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DATAISM AND TWITTER HASHTAG IN MALAYSIA EVERYDAY LIFE

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Abstract

The fourth industrial revolution (IR4 or Industry 4.0) not only offers us advances in technology but has also led to the emergence of a new ideology, dataism. Dataism is an ideology which is centred on artificial intelligence (AI) and computer algorithms; it sees human beings as biochemical algorithms and our preferences, choices, experiences, likes and dislikes accumulated in our usage of internet services – such as social media platforms and search engines – as data patterns. With the expansion of social media platforms (such as Facebook, Instagram and Twitter), these data patterns are displayed through algorithmic suggestions of a trending hierarchy. The main aim of this research is to discuss how Twitter hashtag can be trending and 'viral' in three aspects of social actors' everyday life: economic, social and political. The outcome of this study was derived from a pilot study which employed secondary data analysis of online items accompanied by a hashtag (#) in Twitter obtained in July 2019. The collected data were organised in Nvivo 12 Plus and analysed by sociogram analysis. The findings show that hashtag usage is an important internet algorithm item and its trending and viral ability is dependent on a high functional 'connector' in Twitter.

Keywords: Viral and trending, Twitter, IR4, algorithm.

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1. Introduction

Algorithms are defined as a “problem-solving mechanisms […]. Its selection is essentially defined by the automated assignment of relevance to certain selected pieces of information” (Just & Latzer, 2017, p. 253). Through specific programmed software, algorithms can convert human data input – our choices, preferences, experiences, likes and dislikes accumulated in our usage of internet services – into their ‘assumed-desired’ output.

The algorithm application is divided into nine general functions: to search, to aggregate, to observe or to survey, to filter, to forecast, to propose, to score, to produce content and to allocate (Latzer, Hollnbuchner, Just, & Saurwein, 2014). The search application is widely used around the world by search engines such as Google, Bing, Yahoo and Baidu. It is a basic internet function and the first application to be used by users. The aggregation application or aggregator web content accumulates, catalogues and reorganizes multiple information bits into one entrance, for instance Alltop, Buzzfeed and Google News. The observation/surveillance application is used to monitor users’ online activities, and the main function of the filter application is to block particular internet contents or platforms from being accessed by its users, especially by spam, malware and viruses. For example, in China, IP blocking and keywords filtering are used to block political information which is seen as a national threat from reaching its citizens (MacKinnon, 2008; Xu, Mao, & Halderman, 2011). The forecast application is to predict future outcomes or impacts in circumstances such as natural disasters or financial investment. The recommendation application primarily proposes online contents or material based on personalised interest such as movies in Netflix, video in Youtube and songs in Spotify. Scoring applications are used to collect feedback and score a user’s reputation, particularly in e-trading. The outcome is beneficial for online buyers to trust their sellers (Resnick, Zeckhauser, Swanson, & Lockwood, 2006). Another important function of algorithms is content production which is related to human expression and creativity, such as Evernotes, Quill and Musicnotes. The final function of algorithms is allocation application, particularly in online advertisements such as Google AdSense, Instagram Ads and LinkedIn Ads.

Despite the variety of functions of algorithms, they inevitably invite at least two major concerns. The first concern is related to the privacy of personal data. The internet does not merely accumulate its users’ location, financial confidentiality, health data statistics; personal social networks, interests and activities, but also stores them in Cloud storage which can be accessed by others. In 2018, Facebook and Cambridge Analytica, an election consultancy, gained massive public attention (Isaak & Hanna, 2018; Tarran, 2018) when the former was accused of selling its users’ details to the latter. Another international scandal is the ongoing Huawei security scandal (Gibney, 2019), sparked when the United Stated charged Huawei with online security threats. The scandal consequently led to the withdrawal of the University of California from future research collaboration and funding with Huawei. In Malaysia, the Royal Malaysian Police (PDRM) recently identified seven applications which could violate its users’ data privacy, such as ‘Mobile Tracking’ and ‘SMS Tracker’, and advised users to uninstall them.

