Chapter 9

Contagion of Habitual Behaviour in Social Networks: an Agent-Based Model

This chapter appeared as:

Klein, M.C.A., Mogles, N.M., Treur, J. and Wissen, A. van. (2012). Contagion of Habitual Behaviour in Social Networks: an Agent-Based Model. In: *Proceedings of the Fourth ASE/IEEE International Conference on Social Computing, SocialCom'12*, IEEE Computer Society Press, 2012.

(Authors with comparable contributions)

Contagion of Habitual Behaviour in Social Networks: an Agent-Based Model

M. C. A. Klein, N. M. Mogles, J. Treur, A. van Wissen

[1]VU University Amsterdam, Department of Artificial Intelligence
De Boelelaan 1081, 1081 HV Amsterdam
{michel.klein|nm.mogles|treur|wissen}@few.vu.nl

Abstract. This paper introduces a computational model for contagion and change of habitual behaviour in a social network. It considers both the level of individual mechanisms of habit formation, involving a person's attitudes, goals, intentions and relevant environmental cues, and the level of social mechanisms for the impact of others in a social network. Simulation experiments with the model for small-world networks show that the model exhibits realistic behaviour. The model can be used as an aid for physicians and policymakers addressing lifestyle formation and spread in a population under considered policies.

Keywords: social behavior modeling, social contagion

I. Introduction

Theories and models for social contagion or diffusion show a long history, going back to the spread of diseases, rumours, ideas, innovations and emotions; e.g., [12], [40], [32], [5]. First, population-based approaches dominated (e.g., [4], [12], [40]), but individual based models in social networks have increasingly been contributed (e.g., [7], [19], [23], [35]). Recently also contagion of habitual behaviour has become a focus of interest, in particular, in the context of propagating a healthy lifestyle; e.g. [6], [10], [11], [15], [27]. In the current paper this type of contagion is addressed computationally.

A modelling approach for contagion of habitual behaviour in line with earlier approaches to contagion would be to consider the behaviour itself as the subject of contagion, and apply contagion methods based on a form of mimicking; e.g.,[23]. This is inadequate, however, for two reasons. First, in general such behaviours depend on internal states such as goals, attitudes, valuations, and intentions. When direct contagion of behaviour takes place, its effect has to compete with the impact that these states have on the behaviour, and as these internal effects usually are strong, the net change of behaviour will be limited. In order to achieve more substantial changes of behaviour, the internal states themselves have to change. This implies that contagion should not be directly focused on the behaviour, but on the underlying internal goals, attitudes, valuations, and intentions. Second, behaviours considered are usually not just instantaneous, but persist over longer periods of time, and are only subject to change on a longer time scale. This holds in particular for habitual behaviour, as is the focus of this paper. Such types of behaviour are not instantaneous and reactive but adaptive, subject to a learning process on a longer time scale in which valuations of effects of previous occurrences of the behaviour affect future behaviour (goal satisfaction and related emotions).

Given the analysis briefly described above, in this paper an *agent-based* model for contagion of habitual behaviour is introduced, in which the following elements play a role.

- Goal contagion (e.g., [1], [2], [41])
- Attitude contagion (e.g., [26], [43], [27])
- Emotion and intention contagion (e.g., [5], [18], [24], [29])

Each of these types of contagion can work on a different time scale, and is integrated with the agents' internal processes as an interplay of these internal states; cf.[29] Moreover, the model addresses the adaptivity of habits based on Hebbian learning (cf.[20]), as adopted from [29]. The resulting agent-based model does not directly change the behaviour due to social contagion, but first changes the underlying internal states, which in turn leads to behavioural changes, and these get their persistence due to the Hebbian learning mechanism. The contagion processes in the model depend on the specific relations between the different agents in the social network and their strength.

In the paper, first some background literature on habit learning and contagion is discussed in Section II. Next, in Section III the model is presented globally, and detailed specifications are presented in Section IV. In Section V simulation experiments on different social networks are discussed. Section VI concludes with a discussion.

II. Habit Learning and Contagion

Habits are defined as everyday routines that have been formed to achieve particular goals in the past and persist in the absence of goals [48], and that predict our frequent and typical behaviour [36]. They are learned predispositions, formed as a result of conditional learning if a certain cue or context is present during the execution of particular behaviour [48]. Initially, behaviour is triggered by a distinct goal, but later on after numerous pairings of a cue with the behavioural intention, the cue becomes the trigger that launches the same behaviour even if the initial goal is no longer present. The habit is maintained and strengthened by reinforcement learning; the results of the performed behaviour are valued in relation with positive emotions: feeling satisfied with respect to the goal.

In order to understand the mechanisms of habit formation at a higher aggregation level, one cannot omit the social determinants of behaviour: human behaviour emerges as interplay of social and cognitive factors, as has been found, for example, for health behaviour, ecological behaviour, and consumer behaviour (e.g., [41], [13], [26], [37]). Over the past decades, there has been a growing interest in the effect of *social networks* on individual achievement and group performance; e.g., [8], [33], [39]. Connections define the interdependences between the members of a social network and the strength of influences that they propagate through that network. For the formation of habits, family and friends are considered the most important elements of such social contagion [9], [13].

Social contagion is the spread of affect, attitude, or behaviour from Person A (the initiator) to Person B (the recipient), where the recipient does not perceive an intentional influence attempt on the part of the initiator [31]. Social networks provide a vehicle for social contagion processes. For example, the study of [11] demonstrates person-to-person spread of obesity in a large social network of 12,067 persons. Their findings suggest that *social distance* within this network is more important than geographic distance. Team-based experiments in [30] demonstrate that being on a team with more teammates in the weight loss division was associated with greater percent weight loss. The mechanisms at work may involve goal, attitude, emotion and intention contagion, (e.g., [1], [2], [26], [5], [43]) which in turn result in behaviour change. Thus contagion of habitual behaviour is considered an indirect form of contagion, resulting from contagion of underlying internal states. This approach differs from other theories of social impact (such as the Dynamic Theory of Social Impact [35]), in using individual mental states.

