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PAPER

Pacemaker effects on online social rhythms on a social network

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Abstract

The dynamics of coupled oscillators in a network are a significant topic in complex systems science. People with daily social rhythms interact through social networks in everyday life. This can be considered as a coupled oscillator in social networks, which is also true in online society (online social rhythms). Controlling online social rhythms can contribute to healthy daily rhythms and mental health. We consider controlling online social rhythms by introducing periodic forcing (pacemakers). However, theoretical studies predict that pacemaker effects do not spread widely across mutually connected networks such as social networks. We aimed to investigate the characteristics of the online social rhythms with pacemakers on an empirical online social network. Therefore, we conducted an intervention experiment on the online social rhythms of hundreds of players (participants who were pacemakers) using an avatar communication application ($N = 416$). We found that the intervention had little effect on neighbors' online social rhythms. This may be because mutual entrainment stabilizes the neighbors' and their friends' rhythms. That is, their online social rhythms were stable despite the disturbances. However, the intervention affected on neighbors' rhythms when a participant and their neighbor shared many friends. This suggests that interventions to densely connected player groups may make their and their friends' rhythms better. We discuss the utilization of these properties to improve healthy online social rhythms.

We reveal the characteristics of online social rhythms through periodic forcing (pacemaker). This can be regarded as coupled oscillators with pacemakers in a mutually connected network. Through an online intervention experiment on these social rhythms, we discovered that the intervention minimally influences neighbors' online social patterns unless the participant and their neighbor had a large shared friend group. This may be due to mutual synchronization, which stabilizes the rhythms of neighbors and friends. Essentially, their online social patterns remain undisturbed and stable. We deliberate on the use of these properties to enhance healthy online social rhythms.

1. Introduction

Social physics, a study that uses physical methods to explain social phenomena [1], has been applied to understand the dynamics of human online social rhythms [2]. These rhythms are influenced by social cues [3] and can be modeled as coupled oscillators in complex social networks [2, 4, 5]. The synchronization of coupled oscillators occurs when connections exceed a certain threshold, leading to global patterns [6–9]. Online social rhythms, which reflect everyday lifestyle rhythms, are often driven by online communication and influenced by friends' rhythms. One study [2] showed that the entrainment of people's online social rhythms emerges if their closeness reaches a threshold. This entrainment spreads via densely connected clusters; that is, having many shared friends facilitates the entrainment of online social rhythms. Consequently, long-range correlations of online social rhythms emerge.

We conducted an intervention for online social rhythms to investigate their nature and control further. We considered this system a coupled oscillator on a network with periodic forcing. Theoretical studies [10–16] modeled the control of coupled oscillators in a network by periodic forcing as the entrainment of other nodes by a pacemaker node (periodic forcing). A study [11] showed that the pacemaker effect exponentially decreases with the distance from the pacemaker in mutually connected networks. Long-range correlations with a pacemaker emerge if the networks are directionally biased, that is, closer to feed-forward networks [12]. The characteristics of the coupled oscillations and pacemakers in such unidirectional networks explain the neural mechanisms underlying the circadian rhythms of organisms [12, 13, 17–19]. A previous study [14] also demonstrates the limitations of a pacemaker on a one-dimensional torus network. The pacemaker does not influence the rhythms of distant nodes. This implies that controlling the rhythms of oscillators necessitates the small-world nature of the network. However, even in a network possessing small-world characteristics (like a scale-free network), if the interaction between nodes becomes overly strong, the network's inherent characteristics are lost, making rhythm control by a pacemaker unachievable [15]. Thus, the interaction of oscillators on the network is a significant subject in the study of dynamics on a network [15, 20]. Addressing this issue with new data (human online social rhythms) carries substantial meaning in the field of network science.

Insights for controlling online social rhythms using a pacemaker can contribute to research in clinical psychology because regulating circadian [5, 21, 22] and online social rhythms [23–26] contributes to improved mental health. These findings are supported by Interpersonal and Social Rhythm Therapy (IPSRT) [27]. This reveals the potential usefulness of the online IPSRT [28].

