AN ANALYSIS OF THE KOREAN POPULAR CULTURE ON SOCIAL MEDIA: EXAMINATION OF THE THAI FANDOM THROUGH TWITTER IN THAILAND

Wirapong Chansanam, Khon Kaen University
Kulthida Tuamsuk, Khon Kaen University
Kanyarat Kwiecien, Khon Kaen University
Kittiya Sutthiprapa, Khon Kaen University
Sam Oh, Sungkyunkwan University

ABSTRACT

The analysis aims to study the popularity phenomenon in the Korean culture of online social networks in Thailand. The methodology is digital visualization applies to relations and exchanges of the analysis of social networks (SNA). Through social networking and graph theory, this research explores Twitter data shortly after a tweet by the K-pop popular Twitter accounts to their followers. An implementation of a single case study and the SNA provided interchanges realistic and prompt on Twitter of 5,356 K-pop Twitter accounts tweets. With the growing need to understand social media interaction in various contexts, this paper uses the Gephi Platform for Social Network Research. Gephi is open-source network software used to analyze, draw, and visually present information from relationships between stakeholders in the K-pop popular Twitter accounts on social media networks. The findings clarify the distribution of K-pop famous Twitter accounts data and the network structure. The apparent results identify the influents – the mostly Thai youth, specific Twitter users, and caretakers in the distribution of a Korean pop music culture that will affect all Thai people. The paper contributes theoretically in a less researched subset in social networking and social media research during important events by adding graphic theory.

Keywords: Social network analysis; Social media; K-pop; Korean culture; Twitter; Gephi.

INTRODUCTION

Information and networking processing advancements in particular through the broad selection of social networking resources have demonstrated the right of contributing greatly transparent governance by not just having forums of government records data dissemination but also ways of involving stakeholders (Gao, 2018). In consideration of the increasing importance of social networking as a significant source of power, there is a deeper analysis into who leads the information sharing and above all, the trend of information sharing among such consumers becomes prevalent. The Online social network details, therefore, provide new chances and opinions to the government and control of the evaluation of large social networks and classes (Chansanam & Tuamsuk, 2020). Social networks have recently developed into essential channels

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

for human contact and market administration, exchanging knowledge, and different facets of daily life (Desai et al., 2012).

Online networking has attracted substantial interest from information technology and communications analysts, in general social networks have an impact on variety of interesting committees. Between 1997 and 2017, an analysis of 132 academic articles on social networking mainly examined social media behavior, its marketing incentives, and its resulting organizational impact (Kapoor et al., 2018). In addition, the information sharing and exchange capacities of social media are unanimously shared. However, a particular study cluster that characterizes their efficiency in major events (Kapoor et al., 2018). This post comes under this category and discusses Tweet research by certain outlets of the social network (Oh et al., 2013; Shi et al., 2013; Miranda et al., 2016; Kapoor et al., 2018).

The key practical and theoretical contributions in this review are several studies use the theory of social interaction, network and organizational theory (Kapoor et al., 2018). First, this study uses the theory of social networks, but it adds a graphical theoretical lens to enrich the existing knowledge. In the introduction of a fresh concept in this situation (K-pop popular Twitter accounts), is added to the existing community of experiments centered on social networking analysis at a big case. The third aspect is that it explores both the topology network and the actions of the performers in the network vast K-pop common networked system of Twitter accounts. Therefore, this research not only takes into consideration the prevalent behavioral analysis of social data but also makes the integrated network layout awareness and behavior that is drastically different from the "straight forward" analysis of a single narrow diagram (Albert & Barabási, 2002; Newman, 2003). The basic research aims of this thesis are as follows:

1. To model a new concept (i.e. K-pop famous twitter accounts) that draws on Twitter users and their Twitter interactions.
2. Determine the main players on Twitter as throughout the internet network the famous K-pop Twitter conversation.
3. To define the grade distribution of Twitter relations in K-pop Twitter accounts.

The following segment examines briefly wider research on social networking and following the methodological framework of this study, how the study is positioned therein, with a brief discussion of the K-pop famous Twitter account. The following segment explains how this sample is conducted and evaluated. The K-pop famous twitter account case SNA results segment accompanies it. The paper continues by analyzing the results and their consequences for utilizing social networking to include not only channels for information communication, but also incentives for stakeholder engagement and exchange.

LITERATURE REVIEW

The notion that there is a mechanism to enable individuals gets to know someone, explicitly and implicitly, is based on a social network. People are becoming increasingly concerned about online communication; as they have never been in so much connect before the invention of internet (Churchill & Halverson, 2005). Over and beyond pure sharing networks or interactive congregations, social media also have grown to be known for their ability to facilitate aggregation. Likewise, knowledge technologies grow further organizational borders to form a

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

part of the broader societal context, which requires research of the competitive technical intelligence network environment and social dynamic systems. Social networking is causing a big difference in how citizens perceive and see their environment (Simos, 2015). Twitter has been showing significant user growth as a micro blogging tool, which began in October 2006 (Java, 1970). Usage with Facebook apps quickly transfers and adopts information (Zhang et al., 2016). Social media literature over recent years is abundant, whereas the concept's agreed definition is less precisely stated (Kapoor et al., 2018). The present study defines online networking as a variety of people that allow interactivity and distribution of knowledge amongst users of accessible channels that encourage them to establish social links with the media networks (Struweg, 2002; Kandadai et al., 2016; Kapoor et al., 2018; Lee et al., 2018; Statista, 2018). Social networking literature has been summed up into 12 clusters. These are the following clusters (Kapoor et al., 2018): (1) Social media applications, behaviors, and implications (2) Social media site analyses and recommendations (3) Social media operational impact (4) Social communication technology (5) Social media participatory (6) Risks to social media (7) Social network usage stigmatization (8) Value creation through web based life (9) Social media during a important occasion (10) Support-chasing through web based life (11) Social media in the open area and (12) Traditional/online networking separate.

