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Relationship-Specific and Relationship-Independent Behavioural Adaptivity in Affiliation and Bonding: a Multi-Adaptive Dynamical Systems Approach

Name: Sophie C. F. Hendrikse
Student ID: s1393618
Date: 12/08/2024

Specialisation: N.A.

1st supervisor: Peter W. H. van der Putten
2nd supervisor: Jan Treur

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Leiden Institute of Advanced Computer Science
Leiden University
Niels Bohrweg 1
2333 CA Leiden
The Netherlands

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Sophie C.F. Hendrikse

s.c.f.hendrikse@umail.leidenuniv.nl

Abstract. Humans often adapt their behaviour toward each other when they interact. This adaptivity can include both adaptive connections between and adaptive excitability thresholds of certain states within the mental or neural network. From a neuroscientific perspective, such adaptive connections between states regard synaptic plasticity and adaptive excitability thresholds of states concern nonsynaptic plasticity. It is, however, often left unaddressed which of the types of adaptation are specific for the relationship and which are more general for multiple relationships. We focus on this differentiation between relationship-specific and relationship-independent adaptation in social interactions. We analyse computationally how an interplay of relation-specific and relation-independent adaptive mechanisms occurs within the causal pathways for social interaction. As part of this, we also cover the context-sensitive control of these types of adaptation (adaptive speeds and strengths of adaptation), which is sometimes termed higher-order adaptation or metaplasticity. The model was evaluated by a number of explored runs where within a group of four agents each agent randomly has episodes of interaction with one of the three other agents.

1. Introduction

During social interaction, humans often adapt their interaction behaviour toward each other. This behavioural adaptivity may concern short-term effects such as affiliation but also long-term effects such as bonding. Interaction can involve different modalities like movement, affect and verbal actions. Central mechanisms in the adaptive causal pathways for social interaction can take the form of synaptic plasticity based on adaptive connections (Bear and Malenka, 1994) and nonsynaptic plasticity based on adaptive excitability thresholds (Debanne, Inglebert, Russier, 2019). An interesting issue is which of these mechanisms are specific for the other person and which are more general for multiple persons. In the latter case, transference takes place: what you learn in one relationship will also influence how you interact in another relationship. Attachment theory is a theory that claims that adaptations acquired in one relationship also have their effects in other relationships (Salter Ainsworth and Bowlby, 1965; Salter Ainsworth, 1967; Salter Ainsworth, Blehar, Waters, and Wall, 1978; Salter Ainsworth and Bowlby, 1991; Bowlby, 2008). In accordance with that claim, we assume that at least part of the considered behavioural adaptivity in social interaction is relationship-independent. With this assumption as a point of departure, we analyse computationally how an interplay of adaptive relationship-specific and relationship-independent mechanisms occurs within the causal pathways leading to behavioural adaptivity during social interaction.

In our earlier work, we have already explored how in multi-agent systems short-term and long-term relationship adaptivity can emerge from interpersonal synchrony in interacting agents (Hendrikse, Treur, & Koole, 2023b). Moreover, we have introduced adaptive learning rates of such relationship adaptivity in agents (second-order adaptivity). However, when agents learnt how to bond with a specific other agent, these agents did not benefit from their developed interaction behaviours in this relationship for other relationships. In other words, no transfer learning (relationship-independent second-order adaptivity) happened. Therefore, we attempt to develop multi-adaptive agent models with both relationship-specific and relationship-independent adaptivity.

As part of this, in the current thesis we analyse from a neuroscience perspective which learning or adaptation principles can apply to the mechanisms within the different types of causal pathways indicated above. We do not only cover both relationship-specific and relationship-independent adaptation as forms of first-order adaptation, but also second-order adaptation to control these types of first-order adaptation in a context-sensitive manner, in particular adaptive speeds and strengths of adaptation. As such causal pathways in general involve connections between states and excitability of states, from neuroscience both synaptic and nonsynaptic forms of plasticity are exploited: adaptive connection weights and adaptive excitability thresholds. In addition, metaplasticity (second-order adaptation) is incorporated to control these forms of plasticity depending on the context. We evaluate the model by a number of explored runs where within a group of four agents each agent randomly has episodes of interaction with one of the three other agents and due to these episodes displays both short-term and long-term behavioural adaptivity.