III. A Computational Model for Habit Contagion

The computational model for contagion of habitual behaviour described in this paper incorporates an existing individual habit formation model (cf.[29]), and integrates this with social influences on the internal states underlying the agent's behaviour. An overview of the introduced model is depicted in Fig. 1. For the sake of simplicity only two agents A and B, and their mutual influences are represented in the picture. The agents are embedded in the two bigger boxes. Each agent has its own interrelated internal states: *attitude* (ATT), *long term goal* (LTG), *short term goal* (STG), *intention* (INT), *long term goal satisfaction* (LSAT) and *short term goal satisfaction* (SSAT) and each of the agents displays *behaviour* (BEH). *Short term goal* (STG) refers to what is sometimes called 'implementation intention' [22], and represents the realization of a general abstract goal in specifics of how, when and where the goal will be implemented. Any short term goal is always subordinate to a relevant long term goal. An *intention* (INT) is a more refined concrete plan of actions of a goal's realization. It may also refer to unconscious intentions of an immediate motor action, for example a mental preparation of picking up a toothbrush in order to brush teeth. There is one external element in the model that influences the formation of *short term goals* and *intentions* – the cue. This is a context in which an action takes place [48]. It is represented by double short arrows directing to *short term goal* (STG) and *intention* (INT).

Each concept of the model is represented by a number between 0 and 1 for its activation level; this can be considered an aggregation of a vector of a number of constituents, for example *attitude* ATT can be aggregated of *n* attitudes that normally occur in real human agents, the same holds for the other concepts. Multiple intentions within an agent that may result in numerous simultaneous behaviours inhibit each other and the intention with strongest value 'wins' with the relevant behaviour as an output; this implies the execution of only one type of behaviour per time unit by a single agent. The original model [29] for habit formation was extended here by the concept attitude in order to emphasize the formation of long term goals as a result of interpersonal interactions in human agents according to the Theory of Planned Behaviour [17]. Attitudes are any cognitive representations that summarize our evaluation of an item, which may be the self, other persons, things, actions events or ideas [44]. Attitudes are made, maintained and modified through interpersonal processes within social networks [16].

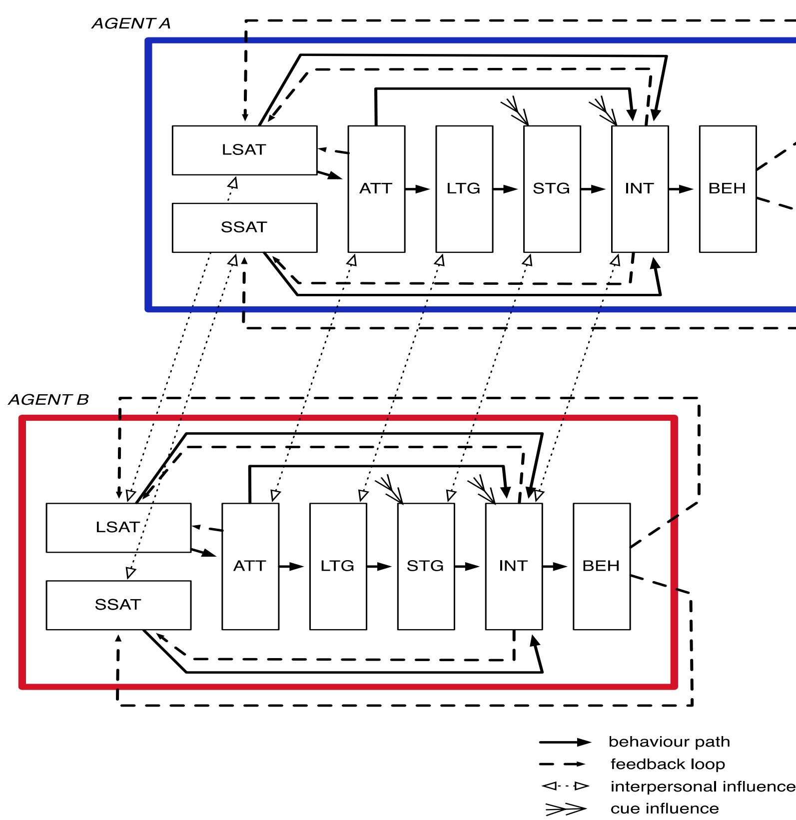


Figure 1. Overview of the Model for Habit Contagion.

Note that forward paths are represented by solid arrows and backward loops by dashed arrows. For example, in addition to the one-directional connection from ATT to LTG in the model, there is also a bi-directional connection of ATT with the long term satisfaction LSAT to express their interrelations. All mutual influences (contagions between corresponding internal states of different agents) are represented by thin dotted bidirectional vertical arrows between the agents. For example, intention contagion, (short-term and long-term) goal contagion, and attitude contagion are depicted by four of these arrows. The model also incorporates emotion contagion applied to emotion-related valuation of satisfaction: the long and short term goal satisfaction (LSAT and SSAT) resulting from execution of certain behaviours relate to the development of feelings of satisfaction. These valuations are both interchanged by emotion contagion and internally function to reinforce particular behaviour. Note that no vertical arrow between the behaviours is depicted, as no direct contagion between behaviours is assumed in the model.

IV. Detailed Specification

This section describes the habit contagion model in a more detailed manner. The model integrates an adaptation of (1) a computational model of individual habit formation and change (cf. [29]), and (2) a social contagion model able to describe the spread of given internal states in a group of agents (cf. [25]). The contagion model formalizes social contagion between the mental states of agents. In the habit contagion model, a number of internal states S of an agent play a role with dynamic values. The different types of states, as introduced in Section 3, are formalised by the set
$\{lsat_{Ai}, ssat_{Ai}, att_{Ai}, ltg_{Ai}, stg_{Ai}, int_{Ai}, beh_{Ai}\}$

Table 2. Overview of the parameters and corresponding states.