Clusters 1 to 8 have certainly provided significant coverage in work on information systems. Cluster 9, as indicated in the introduction, is where this paper was published. Yet it can also be claimed that Cluster 11 overlaps since the case was deemed in this article is freely accessible sector. There has been small research lately in Cluster 12, which might result from widespread social networking recognition outside the mainstream media era.

Social Network Analysis (SNA) is an analysis of human relationships using graphic theory. The viewpoint of the network depends on relationships between actors like those involved in disaster information exchange (Tsvettovat & Kouznetsov, 2011; Samatan et al., 2020). Network research has an essential characteristic (Marin & Wellman, 2011). First, be careful about the relation, not the attribute. Secondly, emphasis on the network, not the community. Thirdly, the requirement for a particular relationship context is meaning context significant. There are numerous Social Network Analysis (SNA) theoretical layers to be conducted, including participant group and device level. Actor Analysis is the centrality factor used for level classification on a whole network. There are four centrality measures that are most widely used namely central, proximity, intercede, and self-vectored. Density, reciprocity, diameter, and distance at the system level, centralization are the most common measure.

The area of social network analysis (SNA), of which this investigation reflects on the connections between the networks and actors and SNA model includes 'relationships and associations, development and associations, and dynamic forces in networks and activities on social media platforms (Struweg, 2002). While SNA has been used in the areas of socio-computational sciences (Wasserman & Faust, 1994; Otte & Rousseau, 2002), recently it is been found in complex fields, economics, industries and medicines (Can & Alatas, 2019). A collection of hypotheses, methods and instruments is often known as SNA (Valente, 2015). It is usually outlined by embedding in three key assumptions (Valente et al., 2015): (1) The nature and characteristics of networks impact system performance (2) The role of actors within a network influences their actions and (3) The behavior of actors conforms to their network context.

In addition, the aim of this study is to make the use of SNA easier (based on graphics) to identify social networks made up of nodes to which actors link with one another by sharing

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

ideas, values, views, human links, and disagreements. This research argues that successful social networks have contradictory effects that can affect human, social, and financial information programs, regulation, ventures, plans, and collaborations (including architecture, implementing, and results) (Serrat, 2010). Social networking thus was essential to the dialogue on democratic society – a forum for popular discussion and conflicts as well as the sharing of ideas. As a public segment, the sharing of social media is as essential as any other broad public gathering. Network charts of digital social networking communications sites such as Facebook will offer insight into the position social media plays in our culture (Can & Alatas, 2019). Such tools and the scale of electronic social media place SNA at the forefront of several problems worldwide. The phenomenon of increasing user behaviors by types in social media enables people to be more linked worldwide than ever before (Zhang & Chang, 2018).

METHODOLOGY

Methodological Framework

This volume investigation follows the implementation of a single case study. The topic (K-popular Twitter accounts) is selected in an instrumental case study because it reflects another issue under review (i.e. social network analysis) that may offer an overview of the subject (Ary et al., 2018). Nevertheless, as a case study system, the analytical choices may be called a very loose system and as such are dealt with in a rational way (Meyer, 2001). Therefore, these options are listed in Table 1:

TABLE 1
METHODOLOGICAL CRITERIA AND RECOMMENDATIONS FOR THIS CASE

Methodological consideration	Methodological choice
Research paradigm	Quantitative research
Research design	Instrumental, single case study design
Sampling strategy	Case selection
The case	K-pop popular twitter accounts for following in Thailand
Sampling units	5,356 tweets: K-pop popular twitter accounts
Data collection	Twitter Streaming Importer plugin through Gephi API
Data analysis	Gephi social network analysis, Gephi advanced network metrics, and Gephi statistics

This section contains a short overview of the popular Twitter case of K-pop, an outline preceded by Gephi as an SNA tool applied to this questionnaire data processing and data analysis for screening.

The Case: Tweet of the K-pop popular twitter accounts in Thailand

Korean singers induce Korean wave to both the Thai entertainment circle as a whole and to teenage fan clubs by bringing in imitation in Korean physical appearances and apparel, eating taste, and tourism, including their verbal and nonverbal expression. Such Korean wave is influenced by internal factors i.e. a singer's own competence, cultural adaptation etc and by external factors i.e. integrated and various kinds of media and channels planning, besides onstage performance to intensify traditional Korean culture and K-pop culture. Most Thai fandom are 11-

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

29 years old and there are more females than males. Formation of each Korean fandom brings about information exchange, group communication, and group culture through certain symbols, such as colors, group-names, and communication networks for common activities (Suwannapisit, 2008). Entertainment - Perception of Korean wave was not correlated with whether consumers choose to buy Korean-style entertainment or not, types of Korean-style entertainment purchased, and spending on Korean-style entertainment, but was correlated with purchase channels of Korean-style entertainment (Jaiwai, 2014). In this study, we use the ten K-pop twitter accounts as popular in Thailand as shown in Table 2.