The second concern is related to algorithms’ ability to influence internet users in their social, political and economic decisions by means of their systematic recommendation system. Unlike the traditional mass media, algorithms’ selection of data is not subject to time-delay, or to a limited audience and market. It personalises the reality through the process and the results are based on users’ active input

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(such as like and dislike) and passive data (such as social contacts) (Just & Latzer, 2017). The personalisation pervades human daily decisions through suggestions of news, social networks, leisure activities and entertainment by calculating previous content scoring and making future predictions (Latzer et al., 2014). The systematic recommendation system works through two premises: link and object. The object recommendation is usually used in e-trading sites such as Amazon, whereas the link recommendation is used in networking sites such as Facebook (Naruchitparames, Gunes, & Louis, 2011), Twitter and Instagram. The social network recommendation in Facebook is linked on the basis of friend-of-friend (Naruchitparames et al., 2011) which would systematically suggest those from similar socio-economic backgrounds such as nationality, ethnicity and educational background. Social recommendation on Twitter is based on 'trending' hashtags and topics. Instagram's social network on the other hand is not only recommended by hashtag by also by users' likes and dislikes in the 'explore' section.

2. Problem Statement

Data published by the Malaysian Communications and Multimedia Commission (2017) show that Malaysian smartphone users steadily increased from 68.7% of the population in 2016 to 75.9% in 2017. With the high percentage of smartphone-cum-internet usage, the same survey also found that Malaysian youngsters are highly dependent on their smartphones, particularly for social connection, consumerism and academic purposes. More than 80% of the respondents in the research aged between 20 and 24 would feel uneasy about being without their smartphone. Their dependency behaviour with their smartphones showed in their tendency to wake up in the middle of night to check the smartphone and to check it within one hour after waking up (Malaysian Communications and Multimedia Commission, 2017). These findings suggest that the internet has now become part of Malaysian everyday life.

Twitter is the fifth preferred social networking platform in Malaysia for online content sharing after Facebook, Instagram, Youtube and Google+ (Malaysian Communications and Multimedia Commission, 2017). Twitter is "what is happening in the world and what people are talking about right now" (Twitter, 2019). Twitter allows its users to embed hashtags within their tweets which immediately allocates a topic, issue or interest discussed in exclusive online trajectories. With these online trajectories, hashtag has the ability to make the topic, issue or interest discussed become infectious (Skaza & Blais, 2017). Additionally, the hashtag trajectories allow Twitter users to search and follow the topic easily. Pressgrove, McKeever, and Jang (2018) stated that the reasons why a hashtag becomes infectious and viral – in their study this was referred to as 'icebucketchallenge' – are because of social currency (such as to look good), emotions (such as inspiration) and public (such as what is acceptable to the local public). In the Malaysian context, there have been limited studies conducted on Twitter hashtag and only a few researchers, such as Kasmani, Sabran, and Ramle (2014), Supian, Razak, and Bakar (2017), Ahmed, Jaidka, and Cho (2018), have focused primarily on Twitter usage. This current research is a preliminary study which focuses specifically on how Twitter hashtag works its trending and viral abilities within Malaysian context.

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3. Research Questions

How has Twitter hashtag become trending and viral in three aspects of Malaysian everyday life: entertainment, political interests and codes of conduct?

4. Purpose of the Study

The main aim of this research is to explore how Twitter hashtag can be trending and viral in social actors' everyday lives.

5. Research Methods

A pilot study is crucial prior to a main study, both for qualitative and quantitative research. It can avoid repeated mistakes and give opportunities for researchers to revise and amend their research protocol (Kim, 2010). This current pilot study used secondary data analysis of *online items* published in July 2019. Secondary data analysis was chosen as the main research method because of its unobtrusive status as it does not involve human respondents in the early research stage, which gives the researcher advantages in terms of the time and financial aspects.

The online items in this study were collected from the Twitter platform. The main focus is on the hashtag (#) usage in the online platforms. Hashtag in Twitter is useful for finding posts and conversations centred around one particular issue or topic. The trending hashtag in Twitter can be found under the 'Trending now' button which changes every day and week depending on that particular hashtag's popularity. The disadvantage of the tracking hashtag is its complicated trajectory post, especially if the hashtag is linked to national or global trending. The data collected is also limited to public Twitter accounts only. In regard to the needs of this research, the researcher had to sign up for Twitter accounts. Based on hashtag popularity, three hashtags were chosen from three aspects: entertainment (#sangkarmovie), political issues (#undi18) and codes of conducts (#bubbletea). The collected data were organised in Nvivo 12 Plus and analysed using sociogram analysis. The main measurements used in sociogram analysis are degree centrality and betweenness centrality. Since the online items were collected in July 2019, additional online items collected in the future using the same hashtag are expected because of Twitter's nature as ongoing and 'live' social interaction platform.

