Transition between distribution patterns in human dynamics with high activity

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Complex interactions among a large number of individuals lead to multiple patterns of collective human behavior. However, the theoretical prediction of pattern transitions has not been empirically confirmed. This is because in previous empirical studies, different patterns were observed in different systems, and the coexistence of multiple patterns in the same system was rarely found. By investigating nearly 10 million messages in 252 QQ groups, we find rich distribution patterns of interevent time for human collective behavior, including the transitions between bimodal distribution, double-power-law distribution, and single-power-law distribution. The model developed in this paper suggests that human physiological rhythms and the high collective activity play key roles in the presentation of the single-power-law distribution. These results enhance the empirical research in the field of human dynamics, and are helpful for understanding many complex socioeconomic phenomena.

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I. INTRODUCTION

The human activity pattern is very complex. People do some routine things from time to time, such as writing letters, shopping, exercising, playing games, watching movies, traveling, using social media, etc. Some activities are regular, such as exercise, while others are irregular, such as writing letters, online messaging, etc. For the irregular cases, there are many uncertain factors that affect the occurrence time of the activity. Therefore, it is assumed in the past that the time intervals of these events follow a homogeneous distribution [1,2], but Barabási revealed that the interevent time distribution of people doing the same things is heavytailed [3], the root of which can be illustrated by the time sequence of the events: people are extremely active for a period of time, silent, active again after a period of time, silent again, and so forth. Overall, the activity and silence occur alternately. This study triggered a new enthusiasm for the study of human activities, and has gained a lot in revealing the statistical patterns of human behavior and uncovering the underlying mechanisms [4–13].

To further explain the heavy-tailed phenomenon in the distribution of human behavioral intervals, scientists investigated the complex decision-making processes, and a number of models have been developed. On the individual side, including task queuing theoretical models driven by individual decisions [3,14–17], memory-based models of human activities [18–21], theoretical models based on physiological and work rhythms [22–24], and models based on interest [25–29]. On the external environment side, models considering the impact of deadlines on tasks [30,31] are proposed. On the interaction side, humans are a social animal and people will influence each other [32–40]. The simplest case is the two-body interaction [41,42]. Specifically, Wu *et al.* [42] found that the interevent time between two individuals sending message to each other follows a bimodal distribution, a piecewise distribution of power-law, and exponent. Moreover, multi-player interaction is much more complicated. In 2016, Zha *et al.* [43] analyzed the multiperson collaboration on updating Wikipedia articles and found that the interupdate time follows a double-power-law distribution. In addition, many other researchers have achieved important results on multiplayer interaction [37,44–49].

However, few studies have focused on the high collective activity due to the multiplayer interaction. Although Zha *et al.* theoretically predicted that with the activity increases, the interevent time distribution of human collective behavior will transit form double-power-law to single-power-law [43]. However, the present of the single-power-law, as well as the transition between different types of distribution, has not been observed empirically. Here, we study the human dynamics in QQ Groups with highly active communication. We analyze nearly 10 million messages in more than two hundred QQ groups and find that bimodal distribution, double-power-law distribution, and single-power-law distribution co-exist in the same system. More importantly, we observe the transition between the three types of distribution above. Moreover, our model shows that human physiological rhythms and the high collective activity are two important factors for the single-power-law distribution.

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TABLE I. The overview of data for 12 representative groups.

Interevent time distribution pattern	Subject of the group	Total number of messages	Number of members, m	Messaging frequency (/hour)
Bimodal distribution	Music	22 076	1128	5.5
	Board game	19 841	290	5.0
	Tourism	11 998	683	3.0
	Outdoor photography	16 580	637	4.1
Double-power-law distribution	Anime	174 070	973	48.7
	Auto music	119 385	1665	33.4
	Astronomical photography	138 281	483	38.7
	Pet	125 725	877	35.2
Single-power-law distribution	Make friends and party	665 921	2704	168
	Literature	689 064	4097	192
	Some video game	338 113	5409	252
	Game periphery	474 274	3566	396

II. DATA DESCRIPTION

Tencent QQ is one of the most widely used online social networks in China. QQ groups are a multiperson communication platform, similar to Facebook groups and WhatsApp groups. Each QQ group usually focuses on a specific subject, such as a hobby (sports, games, programming learning) or social affiliation (class, colleague, city). In a QQ group, members can send message as they like. Meanwhile, other members will receive the message, and they may send a response message.