TABLE 2
K-POP TWITTER POPULAR ACCOUNTS IN THAILAND

Twitter accounts	Followers (K)
https://twitter.com/BTS_Thailand	372.3
https://twitter.com/REDVELVET_TH	86.5
https://twitter.com/NCTZen_TH	73.0
https://twitter.com/MonstaXth_	62.5
https://twitter.com/IZONE_TH	35.0
https://twitter.com/ExoExothailand	34.8
https://twitter.com/MAMAMOO_TH	21.4
https://twitter.com/AB6IX_THAILAND	20.9
https://twitter.com/SNWThai	17.5
https://twitter.com/WOODZ_THAILAND	9.3

Gephi for SNA

In answer to the research issues, this investigation conducted a SNA with Gephi, free/liber software distributed by the Gephi Consortium under the GPL 3 ("GNU General Public License"). Gephi is an open-source visualization and network research program. It uses a 3D rendering system to view big real-time networks and to discover more rapidly. A scalable and multifunctional design provides fresh ways for dealing with diverse data sets and generates useful visual outcomes. In collaborative network discovery and analysis, we present many core features of Gephi. This offers fast and broad links to network data and specializes, filters, navigates, manipulates, and clusters. Finally, we illustrate the main facets of dynamic network visualization by integrating interactive features of Gephi (Bastian et al., 2009). It is a well-organized framework for a workbook made up of multiple workbooks needed to indicate a network diagram. An 'edge list' describes network connections (named 'graph edges') and includes all the network-linked unit pairs. The worksheets often include details on growing clusters and vertex (Struweg, 2002). The interface characteristics of the Gephi program demonstrate various network graphic representations and graphic data features to show things such as form, scale, color, and location (Hansen et al., 2012).

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

The Twitter Stream Plugin offers more modern technologies to draw on Gephi Basic. The plugin uses the Twitter Stream API and represents tweets as a graph. Three methods of representation (network logic): (1) Full Smart Network: Do a full representation of User, Tweet, Hashtag, Url, Media & Symbol (2) User Network: Do a weighted app to device network of RT and Mentions parallel edges, and (3) Hashtag Network: Keyword weighted to the Keyword network.

This analysis mainly covered network simulation, social network APIs, data import and export features, and SNA.

Data Collection and Analysis

Data description and dispersion

For this investigation, the Twitter details are imported in the range of time 1^{st} -14^{th} of July 2020 through Gephi Twitter Streaming Importer plug-in, which moves a question (in this case K-pop popular twitter accounts) to the related Twitter API rather than completeness (Zhang et al., 2020). Gephi restricts that we can only get Twitter messages for fewer than two weeks owing to API restrictions.

The popular Twitter account data from mined K-pop is then accessed regularly into the Gephi template according to edges and vertices. Edges and vertices are the main network theory concepts, which is one of the theories behind this investigation (Banica et al., 2015). First, "links" (such as "links," "ties," "relationships"), are social interactions, organizational structures, physical immediacy, or abstract connections (such as hyperlinks). Secondly, vertices (similarly known as "agents," "nodes," "items," or "entities") may include persons, Sites, activities, societal systems, and contents (such as keyword tags, videos, or websites) (Chae, 2015). From the point of view of network theory, the edge thus connects two social network vertices (Alhajj & Rokne, 2014).

Network structure analysis

Upon the distribution of the popular K-pop Twitter accounts were created, the next step was to quantitatively analyze and view the network structure. The network was visually illustrated with the algorithms of Clauset, Newman, and Moore Clusters and Harel-Koren's Quick Multi-Scale Architecture Algorithm to minimize visibility in the graph (Smith et al., 2014; Lipschultz, 2015). This made things easy to comprehend and at the same time improved the application of structure and analysis (Agapito et al., 2013). The next step in the study of the social network was the measurement of increasing vertical network metrics. The following metrics have been calculated to explain the configuration of the network K-Pop collected popular twitter account data for the purpose of this inquiry.

One of the SNA's main features is that such social networking networks are popular and active 'stars.' This notion of the identification of the important vertices in a graph is based on the classification, which generates the values and in turn is called as centrality (Wang et al., 2010). As the famous K-pop Twitter account network is driven, it needs both the degree and out-degree of centrality to be measured. Similarly, in-degree centrality is defined by the amount of accounts with arrows that lead to either a Twitter address. In this case, the level of popularity is called

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

(Miller et al., 2015). The out-of-degree centrality instead corresponds to the number of twitter arrows. The most sophisticated measurement of the twitter is then pointed as the key donors to the network.

From the perspective of social network theory, the central importance is another central metric that must be considered. A Betweenness Centrality is a function of the frequency of the shortest path between two different vertices has been granted a vertex (Hansen et al. 2012). The twitter with the strongest priority is known as the network bridges. Closity centrality represents the average difference in the social network between a vertex and the second vertex (Struweg, 2002). Presuming vertices that either has communications or execute their current connections (vertices), low central closeness implies that the tweeter is immediately linked to, or "just hop apart" the bulk from the other Social Network vertices (Hansen et al. 2012). Eigenvector centrality explicitly supports vertices with similar vertices (contrary to degree centrality). The eigenvector centrality metric network not only considers the number of vertex contacts (its degree) but also the degree of vertices on which the network is connected (Miller et al., 2015). Finally, Gephi calculates and analyzes the clustering coefficient using an algorithm for group identification resulting in obvious clustering (Clauset et al., 2004). The outcome and the argument of the data analysis follow below.

RESULT AND DISCUSSION

Prevalence and Patterns of K-pop popular twitter accounts

Gephi's advanced 'crawling' of the famous K-pop twitter pages have contributed to 5,356 tweets being extracted. The resulting 5,356 tweet data were "cleaned" by removing tweets that are not relevant to the study's vital tweet relationships. The famous twitter network of mined K-pop accounts contained 10,045 distinctive vertices and 21,248 edges. The edges of this survey featured initial messages, remarks, and mentions. Visualization of the dynamic network provides opportunities to understand changes in structure or content propagation (Moody et al., 2005). Dynamic networks were easily and intuitively explored in Gephi from the outset. The architecture supports graphics with a layout or material that varies with time and provides a timetabled feature that retrieves a part of the network. The program can check all nodes and edges that suit the timeline slice and upgrade the visualization feature. This enables a dynamic network to be treated like a film sequence. The module may be interactive and obtain network data either from a compatible graph file or from an external data source. A data source is able to send dynamic controller network data at any time and display the analysis application test immediately. For e.g., to see the network, a web crawler can be connected to Gephi construct time. The design is interoperable and easy to run and it is established for collaboration with existing software, databases and web services for third parties (Bastian et al., 2009). Figure 1 shows the 'overall diagram' showing the Harel-Koren multi scale layout algorithm (Harel & Koren, 2001) for popular K-pop Twitter accounts. Thus, Figure 1 shows the total networking data of the popular twitter accounts and Table 3 summarizes the overall diagram metrics of the case.