parameter/ variable	**description**
γ_{SBA}	contagion strength for S from sender B to receiver A
γ_{SA}	overall contagion strength from the group towards A
ε_{SA}	extent to which agent A expresses state S
δ_{SA}	extent to which agent A is open to state S
α_{SBA}	channel strength for state S from sender B to receiver A
$\omega_{S,S'}$	connection strength between state S and state S'
$lsat_{Ai}(t)$	satisfaction for agent A of long term goal i at time *t*
$ssat_{Ai}(t)$	satisfaction for agent A of short term goal i at time *t*
$att_{Ai}(t)$	attitude i of agent A at time *t*
$ltg_{Ai}(t)$	long term goal i of agent A at time *t*
$stg_{Ai}(t)$	short term goal i of agent A at time *t*

$int_{Ai}(t)$	intention i of agent A at time *t*
$beh_{Ai}(t)$	behaviour i of agent A at time *t*
$cue_i(t)$	activation value of environmental cue i at time *t*
$q_{SA}(t)$	level for state S for agent A at time *t*
$q_{SA}^*(t)$	aggregated impact of all other agents on state S of agent A at time *t*

Here A is the agent, and i is the specific state concerned (as it is possible for an agent to have multiple intentions, goals, attitudes, etc.). Table 1 summarizes the explanation of the states and parameters used. To determine the value of a state during the process, first the social impact of the other agents on that state is determined. The contagion strength γ_{SBA} from sender agent B to receiver agent A for a particular state S is defined in the following relation:

R1 contagion strength: $\gamma_{SBA} = \varepsilon_{SB} \cdot \alpha_{SBA} \cdot \delta_{SA}$

Contagion strength is thus determined by openness, connection strength and expressiveness. The overall contagion strength γ_{SA} from all other agents in the group towards agent A is then determined as follows:

R2 overall contagion strength: $\gamma_{SA} = \Sigma_{B \neq A}\, \gamma_{SBA}$

The overall contagion strength is used to define the aggregated impact q_{SA}^* of all agents ≠ A on state S of A:

R3 Social impact: $q_{SA}^*(t) = \Sigma_{B \neq A}\, \gamma_{SBA} \cdot q_{SB}(t) / \gamma_{SA}$

Note that unlike γ_{SBA} and γ_{SA}, the value for q_{SA}^* is dynamic over time, as it depends on the dynamic states of all other agents. To illustrate this, imagine a social network of three agents, in which Alice, Bob and Carl are friends, and Alice and Bob have a relationship (see Fig. 2 for the parameter values). The mutual impact between these friends using the habit of stair climbing (instead of taking an elevator), is a good example of habitual physical activity [28]. To determine the social impact of Alice's and Carl's attitudes on the attitude of Bob, first are determined.

$\gamma_{ATT,ALICE,BOB}$ (= 0.7·1·0.5=0.35)
$\gamma_{ATT,CARL,BOB}$ (= 0.2·0.5·0.5=0.05)

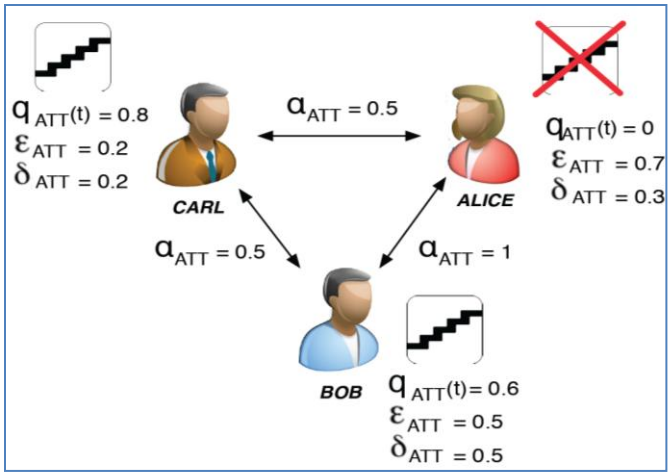


Figure 2. Example of social impact.

These are combined to determine the overall contagion strength $\gamma_{ATT,BOB} = 0.35 + 0.05 = 0.4$. The social impact of Alice and Carl on Bob's attitude is then

$$q_{ATT,BOB}^*(t) = 0.35 \cdot 0 / 0.4 + 0.05 \cdot 0.8 / 0.4 = 0.016.$$

States of agents are not only affected by social impact, but also by an agent's internal processes. As mentioned in Section 3, the model introduced here extends the individual habit model presented in [29] by also incorporating attitudes. The mutual influences between the states are defined by the dynamic relations below. R4 describes the Hebbian learning principle [20] applied for the connections between cues and intentions. This is the core of the habit learning: the connection between the cue and an intention becomes stronger when both the cue and the intention have a high activation level.

R4 Hebbian cue-intention connection learning

$$\omega_{cuei,intAn}(t + \Delta t) = \omega_{cuei,intAn}(t) + [\, \eta\, cue_i(t) int_{An}(t)(1 - \omega_{cuei,intAn}(t)) - \zeta\, \omega_{cuei,intAn}(t)\,]\, \Delta t$$

Here η is the learning rate and ζ the extinction rate.
Now the agent's value for an internal state S can be updated by combining three components: the current state value $S(t)$, the influence $q_S^*(t)$ of others, and the contribution of other internal states (<int_imp>):

R5 State update from social and individual impacts

$$S(t + \Delta t) = S(t) + \theta_S\, ([th(\sigma_S, \tau_S, <int\_imp_S>)\, (1 - \delta_S) + q_S^*\, \delta_S] - S(t)) \cdot \Delta t$$

Here θ_S is an update speed parameter, defining for each state S the influence of the impacts on the new value of that state. Note that the openness δ_S in R1 and R5 determines how much influence the other agents have on the agent's own states, in comparison to the impact of internal states. The higher δ_S, the more dominating social impacts are over the internal impacts. For the function th(σ, τ, X) in R5 various choices are possible. In this case, a logistic threshold function has been chosen:

$$\text{th}(\sigma, \tau, X) = \left(\frac{1}{1+ e^{-\sigma(X-\tau)}} - \frac{1}{1+ e^{\sigma\tau}}\right)(1+ e^{-\sigma\tau})$$

For larger values of $\sigma\tau$ (e.g. >20) this is approximated by:

$$\text{th}(\sigma, \tau, X) = \frac{1}{1+ e^{-\sigma(X-\tau)}}.$$

The internal impacts are defined by a weighted sum of the states of influence with the connection strengths as weights. Table 2 shows which internal impacts contribute to the value of state S (as can be observed from Fig. 1) at any time point t.