In this study, we investigated the effect of pacemakers on online social rhythms in online social networks. Theoretical studies [11, 12] predicted that the pacemaker effect does not spread widely in mutually connected networks. However, clarification about actual human online social rhythms on a social network is essential, which is significant in clinical psychology. It is also crucial to elucidate the relaxation time of the pacemaker effect, effect size, and correlation length. Therefore, we conducted an intervention experiment on online social rhythms using the avatar communication application 'Pigg Party[4]' and analyzed participants' and their neighbors' online social rhythms.

2. Methods

2.1. Pigg Party

Pigg Party is a Japanese avatar communication application, in which players communicate with personally designed avatars in virtual spaces (figure 1). This is available for iOS and Android devices. A previous study [2] indicated the entrainment of online social rhythms among Pigg Party players.

They can communicate synchronously using text through their avatars in virtual spaces. In addition to sending text messages, players can respond to dozens of avatar animations, known as avatar actions.

Players can send a lightweight and asynchronous message 'like' similar to Facebook's. They send 'likes' by choosing a friend's or stranger's avatar or icon[5].

2.2. Intervention and participants

We conducted a four-week intervention experiment (26 July to 24 August 2022) on online social rhythms. In the intervention term, participants were motivated to use Pigg Party at specified times by incentives from the researchers. We call this the intervention on the online social rhythm of participants. At the specified times, if participants talk to their friends or participants' friends find that participants are online at the specified times, participants' friends may also use at the specified times, i.e. their social rhythms may be similar.

The participants of this experiment were recruited from the Pigg Party ($N = 416$; see table 1 for information on gender and age composition).

In the experiment, we randomly split the participants into four groups: morning, evening, all-day, and control (the number of participants in each group was 104).

Morning, evening, and all-day group participants are encouraged to send at least 5 'likes' to other players at the corresponding time for each group (morning: 7:00–8:00 AM; evening: 7:00–8:00 PM; and all-days: 0:00–23:59). The Pigg Party administrator sent reminder messages to the participants at the following times: morning group at 7:00 AM, evening group at 7:00 PM, and all-day group at 1:00 PM. Those who achieved 60 % (17 days) of their tasks in four weeks were rewarded with an Amazon gift card (300 JPY) and virtual coins from Pigg Party worth 500 JPY. The control group did not undergo any intervention. Randomly selected 23% of the control group participants received the same rewards as the other group participants for the lottery.

[4] https://lp.pigg-party.com/.
[5] See the official site (https://ameblo.jp/pigg-party/entry-11994485937.html) for details.

Figure 1. Players chat with each other via their avatars in Pigg Party.

Table 1. Participants' gender and age.

Gender	N	Age (Mean $\pm$ SD)
Female	316	25.6 ± 12.6
Male	70	26.9 ± 12.7
Others	30	22.1 ± 8.18

Table 2. Mean values of the network features.

Feature	Mean $\pm$ SD
Number of nodes	$280\,766.4 \pm 31\,034.5$
Number of edges	$62\,615.2 \pm 6846.4$
Weighted clustering coefficient [29]	$0.148 \pm 0.005\,17$
Powerlaw coefficient of degree distribution	4.58 ± 0.374
Powerlaw coefficient of edge weight distribution	3.13 ± 0.639

2.3. Participants' neighbors

We builted online social networks to study the intervention effects on participants' neighbors for each week, based on a previous study [2]. Therefore, we acquired five networks for the weeks of intervention periods[6]. Table 2 shows the network features.

From these networks, we extracted and analyzed players who connected with the participants as neighbors. The numbers of neighbors in the morning, evening, all-day, and control groups were 804, 683, 784, and 797, respectively.

To construct these networks, we used the logs of users visiting other users' private rooms. As in previous research [2, 25, 30, 31], we established a link between a visitor and the owner of a room because visitors are often friends with the owner [32]. The time spent (in seconds) over a week was used to denote the weights of the links (w). The time spent per week was recorded. Although this network does not directly depict a communication network, it should positively correlate with the actual communication network.

We adopted this network as a proxy because data regarding the actual communication routes between individuals are strictly limited owing to constitutionally protected communication privacy in Japan.

We created two variables expressing the relationships between the participants and their neighbors: 1) *close-frined*: A relationship with $w >= 10^{3.1}$ was considered a close friendship because the players' online social rhythms were synchronized when $w >= 10^{3.1}$ in a previous study [2]. 2) *Number of shared friends*: We counted the number of shared friends between the participants and their neighbors because having more shared friends facilitates the spread of online social rhythms [2].

