Computers in Human Behavior 82 (2018) 167–176

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Full length article

Birds of a schedule flock together: Social networks, peer influence, and digital activity cycles

Hai Liang [a], Fei Shen [b, *]

[a] School of Journalism and Communication, The Chinese University of Hong Kong, New Territory, Hong Kong
[b] Department of Media and Communication, City University of Hong Kong, Kowloon Tong, Hong Kong

ARTICLE INFO

Article history:
Received 2 October 2017
Received in revised form
11 December 2017
Accepted 15 January 2018
Available online 16 January 2018

Keywords:
Social media
Social network
Peer influence
Homophily

ABSTRACT

The use of social media such as Twitter has changed our life routines. Previous studies have found consistent diurnal patterns of user activities on social media platforms. However, the temporal organization of human behavior is partly socially constructed and is determined by numerous factors other than the diurnal cycle. The current study argues that peer influence incurred by social networks is one of these potential factors. To test our hypotheses, we collected a random sample of active Twitter users ($N = 5066$), their followers and followees ($N = 424{,}984$), and all available tweets posted by these users. Results suggest that the temporal patterns between self-posting and interaction behavior differ across individuals. Users' daily activity rhythms are more similar to their followees' rhythms than to their followers' rhythms. Despite the fact that the self-selection mechanism (homophily) cannot be ignored, peer influence seems to be an equally likely mechanism explaining such similarity.
© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

Interpersonal relationships embedded in social media platforms can have important implications for human behavior. Digital activity rhythm (e.g., Aledavood, Lehmann, & Saramaki, 2015; Golder & Macy, 2011; Golder, Wilkinson, & Huberman, 2007; Yasseri, Sumi, & Kertesz, 2012) is an interesting phenomenon that has not received enough scholarly attention in existing literature. The use of social media such as Twitter has changed our life routines. Although many of us live according to a diurnal cycle, the temporal organization of human behaviors is partly socially constructed (Lewis & Weigert, 1981) and is determined by numerous factors, one of which is information technology.

A number of theorists have argued that the emergence of digital technologies has altered the temporal pattern of human activities (e.g., Castells, 1996; Failla & Bagnara, 1992). However, the direction of change remains unclear. Some argue that communication networks and information technologies increase the need for synchronization, and therefore, a more unified timeframe for individual activities will appear (Lee & Liebenau, 2000; Zerubavel, 1982). Others believe that new information technologies can lead to decentralization by enlarging interconnection complexity (Failla & Bagnara, 1992; Hongladarom, 2002; Sawhney, 2004). As a networked community becomes diversified, users might develop more personalized and unique temporal activity patterns. Providing a sweeping answer to the question how digital technologies change human activity patterns might be difficult to achieve in a single study, but at least at the individual user level, we can enhance our understanding of the phenomenon by examining user behavioral and social network data.

Using a representative dataset collected from Twitter, the current study aims to offer some empirical insights into a few specific questions regarding social network use and digital activity patterns. First, we are interested in knowing whether an overall daily rhythm of use still exists on social media platforms (in this case, Twitter). Even if there is a general temporal pattern of social media use, are there significant individual differences across users? Second, we wish to explore whether two different types of Twitter use behavior (self-posting and interaction) differ from each other in terms of use temporal patterns. Third and more importantly, the social networking function of social media can increase user interdependence. If this is true, do connected friends on Twitter share similar daily activity rhythms? Based on homophily theory and peer-influence theory, we also discuss the possible mechanisms leading to such similarity among connected friends on Twitter.

* Corresponding author.
E-mail addresses: hailiang@cuhk.edu.hk (H. Liang), feishen@cityu.edu.hk (F. Shen).

https://doi.org/10.1016/j.chb.2018.01.016
0747-5632/© 2018 Elsevier Ltd. All rights reserved.

2. Theoretical background and hypotheses

2.1. Digital daily rhythms on social media

Our everyday activities are constrained by the sequence of darkness and light of a physical day. A modern society can function properly only if most of its members follow a highly patterned circadian rhythm because people need to communicate and collaborate with each other. Such a daily rhythm is often referred to as cyclic time. According to Lewis and Weigert (1981), daily activity pattern reflects the macrostructure of social time, which is deeply rooted in culture and is resistant to change in modern societies.

Nevertheless, recent developments in information and communication technologies (ICTs) have been said to fragmentize individuals' daily activities (Couclelis, 2000, 2004). Individuals now have higher levels of freedom deciding where and when to engage in different activities (Aledavood, Lehmann, et al., 2015). They can also organize their activities around flexible compartments of time due to technology advancement (Green, 2002). For example, mobile communication technologies give us an always available link to friends, colleagues, and family members. Such a link offers more flexibility in scheduling daily activities. Lenz and Nobis (2007) argued that temporal flexibility and division of activities into different fragments are the two particular side effects of mobile communication in users' daily lives. Similarly, Ling (2004) used the concept of "softening time" to characterize the tendency that mobile technologies gives users a way to master time.

However, empirical evidence suggests that the day–night pattern still exists on most social media platforms, such as Twitter (Dodds, Harris, Kloumann, Bliss, & Danforth, 2011; Golder & Macy, 2011; ten Thij, Bhulai, & Kampstra, 2014) and Facebook (Golder et al., 2007). Golder et al. (2007) considered Facebook messaging and poking as proxies to social interaction in online settings. They found that the temporal pattern of messaging and poking behavior exhibits strong circular regularities: There is very little messaging activity between 3 a.m. and 8 a.m., but there is active messaging behavior from morning to midnight throughout a day. However, Golder et al. (2007) also noticed that email activity in a corporate network shows a different temporal pattern.

Most previous studies analyzed user activity pattern as a whole and ignored the individual variabilities of the daily digital cycle. Even if there is a clear daily trend at the aggregate level, it is still possible that individuals have very different activity rhythms. Aledavood, Lehmann, et al. (2015) found strong individual variation in individual daily patterns. Within the broad day–night pattern, some users are intrinsically active during the morning, while others are more active during the evening. Yasseri et al. (2012) also found that there are four types of daily rhythms of Wikipedia activities.

2.2. Self-time versus interaction time

In additional to cyclic time, which is located at the institutional or organizational level, self-time and interaction time reflect an individual's personal activity habits (Lewis & Weigert, 1981). Self-time refers to the rhythms of human activities that could be entirely defined by an individual. Whenever two or more individuals start to interact with each other, self-time becomes interaction time. Interaction time exhibit a different rhythmic pattern than self-time does because social interaction depends on the availability and actions of others. Cyclic time, interaction time, and self-time follow a hierarchical structure (Lewis & Weigert, 1981). Cyclic time demands precedence over interaction time, and interaction time, in turn, demands precedence over self-time. When a conflict between cyclic time and self-time emerges, cyclic time plays a dominant role in deciding one's activity pattern.

The hierarchical structure of social time has an important implication for social media use; that is, the use of social media is not likely to change the macrostructure of social time, but it is not impossible that social media can exert influence on the micro-aspect of social time (i.e., self-time and interaction time). To further elaborate on this point, it is essential to differentiate individual posting behavior and interaction activities on social media.