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

TABLE 3
TOTAL METRICS OF GRAPH OF K-POP POPULAR TWITTER ACCOUNTS CASE (SOURCE: GEPHI VERSION 0.9.2)

Graph type	Directed
Total Nodes	10,045
Total edges	21,248
Average Degree	2.115
Average path length	2.6289647966414
Epsilon	0.001
Probability	0.85
Number of Weakly Connected Components	2
Number of Strongly Connected Components	10,038
Number of iterations	100
Sum change	0.03505722242787635
Modularity	0.694
Graph density	0.000

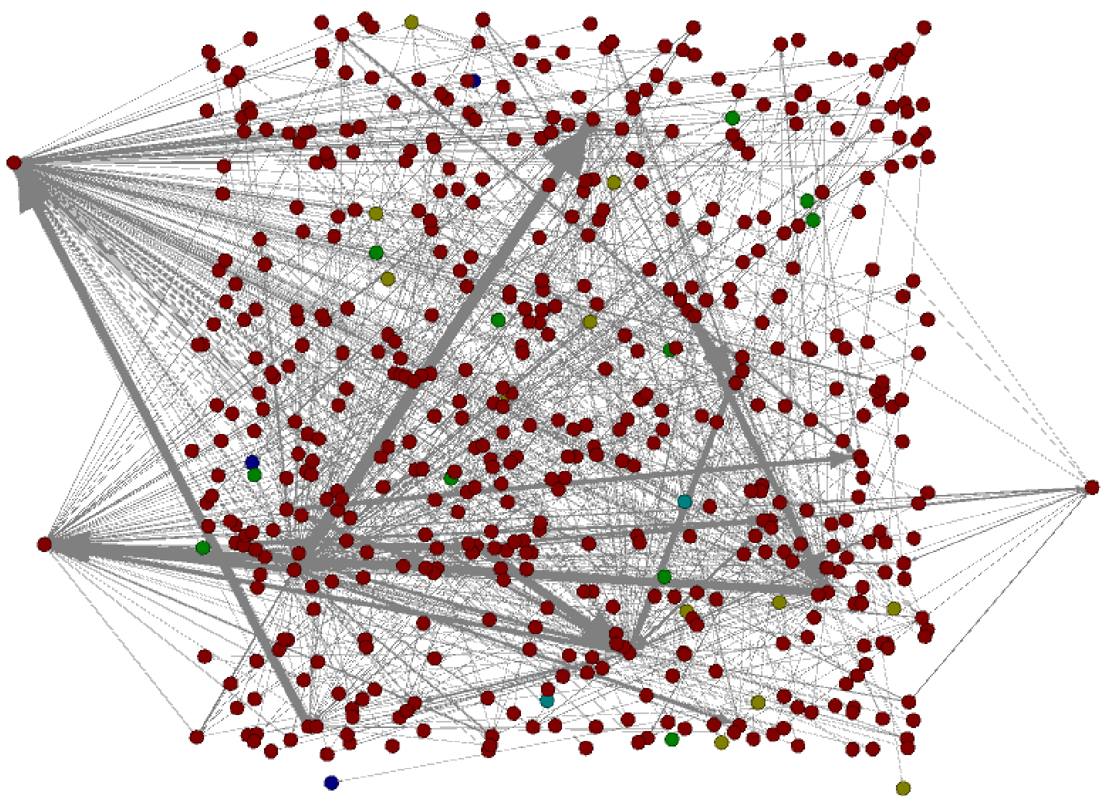


FIGURE 1

OVERALL TWITTER STRUCTURE OF K-POP TWITTER USERS

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

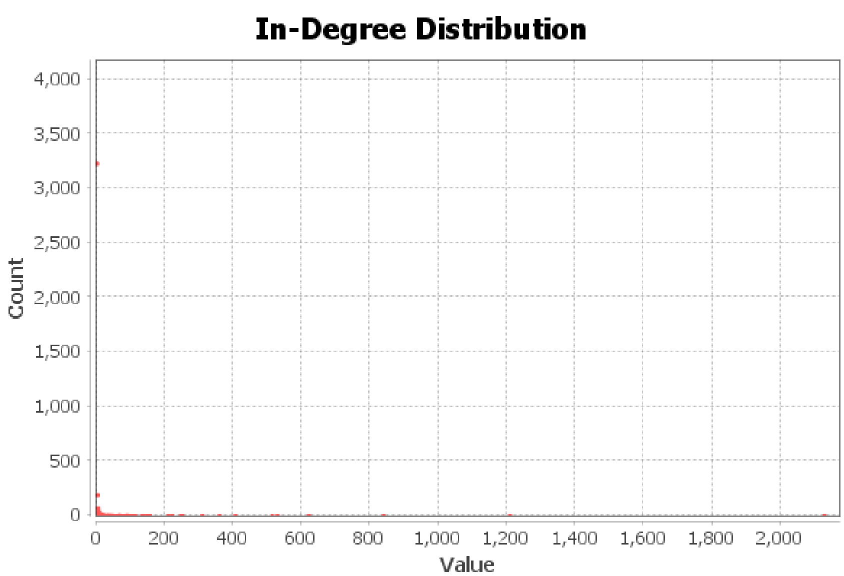
Influence and Network Analysis Results

This segment focus on the internal networking and the scale of the famous social network of K-pop Twitter accounts. It's characteristics shows each vertex is dependent on degree and degree similarity, bias and centrality of the function.