2.4. Online social rhythms

We created vectors representing online social rhythms over a 24 h cycle according to a previous study [2]. Each dimension of the vectors indicated the activity during a specific hour, that is, the dimensions of the vectors were 24. We constructed these vectors using weekly usage data, removing any fluctuations unrelated to the 24 h cycle. This allowed us to construct the social rhythm vectors.

To do this, we first built a time series from users' hourly usage data, then performed discrete Fourier transforms and extracted cycle factors, which were calculated by 24 h divided by integers i ($i = 1, 2, \ldots, 11$),

[6] There are five networks in a four-week intervention period because each week starts on Monday and is numbered.

that is, 24, 12, 8, 6, 4.80, 4, 3.43, 3, 2.67, 2.40, and 2.18 h, and calculated the inverse Fourier transforms of these elements. This implies online social rhythm vectors were constructed based on 11 bandpass-filtered frequencies.

The results were normalized to create a weekly social rhythm vector for each participant. For example, we can evaluate the social rhythm similarity using the inner product of these vectors (cosine similarity).

The source code for online social rhythms is available on https://figshare.com/s/d27b9c4858af977ef81f.

2.5. Morning/evening activities

Each player's morning and evening activities were constructed using online social rhythm vectors. Morning activity was defined as the similarity between a player's online social rhythm vector and a morning vector, which had one in the seventh dimension (7:00 AM) and zero in other dimensions. The evening activity was also a similarity between a player's vector and the evening vector, which was the 19th dimension (7:00 PM) set to 1 and the others to 0.

2.6. Regressions to morning/evening activities

Regression analyses were conducted to evaluate the intervention effects on neighbors' morning and evening activities:

$$y \sim \text{Normal}(\mu, \sigma), \tag{1}$$

$$\mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \gamma_1 c_1 + \gamma_2 c_2 + \gamma_3 c_3 + \gamma_4 c_4 + \gamma_5 c_5 + \gamma_6 c_6 + \gamma_7 c_7 + \gamma_8 c_8, \tag{2}$$

where the objective variable y was morning or evening activities, μ was expected values of y, and σ was a standard deviation. μ was the weighted summation of the following explanatory and control variables. The explanatory variables x_* included information on the participants connected to the analysis target players (the number of days in the morning task achievement or those in the evening; x_1) and the relationships between the players and the participants (a dummy variable expressing close friend relations x_2 and the number of shared friends x_3). These explanatory variables were set to zero when the group was not a morning group (or evening group). For the control, we used the neighbor's morning (evening) activity before the experiment (three-week averages; c_1), time-varying covariates for each week (weeks 2–5; week 1 was a reference variable), and the group of participants connecting with each neighbor (control group was a reference variable). We did not analyze these control variables. β_* and γ_* indicate coefficients of explanatory and control variables.

2.7. Ethics statement

The Pigg Party application provider collects log data based on their terms of service[7] and privacy policy[8]. All Pigg Party users accepted the terms of service and privacy policy, which allowed analysis of their behavioral data for service improvements and academic studies. The data were pseudonymized, and identifying information was removed.

Quantitative data outputs are presented at an aggregate level, meaning no identifying information was included.

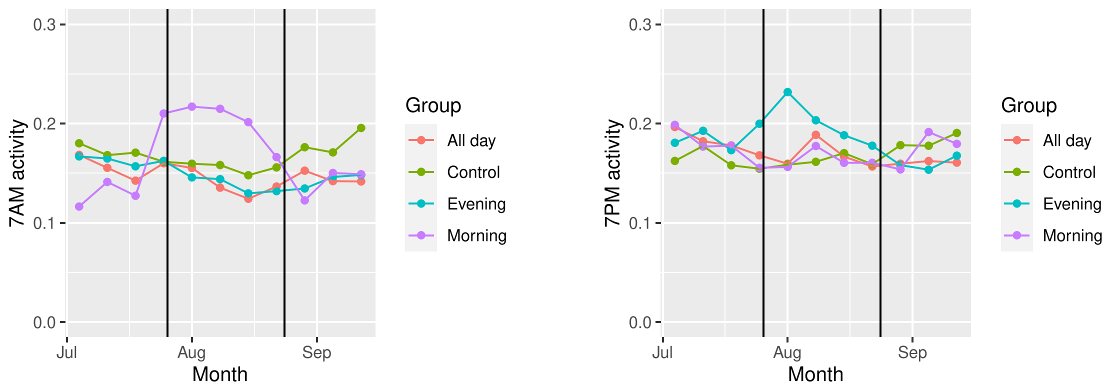
The experiment in this study was approved by the Ethics Committee of Tokushima University. All procedures were conducted in accordance with the guidelines for studies involving human participants, the ethical standards of the institutional research committee, and the 1964 Helsinki Declaration and its later amendments. The participants provided informed consent to participate in our experiment and were allowed to stop at any time. They could also withdraw their responses after the completion of the experimental process.