The message sharing within QQ groups allows us to collect large-scale data. We collected 252 active representative QQ groups, including dormitory groups, students groups, friends groups, interests groups, and industry groups. In total, we recorded the sending time of 9 297 604 messages, with an accuracy of seconds. Of these, the data of 191 groups are collected from September 2, 2018 to January 28, 2019, and 61 groups from February 16, 2019 to August 2, 2019. The overview of data for 12 representative groups is listed in Table I.

III. EMPIRICAL DATA ANALYSIS

For each QQ group we collected, the interevent time τ, i.e., the time interval between two consecutive messages, is counted. Figures 1(b), 1(c), 1(e), and 1(f) show three types of interevent time distribution $P(\tau)$: bimodal distribution (power-law distribution in short interevent time, while exponential tail in long interevent time), double-power-law distribution (two power-law distributions with different power-law exponents), and single-power-law distribution. Of the 252 QQ groups we collected, 198 have a clear pattern of interevent time distribution, 36 representatives of which are presented in Sec. I of the Supplemental Material [50]. The K-S test of power-law distribution are discussed in Sec. II of the Supplemental Material [50]. These empirical results confirm previous theoretical predictions about collaborative human activities [43]: with high initiation rate, the interevent time will appear as single-power-law distribution pattern.

To further investigate the effect of activity level on the transition of distribution pattern, we studied the groups with significantly different frequencies in different periods. For the first time, we find the transitions between different types of distribution within the same system. Figure 1(a) shows the number of daily messages in a yoga group. Since people are

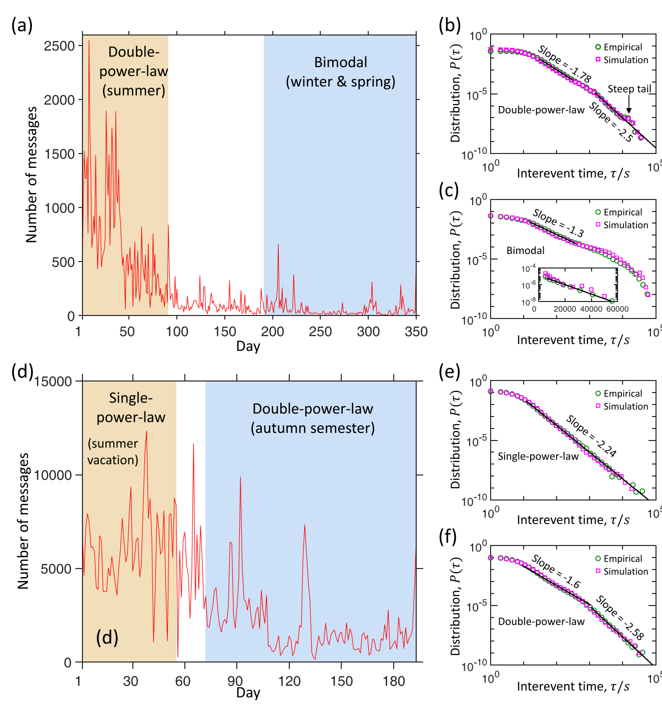

FIG. 1. The transition of the interevent time distribution patterns within the same group. (a) The transition from double power law to bimodal distribution of a yoga group. (b) Double-power-law distribution of the group in summer. (c) Bimodal distribution in winter and spring. Inset: exponential tail of $P(\tau)$ in single logarithmic coordinates. (d) The transition from single-power-law to double-power-law distribution of a video game group. (e) Single-power-law distribution in summer vacation. (f) Double-power-law distributions in autumn semester. In (b), (c), (e), and (f), the average number of daily initiating messages is $\Lambda = 380.42$, 22.48, 1262.35, and 379.56, respectively. The collective response probability is $Q = 0.9$. The number of members in the yoga group and the game group is $m = 1927$ and $m = 864$, respectively.

