

Analysis and Evaluation of Social Contagion of Physical Activity in a Group of Young Adults

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ABSTRACT

It is known that opinions, attitudes and emotions spread through social networks. Several of these cognitions influence behavioral choices. Therefore, it is assumed that the level of physical activity of a person is influenced by the activity levels of the people in its social network. We have performed an experiment with 20 participants between 19 and 28 years old, measuring their physical activity levels for 30 days, in order to observe if there is a contagion effect due to the relationships in the social network. Using our social contagion model, we investigated if people will become more or less active according to the contacts with their peers within the network. Our model correctly predicts the direction of the change (increasing or decreasing) in 80% up to 87% of the cases investigated.

CCS Concepts

• **Applied computing** → *Consumer health; Health informatics;*

Keywords

Computational Modeling; Social Contagion; Social Networks; Healthy Lifestyle; Physical Activity

1. INTRODUCTION

Physical inactivity is a major public health challenge in the developed world and is recognized as a global epidemic [1]. Insufficient physical activity is a risk factor for cardiovascular diseases and other conditions. The amount of physical activity of a person is usually represented by the Physical Activity Level (PAL). It refers to “any bodily movement produced by skeletal muscles that results in energy expenditure” [5]. The global recommendation for daily exercise is an accumulated 30 minutes of moderate intensity activity, such as

cycling, brisk walking or swimming, in segments of at least 10 minutes per activity [15]. Research has shown that a large part of the Western population does not meet these guidelines [9]. Sports medicine and public health constituencies also acknowledged a concern about the deleterious health consequences of insufficient physical activity [7].

It is known that social influences play a key role in lifestyles and are fundamental to whomever wants to maintain healthy behavior. Several aspects underlying a lifestyle, such as emotions, opinions and behaviors, can spread through a social network, in a process called “social contagion”. Social contagion theories explain how one’s social network influences these aspects and how this social environment can provide support in changing them [14].

This research builds on the belief that the social environment can be used as an unobtrusive, even unconscious and therefore suitable way of supporting people to become more physically active [2, 11]. To develop practical applications of lifestyle interventions based on social influence, it is important to have a thorough comprehension of the dynamics underlying the social contagion process. To contribute to this understanding, we have performed an experiment in which we compared the predictions of a model that describes social contagion in a community [6, 3, 4] with the actual change in physical activity level. Our assumption is that the model can be applied to describe the spread of behavior, considering the willingness to be more active is led by the emotions, attitudes and motives of each person. In the experiment, we constructed a graph of the social network of a group of young adults between 19 and 28 years old, using the strength of the relations between the participants. In addition, we assessed the important characteristics of each participant, such as their openness and expressiveness. For all participants, we collected the PAL data during a period of 30 days. The change of the physical activity per participant was compared with the change predicted by the model.

The paper is organized as follows: in Section 2, the social contagion model is explained in more detail. Section 3 describes the setup of the conducted experiment. In Section 4, we present the results obtained, and we discuss the results in Section 5. In Section 6, we conclude our explorations and discuss some ideas about possible future work.

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2. SOCIAL CONTAGION MODEL

In this section, we briefly summarize the computational model of social contagion and explain how it is used to predict the change in the physical activity level [6, 3, 4].

In the context of this research, the factor that is assumed to spread through the social network is the *physical activity level* of the people in the network. The extent to which people express themselves, which affects the strength of their influence on others, is captured by the concept of *expressiveness*. Similarly, the extent to which people are open to receive influence is represented by the *openness*. The strength of the relation between two people in the network is described by the *connection strength*. These concepts form the key parameters of the contagion model, see Table 1. They are formalized as real numbers between 0 and 1.

Table 1: Parameters for personal and social characteristics.

