A Computational Model for Dynamics of Desiring and Feeling[1]

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Abstract

In this paper a computational model is presented for how a desire triggers responses and feelings. The model shows how these feelings can be biased, for example due to addicting experiences in the past. Both the strength of a response and of the associated feeling result from a converging dynamic pattern modelled by reciprocal causal interactions between the two. The model has been used to conduct a number of simulation experiments under varying circumstances. Moreover, it has been evaluated by formal analysis of emerging patterns entailed by the model. Furthermore, it has been pointed out how the computational model can be applied within an ambient agent system supporting a human in not being tempted. In a simple example scenario it is shown such an ambient agent system is able to predict and assess a human's desire state, and use this assessment to suggest alternatives to avoid falling for certain temptations.

Keywords: desire, feeling, computational model

1 Introduction

As many cognitive states, desires trigger responses in the form of preparations for certain actions and associated emotional states. These emotional states in turn induce emotional feelings, and in a reciprocal manner, the generated feelings affect the preparations. For some literature on such reciprocal interactions between cognitive and affective states, see, for example, (Eich, Kihlstrom, Bower, Forgas, and Niedenthal, 2000; Niedenthal, 2007; Winkielman, Niedenthal, and Oberman, 2009; Memon and Treur, 2010). The dynamical model introducd in this paper for these processes is based on neurological theories on the embodiement of emotions as described, for example, in (Damasio, 1994, 1996, 1999, 2003, 2010; Winkielman, Niedenthal, and Oberman, 2009).

More specifically, for feeling the emotion associated to a preparation a converging recursive body loop is assumed (e.g., Damasio, 1999, 2003, 2010). This feedback loop also involves the interaction back from the feeling to the preparation state. For given circumstances, this loop ends up in an equilibrium for both the strength of the preparation and of the feeling. The level of this equilibrium depends on the

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Hoogendoorn, M., Memon, Z.A., Treur, J., and Umair, M., A Model-Based Ambient Agent Providing Support in Handling Desire and Temptation. In: Demazeau, Y., et al. (eds.), *Proceedings of the 8th International Conference on Practical Applications of Agents and Multi-Agent Systems: Trends in Practical Applications of Agents and Multiagent Systems, PAAMS'10*. Advances in Intelligent and Soft Computing Series, vol. 71. Springer Verlag, 2010, pp. 461-475.

strengths of the connections within such a loop. By a Hebbian learning mechanism these connection strengths are assumed to depend on earlier experiences. This is also in line with the Somatic Marker Hypothesis (Damasio, 1994, 1996). By the model it will be shown how through this adaptation process addicting experiences can create serious biases in these loops, that may easily lead to vulnerabilities for temptations.

In the first place the paper introduces a dynamical model for the processes indicated above. In addition the possible use of such a model in supporting persons to handle temptations is discussed. To this end, a design of an ambient agent system is described (e.g., Aarts, Collier, Loenen, Ruyter, 2003; Aarts, Harwig, Schuurmans, 2001; Riva, Vatalaro, Davide, Alcañiz, 2005). One of the more ambitious challenges in this area is to create ambient systems with an appropriate form of human-awareness: awareness of the (mental) states of humans. To obtain an adequate human-aware ambient system, computationally formalised knowledge describing the dynamics and interaction of internal states is needed. To design an ambient system incorporating such a model, agent modelling offers a useful approach, as agents are able to integrate such dynamical models and reason about them (e.g., Bosse, Hoogendoorn, Klein, and Treur, 2009). Human-aware ambient agent systems equipped with the ability to reason about the different types of mental states in principle can be applied to support of humans, for example persons vulnerable to temptations due to a developing addiction. A second possible application of the computational model is as a basis for a virtual agent for a person suffering from addictive behaviour, in a simulation-based training environment for psychotherapists.

In this paper, first in Section 2 the computational model for the dynamics of desires, preparations and feelings is described. Section 3 presents simulation results of the domain model. In Section 4, formal analysis of the computational model is addressed, both by mathematical analysis of equilibria and automated logical verification of properties. In Section 5 it is pointed out how an ambient agent model can be obtained which integrates the computational model. Section 6 is a discussion. Appendices give some more details for the suggestions put forward for application of the computational model within an ambient agent.

2 The Computational Model for Dynamics of Desires and Feelings

In this section the dynamical interaction between desiring, preparing and feeling is discussed in some more detail from a neurological perspective. First an overview is given, next different parts of the model are discussed in more detail.

2.1 Overview of the Computational Model

Any mental state in a person induces emotions felt by this person, as described in (Damasio, 2003):

> '… few if any exceptions of any object or event, actually present or recalled from memory, are ever neutral in emotional terms. Through either innate design or by learning, we react to most, perhaps all, objects with emotions, however weak, and subsequent feelings, however feeble.' (Damasio, 2003, p. 93)

More specifically, in this paper it is assumed that responses in relation to a mental state of desiring roughly proceed according to the following causal chain:

desire $\rightarrow$ preparation for response $\rightarrow$ body state modification $\rightarrow$ sensing body state $\rightarrow$
sensory representation of body state $\rightarrow$ induced feeling

As a variation, an 'as-if body loop' uses a direct causal relation
preparation for response $\rightarrow$ sensory representation of body state

as a shortcut in the causal chain; cf. (Damasio, 1999). The body loop (or as-if body loop) is extended to a *recursive (as-if) body loop* by assuming that the preparation of the bodily response is also affected by the state of feeling the emotion:

feeling $\rightarrow$ preparation for the bodily response

Such recursion is suggested in (Damasio, 2003), noticing that what is felt is a body state which is under control of the person:

> 'The brain has a direct means to respond to the object as feelings unfold because the object at the origin is inside the body, rather than external to it. The brain can act directly on the very object it is perceiving. (…) The object at the origin on the one hand, and the brain map of that object on the other, can influence each other in a sort of reverberative process that is not to be found, for example, in the perception of an external object.' (Damasio, 2003, pp. 91-92)

Within the computational model presented in this paper, both the bodily response and the feeling are assigned a level or gradation, expressed by a number. The causal cycle is modelled as a positive feedback loop, triggered by an activation of the desire and converging to certain activation levels of feeling and preparation for a body state. Here in each round of the cycle the next body state preparation has a level that is affected by both the activation levels of the desiring and the feeling state, and the next level of the feeling is based on the level of the preparation. In this way the activation of a specific action is based on both the activation level of the desire and of the feeling associated to this action. This illustrates Damasio's theory on decision making with a central role for emotions felt, called the Somatic Marker Hypothesis (cf. Bechara and Damasio, 2004; Damasio, 1994, 1996). Each considered decision option induces (via an emotional response) a somatic marker. Viewed from this perspective, based on the recursive as-if body loop, not only the strength of the connection from desire to preparation but also the strength of the connection from feeling to preparation will play an important role in deciding which action to pursue. When one or each of these connections is weak it will not lead to a high activation level of the preparation state, whereas a strong connection strength may result in a high activation level of the preparation state. A strong preparation state can play the role of a strong temptation.

The strengths of the connections from feeling to preparation are subject to learning. Especially when a specific action is performed and it leads to a strong effect in feeling, by Hebbian learning (Bi and Poo, 2001; Hebb, 1949; Gerstner and Kirstner, 2002) this will give a positive effect on the strength of this connection and consequently on future activations of the preparation of this specific action. Through such a mechanism experiences in the past have their effect on behavioural choices made in the future. In the computational model introduced here, by a Hebbian learning rule it is realised that actions induced by a certain desire which result in stronger experiences of satisfaction will be chosen more often to fulfill this desire. This is independent of how benificial these actions are.

In the remainder of this section the dynamical model is presented; for an overview see Figure 1. This picture also shows labels LP0 to LP8 referring to the detailed specifications of dynamical relations explained formally in Box 1 and 2. Note that the precise numerical relations between the indicated variables V shown are not expressed in this picture, but in the detailed specifications of properties in the boxes. Here capitals are used for (assumed universally quantified) variables. The computational model was specified in the hybrid dynamical modelling language LEADSTO (Bosse, Jonker, Meij and Treur, 2007), where the temporal relation a $\twoheadrightarrow$ b denotes that when at some time point a state property a occurs, then after a certain time delay (which can be specified as any positive real number, for example, a small time step Δt), state property b will occur. LEADSTO is a hybrid language in the sense that both logical and numerical relations can be specified in a fully integrated manner. It is supported by a dedicated editor and a simulation environment.

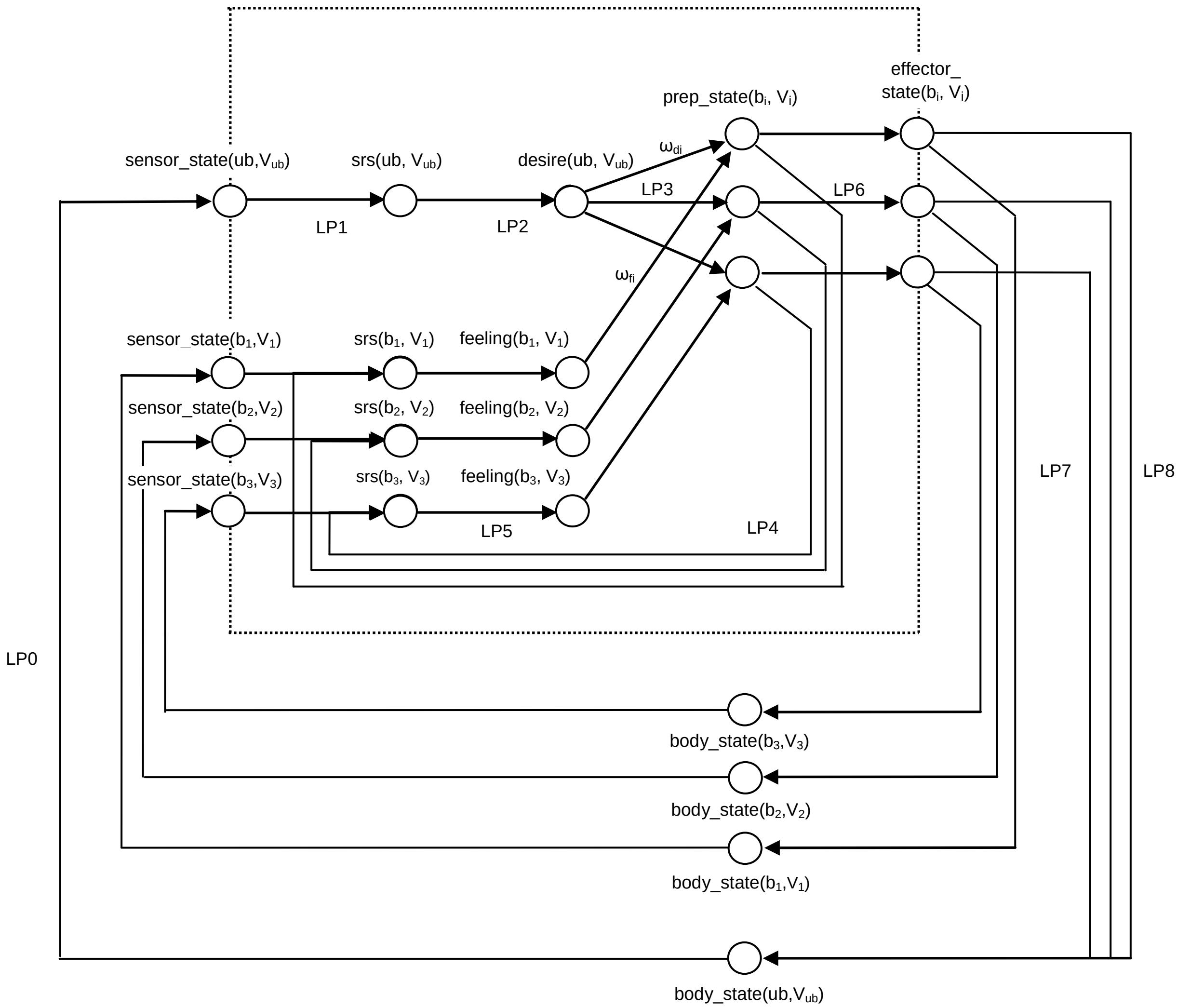

Figure 1. Overview of the dynamical model for desiring and feeling

2.2 The Dynamical Interaction between Preparing and Feeling induced by a Desire

Desires are assumed to be based on sensory representations of unbalances in the body state. This relates to the principle that organisms aim at maintaining homeostasis of their internal milieu. Desires induce preparations for actions and associated feelings which in turn have a mutual interaction.