Table 3. Overview of states and contributing internal impacts.

state S	**internal_impacts$_S$**
$lsat_{Ai}$	$\sum_i int_{Aj}\ \omega_{intAj,\ lsatAi} + \sum_k att_{Ak}\ \omega_{attAk,\ lsatAi} + \sum_l beh_{Al}\ \omega_{behAl,\ lsatAi}$
$ssat_{Ai}$	$\sum_j int_{Aj}\ \omega_{intAj,\ ssatAi} + \sum_k beh_{Ak}\ \omega_{behAk,\ ssatAi}$
att_{Ai}	$\sum_j lsat_{Aj}\ \ \omega_{lsatAj,\ attAi}$
ltg_{Ai}	$\sum_j att_{Aj}\ \omega_{attAj,\ ltgAi}$
stg_{Ai}	$\sum_j ltg_{Aj}\ \ \omega_{ltgAj,\ stgAi} + \sum_k cue_k\ \ \omega_{cuek,\ stgAi}$
int_{Ai}	$\sum_j int_{Aj}\ \omega_{intAj,\ intAi} + \sum_k att_{Ak}\ \omega_{attAk,\ intAi} +$ $\sum_l lsat_{Al}\ \omega_{lsatAk,\ intAi} + \sum_m ssat_{Am}\ \omega_{ssatAm,\ intAi} +$ $\sum_n cue_n\ \omega_{cuen,\ intAi}$

Keeping in mind the case of Alice, Bob and Carl, Bob's stair climbing attitude at time t+Δt can be determined using R5, the parameters θ_{ATT}, σ_{ATT}, τ_{ATT}, his long term goal satisfaction and the connection between his attitude and this satisfaction. Given the values θ_{ATT} = 0.5, σ_{ATT} = 15, τ_{ATT} = 0.1, lsat = 0.8 (a high satisfaction related to his long term goal for stair climbing) and ω(lsat, att) = 0.2, for Δt =1 the function then becomes the following:

$$\begin{aligned} att(t+\Delta t) &= att(t) + \theta_{ATT} \cdot ([th(\sigma_{ATT}, \tau_{ATT}, lsat \cdot \omega(lsat, att)) \cdot \\ &\qquad (1 - \delta_{ATT}) + q_{ATT}^* \cdot \delta_{ATT}] - S(t)) \cdot 1 \\ &= 0.6 + 0.5 \cdot ([0.98 \cdot (1 - 0.5) + 0.016 \cdot 0.5] - 0.6) \cdot 1 \end{aligned}$$

The new value of Bob's attitude is thus 0.549.

Behaviour results from intention and depends on the threshold for behaviour. That is, an agent can have the intention to perform an action, but it can be inhibited by other (contradictory) intentions or the intention can be too low for the agent to act upon it.

R6 Performing behavior

$beh_{Ai}(t+\Delta t) = beh_{Ai}(t) + \lambda \cdot [th(\sigma, \tau, int_{Ai}(t)) - beh_{Ai}(t)] \cdot \Delta t$

For R6, the same threshold function has been chosen as for function R5. Again, λ is an update speed determining how much the agent's intention at t contributes to its new behaviour at time $t+\Delta t$.

V. Simulation Results

The habit contagion model was implemented in Matlab and has been studied in several scenarios with different numbers of agents in order to examine whether the proposed approach indeed exhibits the patterns that are identified in literature. There is not much literature on the specific example of social influence on stair climbing, but there is a vast amount of studies about the influence of social factors on physical activity. For example, [21] shows that for physical activity social factors are more important than environmental factors. In [45] the effect of encouragement and participation of family members and friends on physical activity of children is illustrated.

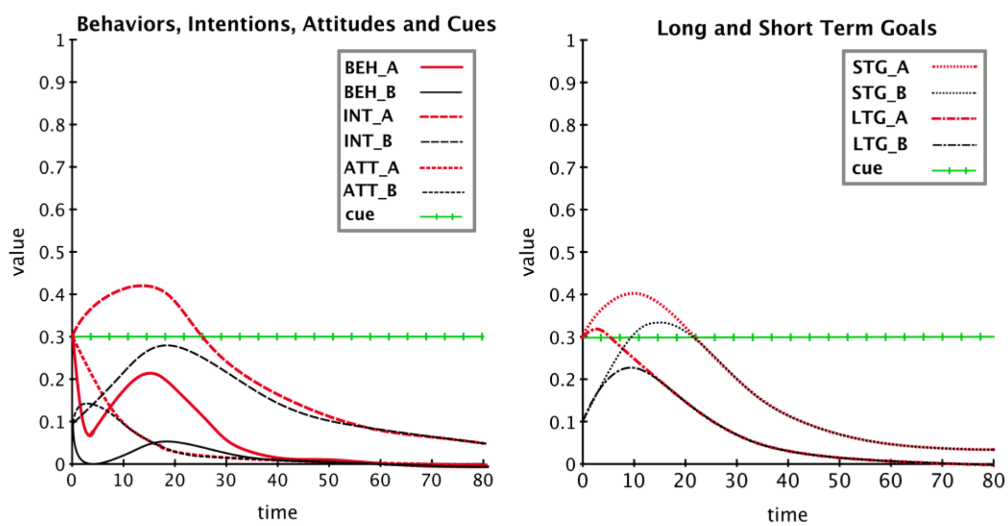
A. Two Partner Agents

The first set of simulation experiments shows the interaction between two agents. For explanation and clarity purposes, for this simulation the personality characteristics of both partners are kept equal. That is, the links between the different internal and external states are of the same weight. For example, the influence of cues on their intentions and short term goals are the same for both (0.3), their long term goals have the same strength of impact on their short term goals (0.8), and the expressiveness of both agents is set at 0.5.. This simplification ensures a transparent view into the mechanisms at work.