Physical activity level of person A	q_A
Expressiveness of person A	ϵ_A
Openness of person A	δ_A
Connection strength between sender B and receiver A	α_{BA}

The contagion process is modeled in terms of the contagion strength γ_{BA} between sender B and receiver A. This contagion strength represents the influence of sender B on receiver A. The contagion strength depends on three aspects of the relationship: the expressiveness of person B, ϵ_B , the openness of node A, δ_A , and the connection strength between person B and person A, α_{BA} . The contagion strength between sender B and receiver A is calculated as in (1).

$$\gamma_{BA} = \epsilon_B \alpha_{BA} \delta_A \quad (1)$$

The overall contagion strength γ_A represents the total contagion strength of all connections of person A in the network. It is computed as in (2).

$$\gamma_A = \sum_{B \neq A} \gamma_{BA} \quad (2)$$

The proportional weight of the contagion from sender B to receiver A is computed as in (3).

$$\omega_{BA} = \epsilon_B \alpha_{BA} / \sum_{C \neq A} \epsilon_C \alpha_{CA} \quad (3)$$

The aggregated impact q_A^* of all connections of person A is calculated by means of a weighted average as in (4).

$$q_A^* = \sum_{B \neq A} \omega_{BA} q_B \quad (4)$$

The set of differential equations for the contagion of the physical activity level is formed by (5) for all persons N in the network.

$$\Delta q_N(t + \Delta t) = q_N(t) + \gamma_N(q_N^*(t) - q_N(t))\Delta t \quad (5)$$

This computational model of social contagion has been used in several studies. For example, it was applied to predict the emotion levels of team members, in order to maintain emotional balance within the team [6]. If the team's

emotion level was found to become deficient, the model, which was embedded in an ambient agent, provided support to the team by proposing the team leader to give his employees a pep talk [6]. Another study experimented with simulations of changes in the social network structure in order to guide the contagion process in a certain direction [10].

In the current research, the contagion model that was developed and simulated on emotions is applied on the contagion of physical activity, which to our knowledge has not been done in earlier research. The involvement of the main aspects, such as expressiveness, openness and connection strength are based on the model of social contagion. A detailed method for determining these parameter values for the computational model is described in Section 3.

3. EXPERIMENTAL SETUP

The goal of the experiment is to compare the actual change in the activity level of people in a network with the change predicted by the computational model explained in Section 2. To do so, an empirical experiment with people that were part of a social network was conducted for 30 days. Characteristics of the persons and their relations were gathered via a questionnaire and objective data about their physical activity was collected with an electronic activity monitor.

The network consisted of 25 participants, all between the age of 19 and 28. The participants were recruited from one person's social network, thus, every participant has at least one connection to another node in the network. Five of the 25 participants provided less than 25 days of useful data and were taken off the experiment, which left a number of 20 participants.

As we use a stable network with relationships that have been established before the start of the experiment, we expected the changes of the physical activity level would be small. This is due to the fact that no external trigger was introduced, e.g., a support system or an encouragement program for doing more activities. Nevertheless, the fact that people are participating in this experiment could intensify their awareness of others' physical activity levels. Therefore, changes could still occur in a smaller ratio.

At the start of the experiment, an intake questionnaire was administered using an online survey software tool. Via this questionnaire, information was obtained about the participants': (1) physical activity level, (2) personal characteristics, (3) level of friendship with the other participants, and (4) frequency of contact with other participants. This information was used to determine the values for the parameters of the computational model.

During the period of 30 days, the participants wore an activity monitor (Fitbit One¹) that kept track of their daily physical activity. In addition to the data obtained from the Fitbit, short questionnaires were used regularly to collect additional data about their exercise.

The data about the participants' characteristics and their relations is used as basis for the parameters values in the model; the activity data is used as initial input for the model simulations and to compare the outcome of the simulations with. In the next sections, we explain the specific steps that were taken to convert the collected data to numerical values that are suitable for the computational model.