Generating a desire by a sensing a bodily unbalance

Sensor states are represented in Figure 1 by sensor_state(ub,V_{ub}) and sensor_state(b_i,V_i) for i = 1, 2, 3 (see LP0 in Box 1). As a next step sensory representations are determined. This takes place by a simple propagation of the respective sensor state value to the respective value for the sensory representation state; see Figure1 srs(B,V) with $B \in \{ub, b_1, b_2, b_3\}$, and Box 1, LP1. The desire considered in the example scenario is assumed to be generated due to sensing an unbalance in a body state indicated by *ub*. The first part of the example scenario proceeds as follows:

- the person senses the bodily unbalance state *ub*
- the desire to address this unbalance *ub* is generated (e.g., a state of being hungry)

- the desire triggers preparations for actions involving body states b_i to fulfill the desire; here also the associated feeling states play their role.

Sensing and sensory representation of body states B ∈ {ub, b_1, b_2, b_3}

LP0 Sensing a body state B ∈ {ub, b_1, b_2, b_3}
If body state property *B* has level *V*
then after Δt a sensor state for *B* will have level *V*.

body_state(B, V) ↠ sensor_state(B, V)

LP1 Generating a sensory representation for a sensed body state B ∈ {ub, b_1, b_2, b_3}
If a sensor state for *B* has level *V*,
then after Δt a sensory representation for *B* will have level *V*.

sensor_state(B, V) ↠ srs(B, V)

Generating a desire to address a body unbalance state ub

LP2 Generating a desire based on a sensory representation for a body unbalance ub
If a sensory representation for body unbalance *ub* has level *V*,
then after Δt a desire to address *ub* will have level *V*.

srs(ub, V) ↠ desire(ub, V)

Inducing preparations for body states B ∈ {b_1, b_2, b_3}

LP3 From desire and feeling to preparation
If the desire to address *ub* has level V_{ub}
and feeling the body state b_i has level V_i
and the preparation state for b_i has level U_i
and ω_{di} is the strength of the connection from desire for *ub* to preparation for b_i
and ω_{fi} is the strength of the connection from feeling of b_i to preparation for b_i
and σ_i is the steepness value for the preparation for b_i
and τ_i is the threshold value for the preparation for b_i
and γ_1 is the person's flexibility for bodily responses
then after Δt the preparation state for b_i will have level $U_i + \gamma_1[\, g(\sigma_i, \tau_i, V_{ub}, V_i, \omega_{di}, \omega_{fi}) - U_i\,]\, \Delta t$.

desire(ub, Vub) & feeling(b_i, V_i) & prep_state(b_i, U_i) &
has_steepness(prep_state(b_i), σ_i) & has_threshold(prep_state(b_i), τ_i)
↠ prep_state(b_i, $U_i + \gamma_1 (g(\sigma_i, \tau_i, Vub, V_i, \omega_{di}, \omega_{fi}) - U_i) \Delta t$)

From preparation to feeling (as-if body loop) of a body state B ∈ {b_1, b_2, b_3}

LP4 From preparation and sensor state to sensory representation of body state B ∈ {b_1, b_2, b_3}
If preparation state for body state *B* has level V_1
and sensor state for *B* has level V_2
and the sensory representation for *B* has level *U*
and σ is the steepness value for the sensory representation of *B*
and τ is the threshold value for the sensory representation of *B*
and γ_2 is the person's flexibility for bodily responses
then after Δt the sensory representation for body state *B* will have level $U + \gamma_2\,[\, g(\sigma, \tau, V_1, V_2, 1, 1) - U\,]\, \Delta t$.

prep_state(B, V_1) & sensor_state(B, V_2) & srs(B, U) & has_steepness(srs(B), σ) & has_threshold(srs(B), τ)
↠ srs(B, $U + \gamma_2 (g(\sigma, \tau, V_1, V_2, 1, 1) - U) \Delta t$)

LP5 From sensory representation of body state B ∈ {b_1, b_2, b_3} to feeling B
If a sensory representation for body state B has level *V*,
then after Δt body state B will be felt with level *V*.

srs(B, V) ↠ feeling(B, V)

Box 1 Detailed specification of the dynamics of preparing and feeling induced by a desire

The dynamic property for the process for desire generation is described as LP2 in Box 1. From the sensory representation of the body state unbalance *ub*, the value *V* in srs(ub,V_{ub}) is passed on to the value for desire(ub,V_{ub}). The parameters γ_i in LP3 and LP4 denote the speed by which activation levels are changing. Low values for γ_i imply that the activation values of the past persist long. Note that in LP4 the strengths of the connections from sensor states and from preparation states to sensory representation states all have been given a default value *1*. This value also could be replaced by other values.

Inducing preparations

The process of propagation of the value was simple as only state was responsible to activate the next state. In contrast, the value of the preparation state depends upon the values of desire and of feeling. Activation of a desire, together with feelings, induce preparations for a number of action options: those actions the person considers relevant options to satisfy the desire (for example based on earlier experiences). Dynamic property LP3 in Box 1 describes such responses to an activated desire in the form of the preparation for specific actions. It combines the activation levels V_{ub} and V_i of two states (desire and feeling) through connection strengths ω_{di} and ω_{fi} respectively. This specifies part of the recursive as-if loop between feeling and body state. This dynamic property uses a combination function $g(\sigma, \tau, V_{ub}, V_i, \omega_{di}, \omega_{fi})$ which is based on a sigmoid threshold function

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

with steepness σ and threshold τ. For this model $g(\sigma, \tau, V_{ub}, V_i, \omega_{di}, \omega_{fi})$ is defined as

$$g(\sigma, \tau, V_{ub}, V_i, \omega_{di}, \omega_{fi}) = th(\sigma, \tau, \omega_{di}V_{ub} + \omega_{fi}V_i)$$

with V_{ub}, V_i activation levels and ω_{di}, ω_{fi} weights of the connections to the preparation state. See Box 1, LP3 for formal specification of this dynamic relationship.

Generating associated feelings

Generating the associated feelings is done in two steps. First the sensory representation of the body state is determined by combining two values:

- the preparation state values, i.e. prep_state(b_i,V_i) generated through the as-if body loop
- the value from the sensor state, i.e sensor state(b_i,V_i) generated through the body loop.

This combination is based on a similar function $g(\sigma, \tau, V_1, V_2, 1,1)$ where V, and V_2 are levels for preparation state and sensor state for the body state respectively. For details see Box 1, LP4 and LP5.

2.3 Dynamics of Action Performance and Desire Satisfaction

Next effects of the preparations for body states b_i on the body states *ub* and b_i are addressed. The idea is that the actions performed based on body states b_i are different means to satisfy the desire related to *ub*. This is due to the impact they have on the body state in decreasing the activation level V_{ub} (indicating the extent of unbalance) of body state *ub*. In addition, when performed, each of these actions b_i has an effect on the specific body state b_i. This can be interpreted as a basis for the form of satisfaction felt for the specific way in which *ub* was satisfied. So, a specific action performance involving b_i has two effects:

- an effect on body state *ub*, by decreasing the level of unbalance entailed by *ub*,
- an effect on the body state b_i by increasing the level of satisfaction entailed by b_i

The level of satisfaction entailed by b_i may be proportional to the extent to which the unbalance *ub* is reduced, but may also be disproportional. For example, taking sugar free chewing gum may give a form of satisfaction, but will not reduce an unbalance in available energy.

As the possible actions to fulfill a desire are considered different, they differ in the extents of their effects on these two types of body states, according to an effectiveness rate α_i between *0* and *1* for *ub*, and an effectiveness rate β_i between 0 and 1 for b_i. The effectiveness rates α_i and β_i can be considered a kind of connection strengths from the effector state to the body states *ub* and b_i, respectively. In common situations for each action these two rates may be equal (i.e., $\alpha_i = \beta_i$). However, especially in more pathological cases they may also have different values where the satisfaction felt based on rate β_i for b_i may be disproportionally higher or lower in comparison to the effect on *ub* based on rate α_i (i.e., $\beta_i > \alpha_i$ or $\beta_i < \alpha_i$). An example of this situation is a case of addiction for one of the actions. To express the extent of disproportionality between β_i and α_i, a parameter λ_i, called *satisfaction disproportion rate,* between -1 and 1 is used. This parameter relates β_i to α_i using a function *f*, by $\beta_i = f(\lambda_i, \alpha_i)$. Here the function $f(\lambda, \alpha)$ satisfies

$$f(0, \alpha) = \alpha \qquad f(-1, \alpha) = 0 \qquad f(1, \alpha) = 1$$

The function $f(\lambda, \alpha)$ can be defined in a continuous (but not differentiable) manner as a piecewise linear function in λ by

$$f(\lambda, \alpha) = \alpha + \lambda(1-\alpha)\,, \qquad \text{if } \lambda \geq 0$$
$$f(\lambda, \alpha) = (1+\lambda)\alpha\,, \qquad \text{if } \lambda \leq 0$$

Using such a function *f*, for normal cases $\lambda_i = 0$ is taken, for cases where satisfaction is disproportionally higher $0 < \lambda_i \leq 1$ and for cases where satisfaction is disproportionally lower $-1 \leq \lambda_i < 0$. For more details see Box 2, LP6 and LP7.

LP6 From preparation to effector state for B∈ {b_1, b_2, b_3}
If preparation state for *B* has level *V*,
then after Δt the effector state for body state *B* will have level *V*.

prep_state(B, V) ↠ effector_state(B, V)

LP7 From effector state to modified body state b_i ∈ {b_1, b_2, b_3}
If the effector state for b_i has level V_i,
and for each *i* the effectivity of b_i for *ub* is α_i
and the satisfaction disproportion rate of b_i for *ub* is λ_i
then after Δt body state b_i will have level $f(\lambda_i, \alpha_i)V_i$.

effector_state(b_i, V_i) & is_effectivity_for(α_i, b_i, ub) &
is_disproportion_rate_for(λ_i, b_i, ub) ↠ body_state(b_i, f(λ_i, α_i)V_i)

LP8 From effector state to modified body state b_i ∈ {b_1, b_2, b_3}
If the effector states for b_i have levels V_i,
and body state *ub* has level V_{ub},
and for each *i* the effectivity of b_i for *b* is α_i
then after Δt body state *ub* will have
level $V_{ub} + (\vartheta * (1-V_{ub}) - \rho * (1 - ((1 - \alpha_1 * V_1) * (1 - \alpha_2 * V_2) * (1 - \alpha_3 * V_3))) * V_{ub})\, \Delta t$.

effector_state(b_1, V_1) & effector_state(b_2, V_2) & effector_state(b_3, V_3) &
body_state(ub, Vub) & is_effectivity_for(α_1, b_1, ub) & is_effectivity_for(α_2, b_2, ub) & is_effectivity_for(α_3, b_3, ub)
↠ body_state(ub, Vub + (ϑ * (1-Vub) – ρ * (1 – ((1 - α_1*V_1) * (1 - α_2*V_2) * (1 - α_3*V_3))) * Vub) Δt

Box 2 Detailed specification of the dynamics of action execution and sensing

Note that in case only one action is performed (i.e., $V_j = 0$ for all $j \neq i$), the formula in Box 2, LP8 reduces to $V_{ub} + (\vartheta (1-V_{ub}) - \rho\, \alpha_i\, V_i\, V_{ub})\, \Delta t$. In the formula ϑ is a rate of developing unbalance over time (for example, getting hungry), and ρ a rate of compensating for this unbalance. Note that the specific formula used here to adapt the level of *ub* is meant as just an example. As no assumptions on body state *ub* are made, this formula is meant as a stand-in for more realistic formulae that could be used for specific body states *ub*. Moreover, actions have been assumed to be nonexclusive. Exclusiveness between two actions can be incorporated by adding mutual inhibiting connections between them.