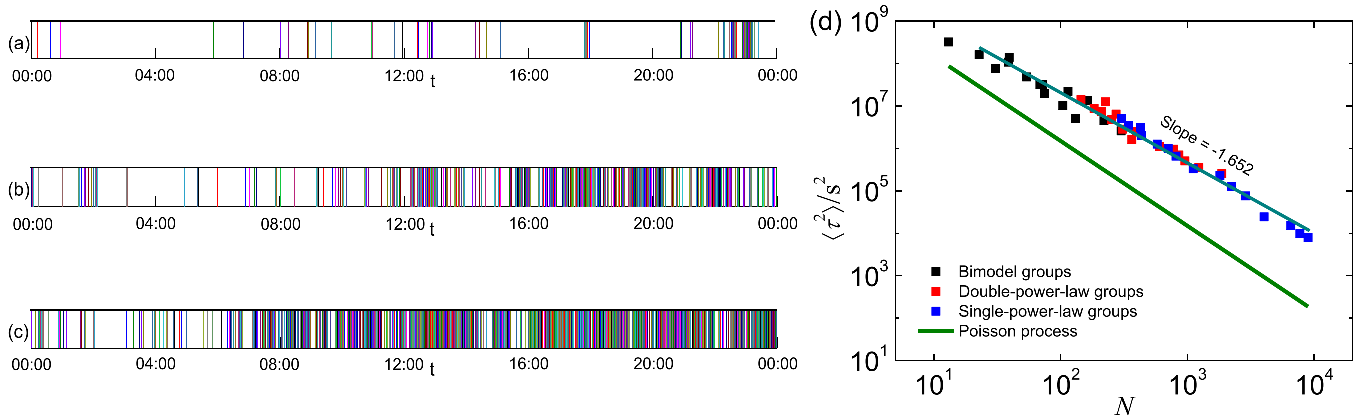

FIG. 2. The heterogeneity of the time series of message sending. [(a)–(c)] Succession of messages sent in three typical QQ groups in one day. Each vertical line represents one message. (a) Bimodal distribution group, (b) double-power-law distribution group, and (c) single-power-law distribution group. (d) The relation between the second moment $\langle \tau^2 \rangle$ and the average number of messages in one day N. Each point represents one QQ group. The green line represents the result of the Poisson process with exponential interevent time distribution.

more concerned about body shape in summer, therefore the group is highly active, and Fig. 1(b) exhibits a double-power-law distribution. While in winter and spring, the group is not so active, the distribution transits into bimodal distribution [see Fig. 1(c)]. Figure 1(d) shows the number of daily messages in a video game group. Since students have more free time over summer vacation, therefore the group is highly active and Fig. 1(e) exhibits a single-power-law distribution. While the weakened activity in autumn semester lead to the transition to double power law [see Fig. 1(f)].

Figure 2 shows the visualization of the time series of messages sending in three typical groups. With a few messages, bimodal groups exhibit a clear initiation-response pattern. Within each segment, messages were sent frequently, separated by long periods of silence [see Fig. 2(a)]. With more messages, the initiation-response pattern in double-power-law groups is blurry, and some initiations are inset into the response of the previous initiations [see Fig. 2(b)]. With the most messages, the initiation-response pattern in single-power-law groups is indistinguishable [see Fig. 2(c)].

Figure 2(d) shows that the interevent time distribution follows Taylor's law $\langle \tau^2 \rangle \propto \langle \tau \rangle^{1.652}$ [51], where $\langle \tau \rangle \propto N^{-1}$. This result indicates that the interevent time distribution is heavy tailed. Note that in a Poisson process, the interevent time distribution is exponential $P(\tau) = \beta e^{-\beta\tau}$. Therefore, $\langle \tau \rangle = \frac{1}{\beta}$, $\langle \tau^2 \rangle = \frac{2}{\beta^2}$, $\langle \tau \rangle N = 86\,400$, $\beta = N/86\,400$, and $\langle \tau^2 \rangle = 2 * 86\,400^2 * N^{-2}$; the slope is -2.