There are two general types of posting behavior on social media: self-posting and interaction with other users. Self-posting is self-initiated whereas interaction activities are triggered by other users, including reposting and replying activities (replying to others' posts or comments). However, almost all previous studies conducted on Facebook (Golder et al., 2007) and mobile communication (Aledavood, Lehmann, et al., 2015) focus on examining the temporal patterns of interaction activities.

Therefore, it remains largely unknown whether self-posting differs from interaction activities in terms of temporal patterns. As self-posting does not necessarily depend on other users' activity, it is possible that people do self-post according to their own schedule, while their reposting and replying activities are influenced by their friends' timelines. For example, it is reasonable to expect that people retweet more if their followees tweet more frequently.

2.3. Egocentric network and activity interdependence: homophily theory vs. peer influence mechanism

Social media make people more connected and therefore increase interdependence among users. If self-time can be influenced by interaction time, and interaction time depends on one's social network configuration, is it possible that the overall social media activity pattern of an individual user could become similar to his or her friends in the network? Lewis and Weigert (1981) hypothesized that interdependence among actors is positively correlated with the need for temporal synchronization. About ten years ago, researchers discovered a special clustering effect on Facebook (Golder et al., 2007): College students tend to group together in terms of their messaging temporal patterns. More specifically, students from the same school displayed similar temporal patterns of Facebook use.

Such a clustering effect could be accounted for by at least two broad theoretical frameworks. First, peer influence could be one possibility. Although peer influence theory is mostly closely associated with the spread of risk behaviors among adolescence (Brechwald & Prinstein, 2011), it has connections to the current study to a certain degree. Peer influence is a socialization process. Students from the same friendship network are more likely to follow a similar temporal pattern due to mutual influence. Social media is used for social interaction by most individuals and social interaction demands synchronization among individual participants. Conformity to the majority time schedule can help individuals acquire higher chances of social interaction.

Second, the homophily theory (Monge & Contractor, 2003) offers an equally possible mechanism. While the peer influence mechanism seems to be reasonable and sound, we shall not ignore the alternative explanation that people with a similar social media activity pattern tend to choose to be friend with each other in the first place. In the previous example, students with a similar social economic background and daily activity pattern join the same school (i.e., homophily). Simply put, "similarity breeds connections" (McPherson, Smith-Lovin, & Cook, 2001, p. 415). Monge and Contractor (2003) provided two reasons for homophily. On the one hand, people who are similar tend to be attracted to each other. On the other hand, individuals tend to self-categorize themselves by different traits and features.

Unfortunately, based on the empirical evidence from Golder et al.'s (2007) study, we do not know whether communication-related factors cause the effect or the effect is simply a result of network homophily. Twitter provides an excellent if not ideal context to test the communication effect hypothesis. Unlike Facebook, Twitter is a directional network. Therefore, Twitter users receive their followees' feeds constantly but do not receive feeds from their followers. If Twitter users intend to interact with their friends, they would probably follow similar activity rhythms as their followees. If people with a similar lifestyle tend to group together, then the temporal patterns of the followers and followees should be the same. The reason is that if homophily is the dominant governing rule on Twitter, then followers and followees abide by the same principle. In addition, followees and followers are less likely to come from the same institution and are less likely to be constrained by the same organization time. To put differently, if an individual is more similar to his or her followees than to his or her followers, the peer influence mechanism seems to be more likely to account for such a relationship (see Fig. 1).

Furthermore, given that users receive messages constantly from their followees, if the activity patterns of the users' followees are different from the users' (i.e., follow the heterogeneity principle), then users may need to communicate with their followees by accommodating to different time frames. If this is the case, then the daily cycle of these users will be interrupted by their friends' schedules, leading to temporal fragmentation.

Temporal fragmentation is a process in which a certain activity is divided into several smaller parts, which are performed at different times (Alexander, Hubers, Schwanen, Dijst, & Ettema, 2011; Couclelis, 2003; Hubers, Schwanen, & Dijst, 2008). In other words, interruption is a mechanism capable of explaining temporal fragmentation. If followees have different activity rhythms from the ego user, then the aggregated daily cycle will be very fragmented for a particular user because the ego's daily rhythm will be interrupted frequently by his or her followees.

Following the same logic, temporal fragmentation also depends on the level of homogeneity of one's followees' activity schedules. If a user has a large number of followees whose temporal activity patterns are very different, then this user will have more severe temporal fragmentation than someone whose followees share similar patterns. The reason is that the user will be interrupted by the followees with many different schedules of social media activity.

To elaborate with a simple example (see Fig. 2): imagine that you are most active on social media around 9 a.m., and your friends are active around 3–4 p.m. If you want to keep interacting with them, you probably have to spend time on social media both in the morning and in the afternoon. In contrast, everything else being equal, if you are most active around 2 p.m., then it would not be difficult to cater to your friends' schedule. In other words, being closer to your followees' schedule would lead to less fragmentation. However, if all your friends have different active time range (e.g., 7 a.m., 11 a.m., or 8 p.m.), then to cater to their schedule, you would have to spend your time on social media throughout the day, which, by definition, leads to fragmentation. In contrast, if all your friends have similar active time ranges, then you would need to be on social media for only one extra time range.

The reasoning mentioned in the previous paragraph could even work in combination, leading to an additive effect on social media users. When a user has a heterogeneous followee network in which everyone is active at different time points throughout a day, then the divergence between a user's active time point and his or her

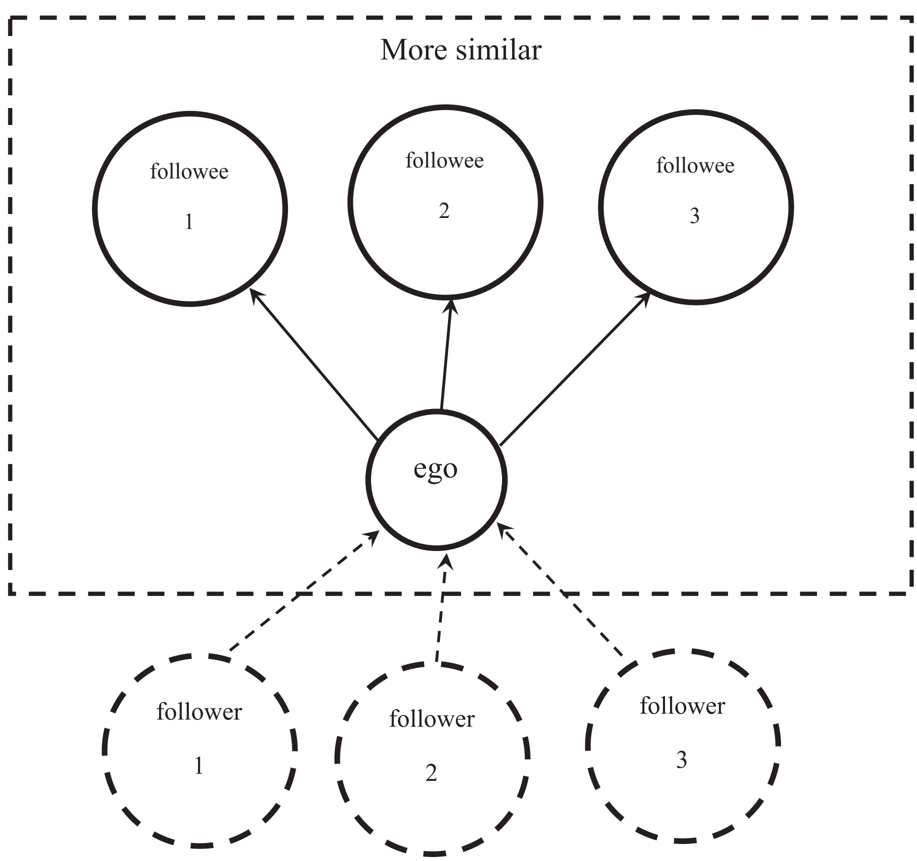

Fig. 1. Social media users' activity rhythm more similar to their followees' than to their followers' (Hypothesis 1).