2.4 Hebbian Learning for the Connections from Feeling to Preparation

The strengths ω_{fi} of the connections from feeling b_i to preparation of b_i are considered to be adapted by learning. When an action involving b_i is performed and leads to a strong effect on b_i, this leads to a stronger feeling for b_i. By Hebbian learning (Hebb, 1949; Bi and Poo, 2001; Gerstner and Kirstner, 2002) this increases the strength of the connection from feeling b_i to preparation for b_i. This is an adaptive mechanism that models how experiences in the past may affect behavioural choices made in the future, as also described in Damasio's Somatic Marker Hypothesis (Damasio, 1994, 1996). The experiencing itself is represented by the feeling states for b_i. When these have a high activation level after the action has been prepared and performed, the connection from feeling to preparation will be strengthened, thus representing the experience in this connection. More specifically, the strength ω_{fi} of the connection from feeling to preparation is adapted using the Hebbian learning rule specified in dynamic property LP9 in Box 3. It takes into account a maximal connection strength *1*, a learning rate η, and an extinction rate ζ. A similar Hebbian learning rule can be found in (Gerstner and Kirstner, 2002, p. 406). For more details see Box 3, LP9.

LP9 Hebbian learning for the connection from feeling to preparation
If the connection from feeling b_i to preparation of b_i has strength ω_{fi}
and the feeling b_i has level V_{1i}
and the preparation of b_i has level V_{2i}
and the learning rate from feeling b_i to preparation of b_i is η
and the extinction rate from feeling b_i to preparation of b_i is ζ
then after Δt the connection from feeling b_i to preparation of b_i will have strength $\omega_{fi} + (\eta V_{1i} V_{2i} (1 - \omega_{fi}) - \zeta\omega_{fi}) \Delta t$.

has_connection_strength(feeling(b_i), preparation(b_i), ω_{fi}) &
feeling(b_i, V_{1i}) & preparation(b_i, V_{2i}) &
has_learning_rate(feeling(b_i), preparation(b_i), η) &
has_extinction_rate(feeling(b_i), preparation(b_i), ζ)
→ has_connection_strength(feeling(b_i), preparation(b_i), $\omega_{fi} + (\eta V_{1i} V_{2i} (1 - \omega_{fi}) - \zeta\omega_{fi}) \Delta t$)

Box 3 Detailed specification of the learning process for the connections from feeling to preparation

3. Simulation Results for the Computational Model

Based on the model described in the previous section, a number of simulations have been performed. A first example simulation trace included in this section as an illustration is shown in Figure 2. In all traces, the time delays within the temporal LEADSTO relations were taken 1 time unit. Note that only a selection of the relevant nodes (represented as state properties in LEADSTO) is shown. In all of the figures shown time is on the horizontal axis, and the activation levels of the different state properties are on the vertical axis. it is shown how activation levels of the state properties gradually increase following the recursive loop. In all of the simulations presented here the strengths ω_{di} of the connections from desire to all considered preparations have been given a default value *1*. Moreover, the initial values of the activation levels for the internal states such as sensory representation states have been chosen *0*.

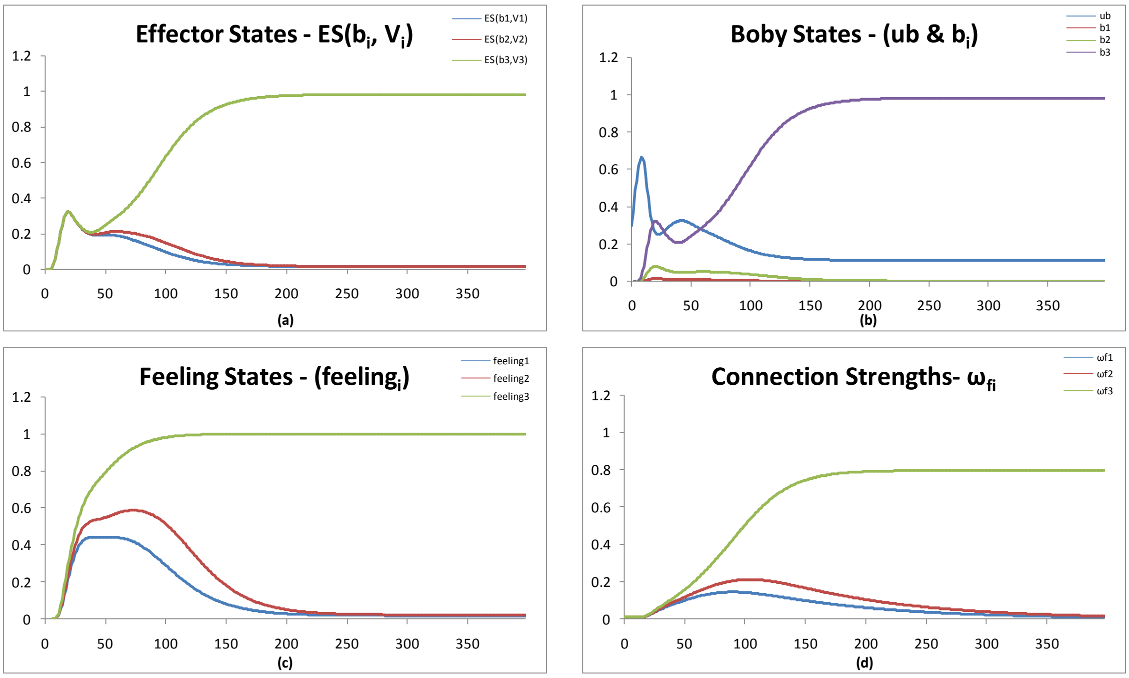

Figure 2: Simulation Trace 1 – Normal behaviour
($\sigma_1=\sigma_2=\sigma_3=10$, $\tau_1=\tau_2=\tau_3=0.5$, $\gamma_1=\gamma_2=\gamma_3=0.05$;
$\alpha_1=\beta_1=0.05$, $\alpha_2=\beta_2=0.25$, $\alpha_3=\beta_3=1$, $\rho=0.8$, $\vartheta=0.1$, $\eta=0.04$, $\zeta=0.01$)

For the example shown in Figure 2, for each i it was put $\lambda_i = 0$, so this shows a case in which satisfaction felt is in proportion with fulfillment of the desire. Action option 3 has the highest effectiveness rate, i.e. $\alpha_3 = 1$. Its value is higher than for the other two action options. This effect propagates to their respective body states as shown in Figure 2(b). All these body states have a positive effect on body state *ub*, decreasing the level of unbalance, as shown in Figure 2(b). Here the value of the bodily unbalance state *ub* (which was set initially to *0.3*) decreases over time until it reaches an equilibrium state. For each of the body states b_i feelings are generated, as shown in Figure 2(c). Furthermore, the Hebbian learning gives a strong effect on the strength of the connection from feeling to preparation for option 1. The connection strength keeps on increasing over time until it reaches an equilibrium state, as shown in Figure 2(d). As the extinction rate ($\zeta=0.01$) is a factor 4 smaller than the learning rate ($\eta=0.04$), the connection strength becomes *0.8*, which is confirmed by the mathematical analysis in Section 4.

Figure 3 shows the simulation of an example scenario where the person is addicted to a particular action, in this case to action option 1, expressed by $\lambda_1 = 1$. Because the effectiveness rate α_1 for this option is very low (*0.05*), the addiction makes that the person is not very effective in fulfilling the desire. The level of unbalance remains around *0.3*; the person mainly selects action option 1 because of its higher satisfaction.

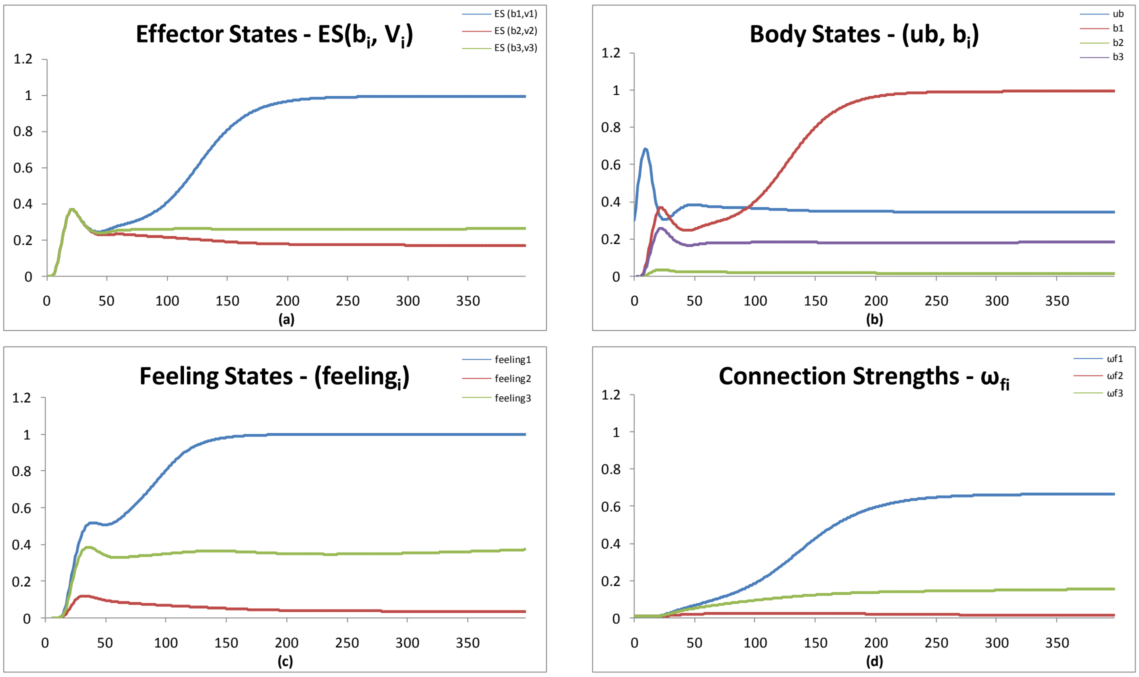

Figure 3: Simulation Trace 2 – Addiction-like behaviour
($\sigma_1=\sigma_2=\sigma_3=10$, $\tau_1=\tau_2=\tau_3=0.5$, $\gamma_1=\gamma_2=\gamma_3=0.05$; $\alpha_1=0.05$, $\beta_1=1$, $\alpha_2=\beta_2=0.1$, $\alpha_3=\beta_3=0.7$, $\rho=0.8$, $\vartheta=0.1$, $\eta=0.02$, $\zeta=0.01$)

In the next trace (see Figure 4), the effectiveness rates for the different action options have been given a varying pattern over time. After some time α_1 has been gradually increased by a term of *0.009*, starting with an initial value of *0.05* until it reaches the value *1*, thereafter it has been kept *1*.