¹<http://www.fitbit.com/one>

3.1 Physical Activity Level

The participants' physical activity data that was collected by the Fitbit activity monitor was automatically stored in the Fitbit servers. After the period of 30 days, this data was exported from the participants' personal Fitbit accounts. The exported data consists of the number of steps taken per day, the number of minutes that the participant was fairly or highly active per day and the number of floors climbed per day. These numbers were divided by the number of recommended steps, fairly/highly active minutes and floors, which are 10,000, 30 and 10 respectively. Days that contained less than 1,500 steps were considered as days that the participant (partly) forgot to wear the Fitbit, so these days were discarded.

Finally, weights were assigned to each aspect, according to their importance. The number of steps taken gives the best estimation of the amount of physical activity and is therefore the most important. The number of fairly/highly active minutes is chosen to be slightly more important than the number of floors, because meeting the recommendation of 30 active minutes per day contributes more to a physically active lifestyle than climbing 10 floors. Therefore, the PAL is calculated as in (6).

$$PAL = \left(\frac{steps}{10000} \times 0.7 \right) + \left(\frac{am}{30} \times 0.2 \right) + \left(\frac{f}{10} \times 0.1 \right), \quad (6)$$

where am is the active minutes and f is the number of floors climbed.

3.2 Tie Characteristics

The strength of connections between people is a combination of the amount of time, emotional intensity, intimacy, frequency of contact and reciprocal services [12]. In this model, a distinction between different types of interaction was added because of the assumption that contact in real life and one-to-one communication (also through private chats) both contribute to a higher level of contagion than contact that takes place in group conversations through smartphones or social media and by observing someone's public posts on social media. Therefore, a combination of the level of friendship and the frequency and type of interaction is used to calculate a value for the strength of the connection.

The parameter used to represent the tie strength from node B to node A is the *connection strength* (α_{BA}). This parameter was operationalized by a combination of the type of relation and the frequency of contact. These aspects were measured through questions included in the intake questionnaire. The levels of friendship were measured using a scale on which each participant rated all other network members as: unknown (0.0), acquaintance (0.2), good acquaintance (0.4), friend (0.6), best friend (0.8) and partner (1.0). In addition, two questions concerning the frequency of interaction were included, distinguished by type. The participants gave an estimation, only for the participants who they stated to be connected to in the previous question, of how often they interact with them. These two questions about contact in real life or in private conversations and contact in groups or on social media were answered by the following scale, using the accompanied assigned values: less than once a month (0.0), 1-2 times a month (0.2), once a week (0.4), 2-5 times a week (0.6), once a day (0.8) and more than once a day (1.0). The formula for the tie strength is shown in (7).

$$\alpha_{BA} = (fl \times 0.6) + (crl \times 0.25) + (cg \times 0.15), \quad (7)$$

where fl is the friendship level, crl is the amount of contact in real life (i.e., private conversations), and cg is contact in groups and social media.

3.3 Personality Traits

Personality traits of a person were measured by statements that give an indication of the expressiveness and openness of this person. We formulated a number of statements based on the aspects extraversion, openness to new experience and agreeableness from the Big Five Inventory [8] that were taken as a measure of the values of the participants' expressiveness and openness. The statements that were used to assess these values are listed in Table 2. For each domain, three out of six statements were reversed. When using questionnaires with only positive (or negative) sentences, the subjects may be biased in a positive (or negative) way.

Table 2: Statements measuring expressiveness and openness. (Reversed statements are marked by *.)

Extraversion
1. I keep my feelings and thoughts to myself.*
2. I am assertive.
3. I am outgoing and enthusiastic.
4. I think carefully before I speak.*
5. I am shy and do not like to be the center of attention.*
6. I often post things on social media (Facebook and Instagram).
Openness to new experience
7. I have a strong opinion.*
8. I am interested in what others do and think.
9. My decisions are thoughtful.*
10. I rather remain in my current safe habits and environment than trying and exploring new things.*
11. I am open for suggestions, ideas and opinions of others.
12. I am a curious person.
Agreeableness
13. I have a rigid personality.*
14. I am easily influenced by what others think or do.
15. I have a strong feeling of empathy.
16. I am difficult to persuade by other people.*
17. I have a distant personality towards others.*
18. I feel sorry for other people very quickly.