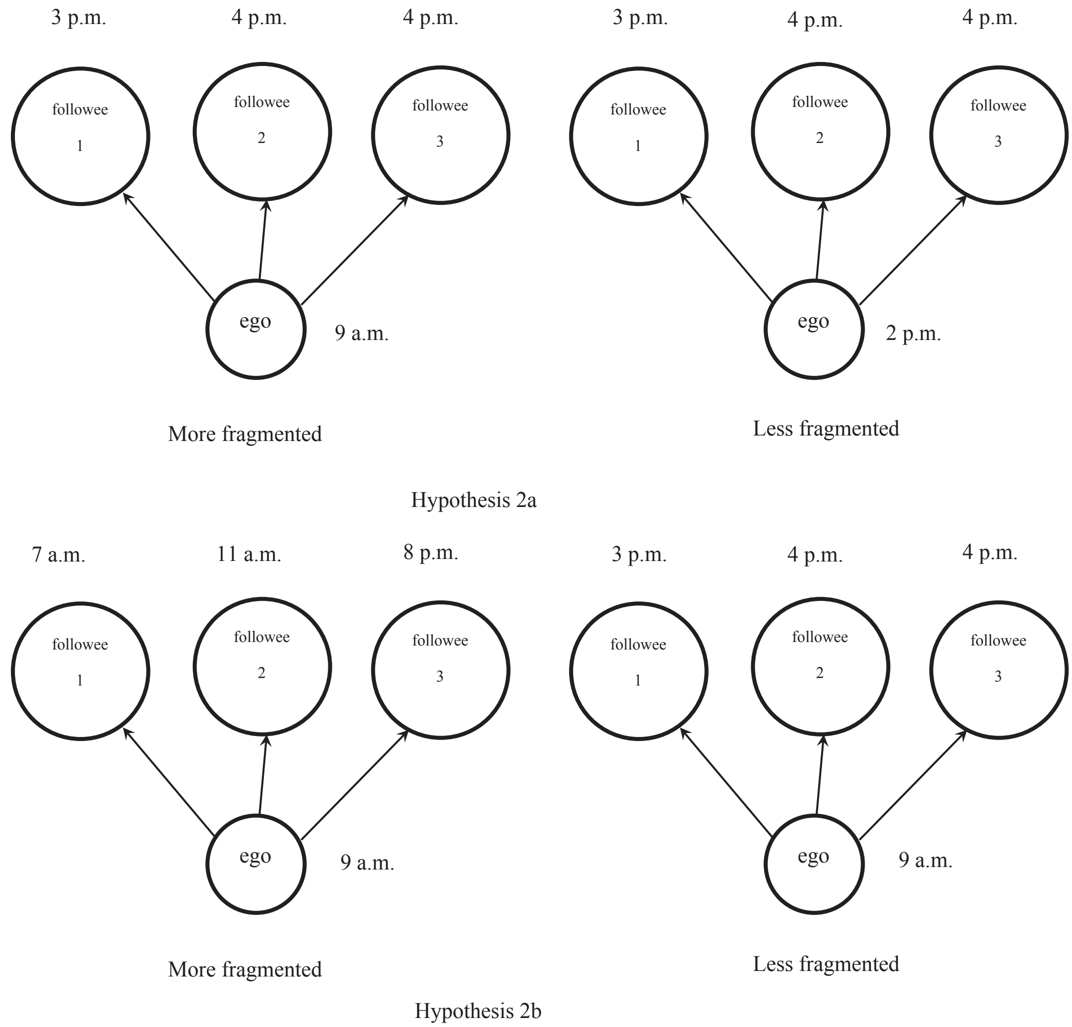

Fig. 2. Social media users' activity rhythm interrupted by their followees' schedule (Hypothesis 2).

followees' averaged active time point does not matter that much because he or she needs to spread his or her time on social media throughout the day anyway. In other words, the impact of the ego–followee divergence will be smaller when the followee–followee divergence is large. Nevertheless, when a user has a homogenous followee network, the ego–followee divergence becomes important and the divergence determines how big a change one has to make.

2.4. Research questions and hypotheses

The discussions in the previous sections lead us to a number of research questions and hypotheses. Broadly speaking, this study investigates three sets of questions. First, we are interested in whether the diurnal circle still exist in terms of Twitter use and whether individual users differ in terms of their usage pattern. Second, since self-time and social time are conceptually distinct, we plan to explore the difference between self-posting behavior and interaction behavior on Twitter. Third and most importantly, the study examines if networked friends on Twitter have similar daily activity rhythms and explore the possible theoretical mechanisms behind. The formal research questions and hypotheses could be put as follows:

RQ1a: Does the daily round still exist on Twitter in terms of user behavior?
RQ1b: How do individuals differ in terms of their digital activity patterns on Twitter?
RQ2: Is there any difference between self-posting and interaction behavior on Twitter in terms of activity rhythm?
H1: Twitter users' daily activity rhythm is more similar to their followees' averaged rhythm than to their followers'.
H2a: Temporal fragmentation is positively associated with the level of the ego–followee (i.e., user–followee) activity pattern divergence.
H2b: Temporal fragmentation is positively related to followee–followee temporal activity pattern divergence.
RQ3: Do levels of ego–followee activity divergence and levels of followee–followee activity divergence have an interaction effect on users' levels of temporal fragmentation?

3. Method

3.1. Data collection

The data were collected using Twitter's representational state transfer (REST) application programming interfaces (APIs). In order to make the data representative of the general Twitter population, we adopted a random sampling method tailored for collecting

Twitter data. First, we employed the method used by Liang and Fu (2015) to generate a list of random Twitter user IDs. Each Twitter account has a unique numeric ID. A list of random Twitter IDs constitutes a random sample of Twitter users. Using this method, we obtained 17,165 valid user accounts with at least one post in March 2015. For ease of reference, we label these users *egos*.