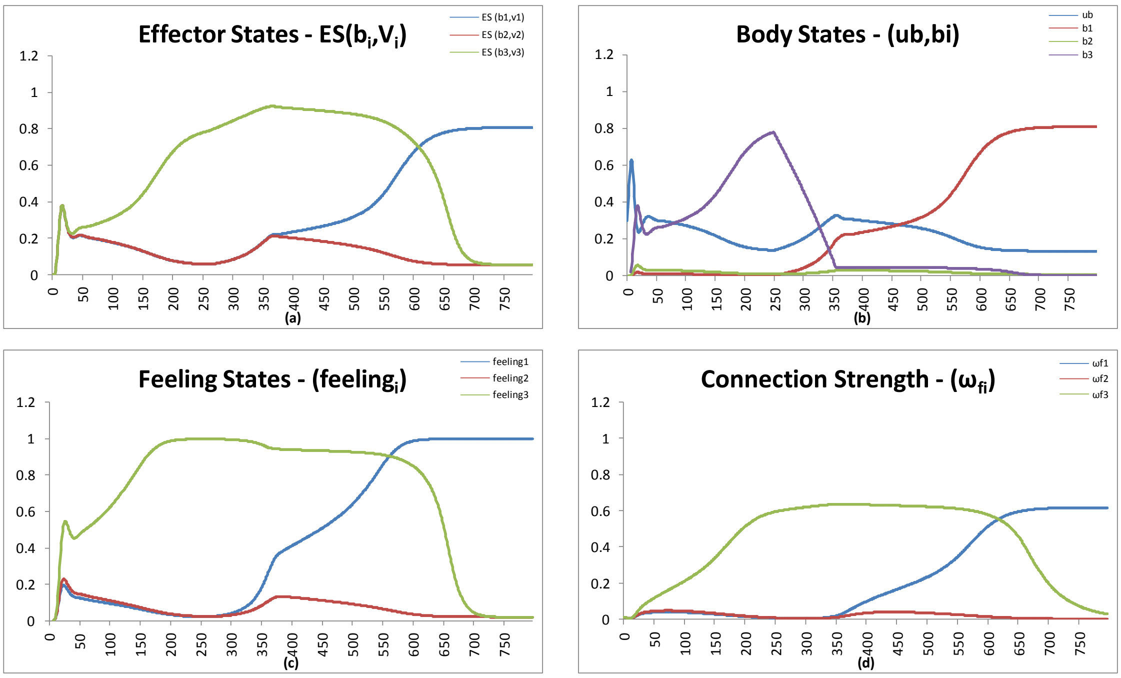

Figure 4: Simulation Trace 3 – Adapting to changing circumstances
($\sigma_1=\sigma_2=\sigma_3=6$, $\tau_1=\tau_2=\tau_3=0.5$, $\gamma_1=\gamma_2=\gamma_3=0.1$; $\alpha_1=\beta_1$ increasing from *0.05* to *1*, $\alpha_2=\beta_2=0.15$, $\alpha_3=\beta_3$ decreasing from *1* to *0.05*; $\rho=0.8$, $\vartheta=0.1$, $\eta=0.04$, $\zeta=0.02$)

In the same period the effectiveness rate α_3 has been gradually decreased by *0.009*, starting with an initial value of *1*, until it reaches the value *0.05*, thereafter it has been kept *0.05*. The latter pattern shows an exact opposite pattern of α_1. The effectiveness rate α_2 was kept constant*: 0.15* for all the time points. As can be seen in Figure 4, first the person selects action option 3 as the most effective one, but after a change in circumstances the person shows adaptation by selecting action option 1, which has now a higher effectiveness rate.

4. Formal Analysis of the Computational Model

This section addresses formal analysis of the domain model and the simulation results presented above. In Section 4.1 a mathematical analysis of the equilibria is presented. Moreover, in Section 4.2, it is discussed how a number of globally emerging dynamic properties have been identified from the literature and verified for a set of simulation traces.

4.1 Mathematical Analysis of Equilibria

For an equilibrium of the strength of the connection from feeling b_i to preparation of b_i, by LP9 the following holds:

$$\eta V_{1i} V_{2i} (1 - \omega_{fi}) - \zeta\omega_{fi} = 0$$

with values V_{1i} for feeling level and V_{2i} for preparation level for b_i. This can be rewritten into

$$\omega_{fi} = \frac{\eta V_{1i} V_{2i}}{\eta V_{1i} V_{2i} + \zeta} = \frac{1}{1 + \frac{\zeta}{\eta V_{1i} V_{2i}}}$$

Using $V_{1i}, V_{2i} \leq 1$ from this it follows that

$$\omega_{fi} \leq \frac{1}{1+\zeta/\eta}$$

gives a maximal connection strength that can be obtained. This shows that given the extinction, the maximal connection strength will be lower than *1*, but may be close to *1* when the extinction rate is small compared to the learning rate. For example, for the trace shown in Figure 2 with $\zeta = 0.01$ and $\eta = 0.04$, this bound is *0.8*, which indeed is reached for option 3. For the traces in Figures 3 and 4 with $\zeta/\eta = 0.5$ this maximum is *0.67*, which is indeed reached for option 1 in Figure 3 and option 3, resp. 1 in Figure 4. Whether or not this maximally possible value for ω_{fi} is approximated for a certain option, also depends on the equilibrium values for feeling level V_{1i} and preparation level V_{2i} for b_i. For values of V_{1i} and V_{2i} that are *1* or close to *1*, the maximal possible value of ω_{fi} is approximated. When in contrast these values are very low, also the equilibrium value for ω_{fi} will be low, since:

$$\omega_{fi} = \frac{\eta V_{1i} V_{2i}}{\eta V_{1i} V_{2i} + \zeta} \leq \eta V_{1i} V_{2i}/\zeta$$

So, when one of V_{1i} and V_{2i} is *0* then also $\omega_{2i} = 0$ (and conversely). This is illustrated by the options 1 and 2 in Figure 2, and option 2 in Figure 3.

Given the sigmoid combination functions it is impossible to solve the equilibrium equations in general. Therefore the patterns emerging in the simulations cannot be derived mathematically in a precise manner. However, as the combination functions are monotonic, some relationships between inequalities can be found:

(1) Options with higher activation levels are those with higher connection strengths
  a. $V_{1j}V_{2j} \leq V_{1k}V_{2k} \Rightarrow \omega_{fj} \leq \omega_{fk}$
  b. $\omega_{fj} < \omega_{fk} \Rightarrow V_{1j}V_{2j} < V_{1k}V_{2k}$

(2) Options with higher feeling levels and connection strengths also have higher preparation levels

a. $\omega_{fj} \leq \omega_{fk}$ & $V_{1j} \leq V_{1k} \Rightarrow \omega_{fj} V_{1j} \leq \omega_{fk} V_{1k} \Rightarrow V_{2j} \leq V_{2k}$

b. $V_{2j} < V_{2k} \Rightarrow \omega_{fj} V_{1j} < \omega_{fk} V_{1k}$

(3) Options with higher effectiveness rates and preparation levels relate to higher satisfaction

a. $\beta_j \leq \beta_k$ & $V_{2j} \leq V_{2k} \Rightarrow (1+\beta_j) V_{2j} \leq (1+\beta_k) V_{2k} \Rightarrow V_{1j} \leq V_{1k}$

b. $V_{1j} < V_{1k} \Rightarrow (1+\beta_j) V_{2j} < (1+\beta_k) V_{2k}$

Here (1) and (2) follow from the above expressions based on LP9. Moreover, (3) and (4) follow from LP3, and (5) and (6) from the properties LP4, LP5, LP6, LP7, LP0 and LP1 describing the body loop and as-if body loop.

For the case that one action dominates exclusively, i.e., $V_{2k} = 0$ and $\omega_{2k} = 0$ for all $k \neq i$, and $V_{2i} > 0$, by LP8 it holds

$$\vartheta * (1-V_{ub}) - \rho * \alpha_i * V_{2i} * V_{ub} = 0$$

where V_{ub} is the level of bodily unbalance state *ub*. Therefore for $\vartheta > 0$ it holds

$$V_{ub} = \frac{1}{1+(\rho\alpha i/\vartheta)V2i} \geq \frac{1}{1+(\rho/\vartheta)\alpha i}$$

As $V_{2i} > 0$ is assumed, this shows that if ϑ is close to 0 (almost no development of unbalance), and $\rho > 0$ and $\alpha_i > 0$, the value V_{ub} can be close to 0 as well. If, in contrast, the value of ϑ is high (strong development of unbalance) compared to ρ and α_i, then the equilibrium value V_{ub} will be close to 1. For the example traces in Figures 2, 3 and 4, $\rho = 0.8$ and $\vartheta = 0.1$, so $\rho/\vartheta = 8$. Therefore for a dominating option with $\alpha_i = 1$, it holds $V_{ub} \geq 0.11$, which can be seen in Figures 2 and 4. In Figure 3 the effectiveness of option 1 is very low ($\alpha_1 = 0.05$), and therefore the potential of this option to decrease V_{ub} is low: $V_{ub} \geq 0.7$.

However, as in Figure 3 also option 3 is partially active, V_{ub} reaches values around 0.35. Note that for the special case $\vartheta = 0$ (no development of unbalance) it follows that $\rho\ \alpha_i\ V_{2i}\ V_{ub} = 0$ which shows that $V_{ub} = 0$. Values for V_{ub} at or close to 0 confirm that in such an equilibrium state the desire is fulfilled or is close to being fulfilled (via LP0, LP1 and LP2 which show that the same value V_{ub} occurs for the desire).

4.2 Logical Verification of Emerging Properties in Simulation Traces

In literature such as (Damasio, 1994, 2003) a number of emerging global properties can be identified, such as that the option with the best feeling is selected, or that the options with more positive experiences get stronger affective connections. In order to investigate such particular emerging patterns in the processes shown in the simulation runs, a number of these properties have been formulated. Formal specification of the properties, enabled automatic verification of them against simulation traces, using the logical language and verification tool TTL (cf. Bosse, Jonker, Meij, Sharpanskykh, and Treur, 2009). The purpose of this type of verification is to check whether the simulation model behaves as it should according to the literature. As this literature has itself has an empirical foundation, this type of verification can be seen as a form of second-order validation. Typical example of property that may be checked are whether certain equilibria occur, whether the appropriate actions are selected, or whether the appropriate learning takes place.

The temporal predicate logical language TTL supports formal specification and analysis of dynamic properties, covering both qualitative and quantitative aspects. TTL is built on atoms referring to *states* of the world, *time points* and *traces*, i.e. trajectories of states over time. *Dynamic properties* are temporal statements formulated with respect to traces based on the state ontology Ont in the following manner. Given a trace γ over state ontology Ont, the state in γ at time point t is denoted by state(γ, t). These states are related to state properties via the infix predicate |=, where state(γ, t) |= p denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties are formulated in a sorted first-order predicate logic, using quantifiers over time and traces and the usual first-order logical connectives such as ¬, ∧, ∨, ⇒, ∀, ∃. For more details, see (cf. Bosse, Jonker, Meij, Sharpanskykh, and Treur, 2009; Sharpanskykh and Treur, 2010).

A number of properties have been identified for the processes modelled. Note that not all properties are expected to always hold for all traces; some of them may be a means to distinguish specific cases. The first property, GP1 (short for Global Property 1), expresses that eventually the preparation state with respect to an action will stabilise.

GP1(d): Equilibrium of preparation state

Eventually, the preparation state for each b_i will stabilise at a certain value: it will not deviate more than a certain value d.

∀γ:TRACE, B:BODY_STATE
[∃t1:TIME [∀t2:TIME > t1, V1, V2 :VALUE
[state(γ, t1) |= prep_state(B, V1) & state(γ, t2) |= prep_state(B, V2)
⇒ V2 ≥ (1 – d) * V1 & V2 ≤ (1 + d) * V1]]]

Next, in property GP2 it is expressed that eventually the action which has the most positive feeling associated with it will have the highest preparation state value.

GP2: Action with best feeling is eventually selected

For all traces there exists a time point such that the b_i with the highest value for feeling eventually also has the highest activation level.

∀γ:TRACE, B:BODY_STATE, t1:TIME<end_time, V:VALUE
[[state(γ, t1) |= feeling(B, V) &
∀B2:BODY_STATE, V2:VALUE
[state(γ, t1) |= feeling(B2, V2) ⇒ V2 ≤ V]
⇒ [∃t2:TIME > t1, V1:VALUE
[state(γ, t2) |= prep_state(B, V1) &
∀B3:BODY_STATE, V3:VALUE
[state(γ, t2) |= prep_state(B3, V3) ⇒ V3 ≤ V1]]]]

Property GP3 expresses that if the accumulated positive feelings experienced in the past are higher compared to another time point, and the number of negative experiences is lower or equal, then the connection strength through Hebbian learning will be higher.

GP3: Accumulation of positive experiences

If at time point t1 the accumulated feeling for b_i is higher than the accumulated feeling at time point t2, then the connection strength for b_i is higher at t1 compared to t2.

∀γ:TRACE, B:BODY_STATE, a:ACTION, t1, t2:TIME<end_time, V1, V2:VALUE
[[state(γ, t1) |= accumulated_feeling(B, V1) & state(γ, t2) |= accumulated_feeling(B, V2) & V1>V2]
⇒ ∃W1, W2:VALUE
[state(γ, t1) |= has_connection_strength(feeling(B), preparation(B), W1) &
state(γ, t2) |= has_connection_strength(feeling(B), preparation(B), W2) & W1 ≥ W2]]

Next, property GP4 specifies a monotonicity property where two traces are compared. It expresses that strictly higher feeling levels result in a higher connection strength between the feeling and the preparation state.

GP4: High feelings lead to high connection strength

If at time point t1 in a trace γ_1 the feelings have been strictly higher level compared to another trace γ_2, then the connection strength from feeling to preparation state will also be strictly higher.