6. Findings

Degree centrality demonstrates who has the most connections and how many people an individual can reach. In the case of Twitter usage, degree centrality is measured by how many followers (connections) a Twitter user has reached through his/her retweet and mentions functions. Betweenness centrality, on the other hand, is a 'connector' to other social circles. In Twitter usage, betweenness centrality is a connector of a hashtag thread to a user's followers through the retweet and mentions functions.

In term of the entertainment algorithm in Twitter, a promotion through hashtag comes directly from those who are involved in the industry, such as actors, directors, script writers and production

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agencies, and is extended within their followers' social circles through Twitter hashtag, retweet and mentions. Those with high numbers of followers could reach more audiences with the *sangkarmovie* hashtag (see Table 01). For example Table 1 shows that the highest degree centrality through the retweet function was for Malaysian Novelist A, Malaysian Actor A and Twitter User A, whereas the highest degree centrality score for the mentions function was for Twitter User B, Malaysian Actor A and Malaysian Actor B. Although Malaysian Actors A and B have high numbers of followers with 876.6k and 126k respectively in comparison with the others, their *sangkarmovie* hashtag could not reach as large an audience as Malaysian Novelist A (2428 followers) through retweet or Twitter User B (92 followers) with the mentions function. In terms of betweenness centrality, it suggests that Malaysian Novelist A, Malaysian Actor A and Twitter User A had the most information of *sangkarmovie* flowing between them through the retweet function. The mentions function on the other hand excluded Malaysian Actor B and Twitter User C as the best connector with highest information about the topic through the mentions function. In other words, Twitter User C was one of the main connectors to other Twitter users even with a small number of followers (36 followers).

Table 01. Degree centrality and betweenness centrality of #sangkarmovie usage

#sangkarmovie	***Degree centrality***	***Betweenness centrality***
Retweet	Malaysian Novelist A Malaysian Actor A Twitter User A	Malaysian Novelist A Malaysian Actor A Twitter User A
Mentions	Twitter User B Malaysian Actor A Malaysian Actor B	Twitter User B Malaysian Actor A Twitter User C

Another example of how hashtag works in Twitter is in the *undi18* thread (*see* Table 02). The *undi18* hashtag is used by Twitter users around the issue of reducing Malaysia's minimum voting age from 21 to 18 years. Table 02 shows that Youth Activist A, Malaysian Politician A and Twitter Users A, B and C scored high in degree centrality. This score suggested that they had reached their followers regarding the issue either through the retweet or the mentions functions. However, beyond the connectors to Twitter users other than Youth Activist A, Malaysian Politician A and Twitter Users A, B and C, connection was extended to Twitter D, Twitter E and Organization Twitter Page A. In other words, the former depended on the latter for extending the *undi18* hahstag thread.

Table 02. Degree centrality and betweenness centrality of #*undi18* usage

#undi18	***Degree centrality***	***Betweenness centrality***
Retweet	Youth activist A Twitter User A Twitter User B	Youth activist A Twitter User A Twitter User D
Mentions	Malaysian Politician A Youth activist A Twitter User C	Malaysian Politician A Twitter User E Online Twitter Page A

In order to make an issue viral or trending in Twitter, it is not necessary to involve both the retweet and the mentions functions. For example, in regard to a concern about the heavy consumption of

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Malaysian bubble tea (bubbletea hashtag) (see Table 03), a Malaysian Fitness Instructor, and Twitter Users A and B reached many of their connections with only the retweet function. However, Twitter Users A and B's bubbletea hashtag retweet depended on other connectors, Twitter Users C and D, in order to extend the dietary concern beyond their social circle.

Table 03. Degree centrality and betweenness centrality of *#bubbletea* usage

#undi18	***Degree centrality***	***Betweenness centrality***
Retweet	Fitness Instructor Twitter User A Twitter User B	Fitness Instructor Twitter User C Twitter User D
Mentions	Fitness Instructor Twitter User A Twitter User B	Fitness Instructor Twitter User A Twitter User B

7. Conclusion

There are two main conclusions to be drawn from this brief preliminary study. First, the power to make a Twitter hashtag trending and viral does not necessarily come from the main source of the hashtag but from the followers through the retweet and mentions functions. Second, a high number of followers on Twitter does not necessarily make a hashtag viral or trending. The main agent for making a hashtag trending depends on a high functional connector in Twitter.

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