Figure 2 also shows that the messaging frequency is nonuniform in one day. In addition, the "steep tail" phenomenon [there is a hump in the tail of Fig. 1(b) at about seven hours] appears in all three distributions. Empirical data shows that the extremely long silences occur during sleep time, indicating that human circadian rhythm significantly affects the temporal distribution of messaging. The effect of circadian rhythm on human dynamics is also discussed in Ref. [52]. This result prompts us to study the changes in messaging frequency over time, both hourly and daily.

One can see from Fig. 3(a) that the hourly number of messages in the three groups is separated into three levels, with the bimodal group being the least active, the double-power-law group being more active, and the single-power-law group being the most active. Despite this, the distributions of message sending times are very similar [see Fig. 3(b)]. Specifically, the sending time of the three groups have three peaks at 11 am, 6 pm, and 11 pm, which are the most leisurely times of the day: the lunch time, the time to leave work, and the time before sleep. In addition, daily number of messages in a week also changes periodically [see Figs. 3(c), 3(d), and 3(e)]. The distribution of the daily number of messages in work or study groups is higher on weekdays, while that in entertainment groups such as games, novels, and yoga are higher on weekends. However, the phase difference does not affect the results of our model.

IV. MODEL

Inspired by our empirical analysis and the previous models in Refs. [42,43], we propose a multiinteracting priority-queues (MIPQ) model to study the high-activity collective human dynamics (see Fig. 4). See Sec. III of the Supplemental Material [50] for the detailed comparison between our MIPQ model and the previous models. Our model describes the message sending process specific to each member. Each member of a QQ group initiates a new topic at each time step t with initiation rate $\lambda(t)$. Each message (either initiation or response) may be responded to by any other member with probability q.

Specifically, in a QQ group with m members, each member owns a task queue with length $L (L = 100)$ and each task owns a priority x. A task queue consists of two types of tasks: interacting tasks (I) and noninteracting tasks (O). At each time step (corresponding to one second), each group member picks a task in its own queue with probability proportional to x^α, and executes the chosen task. If the executing task is type I, the member will send a message to the QQ group, which may be responded to by other members; otherwise, if it is type O, nothing will happen in the group. After the execution, the executed task in a queue is replaced by a new task, whose