∀γ1, γ2:TRACE, B:BODY_STATE, t1:TIME<end_time, W1, W2:VALUE
[∀t' < t1:TIME, V1, V2:VALUE
[[state(γ1, t') |= feeling(B, V1) &
state(γ2, t') |= feeling(B, V2)] ⇒ V1 > V2] &
state(γ1, t1) |= has_connection_strength(feeling(B), preparation(B), W1) &
state(γ2, t1) |= has_connection_strength(feeling(B), preparation(B), W2) ⇒ W1 ≥ W2]

Finally, property GP5 analyses traces that address cases of addiction. In particular, it checks whether it is the case that if a person is addicted to a certain action which has a high value for the satisfaction disproportion rate λ for this action, this results in a situation of unbalance (i.e., a situation in which the feeling caused by this action stays higher than the overall body state). An example of such a situation is found in simulation trace 2 (in Figure 3).

GP5: Addiction leads to unbalance between feeling and body state
For all traces, if a certain action has $\lambda > 0$, then there will be a time point t1 after which the feeling caused by this action stays higher than the overall body state.

∀γ:TRACE, B:BODY_STATE, L:VALUE
[state(γ, 0) |= has_lambda(B,L) & L > 0
⇒ [∃t1:TIME < last_time
∀t2:TIME>t1 Vub,V1:VALUE
[state(γ, t2) |= body_state(ub, Vub) & body_state(B, V1) ⇒ Vub < V1]]]

An overview of the results of the verification process is shown in Table 1 for the three traces that have been considered in Section 3. The results show that several expected global properties of the model were confirmed. For example, the first row indicates that for all traces, eventually an equilibrium occurs in which the values of the preparation states never deviate more than 0.0005 (this number can still be decreased by running the simulation for a longer time period). Also, the checks indicate that some properties do not hold. In such cases, the TTL checker software provides a counter example, i.e., a situation in which the property does not hold. This way, it could be concluded, for example, that property GP1 only holds for the generated traces if d is not chosen too small.

Table 1. Results of verification of emerging patterns

property	**trace 1**	**trace 2**	**trace 3**
GP1(X)	X≥0.0001	X≥0.0005	X≥0.0001
GP2	satisfied	satisfied	satisfied
GP3	satisfied	satisfied	Satisfied
GP4	satisfied for all pairs of traces		
GP5	satisfied	satisfied	satisfied

5 On Application of the Computational Model in an Ambient Agent

As a first step to explore application of the computational model introduced here, the model was embedded within an ambient agent model, in order to enable the agent to reason about this process, and to assess a person's desires, preparations and feelings. The embedding takes place by using the causal relationships of the model described in Section 2 above in relationships for beliefs of the ambient agent on mental states of the person. In order to achieve this, the idea of recursive modelling is used; e.g., (Marsella, Pynadath and Read, 2004). This means that the beliefs that agents have about each other are represented in a nested manner. To this end, each mental state is parameterized with the name of the agent that is considered, thus creating concepts like

has_state(human, feeling(b, 0.5))
has_state(AA, performed(suggest(X))

In addition, a number of meta-representations are introduced. For example,

has_state(AA, belief(has_state(human, feeling(b, 0.7))))

states that the ambient agent (AA) believes that the human has a feeling level of *0.7* for body state b. The following are the resulting agent local properties (ALP) that specify the processes within the ambient agent. Three examples of the dynamic properties making up the ambient agent model are as follows. The first two dynamic properties (ALP1 and ALP2) specify how the ambient agent AA observes the human's body state and creates a belief about it. The third one (ALP6) shows how the computational model was embedded in the ambient agent model. Here ω_{di} is the strength of the connection from desire for *b* to preparation for B_i, ω_{fi} is the strength of the connection from feeling of B_i to preparation for B_i and γ_1 is the person's flexibility for bodily responses.

ALP1 Observing the human's body state B ∈ {ub, b_1, b_2, b_3}
If the human has certain body state B,
then the ambient agent AA will observe this.
has_state(human, body_state(B, V, t))
→ has_state(AA, observed(has_state(human, body_state(B, V, t))))

ALP2 Generating a belief for the human's body state B ∈ {ub, b_1, b_2, b_3}
If the ambient agent AA observes that the human has certain body state,
then it will generate a belief on it.
has_state(AA, observed(has_state(human, body_state(B, V, t))))
→ has_state(AA, belief(has_state(human, body_state(B, V, t))))

ALP6 Generating a belief for the human's preparations b_i ∈ { b_1, b_2, b_3}
If AA believes that the human has a desire to address *ub* with level V_{ub}
and AA believes that the human has feeling b_i with level V_i
and AA believes that the preparation for body state b_i has level U_i
and σ_i is the steepness value for the preparation for b_i
and τ_i is the threshold value for the preparation for b_i
then ambient agent AA will generate the belief that the human's preparation state for body state b_i will occur with level $U_i + \gamma_1(g(\sigma_i, \tau_i, V_{ub}, V_i, \omega_{di}, \omega_{fi}) - U_i) \Delta t$
has_state(AA, belief(has_state(human, desire(ub, Vub, t)))) &
has_state(AA, belief(has_state(human, feeling(bi, V_i, t))))
has_state(AA, belief(has_state(human, prep_state(b_i, U_i, t)))) &
has_steepness(prep_state(b_i), σ_i) & has_threshold(prep_state(b_i), τ_i)
→ has_state(AA, belief(has_state(human, prep_state(b_i, $U_i + \gamma_1$ (g(σ_i, τ_i, Vub, V_i, ω_{di}, ω_{fi}) - U_i) Δt), t+Δt)))

The desire assessment is used to generate an intervention intention, whenever needed. This intention persists until the point in time at which the intervention has to be performed. Table 2 shows the criteria used in the ambient agent's decision process, where the human is assumed to consider an option if the level of the associated preparation state is predicted above a certain threshold, which in the example scenario is set to *0.1*, whereas the different options that are available are characterized as good or bad based on the values of the effectivity rates of those options higher or lower than 0.5. The shaded cases in Table 1 indicate the cases for which intervention is intended: a bad option is considered by the human, or a good option is not considered.

Table 2. Assessment criteria used by the ambient agent

	Preparation state level > 0.1	*Preparation state level ≤ 0.1*
Effectivity rate > 0.5	A good option considered by the human	A good option not considered by the human
Effectivity rate ≤ 0.5	A bad option considered by the human	A bad option not considered by the human

Further dynamic properties for the ambient agent model can be found in detail in Appendix A.

Based on the ambient agent model pointed out above, a number of simulations have been performed within the LEADSTO simulation environment (Bosse, Jonker, Meij and Treur, 2007). The main goal of the ambient agent is to predict the level of desire of the human, assess it and, if needed, to suggest effective options to fulfill the desire. To this end, it starts with some initial values of the human's desire and feeling levels, and then keeps on updating this, using the integrated model explained above. The model was tested in a small scenario, involving an ambient agent and a human, indicated by AA and human, respectively. The example scenario taken here considers a person who is getting hungry which generates a desire to eat for which a number of options is available at that time. As the level of desire increases this makes the person more tempted to eat, and in particular to choose the option that is associated to the best feeling. As the domain model is integrated within the ambient agent, it can predict the human's desire level well in advance, and assesses the extent to which the human will consider the different options that are available to fulfill this desire. Based on the criteria given in Table 2, if the ambient agent predicts that the human will consider those options that are not effective for fulfilling the desire, then it will suggest not to choose them. Similarly, if the assessment process of the ambient agent determines any options that are quite effective for the human to choose, but the human will not consider those, then it will suggest the human to choose them.

An example simulation trace is illustrated in Figure 5 (here the time delays within the temporal LEADSTO relations were taken 1 time unit). In such figures time is on the horizontal axis, and the upper part shows the time periods, in which the binary logical state properties hold (indicated by the dark lines); for example, has_state(AA, assessment(has_state(human, high_desire(ub), 204))). Below this part, quantitative information is provided about the human's actual desire, preparation states, connection strength levels, levels of different body states and the ambient agent AA's prediction of these. Values for these levels for the different time periods are shown by the dark lines. Note that the scale on the vertical axis differs over the different graphs, and only a selection of the relevant state properties is shown. Figure 5 shows the simulation of an example scenario where the person is developing an addiction to a particular action, in this case to action option 1, since $\lambda_1 = 1$ was chosen, which makes the satisfaction rate for this option high: $\beta_1 = 1$. Because the effectiveness rate α_1 for this option is very low (*0.05*), the person is not very effective in fulfilling the desire; the level of unbalance remains around *0.3*. The human selects action option 1 because of its high feeling of satisfaction, as shown in lower part of Figure 7, in the graph of AA prep_state b1, which is strengthening the connection from feeling to preparation for this option. The ambient agent suggests not to choose the option. More details of simulated scenarios for the ambient agent model can be found in Appendix B.

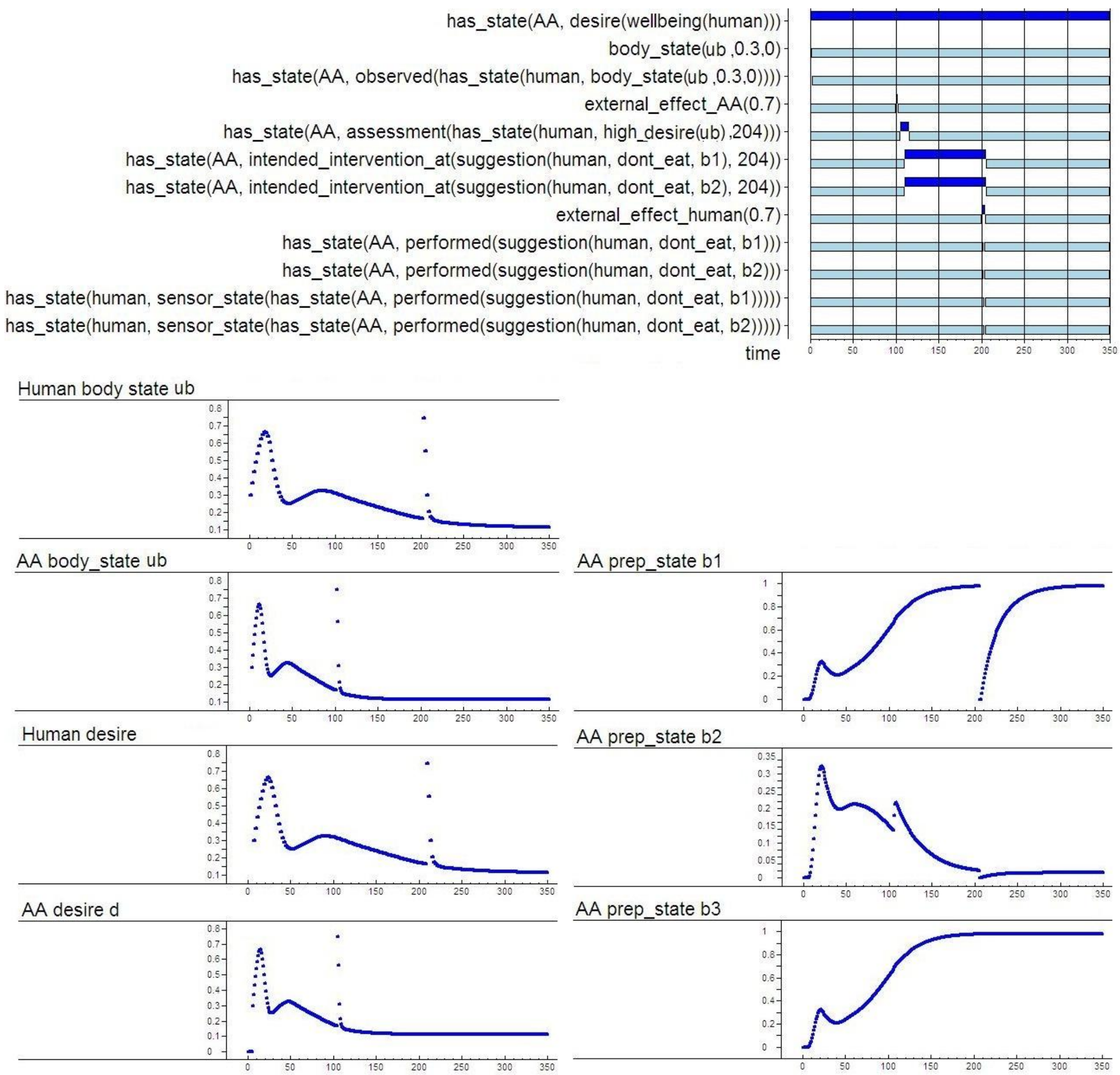

Figure 5 Simulation Trace 2 – Addiction like behavior: desire and preparation states
(α_1=0.05, β_1 =1, α_2=β_2 =0.25, α_3=β_3=1, γ_1=γ_2=0.05,
σ_1=σ_2=10, τ_1=τ_2=0.5, ρ=0.8, ϑ=0.1, η=0.04, ζ=0.01)