Second, we obtained the egos' user profile information, their tweets and retweets (up to 3200 pieces), and a list of their followees' IDs. Due to Twitter's privacy-setting restrictions, we obtained tweets only from public accounts ($N = 17{,}151$). To exclude potential spammers and robots, we included only users with fewer than 5000 followers [0, 5000] and fewer than 2000 followees [0, 2000] ($N = 10{,}873$). Finally, because the present study focuses on examining daily activity rhythms of ordinary users, only users with reasonable levels of activity were included. After excluding users with fewer than 10 posts, a total of 5066 users were left for analysis. The average account age for the 5066 users is around 3 years.

Third, we further collected the 5066 users' followees' and followers' data and their tweets (up to 3200 pieces). For ease of reference, followees and followers were labeled *alters*. Following the same procedures mentioned above, followees whose network relationships were set to private were excluded from analysis and followers whose network relationships were set to private were excluded from analysis. In the end, we were able to collect data of 424,984 unique alters for the 5066 users. More specifically, three types of data were included: user profile information (e.g., number of friends, number of followers, UTC offset), timelines (e.g., text content and time stamps), and network relationships (i.e., followers and followees). The users included in our sample were registered between 2006 and 2014. The tweets were posted between April 2006 and March 2015. The average time duration for the tweets in our sample is 547 days ($Mdn = 390$). More than 75% individuals have a tweeting duration longer than 3 months.

3.2. Measures

Daily digital rhythm. An individual's *daily digital rhythm* was measured by percentages of aggregated activities over 24 h of a day in his or her timeline. First, the hours were extracted from the posting time stamps returned by the Twitter API. We coded time at the level of hours. For instance, "2015-03-24 22:56:54" will be coded as 22. The time stamps were based on Coordinated Universal Time (UTC) standard time. We used UTC directly because the current study primarily focuses on the similarities and differences of the daily patterns for each individual user. For cross-individual analysis, standard time was adjusted to the user's local time according to the time difference information (i.e., UTC offset) provided by Twitter API. The time difference field was only available for accounts that explicitly disclose their geolocations. Second, we counted the number of tweets and retweets by the hour of day for each individual. Third, the aggregated numbers were divided by the total number of tweets and retweets from each individual. With these statistics, daily activity rhythm measure could be represented as a curve expressed by a series of percentage numbers over the hours of a day. The integral of the curve function is, by definition, 1 because the percentages add up to 100%.

Self-activity rhythm and interaction rhythm. Using the exact same operationalization for daily digital rhythm, *self-activity rhythm* counts only self-initiated tweeting behavior (excluding retweeting, mentions, and replies). In contrast, *interaction rhythm* counts only interaction tweeting behaviors (i.e., retweeting, mentions, and replies). The study calculated self- and interaction rhythms for each individual who had both self- and interaction activity. Following the same procedure, we counted the number of activities by the hours of day and then calculated the percentages. As a result, for each ego user, there are two curves indicating the self- and interaction rhythms respectively.

In addition, we quantified each ego's followers and followees' daily rhythms through counting the number of tweets by the hour of day. As the main focus of the study was the influence of alters on egos, self- and interaction rhythms for alters were not differentiated.

Daily activity rhythm divergence. Activity rhythm divergence refers to the difference between two activity rhythms. As activity rhythm was defined above as a bounded distribution (0–1) featuring the percentage of time devoted to each hour of a day, there was no straightforward solution to quantify the difference between two activity rhythm measures. The Jensen-Shannon divergence (JSD) provided a feasible solution to the problem (see Aledavood, Lopez, et al., 2015). The JSD for two probability discrete distributions (in our case, Twitter activity rhythms) P_1 and P_2 is given by the formula: $JSD(P_1, P_2) = H\left(\frac{P_1}{2} + \frac{P_2}{2}\right) - \frac{1}{2}[H(P_1) - H(P_2)]$, where P_1 and P_2 are the percentages of activities over 24 h, and H denotes Shannon entropy function ($H(P) = -\sum_{j=1}^{24} p_j \times \log(p_j)$). In the current study, the maximum value of the JSD is 0.6931 theoretically. Therefore, we created a standard index by dividing the JSD measure by the theoretical maximum JSD value. The standardized index ranged from 0 (being very similar to each other) to 1 (being very different from each other).

Applying the procedure outlined above, we derived a series of divergence measures. The descriptive statistics of these measures will be reported in the results section. First, the *self-interaction JSD* refers to the difference between self-activity and interaction activity rhythms. For this measure, P_1 is the self-activity rhythm, and P_2 is the interaction rhythm measured above. Conceptually, it means the extent to which an individual's self-posting behavior differed from his or her Twitter interaction activity in terms of time.

Second, the *ego–follower JSD* refers to the divergence between an ego and his or her followers' daily activity patterns. In this measure, P_1 is the time distribution of the ego's Twitter activity, and P_2 is the time distribution of the ego's followers' aggregated Twitter activity.

Third, the *ego–followee JSD* refers to the divergence between the ego and his or her followees' daily activity patterns. In this measure, P_1 is the time distribution of the ego's Twitter activity, and P_2 is the time distribution of the ego's followees' aggregated Twitter activity.

Finally, the *followee–followee JSD* refers to the divergence between all followees' daily activity patterns for a particular ego user. The derivation of this measure was a bit more complicated than the previous three because for different individual egos, their numbers of followees vary. Therefore, every ego could have many followee–followee JSD measures. For instance, an individual ego with three followees has three followee–followee JSD measures; an individual ego with n followees has C_n^2 followee–followee JSD measures. The final followee–followee JSD measure was obtained by taking the average of the followee–followee JSD measures for each individual ego. Conceptually, this measure quantifies the degree to which the accounts followed by a particular ego had different activity patterns.

Temporal fragmentation. *Temporal fragmentation* of daily activity rhythm, according to Hubers et al. (2008), was measured with the Shannon entropy ($H(P) = -\sum_{j=1}^{24} p_j \times \log(p_j)$) formula where p indicates an individual's probability of using Twitter in a particular hour in a day. The value ranged from 0 to 1. A high entropy score indicates high uncertainty, for instance, equal spreading of the social media activities over 24 h in a day. A low entropy score indicates low uncertainty, for instance, a user always use social media between 7 p.m. and 8 p.m. on a daily basis. To translate uncertainty to time distribution, high entropy and high uncertainty mean high fragmentation.

Covariates. Several covariates were included in the study as control variables. First, *level of activeness* was measured by the number of tweets and retweets posted by an ego user per year. On average, an ego user posted about 708 ($SD = 3{,}622$, $Mdn = 63$) tweets every year. Second, level of *interaction activeness* is the percentage of interaction activities (retweeting, mentions, and replies) out of all Twitter activities. The mean of this measure was 0.51 ($SD = 0.31$). These two measures quantified how actively an individual used Twitter and how actively an individual interacted with others on Twitter. Finally, number of followers ($M = 53$, $SD = 152$, $Mdn = 19$) and followees ($M = 68$, $SD = 54$, $Mdn = 54$) were directly collected from Twitter's users API.