In the two scenarios there are two agents who work together and have a close relationship: Bob and Alice. Both are influenced by each other and by the same cues (if present): banners on the stairs that stimulate to take the stairs. Table 3 describes the scenarios and the main simulation results. The dynamics of the different concepts are captured in Fig. 3, with the time steps measured in days. Simulation 1a shows that merely an attitude or goal change is not enough to change a habit (see also [22]). Simulation 1b demonstrates that environmental cues are vital to behaviour change, as argued in e.g., [21]. Simulation 1b also shows that a supportive partner can stimulate one to become engaged in physical activities (resembling the results from [45]). These simulations show that the model is able to produce both realistic behaviour that emerges from social interaction between agents, and behavioural patterns as they are identified in empirical literature.

Table 3. Two scenarios: 1a and 1b

a	*Neither Bob nor Alice takes the stairs. There are no banners on the stairs (cues)* **Attitude/goals/satisfactions:** Due to social contagion, Bob influences Alice and her attitude towards stair climbing, her goals to become fit and to take the stairs and her satisfactions from the performed behaviour of stair climbing drop. Bob's attitude towards taking the stairs at first slightly increases due to Alice's attitude. Then, Alice's attitude and goals also drop due to the absence of cues and due to the influence of Bob who has low goals and attitudes . **Behaviour:** Neither Bob nor Alice takes the stairs.
b	*Bob does not take the stairs, while Alice does. There are banners on the stairs (cues)* **Attitude/goals/satisfactions:** Due to social contagion, Bob has a big influence on Alice and as a result her attitude towards stair climbing, her goals to take the stairs and satisfactions from the performed behaviour of stair climbing drop. However, the intentions of Alice are quite high due to the influence of the cues on her goals and intentions. Bob's attitude towards taking the stairs at first slightly increases due Alice's attitude. **Behaviour:** Bob starts taking the stairs and both Bob and Alice keep taking the stairs.



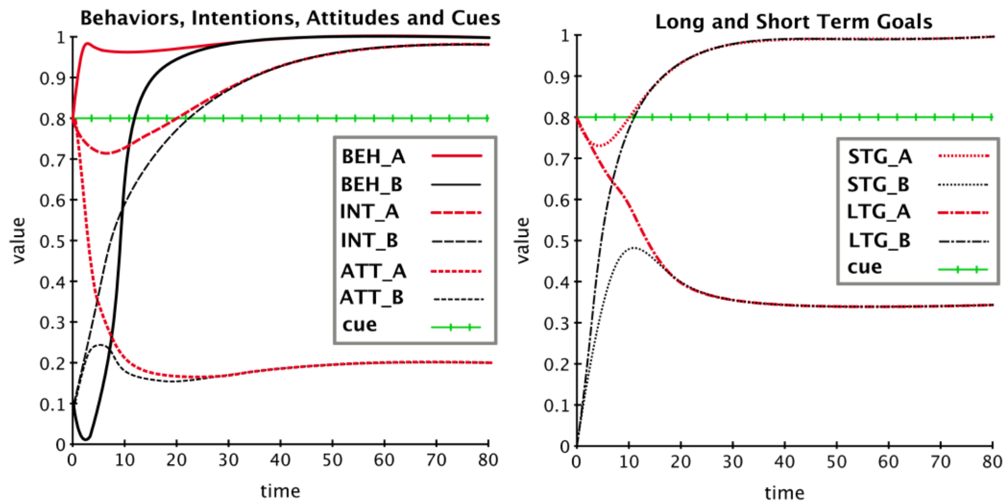


Figure 3. Scenario 1a (above), scenario 1b (below).

In these scenarios the model was applied to agents with the same personality characteristics. However, the model is flexible and the parameters can be adjusted to reflect different agent personalities. For example, some agents can be more prone to cues than others, and some agents attach more value to short-term goals than others. This flexibility ensures that the model is able to deal with a large variety of scenarios in which different types of agents interact. Example simulations with heterogeneous partners can be found in Appendix A.[1]

B. Larger Groups

Section 5A shows how the model predicts behaviour patterns for two agents. However, the social environment that influences people is often not limited to the direct partner or best friend. There is an entire network of colleagues, friends, family and neighbours that determines the social impact on a person. The habit contagion model can equally well be used to deal with these larger groups, such as groups with 10, 100, or 1000 agents.[2] Fig. 4 shows simulation results of a group of 100 agents. In this simulation, the agents form a social network with two groups. The parameter values are listed in Table 4.

Table 4. Settings for group scenarios.

	LTG	STG	LSAT	SSAT	ATT	INT	BEH
learning parameter (θ or λ)	0.2	0.2	0.5	0.2	0.2	0.1	0.5
threshold (τ)	0.1	0.3	0.4	0.5	0.1	0.5	0.5
steepness (σ)	15	15	15	15	15	15	15

In this simulation, a social network that consists of two groups (group 1: agent 1-50, and group 2: agent 51-100) was designed. Within each group, the agents can have (strong)

[1]http://www.few.vu.nl/~wissen/downloads/appendix/AppendixA_SOCIALCOM.pdf
[2]Runtime approx. 1 min for 100 agents and approx. 10 min for 1000 agents, on a Macbook Pro with 2.53 GHz Intel Core 2 Duo and 4 GB 1067 MHz DDR memory

connections with each other. Only 5% of the agents in each group have connections with agents from the other group – see Fig. 5. This form of the network was chosen for two reasons: to resemble for example two families or two different schools, and to clearly demonstrate the functioning of the model in a network with more structure than a random network. The only difference between group 1 and 2 is that all agents in group 1 initially have very low attitudes and long term goals (and consequently, long term satisfactions) concerning taking the stairs. The opposite is true for group 2: the agents in this group have high attitudes and long term goals concerning taking the stairs. All other states and the connections are initialized randomly. This simulation shows the effect that social environment can have in large groups.