In-degree and out-degree centrality results

Figure 2 and 3 represent the in-degree and out-degree centrality of K-pop popular twitter accounts.

The in-degree means the number of users on Twitter responding to or mentioning the popular Twitter accounts of K-pop. Based on the degree of Gephi statistics, over 100 arrows point to the top three vertices. The highest to lowest three most popular accounts included in this survey were: (1) @nctzen_th– an in-degree of 405 (2) @REDVELVET_TH– an in-degree of 246 (3) @UME-- The official Twitter for Universal Music Enterprises, the music catalog for @UMG, @CapitolRecords, @Interscope, @DefJam, @IslandRecords, @Motown&morewith an in-degree of 151. Therefore, the @nctzen_th, @REDVELVET_TH, and @UMEappears to be the most famous in this survey account. The rest of the members of the social network are "in-between" position.



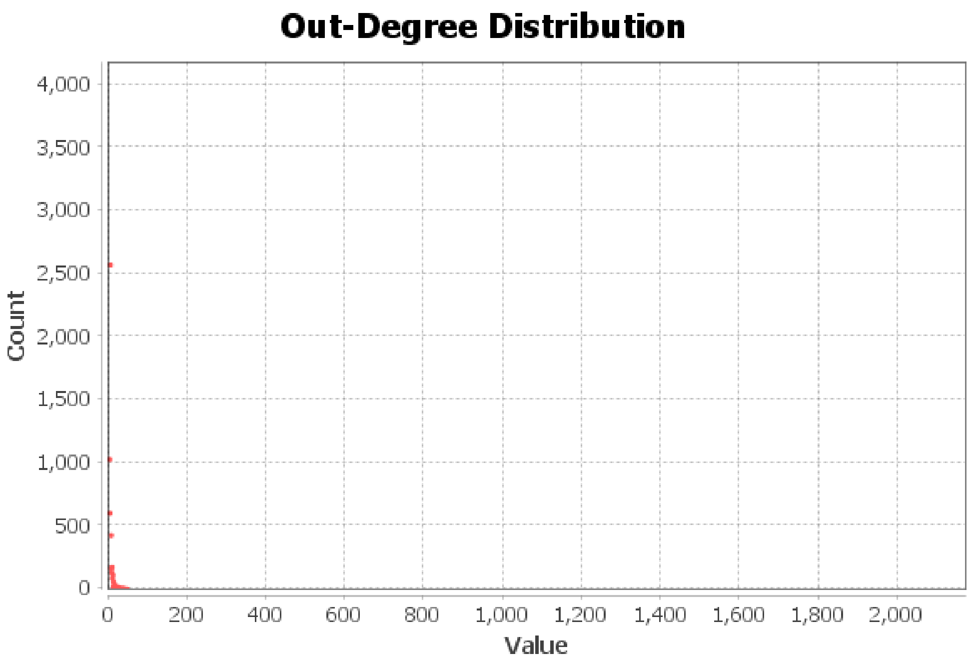
Minimum in-degree	0
Maximum in-degree	838
Average in-degree	1.400066
Median in-degree	0.000

FIGURE 2

IN-DEGREE DISTRIBUTION

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

Popularity in a social networking network is not the only indication of effect. The prominent accounts (out-degree centrality) are regarded for the intent of this investigation. Secondly, only ten users were communicating explicitly with @nctzen_th on Twitter. Nonetheless, the highest Twitter handle was @RVsmtown – which emerges as a resident from Twitter's account information. Actually this often means, though, it is an influent site, which is very outspoken and addresses many others of the K-pop famous Twitter accounts debate. Therefore, the authoring account extracts them into links or interacts if they were previously in the network with them for a second time by referring to others. The extent of a Twitter account refers to the arrow total that is on the network or the number of accounts to which it responds. Thus, this is an indicator to focus and is shown in one account for others.



Minimum out-degree	0
Maximum out-degree	625
Average out-degree	2.926357
Median out-degree	2.000

FIGURE 3

OUT-DEGREE DISTRIBUTION

Closeness centrality results

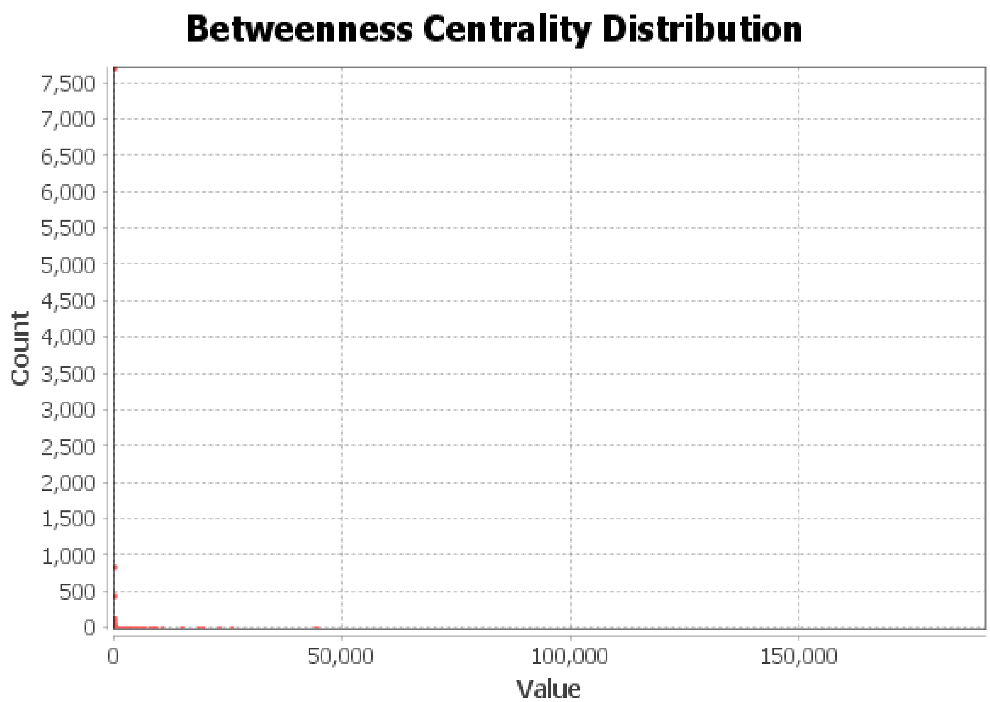
As stated earlier in this article, the centrality of closeness measures determines the shortest paths of all nodes and then allocates a score for every node on the fastest routes. This form of a power station is used to find the people that are best positioned to influence the whole network as quickly as possible. The proximity centrality will also help to identify successful