4. Results

4.1. RQ1: Twitter use daily activity rhythms

Fig. 3 presents the aggregate pattern of daily tweeting behavior. Twitter users come from different regions across the globe in different time zones. The figure summarizes the daily activity cycle of the users who provided accurate time zone information only. Among the 5066 sampled users, only 1828 reported their time zones. We adjusted the UTC time to local time for all users. As shown in Fig. 3, self and interaction activities followed a similar circadian rhythm: People started to increase their activity in the morning, and the activity level peaked around 8 p.m. The relatively narrow 95% confidence intervals (shaded areas) suggest the homogeneity of the pattern across individuals.

The data suggest individuals exhibited different daily rhythm clusters despite the dominance of the circadian cycle. We conducted a k means cluster analysis based on the activity frequency over 24 h of a day. Fig. 4 presents the patterns of the four types of users: morning active, noon active, evening active, and night active. The percentages of the four types of users were pretty evenly distributed. Most users were evening (36.8%) and night active (27.4%), followed by noon active (22.3%) and morning active (13.5%).

4.2. RQ2: self- and interaction-rhythm divergence

Based on the results shown in Fig. 3, self and interaction activities followed a very similar pattern. However, a more careful examination of Fig. 3 suggests discernable discrepancies between the two curves. Looking at the margin between interaction activity (the solid line) and self-activity (the dashed line), Twitter users are more likely to interact with others than to self-post in the early morning (4 a.m.) and in the evening (8–9 p.m.).

However, we do not know whether this difference is statistically significant. In order to formally test the difference against the null hypothesis, we used the JSD to quantify the difference between the two distribution curves. As a few users did not have both curves, the analysis was conducted based on the 5066 users who had data on both curves ($n = 4590$).

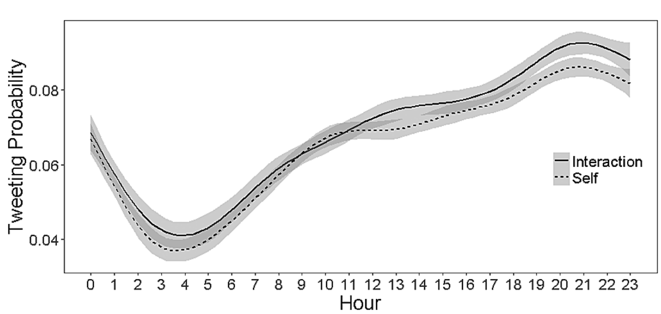

Fig. 3. The daily rhythms of self and interaction activities on Twitter. The shaded areas indicate the 95% confidence intervals ($n = 1828$ ego users – for those who revealed their geolocation data).

The mean of the normalized JSD was 0.38 ($SD = 0.28$, $Mdn = 0.34$). The distribution was skewed toward the left. Permutation method was employed to test the statistical significance of the JSD for each ego user. First, the null hypothesis was that self and interaction activities are randomly spread across 24 h of a day. Second, we randomly shuffled P_1 or P_2 and then calculated a new (random) JSD. Third, we repeated the procedure 100 times and counted how many times the new random JSD is larger than the empirical JSD. Therefore, for each JSD, we had a percentage to indicate the proportion of the random JSDs that are larger than the empirical JSD (i.e., p value). For example, a 95% p value means that 95% of the random JSDs are larger than the empirical JSD. Therefore, the empirical JSD is significantly smaller than the JSD based on a random process. The results of our data indicate that most empirical JSDs were smaller than the random cases (60% of the p values were larger than 95%), whereas a small proportion of the divergences were larger than the random cases (4% of the p values were smaller than 5%). It means that self and interaction activities are similar (60%) or without difference (36%) for most individuals. This is not surprising because both activities are highly structured around the daily pattern and thus exhibited little difference.

If we control for the common daily rhythm, how different are they? In order to answer this question, the two curves were treated as time-series and then detrended (i.e., by taking the first-order difference for each P: $P_{t+1} - P_t$). We then performed a permutation analysis for the detrended activity rhythms. The results indicate that a few JSDs were smaller than the JSDs generated by a random process (17% of the p values were larger than 95%), and a small proportion of JSDs were larger than the JSDs generated by a random process (6% of the p values were smaller than 5%). The distribution of the p values follows a binomial distribution where the most frequent values were either very close to 0 or 1. In other words, the results suggest that for most individuals their self-interaction divergences were not significantly larger than those produced by a random process.

Given JSD is a number ranging from 0 to 1, beta regression was performed to predict the divergence between self-posting activity and interaction activity (self-interaction divergence). The model assumes that the dependent variable is beta-distributed (instead of Gaussian-distributed) and that its mean could be predicted by a linear combination of independent variables (Ferrari & Cribari-Neto, 2004). The model is naturally heteroskedastic and easily accommodates asymmetries. Table 1 presents the findings. The results suggest that Twitter activity and the proportion of interaction activity could predict the divergence very well (the overall model fit was above 69%). The results indicate that the self-interaction divergence was larger for inactive users than for active users. Users with balanced self-posting and interaction (50% self-posting and 50% interaction) were most likely to integrate their two activity time frames into a single time frame (see Fig. 5). Their self-posting activity curve is not so much different from their interaction activity curve.

Another approach to testing the self-interaction activity divergence is to divide self and interaction activity into two segments (i.e., pre- and post-with equal number of tweets) and to compare the divergence between pre- and post-self activities (AB) and the divergence between pre-self and post-interaction activities (AD). The paired Wilcoxon signed-rank test suggests that AB was significantly smaller than AD ($df = 1{,}707$, $p < .01$). Similarly, CD (the divergence between pre- and post-interaction) was smaller than CB (the divergence between pre-interaction and post-self; $df = 1{,}716$,

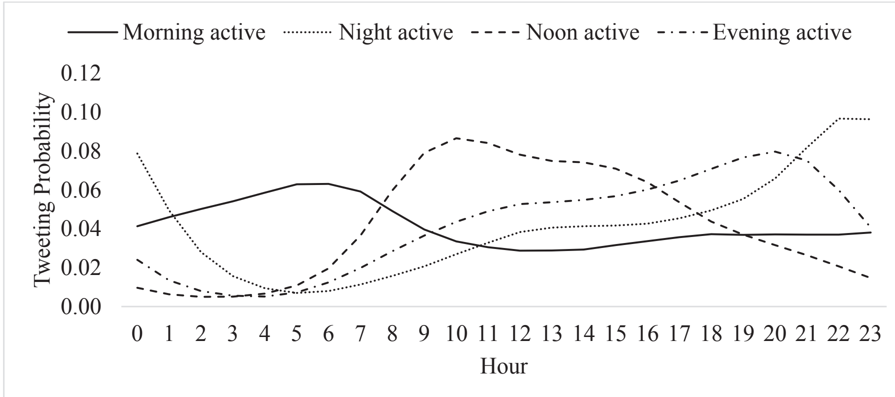

Fig. 4. The centroids of the *k* means cluster analysis of the daily rhythms ($n = 1828$ ego users – for those who revealed their geolocation data). The percentages of the four types of users (morning active, night active, noon active, and evening active) are 13.5% (247), 27.4% (500), 22.3% (408), and 36.8% (673), respectively.

Table 1
Beta regression model to predict self-interaction Jensen-Shannon divergence.