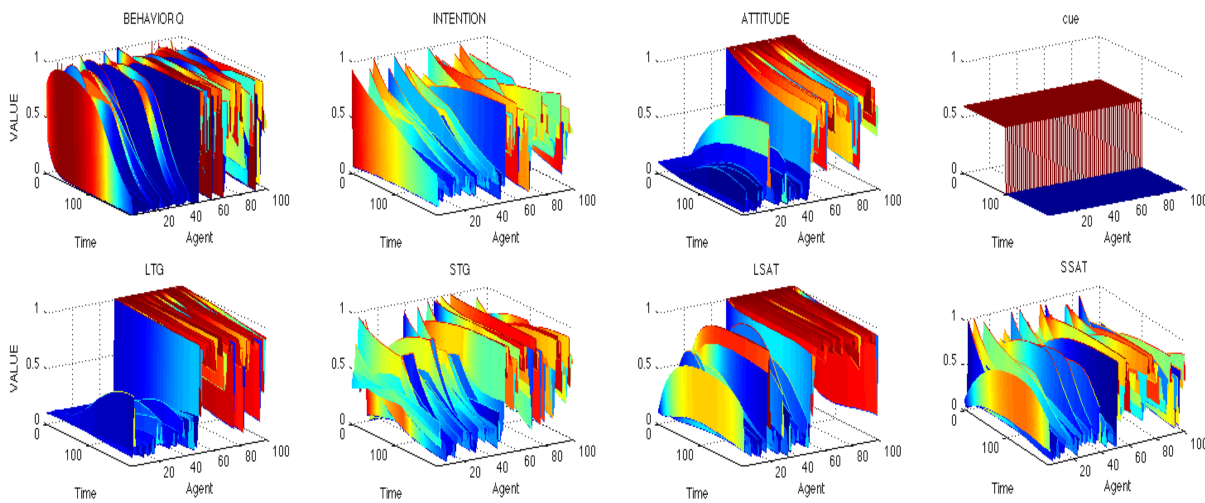


Figure 4. Simulation results including all mental states for 100 agents (right horizontal axis represents 100 distinct agents).

As shown by Fig. 4, many agents start taking the stairs when the cue is present, regardless of their attitudes or goals. There is also a visible effect of the attitudes of the other group, as the attitudes of group 1 are somewhat lowered and those of group 2 are raised. However, when the cue disappears, group 1, who are not able to keep up their goals and intentions, 'relapse' and do not take the stairs any longer. However, many agents in group 2 have learned a new habit and due to their positive social influence of high attitudes, intentions, goals and behaviours, they are able to continue taking the stairs.

A. Small world networks

To demonstrate the workings of the model in more complex (and more realistic) networks, simulations have been run for a small-world network with the properties of (i) a small average shortest path length, and (ii) a large clustering coefficient [47]. Typically these networks also have many *hubs*, which are nodes in the network with a high number of connections. Small world networks are often used to model various types of networks in the world, among which many social networks (such as influence networks, friend connections, web-based communications) [34],[40].

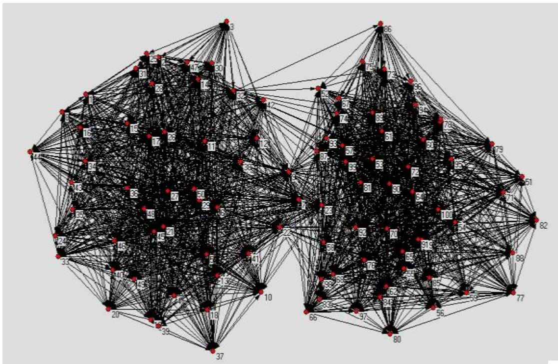


Figure 5. A network of 100 agents divided in 2 groups.

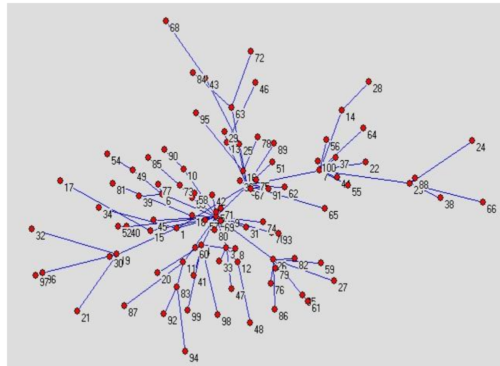


Figure 6. Small world network: hubs with positive attitude.

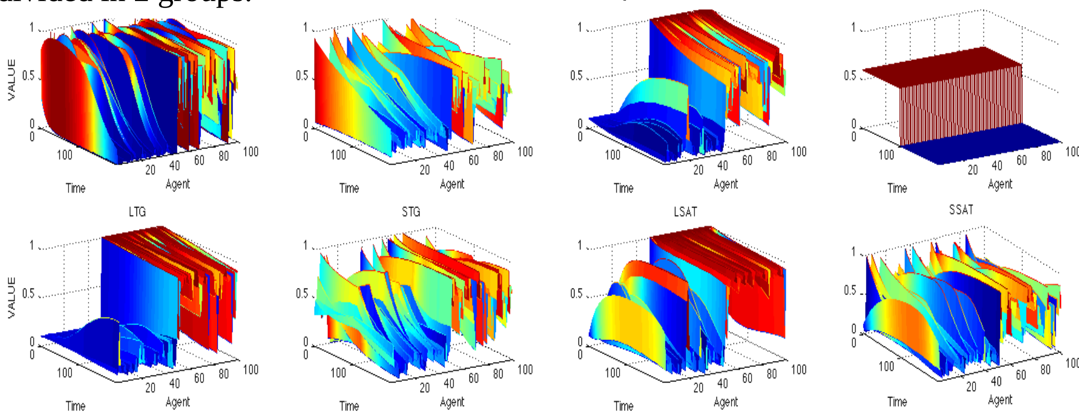


Figure 7. Simulation results for 100 agents in a small world network in which the hubs have positive dispositions.

Simulations were done to show how positive hubs in a small world network are able to influence behaviour of a group of agents. A network of 100 agents is created, divided into two random groups of 50 agents, with the constraint that the hubs (here defined as the 25% of agents with the highest number of connections) are part of group 1 with highly positive attitudes, long term goals and long term satisfactions.
As before, all other states are initially assigned random values between 0 en 1. Fig. 7 shows the results of this simulation and Fig. 6 displays the layout of the network. From Fig. 7 it follows that hubs have a significant influence on the behaviour within the entire population. The average goals and attitudes of the agents remain high resulting in many agents that are able to retain their stair climbing behaviour. On average in 100 runs, the agents had a behaviour value of 0.44, an intention of 0.46, and a 0.65 attitude (which is significantly higher than if the same scenario is run with negative hubs, single-tail paired t-test, alpha < 0.001).[3] These results may be an indication that it is crucial to have important people in the network (with many strong connections to others) that function as role models.