3. Results

First, we confirmed the intervention effects on the participants' morning and evening activities. Figure 2 indicate that the interventions drove their activities according to their clock times. Therefore, they can be considered as pacemaker nodes. The intervention effect decreased in the latter half of the study period, particularly in the evening. All the intervention effects disappeared after the intervention.

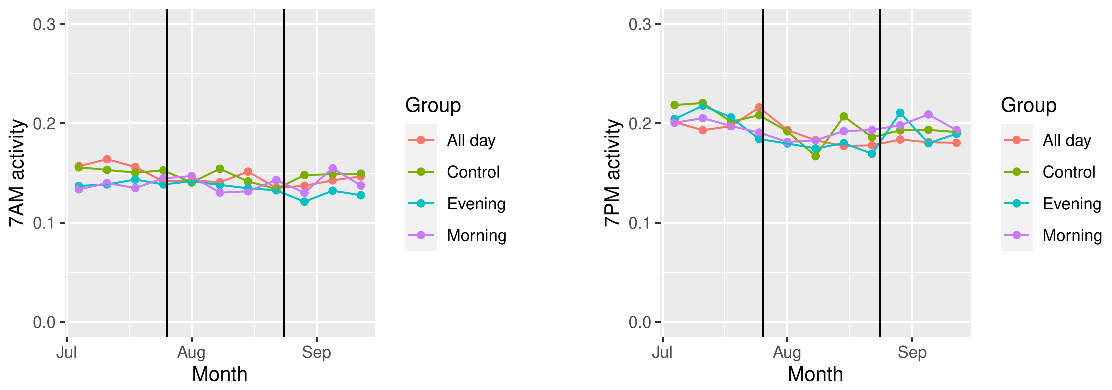
Second, we checked neighbors' morning and evening activities (figure 3). These results did not indicate well-marked intervention effects on neighbors.

[7] https://lp.pigg-party.com/terms.
[8] www.cyberagent.co.jp/way/security/privacy/.



(a) Morning activity (b) Evening activity

Figure 2. Mean activities of morning and evening of each group of partitipants. the periods between the black lines show the intervention terms. the interventions drove their online social rhythms, i.e. we can regard them as pacemaker nodes.



(a) Morning activity (b) Evening activity

Figure 3. Mean activities of morning and evening of players who are participants' friends. these figures show that the intervention effect does not have a clear impact on them.

Table 3. Result of a regression for morning activity. only the number of sharing friends among the explanatory variables was statistically significant.

		Coef.	S. E.	p-value	
Explanatory variables (zero except for the morning group)	Intercept	0.0671	0.0045	0.0000	***
	Number of days in morning task achievement	−0.0001	0.0003	0.6877	
	Close friend	0.0016	0.0057	0.7757	
	Number of sharing friends	0.0005	0.0002	0.0216	*
Control variables	Morning activity before the experiment	0.5734	0.0165	0.0000	***
	Week 2	0.0019	0.0043	0.6554	
	Week 3	−0.0054	0.0044	0.2181	
	Week 4	−0.0025	0.0044	0.5676	
	Week 5	−0.0016	0.0046	0.7273	
	Morning group	−0.0121	0.0066	0.0654	
	Evening group	−0.0049	0.0042	0.2381	
	All day group	−0.0118	0.0040	0.0034	**
Adj. R^2		0.2850			

Note: ***, **, *, and · indicate significant differences at p-values $\leqslant 0.001, 0.01, 0.05,$ and 0.1.

In a previous study [2], shared friends and the closeness between players played crucial roles in the entrainment of online social rhythms. We analyzed these effects on the morning and evening activities of the neighbors from the participants.