6 Discussion

In this paper a formally defined dynamical model was introduced integrating cognitive and affective aspects of desiring, based on informally described theories in the neurological literature. The presented dynamical model describes how a desire induces (as a response) a set of preparations for a number of possible actions, involving certain body states, which each affect sensory representations of the body states involved and thus provide associated feelings. On their turn these feelings affect the preparations, for example, by amplifying them. In this way a dynamical model is obtained for desiring which integrates both cognitive and affective aspects of mental functioning. For the interaction between feeling and preparation of responses, a converging recursive body loop is included in the dynamical model, based on elements taken from (Damasio, 1999, 2003, 2010; Bosse, Jonker and Treur, 2008). Both the strength of the preparation and of the feeling emerge as a result of the dynamic pattern generated by this loop. The dynamical model is adaptive in the sense that within these loops the connection strengths from feelings to preparations are adapted over time by Hebbian learning (cf. Hebb, 1949; Bi and Poo, 2001; Gerstner and Kirstner, 2002). By this adaptation mechanism, in principle the person achieves that the most effective action to fulfill a desire is chosen. However, the dynamical model can also be used to cover humans for whom satisfaction for an action is not in proportion with the fulfillment of the desire, as occurs, for example, in certain cases of earlier addictive experiences which provide temptations for the future. In this case, action choice may become biased by such temptations.

As the introduced model is mainly based on theories of the neurologist Damasio (1994, 1999, 2003, 2010), from this literature it can be seen how different concepts in the model can be related to neural concepts. A brief survey of Damasio's ideas about emotion and feeling, and the 'tightly bound cycle' between them can be found in (Damasio, 2010, pp. 108-129). According to this perspective emotions relate to actions, whereas feelings relate to perceptions:

> 'Emotion and feeling, albeit part of a tightly bound cycle, are distinguishable processes. (…) Emotions are complex, largely automated programs of *actions* concocted by evolution. The actions are complemented by a *cognitive* program that includes certain ideas and modes of cognition, but the world of emotions is largely one of actions carried out in our bodies, from facial expressions and postures to changes in viscera and internal milieu. Feelings of emotion, on the other hand, are composite *perceptions* of what happens in our body and mind when we are emoting. As far as the body is concerned, feelings are images of actions rather than actions themselves; the world of feelings is one of perceptions executed in brain maps. (…) While emotions are actions accompanied by ideas and certain modes of thinking, emotional feelings are mostly perceptions of what our bodies do during the emoting, along with perceptions of our state of mind during that same period of time.' (Damasio, 2010, pp. 109-110)
>
> 'Seen from a neural perspective, the emotion-feeling cycle begins in the brain, with the perception and appraisal of a stimulus potentially capable of causing an emotion and the subsequent triggering of an emotion. The process then spreads elsewhere in the brain and in the body proper, building up the emotional state. In closing, the process returns to the brain for the feeling part of the cycle, although the return involves brain regions different from those in which it all started.' (Damasio, 2010, p. 111)

In the presented computational model the emotion process is modelled by the dynamics of the preparation states, triggered by the desire reflecting the perceived bodily unbalance state, whereas the feeling process is modelled by the dynamics of sensory representations of body states, and indeed they are connected by a cycle by which they mutually affect each other (see Fig. 1).

The states used in the model for sensory representations, desires, emotions and feelings are rather abstract. Viewed from a biological perspective, each of them relates to a combination of neural, biochemical and body states. For example, for emotions Damasio describes the following biological substrate; this can be viewed as the neural correlate of the preparation states in the model (expressed in dynamic relationship LP3):

> ‘Emotions work when images processed in the brain call into action a number of emotion-triggering regions, for example, the amygdala or special regions of the frontal lobe cortex. Once any of these trigger regions is activated, certain consequences ensue – chemical molecules are secreted by endocrine glands and by subcortocol nuclei and delivered to both the brain and the body (e.g., cortisol in the case of fear), certain actions are taken (e.g., fleeing or freezing; contraction of the gut, again in the case of fear), and certain expressions are assumed (e.g., a face and posture of terror).’ (Damasio, 2010, p. 110)

Note that here a role of the amygdala is indicated in the process of generating an emotion, whereas in earlier times often the amygdala was related to feelings. In contrast, Damasio describes the substrate for feelings as follows:

> ‘In the late 1980s I hypothesized a role for the somatosensory cortices in feelings, and I pointed to the insula as a likely provider of feelings. I wanted to move away from the hopeless idea of attributing the origin of feeling states to action-driving regions, such as the amygdalae.’ (Damasio, 2010, p. 118)

At that time this idea had a rather hypothetical character, and was not the accepted view. This changed after 2000:

> ‘Since 2000, however, we have known that activity in the insula is indeed an important correlate for every conceivable kind of feeling (…) The idea that the insular cortex is an important substrate for feelings is certainly correct.’ (…) The anterior cingulate cortex tends to become active in parallel with the insula when we experience feelings. The insula and anterior cingulate are closely interlocked regions, the two being joined by multiple connections. The insula has dual sensory and motor functions, albeit biased toward the sensory side of the process, while the anterior cingulate operates as a motor structure.’ (Damasio, 2010, p. 118)

In addition to these, the process of generating a feeling involves several subcortical regions for certain preprocessing as well, as ‘they are the first recipients of information from the viscera and internal milieu with the ability to integrate signals from the entire range of the body’s interior’ (Damasio, 2010, p. 118-119). So, these elements can be seen as the neural correlates of the sensory representation states for body states (expressed in dynamic relationship LP1), the desire state (expressed in LP2), and the feeling states (expressed in LP5).

The computational model for the dynamics of desires, preparations and feelings was specified in the hybrid dynamic modelling language LEADSTO, and simulations were performed in its software environment (cf. Bosse, Jonker, Meij, and Treur, 2007). The presented model uses neurological knowledge and technical elements from the neural modelling area. More specifically, it takes states as having a certain activation level (instead of binary states), thus making reciprocal cognitive/affective loops possible. To achieve this, the modelling approach exploits techniques used in continuous-time recurrent neural networks, in line with what is proposed in (Beer, 1995), adopting elements from (Hopfield, 1982; 1984). In particular, for a state connected to and affected by multiple other states, values for incoming activation levels are combined, using a combination function based on a logistic threshold function applied to an addition of all incoming activations. Simulation experiments show that the model behaves as expected, which also has been verified formally.

Two models that address similar processes are CAGE (Wagar & Thagard, 2004) and ANDREA (Litt, Eliasmith, Thagard, 2008) based on the neural engineering framework NESim (Eliasmith and Anderson, 2003). Some commonalities with the approach presented here are that decision making is addressed in which emotions play an important role, and that neurological knowledge is used as a point of departure. There are also a number of differences. In the first place the grain size is quite different; the model introduced here is at a more abstract level. In CAGE and ANDREA spiking neural networks are used consisting of thousands of neurons of different types. The presented model abstracts from spiking and uses activation levels instead, and abstracts from individual neurons by considering groups of neurons and their activations as single states and activations. A further difference in abstraction is that in the model presented here only one (positive) valency for emotion is used, whereas in CAGE and ANDREA positive and negative valencies of emotions are distinguished. Furthermore, in all three models learning techniques are used: Hebbian learning in the current model (following Gerstner and Kirstner, 2002) and CAGE (following Kempter, Gerstner, and van Hemmen, 1999), and temporal difference learning (cf. Sutton and Barto, 1998) in ANDREA.

A further difference is that in contrast to CAGE and ANDREA, in the current model body states are explicitly modelled, and getting impact from them by sensing processes, and the stimulus provided by a desire related to a bodily unbalance are part of the model. Moreover, discrepancies between feelings of satisfaction and contributing to decrease bodily unbalance are explicitly modelled, due to the aim of the model to make such discrepancies explicit, for example, in the context of addiction.

As a form of second-order validation, claims made in the cognitive or neurological literature have been expressed and formalised in the form of dynamic properties (Section 4.2). Examples of such properties are that a decision takes the option with most positive feeling (GP2), and that better experiences with an option lead to stronger connections for that option (GP4). It turned out that the model indeed satisfies such properties. This is not a direct validation with empirical data, but at least an indirect, second-order validation against the empirically-based theories on which the model is grounded. More direct forms of validation will be an interesting challenge for the future.

Possible applications of the introduced model can be twofold. In a first type of application the model can be used as a way to represent domain knowledge in intelligent software to support persons suffering from addictive behaviour, for example, in the context of Ambient Intelligence. To function in a knowledgeable manner, ambient agents (e.g., Aarts, Collier, Loenen, Ruyter, 2003; Aarts, Harwig, Schuurmans, 2001; Riva, Vatalaro, Davide, Alcañiz, 2005) need a model of the humans they are supporting. Such a model enables them to obtain human-awareness. It has been pointed out above how the introduced model can be integrated within an ambient agent model to be able to analyse and support a person's functioning. A second type of application of the computational model is in simulation-based training. The model can be used as a basis for a virtual patient that can be used by (candidate) psychotherapists, to learn how a person suffering from adictive behaviour may function. In addition it can be studied how certain interventions may work out for the patient.

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Appendix A: Ambient Agent Model Properties

This appendix includes the details of the explored ambient agent model. The first two properties specify how the agent AA observes the human's body state and creates a belief about it.

ALP1 Observing the human's body state B $\in$ {ub, b_1, b_2, b_3}
If the human has certain body state B,
then the ambient agent AA will observe this.
has_state(human, body_state(B, V, t))
$\rightarrow$ has_state(AA, observed(has_state(human, body_state(B, V, t))))

ALP2 Generating a belief for the human's body state B $\in$ {ub, b_1, b_2, b_3}
If the ambient agent AA observes that the human has certain body state,
then it will generate a belief on it.
has_state(AA, observed(has_state(human, body_state(B, V, t))))
$\rightarrow$ has_state(AA, belief(has_state(human, body_state(B, V, t))))

The following properties specify how the ambient agent observes and generates beliefs about the human's sensing and sensory representation process.

ALP3 Generating a belief for a human's sensing B $\in$ {ub, b_1, b_2, b_3}
If AA believes that the human has certain body state B,
then it will generate a belief that after Δt the human will sense this body state B
has_state(AA, belief(has_state(human, body_state(B, V, t))))
$\rightarrow$ has_state(AA, belief(has_state(human, sensor_state(B, V, t+Δt))))

ALP4 Generating a belief for the human's sensory representation for B $\in$ {ub, b_1, b_2, b_3}
If AA believes that the human senses body state B,
then it will generate a belief that after Δt the human will have a sensory representation for B.
has_state(AA, belief(has_state(human, sensor_state(B, V, t))))
$\rightarrow$ has_state(AA, belief(has_state(human, srs(B, V, t+Δt))))

The ambient agent generates a belief on the human's desires by:

ALP5 Generating a belief for the human's desire to address ub
If AA believes that the human has a sensory representation for body state *ub*
then it will generate a belief that after Δt the human will generate a desire to address *ub*
has_state(AA, belief(has_state(human, srs(ub, Vub, t))))
$\rightarrow$ has_state(AA, belief(has_state(human, desire(ub, Vub, t+Δt))))

Next it is shown how the ambient agent estimates the preparations that are triggered.