[3] See Appendix A for the results of a simulation with negative hubs.

VI. Discussion

The agent-based model for contagion of habitual behaviour in social networks introduced in this paper is based on the following elements:

- the behaviour is generated based on internal states: goals, attitudes, valuations, intentions
- based on the (emotion-related) valuation states and their reinforcing role, habits are learned by Hebbian learning
- not the behaviour, but the underlying internal goal, attitude, valuation, intention states are subject of contagion
- the dynamics of each of these internal states is modelled by combining the effects of internal states on each other and the contagion from the corresponding state of other agents
- the changes in internal functioning and behaviour due to the contagion from other agents affect the habitual learning process; thus habits are changed based on social contagion

For contagion of each of these types of states some informal, non-computational literature is available: goal contagion (e.g., [1], [2], [42]), attitude contagion (e.g., [26], [43], [27]), emotion and intention contagion (e.g., [5]). For the latter types of states also some computational models are available, e.g., [25], [46].

Most computational models for social contagion have been inspired by models for epidemics; e.g., [4], [14], [23]. A limitation of most of these computational models for contagion of, for example intention, behaviour or emotion, is that (1) only the contagion process is modelled, without taking into account an agent's internal processes that affect the emotion or behaviour as well, and (2) no adaptation of the own internal agent processes takes place. For example, in [23] the interaction between members of the group N of normal persons, and members of groups L, S and O with unhealthy behaviour leads to transitions of persons from this group N to the group L with unhealthy behaviour. Due to these limitations, in such models the mutual impact of agents on each other has a purely reactive and instantaneous character. Some exceptions on limitation (1) can be found in [25], where the contagion is integrated with the internal interplay of beliefs, emotions and intentions, and [3], where the contagion is integrated with internal emotion regulation processes. In [7], [19] and [38] some internal cognitive mechanisms of behaviour in social networks are addressed, but these mechanisms are limited to the modelling of memory or attitudes. In the current paper the contagion is integrated not only with the interplay of the four types of internal states (addressing limitation (1)), but also with the Hebbian learning mechanism, and in this way adapts the agent's own internal processes (addressing limitation (2)). Thus the presented model goes beyond reactive and instantaneous effects of the agents on each other, it shows how habitual behaviour learned as an effect of social contagion can persist individually.

The introduced model for habit contagion can be used to study the process of social influence on behaviour, in particular on habitual behaviour. This can be an aid for policymakers in making predictions and what-if analyses of habits formation and spread in a population. Specifically, public health workers might be interested in the spread of healthy habits. Moreover, the introduced model may be embedded in a support agent that may provide support for humans in their everyday life with respect to their lifestyle change and developing good habits. If such a system can predict the effect of social influences and cues on habitual behaviour, it may try to adapt the environment in such a way that the habit will be changed, for example by drawing one's attention to the long term goals, or by suggesting changes in the (virtual) social network around persons to stimulate contagion of states that will have a positive influence on the habit.

References

[1] Aarts, H., Gollwitzer, P.M., Hassin, R.R., "Goal Contagion: Perceiving Is for Pursuing", Journal of Personality and Social Psychology 87, 2004, pp. 23–37.

[2] Aarts, H., Hassin, R. R., "Automatic goal inference and contagion: On pursuing goals one perceives in other people's behaviour", in S.M. Latham et al. (eds.), Social motivation: Conscious and unconscious processes, New York: Cambridge University Press, 2005, pp. 153-167.

[3] Aziz, A.A., Treur, J., and Wal, C.N. van der, "An Agent-Based Model for Integrated Contagion and Regulation of Negative Mood", in Kinny, D., et al. (eds.), Proc. PRIMA'11. Lecture Notes in AI, vol. 7047, Springer-Verlag, 2011, pp. 83-96.

[4] Bailey, N.T.J., The Mathematical Theory of Epidemics. Griffin, 1960.

[5] Barsade, S.G., "The ripple effect: Emotional contagion and its influence on group behaviour", Administrative Science Quarterly 47, 2002, pp. 644–675.

[6] Berman, M.E., Walley, J.C., "Imitation of Self-Aggressive Behaviour: An Experimental Test of the Contagion Hypothesis", J. of Applied Social Psychology 33, 2003, pp. 1036-1057.

[7] Bhattacharyya, S. & Ohlsson, S., "Social Creativity as a function of agent cognition and network properties: A computer model", Social Networks, 32, 2010, pp. 263-278.

[8] Burger, M. J. and Buskens, V., "Social context and network formation: An experimental study", Social Networks 31, 2009, pp. 63–75.

[9] Campbell, J. M., and Oei, T.P., "A cognitive model for the intergenerational transference of alcohol use behaviour", Addictive Behaviours 35, 2010, pp. 73–83.

[10] Christakis, N.A., and Fowler, J.H., "The Collective Dynamics of Smoking in a Large Social Network", N Engl J Med 358, 2008, pp. 2249-2258.

[11] Christakis, N. A., and Fowler, J. J., "The Spread of Obesity in a Large Social Network over 32 Years", N. Engl. J. Med. 357, 2007, pp. 370-379.

[12] Daley, D.J., Kendall, D.G., "Epidemics and rumours", Nature 204, 1118, 1964.

[13] DiClemente, R.I., Crosby. R.A. and Kegler, M.C., Health Promotion Practice and Research. John Wiley, 2009.

[14] Dodds, P.S., Watts, D.J., "A generalised model of social and biological contagion", Journal of Theoretical Biology 232, 2005, pp. 587-604.

[15] Duncan, G.J., Boisjoly, J., Kremer, M., Levy, D.M., Eccles, J., "Peer Effects in Drug Use and Sex Among College Students", J. of Abnormal Child Psychology 33, 2005, pp. 375–385.