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

"broadcasters" in a social network. From the 3,301 K-pop popular twitter accounts only 66.92% (2,209) users had a comparable ranking of 1 but 33.08% of the entire K-pop popular twitter accounts ,Twitter users have a main closeness ranking of 0. In this analysis of K-pop popular twitter accounts, consequently, the network may be deduced and still the connectivity is linked significantly in a complex way.

Betweenness centrality results

Figure 4 represents the betweenness centrality results of the K-pop popular twitter accounts inquiry. This calculation shows why famous K-pop twitter accounts serve as 'bridges' to all social vertices connecting the network by defining the shortest of every routes and how much a vertex dropped in one.



Minimum Betweeness Centrality	0
Maximum Betweeness Centrality	44079.61742
Average Betweeness Centrality	21.0044739
Median Betweeness Centrality	0.000

FIGURE 4

BETWEENNESS CENTRALITY DISTRIBUTION

For the purpose of the Network, Diameter included betweenness centrality, closeness centrality, and eccentricity, the Fastest algorithm for betweenness centrality (Brandes, 2001). It was applied to display this graph-distance between both node pairs. The information is spreading

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

over quite fast routes on Twitter. Such pages for Twitter on short routes, thus, monitor the dissemination of knowledge through this social network. Therefore, accounts via Email are the significant number of quick paths that are perceived to be essential knowledge gatekeepers. The Facebook page of the highest quality was in the K-pop famous Twitter account event, @nctzen_th, accompanied by @sunflowercharts and @redvelvet the Twitter users listed in the above centrality topic degree. These three apps of Twitter may, therefore, be considered not only the most famous but still the most critical on the popular social network of K-pop Twitter accounts.

Eigenvector centrality results

The centrality of Eigenvector is considered as centrality type of "higher level." A less linked Twitter user might have a really big one central vector with Eigenvector centrality. Nonetheless, no links have been really well defined to enable high variable value connections. This implies that it is better to connect several vertices to others. The centrality ratings in the popular Twitter K-pop survey were significantly low, which implied insufficient evidence that connecting to certain K-pop popular Twitter accounts would be more useful for other social network users.

Analytics and Visualizations

Figure 5 shows the sociogram style as classes. The vertices of the groups by means of a clustering algorithm. There are categories grouped by their relative network density. These clusters help to combine vertical groups (network users) that display high network density. This applies to network customers that are extremely important in-degree and/or out-degree. There are network applications also considered to be influencers of the network. The groups further help network user's cluster with a lower level of network density and ignore as specific cases that do not matter in network analysis. Mostly since, they cannot speak on the network with others. The Clauset, Newman, and Moore algorithms (Clauset et al., 2004) were used for this analysis and visualization to display the connections between these vertices. In this algorithm, modularity as network infrastructure is used to shape a community-distributed network.

The classes have been organized individual boxes to display isolates in the human party. Gephi then measures the clusters according to the criteria used in community selection (Udanor, Aneke & Ogbuokiri, 2016). In the popular case of K-pop Twitter, Gephi generated 19 groups. The sociogram affecting (Figure 5) shows the clusters in separate boxes with links to various clusters across a range of colors. Such isolates do not impact the visualization overall, regardless of their non-network connectivity. This is also why the links in the figure are shown in a revolving way. There should also be a communication between the groups. The main clusters in Figure 5 are focused on the west, with connections to several other social network nodes.

The primary drawback of this analysis may be claimed that it does not have a certain degree of reduced effects. This refers more specifically to the apparent lack of general social networking engagement with the popular K-pop twitter case. This seeming absence of social media attention, especially on Twitter, may have been affected both locally and nationally by several other big news events. While knowledge is overwhelmed, it is a fact that will not change in the immediate future, particularly through social media. This might then offer more study the

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

ability to investigate the spread of social media users, particularly those who influence the person during critical events directly.