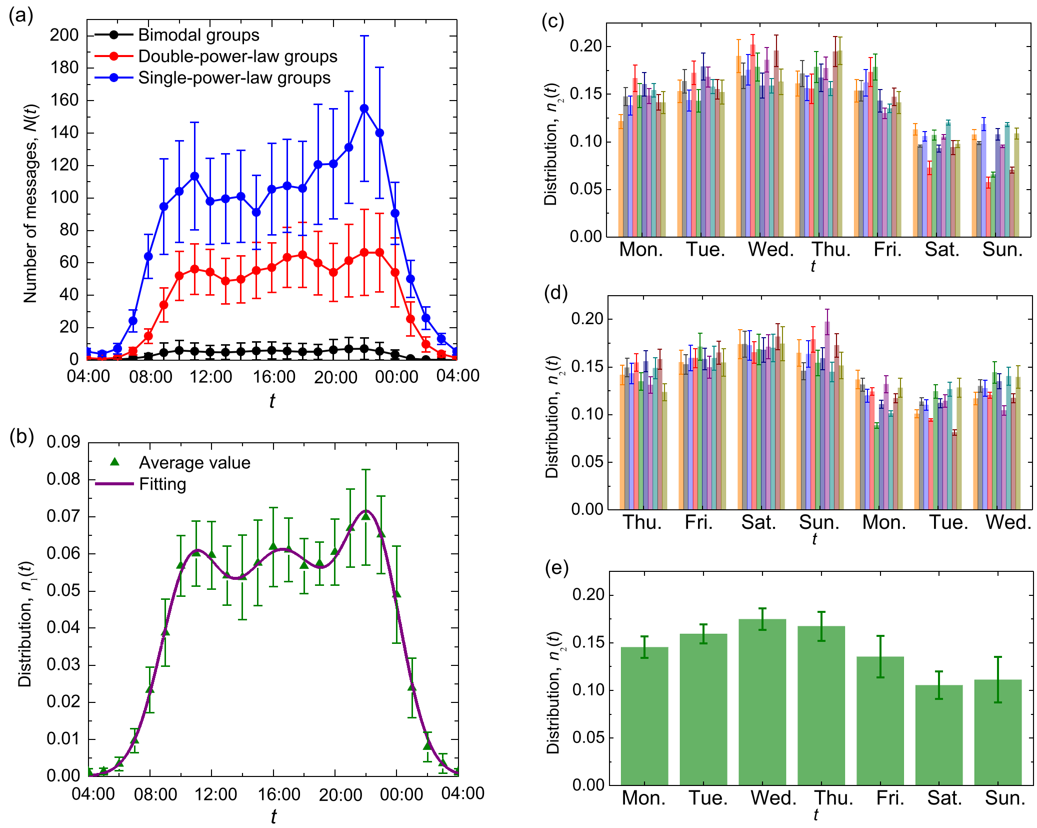

FIG. 3. Hourly and daily number of messages. (a) Hourly number of messages in groups with different types of distribution. Each dot represents the average number of messages in 13 typical groups within an hour. (b) The fitting distribution of the hourly number of messages. Each dot represents the average of distribution over the 39 groups in (a). (c) and (d) Distributions of daily number of messages in a week. Each color represents the distribution of one group. (c) Results of ten work or study groups. (d) Results of ten entertainment groups. (e) The average results of 20 groups in (c) and (d), but with a phase difference of three days. For example, the first column is the average of Monday in (c) and Thursday in (d). All error bars represent standard deviations.

priority x is randomly assigned from zero to one. The type of the new task is affected by the type of executing tasks of other members. Specifically, if each other member executes an O task, the probability that the new task is type I is $\lambda(t)$. Otherwise, if at least one other member executes a I task, the probability that the new task is type I is $\lambda(t) + q$.

Based on the empirical data, the parameters of message initiation rate $\lambda(t)$ and response probability q in the model