ALP6 Generating a belief for the human's preparations for $b_i \in$ {b_1, b_2, b_3}
If AA believes that the human has a desire to address *ub* with level V_{ub}
and AA believes that the human has feeling b_i with level V_i
and AA believes that the preparation for body state b_i has level U_i
and ω_{di} is the strength of the connection from desire for *b* to preparation for b_i
and ω_{fi} is the strength of the connection from feeling of B_i to preparation for b_i
and σ_i is the steepness value for the preparation for b_i
and τ_i is the threshold value for the preparation for b_i
and γ_1 is the person's flexibility for bodily responses
then ambient agent AA will generate the belief that the human's preparation state for body state b_i will occur with level $U_i + \gamma_1(g(\sigma_i, \tau_i, V_{ub}, V_i, \omega_{di}, \omega_{fi}) - U_i)\Delta t$
has_state(AA, belief(has_state(human, desire(ub, Vub, t)))) &
has_state(AA, belief(has_state(human, feeling(b_i, V_i, t))))
has_state(AA, belief(has_state(human, prep_state(b_i, U_i, t)))) &
has_steepness(prep_state(b_i), σ_i) & has_threshold(prep_state(b_i), τ_i)
$\rightarrow$ has_state(AA, belief(has_state(human, prep_state(b_i, $U_i + \gamma_1$ (g(σ_i, τ_i, Vub, V_i, ω_{di}, ω_{fi}) - U_i) Δt), t+Δt)))

Variants of this property have been used to incorporate interventions which affect the preparations of some B_i in the sense that they are assumed to become *0* (suggestion not to do that) or *1* (suggestion to do that). For example:

has_state(AA, belief(has_state(human, desire(ub, Vub, t)))) &
has_state(AA, belief(has_state(human, feeling(b_i, V_i, t))))
has_state(AA, belief(has_state(human, prep_state(b_i, U_i)))) &
has_steepness(prep_state(b_i), σ_i) & has_threshold(prep_state(b_i), τ_i) &
has_state(human, sensor_state(suggestion(do, b_i))))) &
$\rightarrow$ has_state(AA, belief(has_state(human, prep_state(b_i, 1, t+Δt))))

The following five properties describe how the ambient agent reasons about the human's body loop.

ALP7 Generating a belief for the human's sensory representation of body state $b_i \in \{b_1, b_2, b_3\}$

If AA believes that the human's preparation state for body state b_i with level V_1 occurred
and AA believes that the human senses his body state b_i with level V_2
and AA believes that the human has sensory representation for b_i with level U
and σ is the steepness value for the sensory representation for b_i
and τ is the threshold value for the sensory representation for b_i
and γ is the person's flexibility for bodily responses
then ambient agent AA will generate the belief that the human's sensory representation for body state b_i will occur with level $U + \gamma_2\ (g(\sigma, \tau, V_1, V_2, 1, 1) - U)\ \Delta t$.

has_state(AA, belief(has_state(human, prep_state(b_i, V_1, t)))) &
has_state(AA, belief(has_state(human, sensor_state(b_i, V_2, t))))
has_state(AA, belief(has_state(human, srs(b_i, U, t)))) &
has_steepness(srs(b_i), σ) & has_threshold(srs(b_i), τ)
→ has_state(AA, belief(has_state(human, srs((b_i, U + γ_2 (g(σ, τ, V_1, V_2, 1, 1) - U) Δt), t+Δt)

ALP8 Generating a belief for the human's feeling of $b_i \in \{b_1, b_2, b_3\}$

If AA believes that the human has a sensory representation for body state b_i with level V,
then it will believe that the human has feeling b_i with level V.

has_state(AA, belief(has_state(human, srs(b_i, V, t))))
→ has_state(AA, belief(has_state(human, feeling(b_i, V, t+Δt))))

ALP9 Generating a belief for the human's body modification of $b_i \in \{b_1, b_2, b_3\}$

If AA believes that the human's preparation state for body state b_i with level V occurred,
then it will believe that the human's body state b_i is modified with level V.

has_state(AA, belief(has_state(human, prep_state(b_i, V, t))))
→ has_state(AA, belief(has_state(human, effector_state(b_i, V, t+Δt))))

ALP10 Generating a belief for the human from effector state to modified body state $b_i \in \{b_1, b_2, b_3\}$

If AA believes that the human's body b_i is modified with level V_i,
and AA believes that for each i the effectivity of b_i for ub is α_i
and AA believes that the satisfaction disproportion rate of b_i for ub is λ_i
then AA will believe that the human's body state b_i will have level $f(\lambda_i, \alpha_i)V_i$.

has_state(AA, belief(has_state(human, effector_state(b_i, V_i, t)))) &
has_state(AA, belief(is_effectivity_for(α_i, b_i, ub))) &
has_state(AA, belief(is_disproportion_rate_for(λ_i, b_i, ub)))
→ has_state(AA, belief(has_state(human, body_state(b_i, f(λ_i, α_i)V_i), t+Δt)))

ALP11 Generating a belief for the human from effector state to modified body state $b_i \in \{b_1, b_2, b_3\}$

If AA believes that the human's body b_i is modified with level V_i,
and AA believes that human's body state unbalance ub has level V_{ub},
and AA believes that for each $_i$ the effectivity of b_i for ub is α_i
then AA believes that human's body state unbalance ub will have level $V_{ub} + (\vartheta * (1-V_{ub}) - \rho * (1 - ((1 - \alpha_1 * V_1) * (1 - \alpha_2 * V_2) * (1 - \alpha_3 * V_3))) * V_{ub})\ \Delta t$.

has_state(AA, belief(has_state(human, effector_state(b_i, V_i, t)))) &
has_state(AA, belief(has_state(human, body_state(ub, Vub, t)))) &
has_state(AA, belief(is_effectivity_for(α_i, b_i , ub)))
→ has_state(AA, belief(has_state(human, body_state(ub,
Vub + (ϑ * (1-Vub) – ρ * (1 – ((1 - α_1*V_1) * (1 - α_2*V_2) * (1 - α_3*V_3))) * Vub) Δt), t+Δt))

A variant of this property has been used to incorporate external events p that incidentally increases the level of the body state (such as exercising):

has_state(AA, belief(has_state(human, effector_state(b_i, V_i, t)))) &
has_state(AA, belief(has_state(human, body_state(ub, Vub, t)))) &
has_state(AA, belief(is_effectivity_for(α_i, b_i , ub))) & external_effect(p)
→ has_state(AA, belief(has_state(human, body_state(ub,
Vub + ((ϑ+p) * (1-Vub) – ρ * (1 – ((1 - α_1*V_1) * (1 - α_2*V_2) * (1 - α_3*V_3))) * Vub) Δt), t+Δt))

The ambient agent AA generates beliefs about the connection strengths based on Hebbian learning

ALP12 Generating a belief for the human's learning of the connection from feeling to preparation of $b_i \in \{b_1, b_2, b_3\}$

If AA believes that the connection from feeling b_i to preparation of b_i has strength ω_{fi}
and AA believes that human has feeling b_i with level V_{1i}
and AA believes that the human's preparation of b_i has level V_{2i}
and the learning rate from feeling b_i to preparation of b_i is η
and the extinction rate from feeling b_i to preparation of b_i is ζ
then after Δt AA will believe that the connection from feeling b_i to preparation of b_i will have

strength $\omega_{fi} + (\eta V_{1i} V_{2i} (1 - \omega_{fi}) - \zeta\omega_{fi}) \Delta t$.

has_state(AA, belief(has_connection_strength(feeling(b_i), preparation(b_i), ω_{fi}, t))) &
has_state(AA, belief(has_state(human, feeling(b_i, V_{1i}, t)))) &
has_state(AA, belief(has_state(human, prep_state(b_i, V_{2i}, t)))) &
has_learning_rate(feeling(b_i), preparation(b_i), η) &
has_extinction_rate(feeling(b_i), preparation(b_i), ζ)
$\rightarrow$ has_state(AA, belief(has_connection_strength(feeling(b_i), preparation(b_i),
$\omega_{fi} + (\eta V_{1i} V_{2i} (1 - \omega_{fi}) - \zeta\omega_{fi}) \Delta t$)), t+$\Delta$t)

Based on the beliefs about the human's states an assessment is made on the level of desire, as follows (where, for example $th = 0.7$):

ALP13 Assessment generation

If AA believes that the human has a desire to address *ub* with level *V* at time *t* which is higher than threshold *th1*,
then an assessment will be generated by AA that human will have a high desire to address *ub* at time *t*

has_state(AA, belief(has_state(human, desire(ub, V, t)))) & V $\geq$ th1
$\rightarrow$ has_state(AA, assessment(has_state(human, high_desire(ub), t)))

ALP14a Generation of intended intervention by the ambient agent: positive suggestion

If AA has generated an assessment that human will have a high desire to address *ub* at time *t*
and AA has desire of human's wellbeing
and AA believes that the human's preparation of b_i has level V_i
and AA believes that for each *i* the effectivity of b_i for *ub* is α_i
and $V_i < 0.1$ and $\alpha_i > 0.5$
then AA will intends to intervene the human at a later time *t* to suggest for doing b_i

has_state(AA, assessment(has_state(human, high_desire(ub), t))) &
has_state(AA, desire(wellbeing(human))) &
has_state(AA, belief(has_state(human, prep_state(b_i, V_i, t+20)))) & V_i < 0.1 &
has_state(AA, belief(is_effectivity_for(α_i, b_i, ub))) & α_i > 0.5
$\rightarrow$ has_state(AA, intended_intervention_at(suggestion(human, do, b_i), t))

ALP14b Generation of intended intervention by the ambient agent: negative suggestion

If AA has generated an assessment that human will have a high desire to address *ub* at time *t*
and AA has desire of human's wellbeing
and AA believes that the human's preparation of b_i has level V_i
and AA believes that for each *i* the effectivity of b_i for *ub* is α_i
and $V_i > 0.1$ and $\alpha_i < 0.5$
then AA will intends to intervene the human at a later time *t* to suggest for not doing b_i

has_state(AA, assessment(has_state(human, high_desire(ub), t))) &
has_state(AA, desire(wellbeing(human))) &
has_state(AA, belief(has_state(human, prep_state(b_i, V_i, t+20)))) & V_i > 0.1 &
has_state(AA, belief(is_effectivity_for(α_i, b_i, ub))) & α_i < 0.5
$\rightarrow$ has_state(AA, intended_intervention_at(suggestion(human, don't_do, b_i), t))

ALP15 Propagation of the intended intervention by the ambient agent

If AA intends to intervene the human at a later time *t1* to suggest X
and the current time is *t2* and t2 < t1
then the intended intervention for X by AA will persist

has_state(AA, intended_intervention_at(X, t1)) & current_time(t2) & t2 < t1
$\rightarrow$ has_state(AA, intended_intervention_at(X, t1))

Finally the intervention is performed:

ALP16 Intervention by the ambient agent

If AA intends to intervene the human at a later time *t1* to suggest doing X
and the current time is *t2*
and t2 = t1-3
and AA does not observes the human in doing X
then AA will suggest the human to do X

has_state(AA, intended_intervention_at(X, t1)) & current_time(t2) & t2 = t1 - 3
$\rightarrow$ has_state(AA, performed(X))

ALP17 The human responding to the action performed by the ambient agent

If AA suggests human to do X
then human will perform X

has_state(AA, performed(suggestion(human, X, B)))
$\rightarrow$ has_state(human, sensor_state(has_state(AA, performed(suggestion(human, X, B)))))

Appendix B Simulation Results for the Ambient Agent Model

This appendix gives some more details of an example simulation scenarios for the ambient agent model. An example simulation trace is illustrated in Figure 6 and 7 (here the time delays within the temporal LEADSTO relations were taken 1 time unit). Recall that in all of these figures, where time is on the horizontal axis, the upper part shows the time periods, in which the binary logical state properties hold (indicated by the dark lines); for example, has_state(AA, assessment(has_state(human, high_desire(ub), 204))). Below this part, quantitative information is provided about the human's actual desire, preparation states, connection strength levels, levels of different body states and the ambient agent AA's prediction of these.