Participants were asked to assess how strongly they agreed or disagreed with each statement. A value was assigned to each answer as follows: strongly disagree (0.0), disagree (0.25), neutral (0.5), agree (0.75) and strongly agree (1.0). Some statements were reversed and therefore, the score was subtracted from 1 to obtain the right score for these answers.

We assumed that the expressiveness in our model depends on the Extraversion domain from the Big Five Inventory, and that the Openness and Agreeableness can be used for the degree of openness of the receiver in our model. Thus, statements 1 to 6 determined the value for expressiveness, which is the average of the calculated score over these six questions. The average value of statements 7 to 18 represents the overall value for openness.

3.4 Network Structure

Figure 1 shows the social network of the participants. Each node represents a participant in the experiment, and the arrows are the direction of the connection, according to the questionnaires filled out by the participants. The thickness of the edges represents the weight of the connection. An overview of the structural characteristics of the network can be found in Table 3.

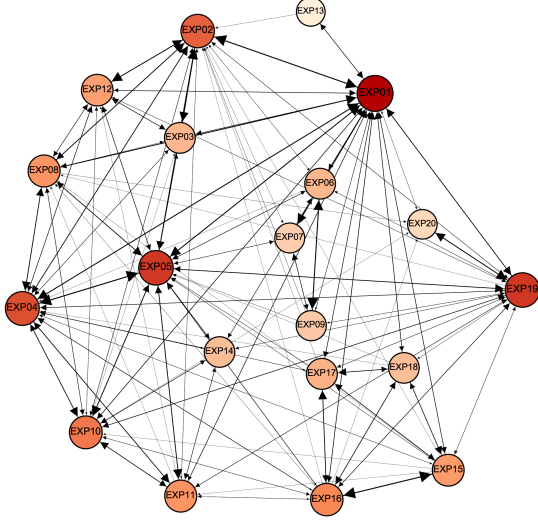


Figure 1: Network structure of the experiment.

The degrees of the nodes in the graph follow a normal distribution, according to the Shapiro-Wilk test ($p = 0.723$, $H_0 = \text{normal distribution}$), Anderson-Darling test ($p = 0.585$, $H_0 = \text{normal distribution}$), and Jarque-Bera test ($p = 0.629$, $H_0 = \text{normal distribution}$).

The network forms one connected component, which is due to the nature of the selection of the participants. Despite the fact that all of the participants are from the same class, the density of the network is not too high (47.9% of the possible edges existing).

Table 3: Structural characteristics of the network.

Measure	Value
Sample Size	20
Edges	182
Minimum Degree	3.0
Maximum Degree	38.0
Mean Degree	18.2
Std. Deviation Degree	9.082
Graph density	0.479

3.5 Data Preparation & Analysis

This study aims to investigate whether the computational model of social contagion is able to predict the change in the PALs of the participants correctly. In order to derive the direction of change of the PAL of each person, the trendlines for each participant were calculated. They were used to

determine whether there was an increase or decrease in their physical activity during the experimental period. This is later compared with the direction of change predicted by the model.

The computational model needs an initial value for the activity level of each of the participants to start the simulation with. Therefore, the initial value is highly important and needs to be chosen carefully. As there is a relatively large variation in the PAL values for different days, it would be unrealistic to use only the PAL from one single day as the starting point for the model. Figure 2 shows the PAL values for one participant during the 30 days of the experiment. Since trendlines of the real data were calculated and the value of the trendline at the start provide a good aggregation of the first days of activities, we used the first point of the trendline for each participant as the initial value for the model. The model was then used to simulate the activity level of all participants for 30 days.

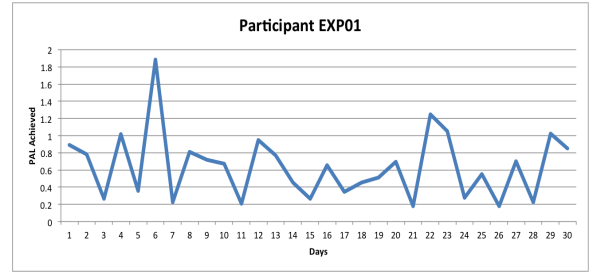


Figure 2: Physical Activity Level achievement of participant EXP01 during 30 days.