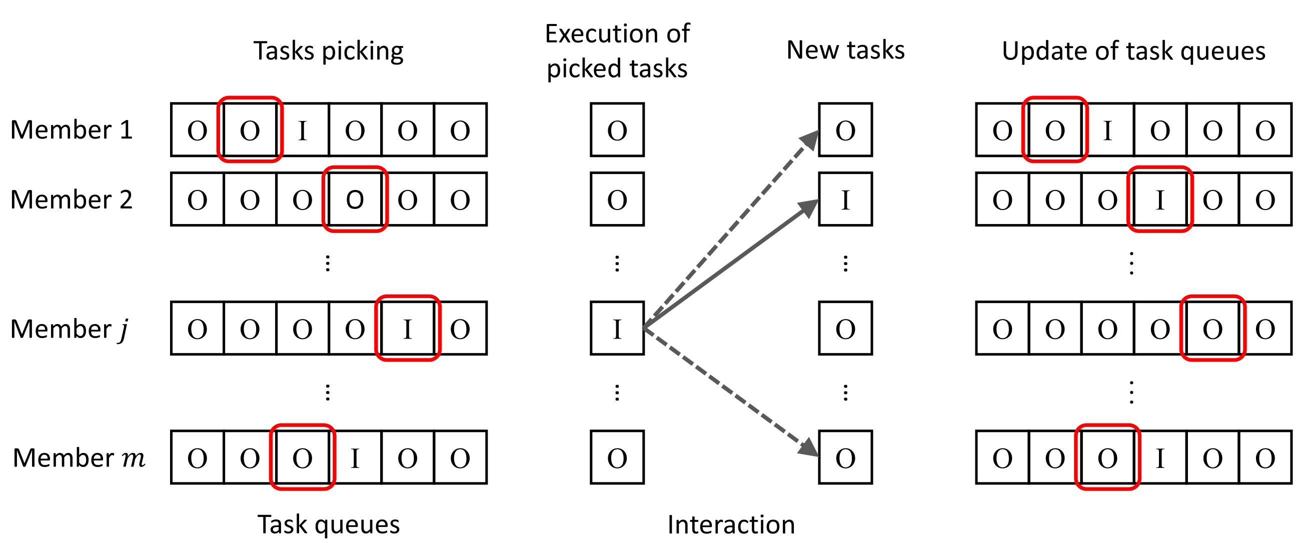

FIG. 4. Illustration of our multiinteracting priority-queues (MIPQ) model.