	Estimate	Standard error (*SE*)	*Z* value
log (Activity frequency)	−0.50	0.01	−55.94**
Percentage of interaction activity	−6.81	0.16	−41.81**
Percentage of interaction activity (squared)	6.55	0.06	42.05**
log(Followers count)	−0.02	0.01	−1.93
log (Followees count)	−0.00	0.01	−0.12
Intercept	−0.78	0.06	−12.36**
ϕ	7.48	0.16	48.2**
Pseudo R^2	69.2%		
Log-likelihood (*df*)	2842 (7)		
N	4409		

Note. Some variables were log-transformed due to the highly skewed distribution, and ϕ is the precision parameter of the beta distribution.
$^{*}p < .05$. $^{**}p < .01$.

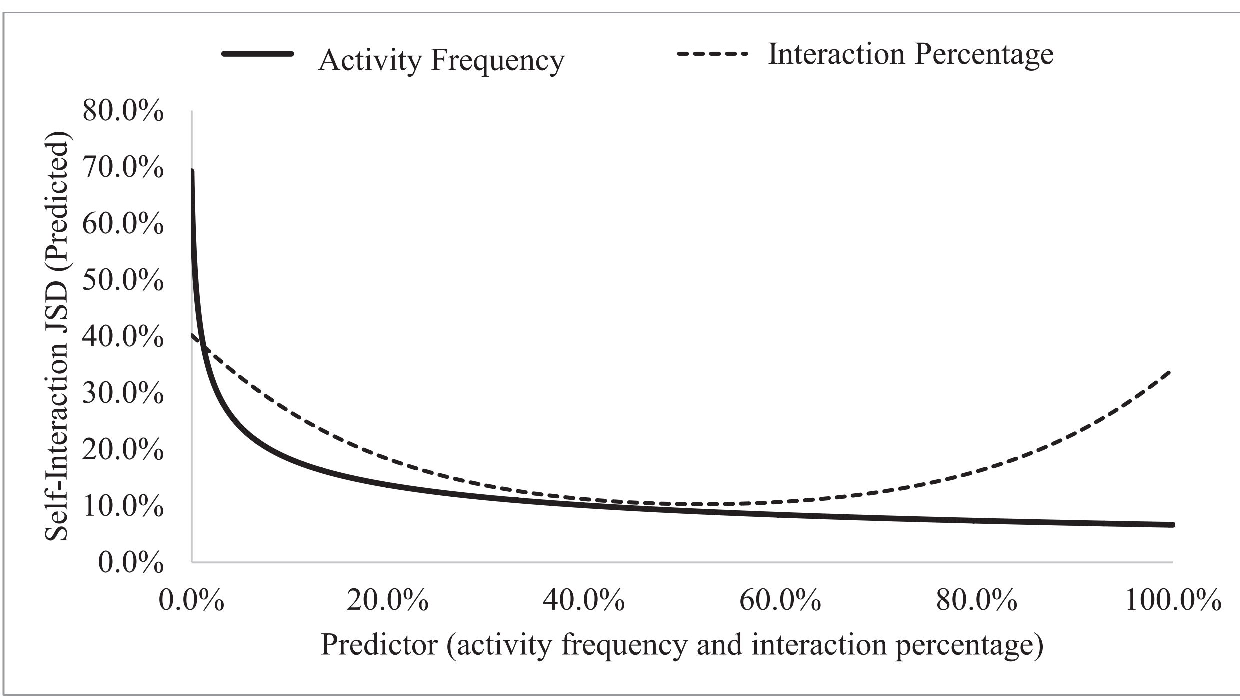

Fig. 5. Predicting the self-interaction Jensen-Shannon divergence (JSD) using communication activity and interaction probability. The figure is based on the beta regression model in Table 1.

$p < .01$). In sum, the average difference between pre- and post-activity rhythms within an individual is smaller than the average difference between self-activity rhythm and interaction-activity rhythm.

4.3. H1: social network and activity interdependence

The major question of this study is whether user activities can be influenced by others in a network. To answer this question, the current study compared (a) the divergence between ego activity and followees' activity and (b) the divergence between ego activity and followers' activity.

As expected, the activity pattern divergence between ego and followees is smaller than the ego–follower divergence ($V = 2{,}452{,}500$, $p < .01$, $n = 3{,}986$, paired Wilcoxon signed-rank test). The data clearly indicated that users' tweeting behavior was more similar to their followees' than to their followers'. To take the analysis a step further, we divided followees into two categories: followees with whom the egos had interacted (i.e., mentioned) and followees with whom the egos had not interacted. According to the Wilcoxon test, the difference between the two activity divergence levels was not statistically significant ($V = 2{,}784{,}300$, $p = .169$). It seems followees had an impact on ego activity regardless of whether they had interacted with a particular ego or not.

4.4. H2: peer influence and temporal fragmentation

The ego–followees divergence can be considered a measure of the impact of followees' tweeting behavior on ego users' temporal pattern. However, we do not know whether the similarity is a consequence of homophily or peer influence. One method for answering this question is to test whether the impact from followees leads to fragmentation. This study formally measured temporal fragmentation using entropy. Table 2 presents the results of the beta regression predicting user temporal fragmentation. First, regarding H2a, the data (Model 1) suggested that the ego–followee JSD was negatively associated with temporal fragmentation ($B = -4.37$, $SE = 0.09$, $p < .01$). This result contradicts our prediction that the ego–followee divergence was positively related to temporal fragmentation. Therefore, H2a was not supported, and instead, we found a reverse pattern. Second, regarding H2b, the data showed that the followee–followee JSD was not statistically significantly related to temporal fragmentation. However, when the interaction term was added in the equation, a statistically significant positive relationship emerged ($B = 0.78$, $SE = 0.35$, $p < .05$). Therefore, H2b was supported. Finally, RQ3 explored whether there is an interaction effect between the two predictors in predicting temporal fragmentation. According to Model 2 in Table 1, the interaction term was statistically significant ($B = -2.04$, $SE = 0.84$, $p < .05$). Therefore, there was an interaction effect between the ego–followee divergence and the followee–followee divergence in determining temporal fragmentation.

Table 2
Beta regression models in predicting temporal fragmentation.

	Model 1	Model 2
	Estimate (*SE*)	Estimate (*SE*)
Ego–followee JSD (EF JSD)	-4.56^{**}(0.05)	-4.37^{**}(0.09)
Followee–followee JSD (FF JSD)	-0.02 (0.17)	0.78^{*}(0.35)
EF JSD × FF JSD		-2.04^{*}(0.84)
log (Activity frequency)	0.03^{**}(0.01)	0.03^{**}(0.01)
Percentage of interaction activity	-0.20^{*}(0.10)	-0.19 (0.10)
Percentage of interaction activity (squared)	-0.02 (0.10)	0.01 (0.10)
log (Followers count)	-0.04^{**}(0.01)	-0.03^{**}(0.01)
log (Followees count)	-0.01 (0.01)	-0.01 (0.01)
Intercept	2.68^{**}(0.05)	2.61^{**}(0.05)
ϕ	32.12^{**}(0.73)	32.18^{**}(0.73)
Pseudo R^2	70.7%	70.7%
Log-likelihood (*df*)	5158 (9)	5162 (10)
N	3, 986	

Note. JSD = Jensen-Shannon divergence. Some variables were log-transformed due to the highly skewed distribution, and ϕ is the precision parameter of the beta distribution.