The remainder of this thesis is structured as follows: Section 2 discusses the background knowledge from empirical research in psychology and neuroscience on which our proposed adaptive agent model is based. In Section 3, the research question and hypothesis are conceptually formulated. This is followed in Section 4 by a description of the method in general to construct the agent model and from there, our specific agent model is outlined in Section 5. Section 6 operationalises the research question and hypotheses more technically to be directly testable based on simulation outcomes. We continue with the simulation setup and the evaluation of the one simulation over time in Section 7. Then, Section 8 regards an extensive analysis is presented for a collection of 20 simulation runs performed according to this setup. We end with a discussion and conclusion in Section 9.

2. Background

In this section, we elaborate on the main assumptions behind our multi-adaptive dynamical systems approach applied here. These main assumptions are grounded in the neuroscience literature. There are relationships between interpersonal synchrony and nonsynaptic plasticity (Debanne, Inglebert, Russier, 2019) and synaptic plasticity (Bear and Malenka, 1994) respectively. Such nonsynaptic plasticity functions on short-term time scales, whereas synaptic plasticity functions on the long-term time scales. More specifically, we assume the following mechanisms for the causal pathways leading to behavioural adaptivity in social interaction.

2.1 Emerging interpersonal synchrony and related adaptivity of interaction behaviour

Interpersonal synchrony has been found to be at the basis of mutual adaptation of behaviour, leading to changes in the interaction. Numerous studies have demonstrated this phenomenon, including (but not limited to) those conducted by Fairhurst, Janata, and Keller (2013), Feldman, 2007; Hove and Risen (2009), Kirschner and Tomasello (2010), Koole and Tschacher (2016), Koole et al. (2020), Palumbo et al. (2017), Prince and Brown (2022), Tarr, Launay, and Dunbar (2016), Valdesolo, Ouyang, and DeSteno (2010), Valdesolo and DeSteno (2011), and Wiltermuth and Heath (2009). The adaptive shift in mutual behavioural coordination has been observed in various contexts, including psychotherapy sessions (Maurer and Tindall, 1983; Sharpley et al., 2001; Trout and Rosenfeld, 1980; Ramseyer and Tschacher, 2011; Koole and Tschacher, 2016).

Behavioural adaptation following interpersonal synchrony can take the form of both short-term changes and long-term changes in behaviour. While many studies have focused on short-term adaptive shifts in coordination (Hove and Risen, 2009; Tarr, Launay, Dunbar, 2016; Wiltermuth and Heath, 2009), there is also evidence for long-term effects of interpersonal synchrony. For example, developmental research has shown that movement synchrony between infants and caregivers can predict social interaction patterns in the child several years later (Feldman, 2007). Similarly, research on close relationships has found that early patterns of interpersonal synchrony can predict subsequent indicators of relationship functioning, such as converging patterns of cortisol variation in spouses over a period of years (Laws et al., 2015).

Attachment theory also considers that behavioural adaptivity acquired in one relationship can influence interaction behaviour in other relationships, which can be seen as a form of transference, and the attachment theory has been studied in numerous settings and has been commonly applied to therapeutic contexts (Bowlby, 2008; Feeney, 2004; Fonagy, 2001; Fraley and Hudson, 2017; Fraley, Hudson, Heffernan, Segal, 2015; Johnson, 2019; Marmarosh, Markin, Spiegel, 2013; Salter Ainsworth and Bowlby, 1965; Salter Ainsworth, 1967; Salter Ainsworth, Blehar, Waters, and Wall, 1978; Salter Ainsworth and Bowlby, 1991). According to the attachment theory, the first attachment relationship between children and their primary caregiver significantly impacts children's future functioning in relationships. While the attachment theory originally has been mainly applied to intimate, romantic relationships, since more recently also friendship relationships are addressed, for example (Cronin, Pepping, O'donovan, 2018; Heinze, Cook, Wood, Dumadag, Zimmerman 2018; Welch and Houser, 2010). Moreover, the neuroscientific mechanisms underlying attachment theory have gathered attention (Beckes and Coan, 2015; Beckes, IJzerman, Tops, 2015; Coan, 2016; White, Kungl, Vrticka, 2023).