[16] Erickson, B.H., “The Relational Basis of Attitudes”, in B. Wellman and S.D. Berkowitz: Social Structures: A Network Approach. Cambridge University Press, 1988.
[17] Fishbein, M. and Ajzen, I, Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research. Addison-Wesley, 1975.
[18] Fowler, J.H. and Christakis, N.A., “The Dynamic Spread of Happiness in a Large Social Network: Longitudinal Analysis Over 20 Years in the Framingham Heart Study”, British Medical Journal 337, a2338, 2008.
[19] Friedkin, N. E., “The Attitude-Behavior Linkage in Behavioral Cascades”, Social Psychology Quarterly 73, 2010, pp. 196-213.
[20] Gerstner, W., Kistler, W.M., “Mathematical Formulations of Hebbian Learning”, Biol. Cybern. 87, 2002, pp. 404-415.
[21] Giles-Corti, B., Donovan, R.J., “The relative influence of individual, social and physical environment determinants of physical activity”, Social Science & Medicine, 54, 2002, pp. 1793-1812
[22] Gollwitzer, P.M. and Sheeran, P., “Implementation Intentions and Goal Achievement: A Meta-analysis of Effects and Processes”, Advances in Experimental Social Psychology 38, 2006, pp. 69-119.
[23] González-Parra, G., Acedo, L., Villanueva Micó, R.J., Arenas, A.J., “Modeling the social obesity epidemic with stochastic networks”, Physica A 389, 2010, pp. 3692-3701.
[24] Hill, A.L., Rand, D.G., Nowak, M.A. and Christakis, N.A., “Emotions as Infectious Diseases in a Large Social Network: The SISa Model”, Proc. of the Royal Society B 277(1701), 2010, pp. 3827-3835.
[25] Hoogendoorn, M., Treur, J., Wal, C. van der, and Wissen, A. van., “Agent-Based Modelling of the Emergence of Collective States Based on Contagion of Individual States in Groups”, Collective Intelligence 3, 2011, pp. 152–179.
[26] Howard, D.J., Gengler, C., “Emotional Contagion Effects on Product Attitudes”, J. of Cons. Res. 28, 2001, pp. 189-201.
[27] Kawaguchi, D., “Peer effects on substance use among American teenagers”, J. of Popul. Economics 17, 2004, pp. 351–367.
[28] Kerr, J., Eves, F., Carroll, D., “Six-Month Observational Study of Prompted Stair Climbing”, Preventive Medicine, Volume 33, Issue 5, 2001, pp. 422-427.
[29] Klein, M., Mogles, N., Treur, J., and Wissen, A. van., “A Computational Model of Habit Learning to Enable Ambient Support for Lifestyle Change”, Proceedings of IEA-AIE’11 LNCS 6704, Springer Verlag, 2011, pp. 130-142.
[30] Leahey, T.M., Kumar, R., Weinberg, B.M., and Wing, R.R., “Teammates and Social Influence Affect Weight Loss Outcomes in a Team-Based Weight Loss Competition”, Obesity, 2012, pp. 1-6.
[31] Levy, D.A., Nail, P.R., “{Contagion: A theoretical and empirical review and reconceptualization”, Genetic, Social & General Psychology Monographs 119, 1993, pp. 233–284.
[32] Lynch, A., Thought Contagion: How Belief Spreads Through Society. New York: Basic Books, 1996.

[33] Mitchel, L. E. and Trickett, E.J., “Task Force Report: Social Networks as Mediators of Social Support, An Analysis of the Effects and Determinants of Social Networks”, Community Mental Health Journal 16, 1980, pp. 27-44.
[34] Newman, M.E.J., “Models of the Small World”, Journal of Statistical Physics, 101, Nos. 3/4, 2000, pp. 819-841.
[35] Nowak, A., Szamrej, J. and Latane, B., “From Private Attitude to Public Opinion: A Dynamic Theory of Social Impact”, Psychological Review 97, 1990, pp. 362-376.
[36] Oulette, E. A. and Wood, W., “Habit and Intention in Everyday Life: The Multiple Processes by Which Past Predicts Future Behaviour”, Psychol. Bulletin 124, 1998, pp. 54-74.
[37] Peattie, K. and Peattie, S., “Social marketing: A pathway to consumption reduction?”, J of Business Res. 62, 2009, pp. 260–268.
[38] Reitter, D. & Lebiere, C., “How groups develop a specialized domain vocabulary: A cognitive multi-agent model”, Cognitive Systems Research, 12, 2011, pp. 175-185.
[39] Ritter, C., “Social Supports, Social Networks, and Health Behaviours”, in D.S. Gochman (ed.), Health Behaviour: Emerging Research Perspectives. Plenum Press, 1988.
[40] Rogers, E., Diffusion of Innovations. Free Press, New York, 1983.
[41] Sallis, J. F. and Nader, P.R., “Family Determinants of Health Behaviours”, in: D.S. Gochman (ed.), Health Behaviour: Emerging Research Perspectives. Plenum Press, 1988.
[42] Sheeran, P., Aarts, H., Custers, R., Rivis, A., Webb, T.L., Cooke, R., “The goal-dependent automaticity of drinking habits”, Br. J. of Social Psychology 44, 2005, pp. 47–63.
[43] Sinha, J., Contagious Likes and Dislikes. Ph.D. Thesis. University of Iowa, 2011.
[44] Smith, E.R. and Mackie, D.M., Social Psychology, Philadelphia: Psychology Press. 2008.
[45] Springer. A., Kelder, S., Hoelscher, D., “Social support, physical activity and sedentary behavior among 6th grade girls: a cross-sectional study”, Int J Behav Nutr Phys Act 3:8, 2006.
[46] Tsai, J., Bowring, E., Marsella, S., and Tambe, M., “Empirical Evaluation of Computational Emotional Contagion Models”, in: Vilhjalmsson, H., et al. (eds.), Intelligent Virtual Agents, Proc. IVA’11. LNCS 6895, 2011, pp. 384-397.
[47] Watts, D. J. & Strogatz, S. H., “Collective Dynamics of 'small-world' networks”, Nature 393, 1998, pp. 440-442.
[48] Wood, W. and Neal, D.T., “A New Look at Habits and the Habit-Goal Interface”, Psychol. Review 114, 2007, pp. 843-863.