Table 4. Result of a regression for evening activity. as with table 3, only the number of sharing friends among the explanatory variables was statistically significant.

	Variables	Coef.	S. E.	*p-value*	
Explanatory variables (zero except for the evening group)	Intercept	0.1454	0.0057	0.0000	***
	Number of days in evening task achievement	−0.0003	0.0008	0.7106	
	Close friend	0.0020	0.0074	0.7859	
	Number of sharing friends	0.0008	0.0003	0.0127	*
Control variables	Evening activity before the experiment	0.2759	0.0179	0.0000	***
	Week 2	−0.0107	0.0052	0.0378	*
	Week 3	−0.0115	0.0052	0.0289	*
	Week 4	−0.0115	0.0053	0.0291	*
	Week 5	−0.0136	0.0055	0.0132	*
	Morning group	−0.0037	0.0047	0.4390	
	Evening group	−0.0200	0.0077	0.0099	**
	All day group	−0.0027	0.0048	0.5666	
Adj. R^2		0.0774			

Note: ***, **, *, and · indicate significant differences at p-values $\leqslant 0.001, 0.01, 0.05$, and 0.1.

Tables 3 and 4 provide the regression analysis results. The number of friends shared indicated significance for morning and evening activities. The effect sizes for sharing friends were limited. The morning activities (mean: 0.143) increased by 0.34%, and evening activities (mean: 0.186) increased by 0.43% when a player and an intervention participant had one more friend. The effects of being close to the participants and the number of days of morning task achievement were not statistically significant.

4. Discussion

Despite the intervention in online social rhythms affecting the participants' rhythms, these effects were less widespread. A slight impact was observed only when players shared many friends. Therefore, the correlation length of the pacemaker effect was very short, and the effect size was small. After the experiments, the intervention effect on participants' rhythms rapidly disappeared. This indicates that the relaxation time was also short. These results support theoretical studies [11, 12] that show that pacemaker effects do not spread across mutually connected networks. This is because mutually connected oscillator rhythms are insensitive to periodic forcing owing to mutual entrainment. This means that the online bandwagon effect (majority synching bias) [33] also plays out on social rhythms. This finding suggests that it is difficult to expect a spreading effect from a mere intervention in online social rhythms to enhance the spreading effects of IPSRT on online communication platforms such as social networking services.

This implies online social rhythms with mutual entrainment may remain stable despite disturbances. Therefore, if we create player clusters with good rhythms, for example, early to bed and early to rise, their rhythms may be stable from disturbances. Having shared friends drove entrainment between the intervention participants and their friends. This is consistent with a previous study [2], which showed that more densely connected clusters of players indicate more synchronization.

It may be possible to improve the correlation length, effect size, and relaxation time of intervention effects. For example, interventions with an entire group of closely interconnected nodes would solidify the intervention effect on them and improve the spillover effect on their friends (who inevitably have many mutual friends). This is because densely connected cluster [2] and strong interaction between nodes [15] stabilize rhythms. It would also be important to isolate the appropriate subgraphs (groups) because small-size networks enhance the effects of pacemaker [14]. Interventions through highly synchronous communication, such as online chat, rather than asynchronous communication, such as 'like' communication, may also strengthen the spread effects. If we create a cluster in which people have healthy online social rhythms, they can maintain their healthy rhythms through mutual entrainment of their rhythms. The development of intervention methods to achieve these clusters will be a topic for future research.

4.1. Limitations and future work

We studied players on an avatar communication application, Pigg Party. Considering other online communication platforms, e.g. social networking services (SNS) and massively multiplayer online role-playing games (MMO-RPG) where players' demographic composition will be different and providing different user experiences, etc would broaden the scope of our findings.

As mentioned above, there is room for ingenuity in intervention. Various forms of intervention, such as involving synchronous communication, will need to be considered, although we considered the intervention to asynchronous communication in this study. The ratio of participants was tiny compared to the total number of active users (several hundred thousand active users of Pigparty over a six-month period [34]). Intervening with a more significant number of players or in density clusters may strengthen the ripple effect of the intervention.

Data availability statement

The data cannot be made publicly available upon publication because they contain commercially sensitive information. The data that support the findings of this study are available upon reasonable request from the authors.

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