This thesis analyses such transfer learning from one relationship to another relationship in relation to basic mechanisms from neuroscience and their plasticity. To enable an individual to adapt behaviour upon being in synchrony, it is assumed that the individual has the ability to detect synchrony patterns across different modalities, as introduced in (Hendrikse et al, 2023c). From an overall conceptual analysis perspective, mental states representing detected synchrony can be considered mediating mental states in the pathway from synchrony patterns to changed interaction behaviour (Treur, 2007a; Treur, 2007b).

2.2 Using mechanisms from neuroscience: synaptic and nonsynaptic plasticity, and metaplasticity

The field of neuroscience distinguishes between synaptic plasticity and nonsynaptic plasticity (also called intrinsic plasticity). Synaptic plasticity is a classical concept explaining how the strength of a connection between different neural states adapts over time (Bear and Malenka, 1994; Hebb, 1949; Shatz, 1992; Stanton, 1996). In contrast, nonsynaptic adaptation of intrinsic excitability of neural states has been more recently addressed and linked to homeostatic regulation (Chandra and Barkai, 2016; Debanne, Inglebert, Russier, 2019; Zhang et al., 2021; Boot et al., 2017; Williams, O'Leary, Marder, 2013). Nonsynaptic plasticity and synaptic plasticity can work together, allowing for the modelling of simultaneously working mechanisms for different types of behavioural adaptivity in the multi-adaptive dynamical systems model for short-term adaptation and long-term adaptation. In this way, via multiple circular pathways an interplay between synchrony, short-term adaptivity, and long-term adaptivity occurs. Synchrony does not only lead to short-term adaptation but through this also intensifies interaction, leading to more synchrony and strengthening long-term adaptation. Conversely, long-term adaptivity strengthens interaction, leading to more synchrony and consequently stronger short-term adaptivity. Metaplasticity (Abraham and Bear, 1996) controls the plasticity in a context-sensitive manner. Second-order adaptation (adaptation of the adaptation) has been included in our model to allow for more realistic and context-sensitive control of plasticity. This has been applied particularly to address adaptive speeds and strengths of the different types of first-order adaptation that form the plasticity.

3. Research Questions and Hypothesis

The general focus is on how interaction with other agents leads to adaptation of the interaction behaviour. The main research question considered is:

> How can an adaptive agent model for interacting agents be designed that captures how an agent achieves relationship-specific and relationship-independent adaptivity concerning interaction behaviour, based on the duration of interactions with other agents?

In the experimental setup chosen, the interaction episodes and their durations form the independent variable (per simulation run chosen in a stochastic manner) whereas the agent's processes and adaptations depend on that. The main research question can be detailed by the following more specific hypotheses that will be verified through simulations:

A. Adaptation in basic interaction behaviour can be observed for
   (a) representing the other agent
   (b) responding to the representations of the other agent
   (c) executing interaction actions
   (d) emergence of synchrony shown by its detection
B. The adaptation can be considered for multiple modalities (movement *m*, affect *b*, verbal *v*).
C. Two types of adaptation will occur, (a) relationship-specific and (b) relationship-independent adaptation:
   (i) More experiences with interactions with a given agent A lead to faster and stronger adaptation in interactions with A in the future.
   (ii) More experiences with interactions with any agent A lead to faster and stronger adaptation in interactions with any agent B in the future (transference).
D. Such adaptation occurs both (i) in the short-term and (ii) in the long-term:
   (i) Interaction within episodes
   (ii) Interaction over multiple episodes
E. The relation between the extents of interaction and adaptation can be observed in two ways:
   (i) Within a given simulation run over time adaptation becomes stronger after more interaction has taken place

(ii) In a comparative manner, simulation runs that show longer interaction durations will also show more adaptation compared to simulation runs with shorter interaction durations

F. More experiences with interactions will in general not only lead to adaptations in interaction behaviour (first-order adaptation effect) but also to faster and stronger adaptation in interactions in the future (second-order adaptation effect). This happens (i) within a given simulation and (ii) more in simulations where more interaction occurs.