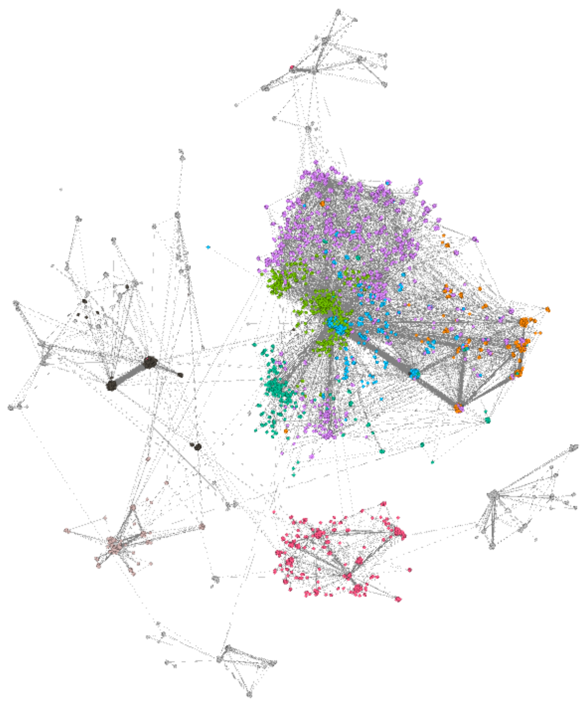


FIGURE 5

CLUSTER CLASSES AND CLUSTER ORIENTATION LINKING OF K-POP POPULAR TWITTER ACCOUNTS

CONCLUSION

Big data on social networking networks are among the most critical, yet some of them remain subject to research. For this inquiry, Facebook, a commonly used social networking site, utilizing K-pop famous Facebook profiles, was used to collect big data. The Twitter pages were chosen based on the majority of the K-pop fandom group in Thailand. This research was focused on graphical and network theory to perform a social network study of the K-pop famous Twitter accounts regional discussion. This culminated in a visual map analysis focused on 5,356 K common twitter accounts of 3,301Twitter users (vertices) showing 21,248 connections with Twitter (edges). The main players in this SNA were @nctzen_th, the fandom, and Thai citizens to a small degree who are inspired by K-pop music. The distributions revealed that the relationships between the ten key K-pop famous twitter accounts were small, as the majority of proximity and centrality were weak. This could demonstrate how well Thai fandom have been involved in pop music in Korean culture which will affect everyone in Thailand. It is obvious from the previous discussions social networking is inherently key to today's society, with broad

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

influence, and which cannot be refuted or neglected. This paper shows how broad real-time Twitter data can be used to gain insight into social networking analytics with visualizations utilizing Gephi and Twitter Streaming Importer plugins. The paper also demonstrated Gephi as a way to utilize massive unstructured data that are mass-produced every day. However, it permits the conclusion of apparently uncoordinated microblogs by employing effective computational methods that can help the company and decision-making regimes. The famous case study of K-pop Twitter confirms further that digital economies are part of the battle of social networking.

ACKNOWLEDGMENT

This research is financial supported by the faculty of humanities and social sciences, Khon Kaen University, Thailand.

REFERENCES

Agapito, G., Guzzi, P. H., & Cannataro, M. (2013). Visualization of protein interaction networks: problems and solutions. *BMC bioinformatics*, *14*(1), 1-30.

Albert, R., & Barabási, A. L. (2002). Statistical mechanics of complex networks. *Reviews of modern physics*, *74*(1), 47.

Alhajj, R., & Rokne, J. (2014). *Encyclopedia of social network analysis and mining*. Springer.

Ary, D., Jacobs, L. C., Irvine, C. K. S., & Walker, D. (2018). *Introduction to research in education*. Cengage Learning.

Banica, L., Brinzea, V. M., & Radulescu, M. (2015). Analyzing social networks from the perspective of marketing decisions. *Scientific Bulletin: Economic Sciences*, *14*(3), 37-50.

Bastian, M., Heymann, S., & Jacomy, M. (2009, March). Gephi: an open source software for exploring and manipulating networks. In *Proceedings of the International AAAI Conference on Web and Social Media* (Vol. 3, No. 1).

Brandes, U. (2001). A faster algorithm for betweenness centrality. *Journal of mathematical sociology*, *25*(2), 163-177.

Can, U., & Alatas, B. (2019). A new direction in social network analysis: Online social network analysis problems and applications. *Physica A: Statistical Mechanics and its Applications*, *535*, 122372.

Chae, B. K. (2015). Insights from hashtag# supplychain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research. *International Journal of Production Economics*, *165*, 247-259.

Chansanam, W., & Tuamsuk, K. (2020). Thai Twitter Sentiment Analysis: Performance Monitoring of Politics in Thailand using Text Mining Techniques. *International Journal of Innovation, Creativity and Change*, *11*(12), 436-452.

Churchill, E. F., & Halverson, C. A. (2005). IEEE Internet Computing, volume 9, chapter Social Networks and Social Networking. *IEEE Computer Society*, 14-19.

Clauset, A., Newman, M. E., & Moore, C. (2004). Finding community structure in very large networks. *Physical review E*, *70*(6), 066111.

Desai, T., Shariff, A., Shariff, A., Kats, M., Fang, X., Christiano, C., & Ferris, M. (2012). Tweeting the meeting: an in-depth analysis of Twitter activity at Kidney Week 2011. *PloS one*, *7*(7), e40253.

Gao, X. (2018). Networked co-production of 311 services: investigating the use of Twitter in five US cities. *International Journal of Public Administration*, *41*(9), 712-724.

Hansen, D. L., Rotman, D., Bonsignore, E., Milic-Frayling, N., Rodrigues, E. M., Smith, M., & Shneiderman, B. (2012, December). Do You Know the Way to SNA?: A process model for analyzing and visualizing social media network data. In *2012 International Conference on Social Informatics* (pp. 304-313). IEEE.

Harel, D., & Koren, Y. (2000, September). A fast multi-scale method for drawing large graphs. In *International symposium on graph drawing* (pp. 183-196). Springer, Berlin, Heidelberg.

Jaiwai, P. (2014). Consumer's perceptions and behaviors toward Korean wave in Lampang city Municipality, Lampang Province. *Unpublished master" s thesis. Nation University, Lampang.*

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

Java, A., Song, X., Finin, T., & Tseng, B. (2007, August). Why we twitter: An analysis of a microblogging community. In *International Workshop on Social Network Mining and Analysis* (pp. 118-138). Springer, Berlin, Heidelberg.

Kandadai, V., Yang, H., Jiang, L., Yang, C. C., Fleisher, L., & Winston, F. K. (2016). Measuring health information dissemination and identifying target interest communities on Twitter: methods development and case study of the@ SafetyMD network. *JMIR research protocols*, *5*(2), e50.