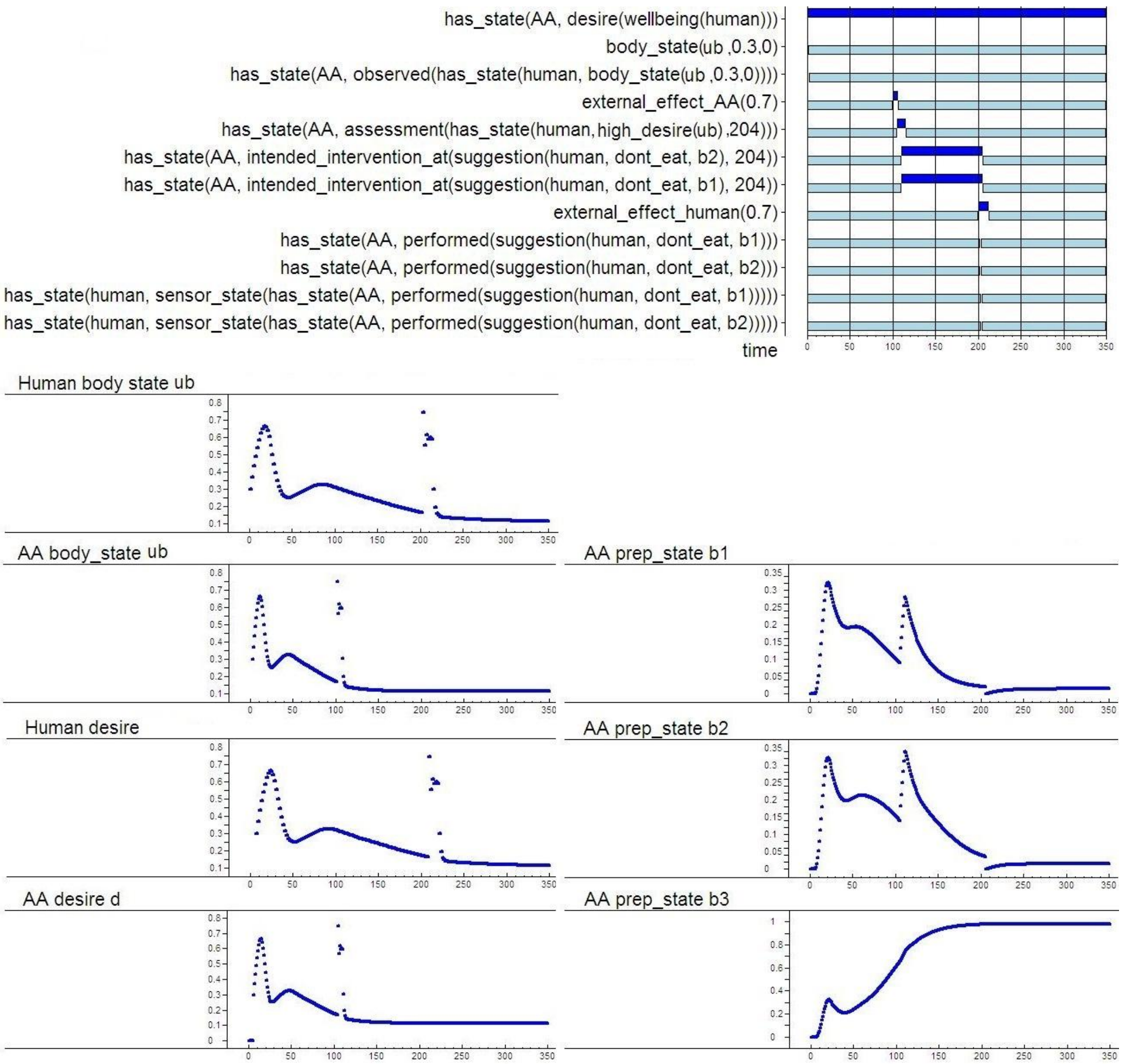

Figure 6 Simulation Trace 1 – Normal behaviour: desire and preparation states
(α_1=β_1 =0.05, α_2=β_2 =0.25, α_3=β_3=1, γ_1=γ_2=0.05,
σ_1=σ_2=10, τ_1=τ_2=0.5, ρ =0.8, ϑ=0.1, η=0.04, ζ=0.01)

Values for these levels for the different time periods are shown by the dark lines. Note that the scale on the vertical axis differs over the different graphs, and only a selection of the relevant state properties is shown. For the example trace shown in Figures 6 and 7, for each *i* that represents an option, λ_i = *0* was taken, so in this example simulation the human is not developing an addiction to any option. Option 3 has the highest effectiveness rate, i.e. $\alpha_3 = 1$. Its value is substantially higher than the rates for the other two available options. This affects the respective body states. Furthermore, as can be seen in Figure 7 by the Hebbian learning it gives a strong effect on the strength of the connection from feeling to preparation for this option: the connection strength for option 3 increases over time until it reaches an equilibrium state.

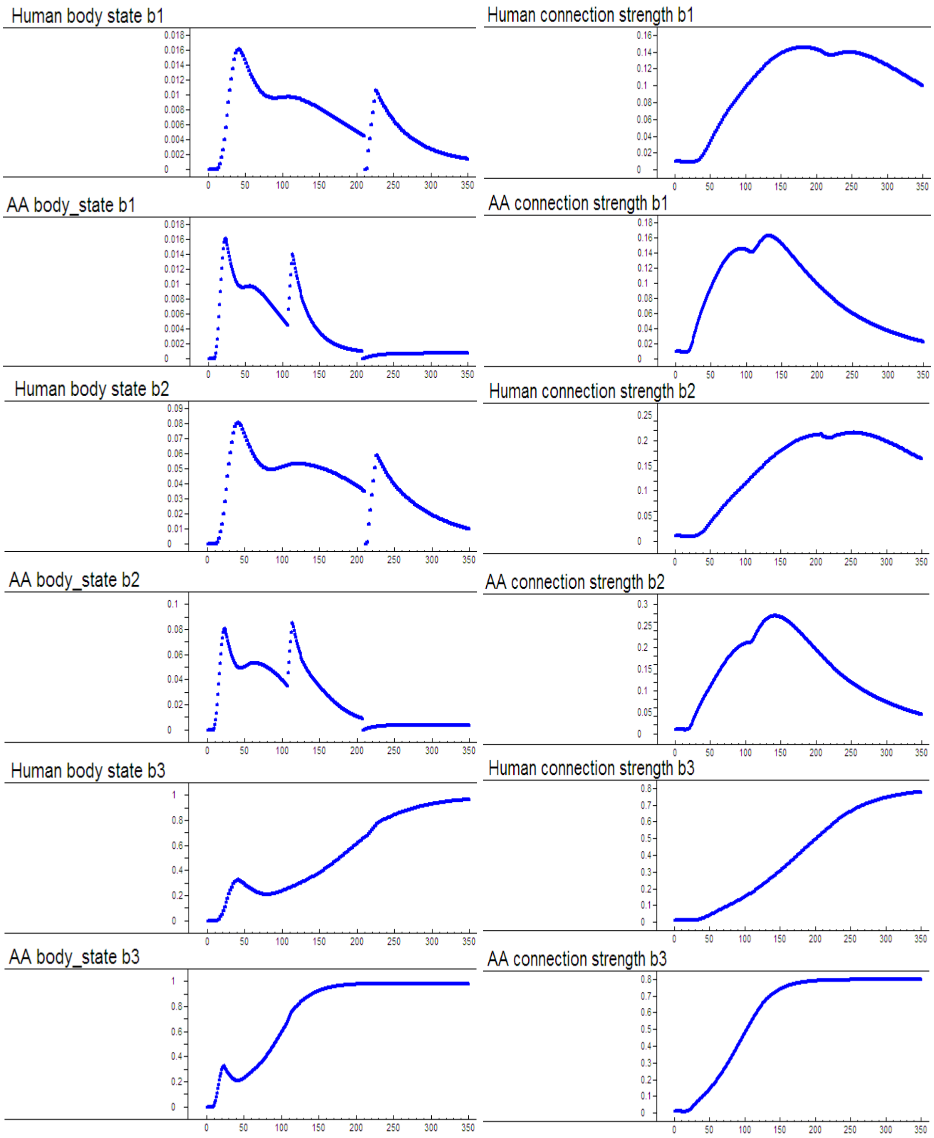

Figure 7 Simulation Trace 1 – Normal behaviour: adaptation process

As shown in the lower part of the Figure 6, at time point 10, the ambient agent predicts that the desire level of human will increase but it will not cross the threshold set to *0.7*, i.e., it is not considered sufficient enough to make the human tempted to choose this option. This is confirmed by the graph of the desire level of the human, where at time point 20, it increases but does not cross the threshold. Hence the ambient agent does not intend to perform any action. But later, some external effects (e.g., the human's habit to attend gym) causes an increase in this desire level, which is predicted by the ambient agent AA in the simulation at time point 102, as shown in the upper part of the Figure 6, by the state property has_state(AA, assessment(has_state(human, high_desire(ub), 204))), expressing that an assessment has been generated that the human will have a high desire for b at time 204. Thereafter, as described in Table 2, AA predicts that the human will choose all three options because of the high values of the preparation states for those options, as shown in Figure 6, in the graph of AA prep_state b1, AA prep_state b2 and AA prep_state b3. After this, the ambient agent will assess for these options whether they are good or bad, based on their effectivity rates. For this particular example simulation, the options b_1 and b_2 are assessed as bad because of their low effectivity rates, i.e., $\alpha_1 = 0.05$, $\alpha_2 = 0.25$, which are lower than the threshold set to *0.5*.

On the other hand, option *b3* is assessed as good because its effectivity rate is higher than threshold, i.e., $\alpha_3 = 1$. Hence the ambient agent generates the intention to suggest the human not to choose options b_1 and b_2 as shown in the upper part of Figure 6, by the state property has_state(AA, intended_intervention_at(suggestion(human, don't_eat, b1), 204)) and similarly for b_2. In Figure 7 it is shown how the ambient agent can reason about the human's adaptation process.

Appendix C Analysis of the ambient agent model by automated verification

In order to investigate whether the ambient agent indeed acts according to what is expected, some hybrid-logical specifications (requirements) for emerging properties have been identified, formalised, and verified against the simulation traces of the model. In this section, specification of the actual properties, and the result of their verification are described using TTL, the language introduced on Section 4.

An overall property to be satisfied by the ambient agent is that if the level of a desire of the human exceeds a particular threshold, it should eventually become below the threshold.

AGP1(th:real): Successful support
In all traces γ and all time points t the level of a desire of the human to address *ub* if the desire of a human exceeds the threshold, then there exists a later time point at which this is not the case.

∀t:TIME, γ:TRACE, Vub1:REAL
[state(γ, t) |= desire(ub, Vub1) & Vub1 > th ⇒ ∃t2:TIME, Vub2:REAL [state(γ, t2) |= desire(ub, Vub2) & Vub2 < th]]

For the simulation traces generated using the ambient agent model, this property is satisfied for all traces (with a threshold value of *0.7*). The overall behavior as expressed in AGP1 can be accomplished by intervention by giving one or more suggestions at the right moment (expressed in AGP2) in combination with the human responding to these suggestions (expressed in AGP3).

AGP2(th:real, d:duration): Right moment for intervention
In all traces γ, if the ambient agent at time point t1 predicts that at time point t2 the human will have a desire to address *ub* exceeding the threshold th, then the ambient agent will give a suggestion to the human.

∀t1, t2:TIME, γ:TRACE, Vub:REAL
[[state(γ, t1) |= has_state(AA, belief(has_state(human, desire(ub, Vub, t2)))) & Vub > th]
⇒ ∃t3:TIME > t1:TIME, A:ACTION, B:BODY_STATE
[state(γ, t3) |= has_state(AA, performed(suggestion(human, A, B)))]]

This property holds for all traces (when a threshold of *0.7* is chosen).

AGP3(d:duration): Right response B ∈ {b₁, b₂, b₃}
In all traces γ, if the ambient agent gives a suggestion to the human at time point t to either avoid a body state $B \in \{b_1, b_2, b_3\}$ (don't eat for this case) or accomplish a body state $B \in \{b_1, b_2, b_3\}$ (i.e., eat), then the human will follow this suggestion, indicated by a preparation state for *B* being *0* for the case of an avoidance suggestion, or a *1* in the case of an accomplish suggestion for the body state *B*.

∀t1:TIME, γ:TRACE, V:REAL, B:BODY_STATE
[[state(γ, t1) |= has_state(AA, performed(suggestion(human, dont_do, B)))
⇒ ∃t2:TIME > t1 [state(γ, t2) |= prep_state(B, 0)]] &
[state(γ, t1) |= has_state(AA, performed(suggestion(human, do, B)))
⇒ ∃t2:TIME > t1 [state(γ, t2) |= prep_state(B, 1)]]

This last property is satisfied for all traces as well.