4. Methods: Adaptive Dynamical Systems Modeled by Self-Modelling Networks

Each dynamical system can be represented as a network, and each adaptive dynamical system as a self-modelling network (Hendrikse, Treur, Koole, 2023b). The dynamical systems view as a useful perspective on cognition has been put forward, for example, in (Ashby, 1960; Port and Van Gelder, 1995; Schurger and Uithol, 2015). Dynamical systems are usually considered as state-determined systems which are systems for which each (current) state at some time *t* determines the future states after *t*, e.g., (Ashby, 1960; Van Gelder and Port, 1995), similar to Markov chains. For example:

> 'the fact that the current state determines future behaviour implies the existence of some *rule of evolution* describing the behaviour of the system as a function of its current state. For systems we wish to understand we always hope that this rule can be specified in some reasonably succinct and useful fashion.' (Van Gelder and Port, 1995), p. 6.

Concerning the issue how 'this rule can be specified in some reasonably succinct and useful fashion', often a first-order difference or differential equations format is suggested (Ashby, 1960; Port and Van Gelder, 1995). However, also causally oriented views have been developed, which may provide more intuitive conceptualisations than mathematical difference or differential equations. For example, it has been shown by several applications how a causal format can be a useful format to model complex dynamic and adaptive processes, as long as dynamics of states (Treur, 2016) and adaptivity for causal relations and their characteristics (Treur, 2020) are taken into account in that format. Moreover, it has been mathematically proven in a general manner in (Treur, 2021b; Hendrikse, Treur, Koole, 2023b) that any smooth dynamical system has a canonical representation in network format based on temporal-causal networks and that any smooth adaptive dynamical system has a canonical representation in self-modelling temporal-causal network format. It is this format that is used in the current paper.

4.1 Modelling dynamical systems by a temporal-causal network format

A temporal-causal network model, as characterized by Treur (2020a, 2020b), is composed of nodes (also referred to as states) denoted by *X* and *Y* with activation values *X(t)* and *Y(t)* over time *t*. A specific model is defined by the following network characteristics:

- **Connectivity characteristics**
  There exist connections from states *X* to *Y*, each with a corresponding weight specified, denoted by $\boldsymbol{\omega}_{X,Y}$.
- **Aggregation characteristics**
  For any state *Y*, a combination function $\mathbf{c}_{\boldsymbol{\pi}_Y,Y}(V_1,..,V_k)$ with function parameter values $\boldsymbol{\pi}_Y = (\boldsymbol{\pi}_{1,Y},...,\boldsymbol{\pi}_{m,Y})$ aggregates the impacts $V_i = \boldsymbol{\omega}_{X_i,Y}X_i(t)$ on *Y* from its incoming connections from states X_i.
- **Timing characteristics**
  Each state *Y* has a speed factor denoted by $\boldsymbol{\eta}_Y$, which determines the rate at which it changes for a given causal impact.

Note that sometimes the parameters in combination functions are left implicit and $\mathbf{c}_{\boldsymbol{\pi}_Y,Y}(V_1,..,V_k)$ is simply denoted by $\mathbf{c}_Y(V_1,..,V_k)$. For the network's dynamics, these network characteristics are incorporated into a canonical difference equation (or related differential equation) used for both simulation and analysis purposes:

$$Y(t+\Delta t) = Y(t) + \mathbf{\eta}_Y[\mathbf{c}_{\pi_{Y,Y}}(\mathbf{\omega}_{X_1,Y}X_1(t), \ldots, \mathbf{\omega}_{X_k,Y}X_k(t)) - Y(t)]\,\Delta t \qquad (1)$$

where X_1 to X_k represent states from which Y receives incoming connections. Equation (1) bears a resemblance to the format of recurrent neural networks.

The software environment outlined in Treur (2020a, Ch. 9) includes a library of approximately 70 basic combination functions for use in the model design process. Examples of these functions are discussed in Section 5. Note that if the function $\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$ is applied to some negative values and its formula produces a negative value, it is cut off at 0. However, this cut-off is not applied when the function is applied to obtained negative values. Overall, these concepts enable the declarative design of network models and their dynamics based on mathematically defined functions and relations. By instantiating this general difference equation (1) by proper values for the network characteristics for all states Y, the software environment runs a system of n difference equations where n is the number of states in the network.