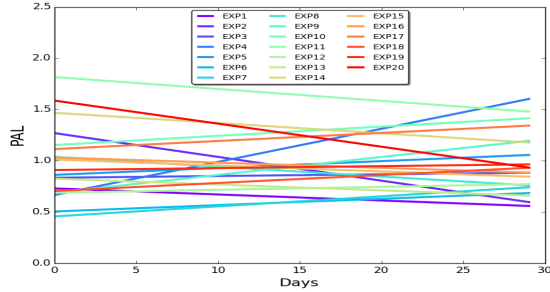
The computational model of contagion [6, 3, 4] was implemented in Python, which performed calculations following the formulas discussed in Section 2. It takes three matrices as input for computing the change of PAL over time for each person. The first matrix contains the initial PALs for each participants, the second one contains values of the connection strengths in the network, and the third one contains values for each person's expressiveness and openness. The values in the latter two matrices were the same for all days, as it was assumed that the network structure and the personality characteristics did not change in the period of 30 days.

Before the model was run for the first set of experiments, some tuning was performed. To achieve a realistic speed of change, all contagion strengths were divided by 10, which resulted in realistic levels of contagion over time and in plausible values for changes in the levels of physical activity.

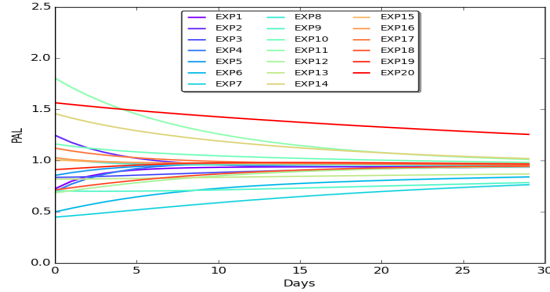
4. RESULTS

The trendlines of the physical activity levels (based on the real data) can be seen in Figure 3(a). Mann-Kendall tests showed that the trendlines are not significant in 75% of the cases. That fits in our assumption that big changes should not occur in a relatively short period of time within a stable network.

Figure 3(b) shows the simulation results for each participant, using a simulation period of 30 days and with parameter values calculated as described in Section 3.2 and Section 3.3.



(a) Trendlines for each participant during 30 days.



(b) Simulation results of the social contagion model.

Figure 3: Graphs with trendlines of real data and simulation results of the model.

Table 4 shows that in 80% of the cases, the slopes of the trendlines have the same direction (increasing or decreasing) as the model predicts. It shows that, for stable networks and for a short period of time, the model can predict the direction of the change of the activity level of people with high precision.

As not all of the trendlines presented a clear slope, we took off the slopes with a tau value less than 0.03, i.e. the lines that were almost flat. This value is obtained by a Mann-Kendall test for analyzing the significance of the trendlines for the experiment. The Mann-Kendall test statistically assesses if there is a monotonic upward or downward trend over time of the variable under analysis. In our case, this variable is the PAL of each person. The test has the initial assumption that there is no monotonic trend as its null hypothesis (H_0). If the null hypothesis is rejected, then we have a reasonable indication that there is a trend. The tau value is the variable that assesses the slope of the trend, in case H_0 is rejected. Table 4 shows an 87% accuracy after taking out the trendlines that were almost flat.

Another way to determine the adequacy of the model is to compare the error of the model predictions with the error of the trendlines. However, this comparison is not fair, as the trendlines consider all the data points in the period, fitting the best linear regression to the entire data set, while the model simulations only use one initial value (based on the start value of the trendline). To make the predictions of a regression line comparable to the model, we created linear graphs using only the first 7 days of data, so it uses the same amount of input data as the model.