To be more specific, Fig. 6 presents a more detailed characterization of the relationship among the three variables. When the followee–followee divergence was low, the impact of the ego–followee divergence on temporal fragmentation was small. In contrast, when the followee–followee divergence was high, the impact of the ego–followee divergence on temporal fragmentation was large.

5. Discussion and conclusion

The current study examined the Twitter use to advance our understanding of the impact of online social networks on the temporal pattern of human activities. The main contribution of the current study lies in its focus on social media use's activity temporal pattern. We argued that the temporal organization of human behaviors is partly socially constructed and is determined by numerous factors other than the diurnal cycle. Peer influence incurred by social networks is one of these potential factors. Despite the fact that the possibility of homophily cannot be ignored, peer influence seems to be an equally likely explanatory mechanism.

5.1. Digital activity rhythms

As expected, the diurnal cycle still exists as a strong temporal pattern on Twitter. Although the pattern we identified (see Fig. 3) is slightly different from other existing findings (e.g., Golder et al., 2007), it is true that most users are less likely to tweet at midnight. But our data have shown that the diurnal cycle has individual variability because the current study measured temporal patterns at the individual level (see Fig. 4). Twitter users could roughly be clustered into four types of schedules.

In addition, the present study differentiated between self- and interaction times when measuring individual activities. According to the hierarchical structure of social time, users may exhibit different activity patterns at different levels of social hierarchies. Consistent with our expectation, we found that self- and interaction activities follow the daily cycle and thus have a strong similarity to each other. Nevertheless, there were statistically significant differences between the two curves. Users are more likely to interact with other users than to do self-posting during the early morning (4 a.m.) and in the evening (8–9 p.m.). In other words, people are more likely to be influenced by their followees during early morning and evening time.

Furthermore, as suggested in the regression model (Table 1), it is

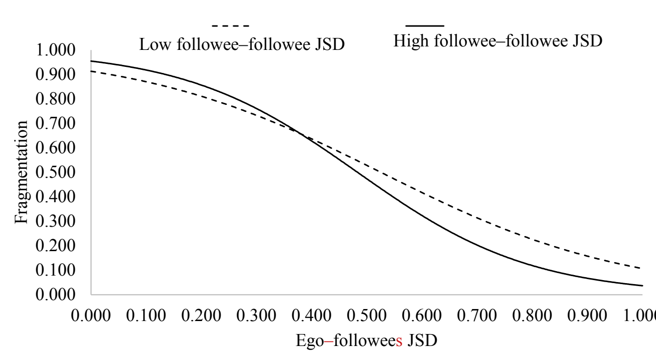

Fig. 6. Predicting temporal fragmentation using the ego–followees divergence and the followee–followee divergence (Beta regression). The figure is based on the beta regression in Table 2.

plausible that experienced users need to synchronize their different time schedules in order to cope with their social life online. For example, we found active users with balanced self-posting and interaction are more likely to integrate the two time frames into a single time frame. This is a salient effect of social media use on individual activity patterns.

5.2. Homophily v.s. peer influence

The most important part of this study examined the impact of online social networks on Twitter users' daily rhythms. Previous studies have documented evidence for the clustering effect of temporal patterns of social media use (Golder et al., 2007), but no studies have made an effort to sort out the mechanisms of such clustering effect. A major purpose of this study was to examine whether such clustering effect on social media is induced by peer influence mechanism or homophily mechanism.

We explicitly tested such clustering effect with connected friends on Twitter. We found that users are more similar to their followees than followers in terms of the daily rhythm. This evidence is in favor of the peer influence–based explanation rather than the homophily explanation, as individual users are constantly exposed to their followees' posting behaviors but not to their followers' posting behaviors (except for those who are both followees and followers). Assuming seeking social interaction is a primary motivation behind social media use, individual users who are exposed to their followees' updates will naturally like, comment on or retweet their followees' tweets. Consequently, the ego's activity pattern becomes more similar to his or her followees'.

Nevertheless, we would not say this piece of evidence is conclusive because it is also possible that for most Twitter users, their followees might be less diverse in terms of background than their followers. This is because we can choose our followees on Twitter but we usually do not decide who our followers are. To rule out such alternative explanation, we conducted an ad hoc test: a paired Wilcoxon signed-rank test on the follower–follower JSD and the followee–followee JSD. Interestingly, we found the temporal patterns of followees, on average, was actually more diverse than those of the users' followers ($V = 4{,}147{,}900$, $p = .01$, $n = 4583$). Therefore, it seems the peer influence mechanism is more plausible.

Besides, several additional pieces of evidence were found to support the peer influence mechanism. We found when the ego–followee divergence is large, users are more likely to have less severe temporal fragmentation; we also found that when the followee–followee divergence is large, users are more likely to have severe temporal fragmentation. It is important to acknowledge that we found the opposite pattern for the relationship between ego–followee divergence and temporal fragmentation. Though inconsistent with our original expectation, this result could be explained. When we proposed our hypothesis, we assumed that every user is forced to interact with his or her followees. This assumption is not necessarily true. As a matter of fact, the ego–followee divergence could take on the properties of a magnet: The attraction force is larger when two entities are close to each other, and the attraction force is negatively proportional to the divergence. To put it in perspective, when a user's activity schedule is close to another's, it is relatively easy to make an adjustment, whereas when a user's activity schedule is different from that of another user, the user will give up and try to interact with others through an asynchronous process. Followee-followee divergence might also suggest social heterogeneity or geographic dispersion, which can influence time fragmentation and even the ego-followee divergence. Additional analysis suggests that the ego-followee divergence is correlated with followee-followee divergence (spearman rho $= 0.15$, $p < .01$).

However, we acknowledge that the real world situation could be far more complicated. The interdependence among the users' activities can go beyond the immediate neighbors. According to Christakis and Fowler (2013), influence can extend to three degrees of separation on a social network. In the current context, an ego's daily rhythm may be interrupted by their friends, friends of friends, and friends of friends of friends. Distinguishing homophily from peer influence and modeling the higher-order dependence require panel data and whole network data (we used ego networks in the current study). These data are very difficult to collect even on social media platforms.

5.3. Implications

In general, we discovered the phenomenon "birds of a schedule flock together." What are the social and practical implications of these findings? We confirmed the social nature of human activity: People of different backgrounds tend to cluster together in terms of their social media activities. This finding has important implications for social media marketers. Social media use temporal patterns reflect users' lifestyles online. Identifying the right time to send out messages is essential for maximizing the impact of social media content. Otherwise, the right message can be sent to the right person at the wrong time with little effect. For example, Wang, Goh, Phan, and Cai (2013) found that online content is more likely to be shared by a user when the content is posted during the user's active time periods. For social media marketers, it is important to identify potential audience's typical activity schedule. To maximize communication effects, it also seems sensible to identify multiple opinion leaders of different activity patterns to spread the message.

