعي أثناء الحملة.