Table 5 shows the mean squared error for three situations: trendlines based on all data, linear graphs extrapolated from

Table 4: Comparison of line tendency between contagion model and real data^a and comparison of line tendency between contagion model and real data after removing trendlines with a slope less than 0.03^b. Correct predictions^c are shown in the last row.

	Model	Real data	Matches ^a	Matches ^b
EXP01	Up	Down	No	–
EXP02	Down	Down	Yes	Yes
EXP03	Up	Up	Yes	Yes
EXP04	Up	Up	Yes	Yes
EXP05	Up	Up	Yes	Yes
EXP06	Up	Up	Yes	Yes
EXP07	Up	Up	Yes	–
EXP08	Down	Down	Yes	Yes
EXP09	Up	Up	Yes	Yes
EXP10	Down	Up	No	No
EXP11	Down	Down	Yes	Yes
EXP12	Up	Up	Yes	Yes
EXP13	Up	Down	No	–
EXP14	Down	Down	Yes	Yes
EXP15	Down	Down	Yes	–
EXP16	Down	Down	Yes	Yes
EXP17	Down	Up	No	No
EXP18	Up	Up	Yes	Yes
EXP19	Up	Up	Yes	Yes
EXP20	Down	Down	Yes	No
Total matches ^c			16 (80%)	13 (87%)

Table 5: Mean Squared Errors of prediction lines

Method	MSE
Trendline	0.3613
Extrapolation	6.8992
Contagion Model	0.4272

the first 7 days and the predictions of the contagion model. The values of the lines or model predictions in the three cases were compared with the actual data, the differences were squared and the average of these errors was calculated.

5. DISCUSSION

Considering that our network is stable, with no formations of new connections nor additional support systems attached to it, we would not expect major changes in the daily level of activities of the participants. Still, we would expect some changes to happen due to the continuous social contagion effect between people from the same class and the increased awareness because of their participation in the experiment.

Figure 3(b) shows that the activity levels in the model simulations tend to converge to an average after some time. This is a consequence of the fact that the simulations assume that neither the network nor the personal characteristics of the participants change.

There is a large difference between the mean squared errors shown in Table 5 for the model predictions and the extrapolation of the first 7 days. Extrapolating the first 7 days of physical activity and creating new trendlines for each participant increased the mean squared error to 6.8992. This shows that our model results in a far better prediction

than linear regression using a similar amount of information. The large error for the extrapolation can be explained by the high variation in the PALs of the participants per day, which makes it difficult to predict the trend based on a few days only. If we take a longer period of analysis, we can reduce the error for the statistical trendline.

In this experiment, we assumed that social contagion was the only factor that influences change in physical activity level. However, this is a clear simplification. Factors like weather and daily duties also have an effect on a person's changes in activity. Similarly, there are also other factors than stated in this research that influence the contagion, such as group norms, physical closeness, age and many more. This makes that our model does not provide a complete description of the contagion process. Related to this, the structure of a social network itself is usually not independent of the characteristics of the participants. This effect is called homophily, which describes the tendency of people to connect with others that have the same lifestyle [13].

6. CONCLUSIONS

The results of the experiment show changes in physical activity levels of all members of the social network, in smaller or bigger ratios. The computational model of contagion predicted in 80% of cases correctly whether the PAL increases or decreases, which is the vast majority of the participants, and it grows to 87% if only people with a clear change in activity level are considered. We can conclude that the model has a good accuracy in predicting the tendency of the physical activity levels in a small network of 20 people, in a relatively short period of time.

The current experiment aims to understand the behavior of a stable network and answers the question whether it is possible to use the model to predict the direction of change of activity. These outcomes provide valuable insights for further explorations. To be able to draw conclusions about more dynamic situations, additional experiments should be done. These experiments should last longer, have a higher number of participants, and include changes in the network, e.g. changes in connections or applying interventions in order to influence people's behavior using external triggers.

Future work should also investigate other strategies for parameter tuning and compare the resulting parameters with the values obtained from the questionnaires.

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