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present and future. *Information Systems Frontiers*, *20*(3), 531-558.

Lee, Y. J., O'Donnell, N. H., & Hust, S. J. (2019). Interaction effects of system-generated information and consumer skepticism: An evaluation of issue support behavior in CSR Twitter campaigns. *Journal of Interactive Advertising*, *19*(1), 15-28.

Lipschultz, J. H. (2015). Social media communication in the classroom: A pedagogical case study of social network analysis. *Digital Media in Teaching and Its Added Value*, 191-207.

Lohmann, G., Margulies, D. S., Horstmann, A., Pleger, B., Lepsien, J., Goldhahn, D., ... & Turner, R. (2010). Eigenvector centrality mapping for analyzing connectivity patterns in fMRI data of the human brain. *PloS one*, *5*(4), e10232.

Marin, A., & Wellman, B. (2011). Social network analysis: An introduction. *The SAGE handbook of social network analysis*, *11*, 25.

Meyer, C. B. (2001). A case in case study methodology. *Field methods*, *13*(4), 329-352.

Miller, P. R., Bobkowski, P. S., Maliniak, D., & Rapoport, R. B. (2015). Talking politics on Facebook: Network centrality and political discussion practices in social media. *Political Research Quarterly*, *68*(2), 377-391.

Miranda, S. M., Young, A., & Yetgin, E. (2016). Are social media emancipatory or hegemonic? Societal effects of mass media digitization in the case of the SOPA discourse. *MIS quarterly*, *40*(2), 303-329.

Moody, J., McFarland, D., & Bender-deMoll, S. (2005). Dynamic network visualization. *American journal of sociology*, *110*(4), 1206-1241.

Newman, M. E. (2003). The structure and function of complex networks. *SIAM review*, *45*(2), 167-256.

Oh, O., Agrawal, M., & Rao, H. R. (2013). Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *MIS quarterly*, 407-426.

Otte, E., & Rousseau, R. (2002). Social network analysis: a powerful strategy, also for the information sciences. *Journal of information Science*, *28*(6), 441-453.

Samatan, N., Fatoni, A., & Murtiasih, S. (2020). Disaster Communication Patterns and Bhaviors On Social Media: A Study Social NEtwork# Banjir2020 On Twitter. *Humanities & Social Sciences Reviews*, *29*.

Serrat, O. (2017). *Knowledge solutions: Tools, methods, and approaches to drive organizational performance* (p. 1140). Springer Nature.

Shi, Z., Rui, H., & Whinston, A. B. (2014). Content sharing in a social broadcasting environment: evidence from twitter. *MIS quarterly, 38*(1), 123-142.

Carey-Simos, G. (2015). How Much Data Is Generated Every Minute on Social Media?. *Wersm. com. http://wersm. com/how-much-data-is-generated-every-minute-on-social-media*.

Smith, M. A., Rainie, L., Shneiderman, B., & Himelboim, I. (2014). Mapping twitter topic networks: From polarized crowds to community clusters. Pew Research Internet Project.

Statista. (2018). Number of monthly active users worldwide from first quarter 2010 to first quarter 2018. Retrieved 25 June 2018, from https://www.statista.com/statistics/282087/number-of-monthly-active-twitterusers/.

Struweg, I. (2020, April). A Twitter Social Network Analysis: The South African Health Insurance Bill Case. In *Conference on e-Business, e-Services and e-Society* (pp. 120-132). Springer, Cham.

Struweg, I. (2018). # Liberty breach: An exploratory usage case of NodeXL Pro as a social media analytics tool for Twitter.

Suwannapisit, K. (2008). Korean singers and Korean wave as experienced by Thai fan clubs. *Unpublished master" s thesis). Chulalongkorn University, Bangkok.*

Tsvetovat, M., & Kouznetsov, A. (2011). *Social Network Analysis for Startups: Finding connections on the social web*. " O'Reilly Media, Inc.".

Udanor, C., Aneke, S., & Ogbuokiri, B. O. (2016). Determining social media impact on the politics of developing countries using social network analytics. *Program*.

Valente, T. W. (2015). Social networks and health behavior. *Health behavior: Theory, research and practice*, *5*, 205-222.

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.

Valente, T. W., Dyal, S. R., Chu, K. H., Wipfli, H., & Fujimoto, K. (2015). Diffusion of innovations theory applied to global tobacco control treaty ratification. *Social Science & Medicine*, *145*, 89-97.

Wang, Z., Tan, Y., & Zhang, M. (2010, April). Graph-based recommendation on social networks. In *2010 12th International Asia-Pacific Web Conference* (pp. 116-122). IEEE.

Wassaerman, S., & Faust, K. (1994). Social network analysis in the social and behavioural sciences. *Social Network Analysis: Methods and Applications, Cambridge University Press, Cambridge*.

Zhang, C., Gao, Z., & Liu, X. (2016). How others affect your twitter# hashtag adoption? examination of community-based and context-based information diffusion in twitter. *IConference 2016 Proceedings*.

Zhang, L., Luo, M., & Boncella, R. J. (2020). Product information diffusion in a social network. *Electronic Commerce Research*, *20*(1), 3-19.

Zhang, Y., & Chang, H. C. (2018, January). Selfies of Twitter data stream through the lens of information theory: a comparative case study of tweet-trails with healthcare hashtags. In *Proceedings of the 51st Hawaii International Conference on System Sciences*.

Citation Information: Chansanam, W., Tuamsuk, K., Kwiecien, K., Sutthiprapa, K., & Oh, S. (2021). An analysis of the Korean popular culture on social media: examination of the Thai fandom through Twitter in Thailand. *Journal of management Information and Decision Sciences, 24*(S2), 1-16.