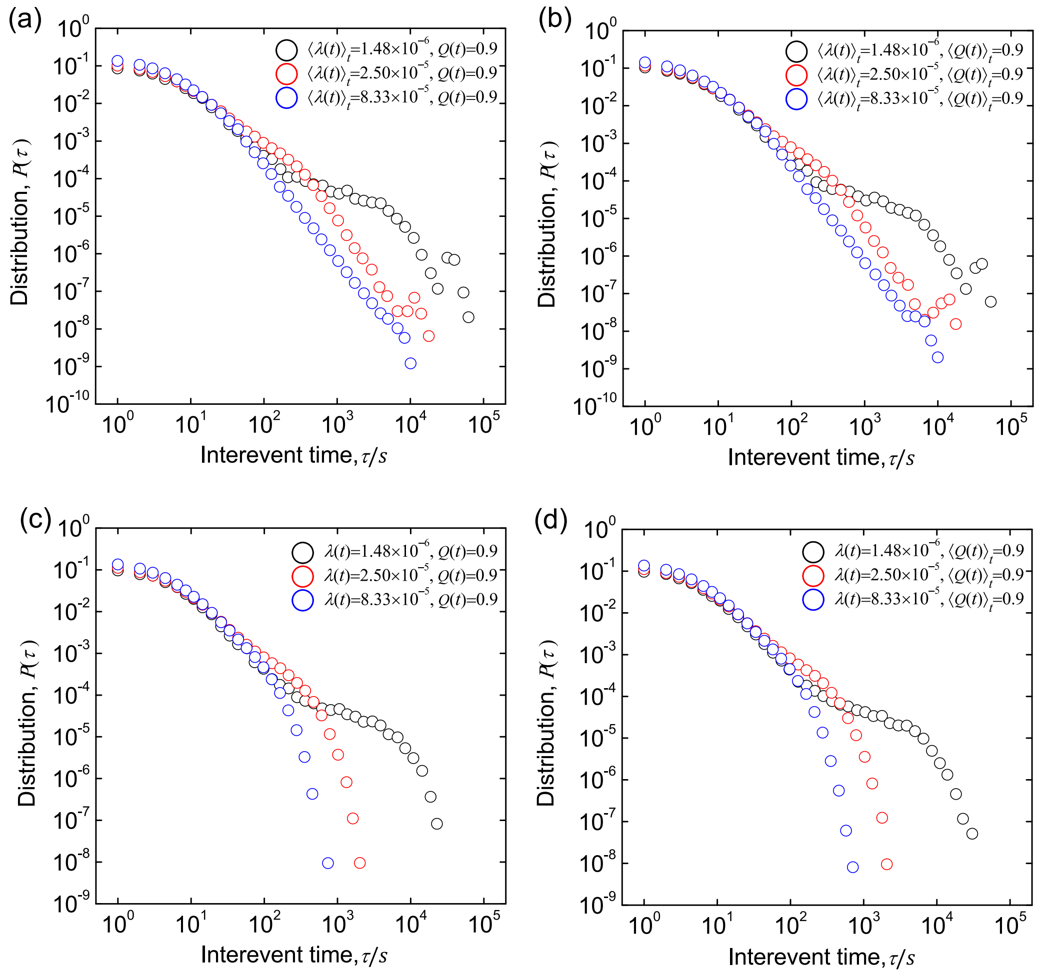

FIG. 5. The influence of the time independence of initiation rate λ and collective response probability Q on the interevent time distribution. (a) Time dependent initiation rate and time independent response probability. (b) Time dependent initiation rate and response probability. (c) Time independent initiation rate and response probability. (d) Time independent initiation rate and time dependent response probability. In all figures, $m = 200$, $\alpha = 1.0$, and the time dependent variables follow a periodic function proportional to $n(t)$ in Eq. (3).

are estimated. Statistics reveal that the number of initiative messages is positively correlated with the total number of messages (see Sec. IV of the Supplemental Material [50]). Therefore, the initiation rate $\lambda(t)$ is proportional to the temporal distribution of number of messages

$$\lambda(t) = \frac{\Lambda n(t)}{m}, \tag{1}$$

in which Λ denotes the average number of initiative messages in a day, and m is the number of members, $n(t)$ is the temporal distribution of the number of messages. See Secs. V, VI, and VII of the Supplemental Material [50] for the parameters estimation of MIPQ model and the robustness analyses of the parameters.

One can see from Fig. 1 that with the increasing of the collective activity, our MIPQ model exhibits three types of distribution, as well as the transition between them. The results indicate that the high-activity is an important factor for the double-power-law and single-power-law distribution patterns. These results agree well with the empirical data, both qualitatively and quantitatively. Moreover, our model also reproduces the deviations from the standard power law, such as "steep tail" and "flat head." Here, the "flat head" phenomenon describes the slow decay of $P(\tau)$ when τ is small [53], which may be caused by human reaction delay times. In addition, we find that the time dependence of initiation rate and high activity level are two factors of double-power-law and single-power-law distribution. Figure 5 shows that when the initiation rate changes over time, three types of distributions present despite the response probability being a constant or a variable. On the contrary, when the initiation rate is time independent, both double-power-law distribution and single-power-law distribution are absent. Figure 5(a) shows that the high-activity is also a factor of the two patterns. See Sec. III of the Supplemental Material [50] for the comparison of our model and Ref. [43] on the factors of single-power-law distribution.

The above results suggest that circadian rhythm plays a key role in $P(\tau)$, which prompts us to investigate the effects of different habits in different cultures. Figure 3(a) shows that the messaging frequency decreases during the noon hour, which is related to the siesta of Chinese. Milan Vojnović found that the messaging frequency of Americans in searching information on mobile devices presents a single-peak pattern with a cycle