Temporal patterns are also related to a number of different social and psychological concepts such as lifestyle (Michelson, 2016) and emotions (Dodds et al., 2011; Golder & Macy, 2011), etc. Thus clustering effect with respect to daily activity rhythms could confound with a lot of clustering effects in social sciences. For example, the spread of obesity, as argued byChristakis and Fowler (2007), could be caused by the clustering effect of daily rhythms: people with similar daily rhythms (lifestyles) may group together and influence each other. In other words, activity schedule matters. More future research on social media activity pattern needs to be done because researchers could use social media activity schedule to identify individuals of a particular feature.

5.4. Limitations

Despite our interesting findings, the current study has several limitations. First, not everyone labeled their geographic location information so that we could calculate their relative time to other individuals in the network. It is possible that people who tend to expose their geolocation information are different from those who care more about privacy and do not expose such information. Future studies can combine obtrusive and unobtrusive ways to improve data representativeness. Second, the study demonstrated the existence of the peer influence of temporal activity rhythms. However, the results did not exclusively rule out the possibility of homophily and estimate the relative effect sizes of both mechanisms. A plausible solution is to use the longitudinal network analysis design in future studies (see Snijders, van de Bunt, & Steglich, 2010). Third, the study investigated the temporal pattern on a single social media platform. Twitter could have very different features from other types of social media platforms, such as Facebook and Instagram. Future studies can extend the framework to incorporate more online platforms and offline activities. Finally, there are different temporal patterns of human activities. The current study focused on daily patterns. Future studies can examine other aspects of social time on social media, such as weekly and yearly patterns.

References

Aledavood, T., Lehmann, S., & Saramaki, J. (2015). Digital daily cycles of individuals. *Frontiers in Physics, 3*. https://doi.org/10.3389/fphy.2015.00073.

Aledavood, T., Lopez, E., Roberts, S. G. B., Reed-Tsochas, F., Moro, E., Dunbar, R. I. M., et al. (2015). Daily rhythms in mobile telephone communication. *Plos One, 10*(9). https://doi.org/10.1371/journal.pone.0138098.

Alexander, B., Hubers, C., Schwanen, T., Dijst, M., & Ettema, D. (2011). Anything, anywhere, anytime? Developing indicators to assess the spatial and temporal fragmentation of activities. *Environment and Planning B-Planning & Design, 38*(4), 678–705. https://doi.org/10.1068/b35132.

Brechwald, W. A., & Prinstein, M. J. (2011). Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence, 21*(1), 166–179.

Castells, M. (1996). *The rise of network society*. Oxford: Blackwell.

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine, 357*(4), 370–379. https://doi.org/10.1056/NEJMsa066082.

Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: Examining dynamic social networks and human behavior. *Statistics in Medicine, 32*(4), 556–577. https://doi.org/10.1002/sim.5408.

Couclelis, H. (2000). *From sustainable transportation to sustainable accessibility: Can we avoid a new tragedy of the commons? Information, place, and cyberspace* (pp. 341–356). Springer.

Couclelis, H. (2003). Housing and the new geography of accessibility in the information age. *Open House International, 28*(4), 7–13.

Couclelis, H. (2004). Pizza over the internet: E-commerce, the fragmentation of activity and the tyranny of the region. *Entrepreneurship and Regional Development, 16*(1), 41–54. https://doi.org/10.1080/0898562042000205027.

Dodds, P. S., Harris, K. D., Kloumann, I. M., Bliss, C. A., & Danforth, C. M. (2011). Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter. *Plos One, 6*(12). https://doi.org/10.1371/journal.pone.0026752.

Failla, A., & Bagnara, S. (1992). Information technology, decision, time. *Social Science Information Sur Les Sciences Sociales, 31*(4), 669–681. https://doi.org/10.1177/053901892031004003.

Ferrari, S. L. P., & Cribari-Neto, F. (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics, 31*(7), 799–815. https://doi.org/10.1080/0266476042000214501.

Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science, 333*(6051), 1878–1881. https://doi.org/10.1126/science.1202775.

Golder, S. A., Wilkinson, D. M., & Huberman, B. A. (2007). Rhythms of social interaction: Messaging within a massive online network. *Communities and Technologies, 2007*, 41–66. https://doi.org/10.1007/978-1-84628-905-7_3.

Green, N. (2002). On the move: Technology, mobility, and the mediation of social time and space. *Information Society, 18*(4), 281–292. https://doi.org/10.1080/01972240290075129.

Hongladarom, S. (2002). The web of time and the dilemma of globalization. *Information Society, 18*(4), 241–249. https://doi.org/10.1080/01972240290075093.

Hubers, C., Schwanen, T., & Dijst, M. (2008). ICT and temporal fragmentation of Activities: An analytical framework and initial empirical findings. *Tijdschrift Voor Economische En Sociale Geografie, 99*(5), 528–546. https://doi.org/10.1111/j.1467-9663.2008.00490.x.

Lee, H., & Liebenau, J. (2000). Time and the Internet at the turn of the millennium. *Time & Society, 9*(1), 43–56. https://doi.org/10.1177/0961463x00009001003.

Lenz, B., & Nobis, C. (2007). The changing allocation of activities in space and time by the use of ICT - "Fragmentation" as a new concept and empirical results. *Transportation Research Part a-Policy and Practice, 41*(2), 190–204. https://doi.org/10.1016/j.tra.2006.03.004.

Lewis, J. D., & Weigert, A. J. (1981). The structures and meanings of social time. *Social Forces, 60*(2), 432–462. https://doi.org/10.2307/2578444.

Liang, H., & Fu, K. W. (2015). Testing propositions derived from Twitter studies: Generalization and replication in computational social science. *Plos One*. https://doi.org/10.1371/journal.pone.0134270.

Ling, R. (2004). *The mobile connection: The cell phone's impact on society*. Morgan Kaufmann.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*, 415–444.

Michelson, W. H. (2016). *Time use: Expanding explanation in the social sciences*. New York: Routledge.

Monge, P. R., & Contractor, N. (2003). *Theories of communication networks*. Oxford: Oxford University Press.

Sawhney, H. (2004). The slide towards decentralization: Clock and computer. *Media Culture & Society, 26*(3), 359. https://doi.org/10.1177/0163443704042257.

Snijders, T. A. B., van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks, 32*(1), 44–60. https://doi.org/10.1016/j.socnet.2009.02.004.

ten Thij, M., Bhulai, S., & Kampstra, P. (2014). Circadian patterns in twitter. *Data Analytics*, 12–17.

Wang, Q., Goh, K.-Y., Phan, T., & Cai, S. (2013). Examining the timing effect of information diffusion on social media platforms: A temporal network approach. In *Paper presented at the ECIS 2013 research in progress*.

Yasseri, T., Sumi, R., & Kertesz, J. (2012). Circadian patterns of Wikipedia editorial activity: A demographic analysis. *Plos One, 7*(1), e30091. https://doi.org/10.1371/journal.pone.0030091.

Zerubavel, E. (1982). The standardization of time: A sociohistorical perspective. *American Journal of Sociology, 88*(1), 1–23. https://doi.org/10.1086/227631.