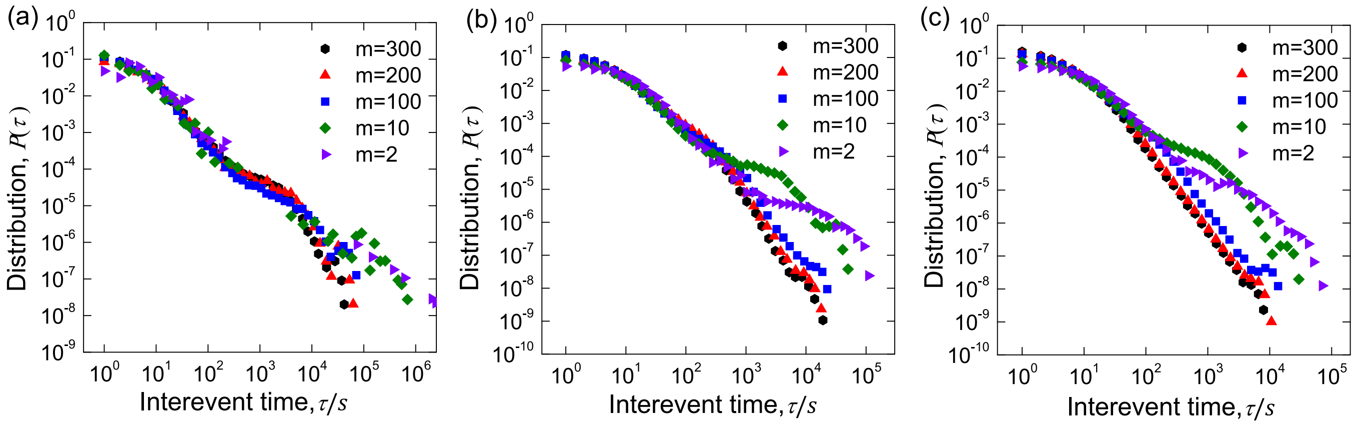

FIG. 6. Simulation of interevent time distribution $P(\tau)$ with different numbers of group members m. (a) Bimodal distribution. (b) Double-power-law distribution. (c) Single-power-law distribution. In (a), (b), and (c), the average initiation rate is $\langle\lambda(t)\rangle_t = 1.48 \times 10^{-6}$, 2.50×10^{-5}, and 8.33×10^{-5}, respectively, and $\alpha = 2.381, 1.389, 0.719$, respectively. The collective response probability is $Q = 0.9$.

of one day [54]. Therefore, three other cases are studied, in which the initiation rate follows periodic function of unimodal Gaussian, triangular shape, and sine, respectively. It is found that the three types of distribution still present, indicating the universality of our results in different cultures.

We also study the effects of the number of group members m. Figure 6 shows that when m is small, the distributions change dramatically with m, while when m is large, the distributions are almost unchanged. The results show that the double-power-law distribution and single-power-law distribution appear only when m is large. This can be explained by Eq. (1): the high collective activity requires a high individual activity or a large m. However, in reality the individual activity is limited, therefore the collective activity mainly depends on m. In the simulation, first, we kept the individual initiation rate $\lambda(t)$ [as well as $\langle\lambda(t)\rangle_t$] and the collective response probability Q fixed. Second, we executed our model with different numbers of group members m and set the response probability $q = \frac{Q}{m-1}$. Note that in a simulation, m is a constant. See Sec. IV of the Supplemental Material [50] for the reason of these settings.

V. DISCUSSION

Using the QQ group communication data, we conduct empirical and modeling analysis on the collective human communication behavior. For the first time, we find the transition between bimodal distribution, double-power-law distribution, and single-power-law distribution of interevent time in the same system. Although the previous models can also show these three types of distribution, but different distributions present in different models [42,43]. Moreover, the single-power-law distribution of collective human behavior and the transition between different distributions are just theoretical predictions without empirical evidence in the previous studies. In this paper, the theoretical predictions are confirmed by empirical data. And all three distributions are presented together in our single model.

Our proposed model agrees well with the empirical results in terms of the emergence of the three types of distribution, the transition between them, and the deviations of empirical results from the standard power-law or exponential distribution, such as the "steep tail" and "flat head" phenomenon. These results indicating the validity of our model, which can be used in other online communication platforms, such as WeChat, Facebook Groups, Microblog, and so on.

Both our results and the results in Ref. [43] show that the fundamental factors of single-power-law distribution in human dynamics are high activity levels and a broad enough distribution of activity. In our work, the above conditions are achieved by the periodic variation of the initiation rate and relatively large average value of initiation rate. Our results expand the scope of the single-power-law distribution, implying that the single-power-law distribution may be more ubiquitous than previously thought.

Our empirical results provide an important insight to deeper understanding of the mechanism of human dynamical social behaviors and better prediction of their messaging trend for the information sharing, public opinion orientation, personalized recommendation of social software, and other applications.

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[50] See Supplemental Material at http://link.aps.org/supplemental/10.1103/PhysRevResearch.5.033179 for more information about the empirical data, K-S test of power-law distribution, comparison between our model and previous models, more empirical evidences to support the model, and the parameters estimation of our model and robustness analysis of patameters.

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