4.2 Modelling adaptive dynamical systems by self-modelling networks

Dynamical systems for real-world cases often involve a number of parameters that for changing contextual circumstances have to be adaptive, resulting in an adaptive dynamical system. For network models representing adaptive dynamical systems, such parameters have the form of network characteristics: connection weights, combination functions and their parameters, and speed factors, such as indicated in Section 4.1. To achieve a transparent declarative description for adaptive networks, self-modelling networks (also called reified networks) have been introduced (Treur, 2020a; Treur, 2020b). Self-model states are added to the (base) network to represent adaptive network characteristics, which are depicted at a next level known as the self-model level or reification level in the graphical 3D-format shown in Fig. 1. The original network is situated at the base level.

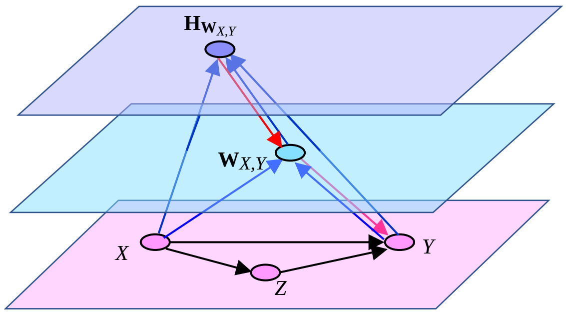

Fig. 1 Example of a three-level self-modelling network architecture.

For example, the weight $\mathbf{\omega}_{X,Y}$ of a connection from state X to state Y can be represented by a self-model state named $\mathbf{W}_{X,Y}$ at the first-order self-model level (see the blue plane in Fig. 1). The activation value of state $\mathbf{W}_{X,Y}$ is used for $\mathbf{\omega}_{X,Y}$ when updating the activation level of state Y over time using equation (1). If the activation level of the self-model state $\mathbf{W}_{X,Y}$ changes over time, this reflects the adaptivity of the weight of the connection from X to Y represented by $\mathbf{W}_{X,Y}$. This concept corresponds to the notion of synaptic plasticity in neuroscience, which, for example, is described by (Bear and Malenka, 1994; Stanton, 1996). In contrast to this synaptic type of plasticity, an example of nonsynaptic plasticity (Chandra and Barkai, 2016; Debanne, Inglebert, Russier, 2019; Zhang et al, 2021) is modulation of excitability thresholds. This can be modelled for a given state Y by a self-model state $\mathbf{T}_Y$ which represents the excitability threshold $\mathbf{\tau}_Y$ of Y.

Similarly, the other network characteristics from $\mathbf{\omega}_{X,Y}$, $\mathbf{c}_{\pi_{Y,Y}}(..)$ and $\mathbf{\eta}_Y$ can be made adaptive by including self-model states for them. For example, an adaptive speed factor $\mathbf{\eta}_{\mathbf{W}_{X,Y}}$ can be represented by a second-order self-model state named $\mathbf{H}_{\mathbf{W}_{X,Y}}$ (see the purple plane in Fig. 1) and an adaptive parameter $\mathbf{\pi}_{i,Y}$ can be represented by a self-model state $\mathbf{P}_{i,Y}$. If for all network characteristics $\mathbf{\omega}$, $\mathbf{\pi}$, $\mathbf{\eta}$ for all base level states, respective self-model states $\mathbf{W}$, $\mathbf{P}$, $\mathbf{H}$ are introduced representing these network characteristics, then the canonical difference equation for the base level states of the self-modelling network model is:

$$Y(t+\Delta t) = Y(t) + \mathbf{H}_Y(t)[\mathbf{c}_{\mathbf{P}_Y(t),Y}(\mathbf{W}_{X_1,Y}(t)X_1(t), \ldots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - Y(t)]\Delta t \qquad (2)$$

where $\mathbf{P}_Y(t) = (\mathbf{P}_{1,Y}(t), \ldots, \mathbf{P}_{m,Y}(t))$.

This universal difference equation is incorporated in the dedicated software environment. By instantiating this general difference equation (2) by proper values for the network characteristics for all base states Y and instantiating equation (1) for all self-model states, the software environment runs a system of $\boldsymbol{n}$ difference equations where $\boldsymbol{n}$ is the number of base states plus self-model states in the network. For the adaptive dynamical system model introduced in the current paper, $\boldsymbol{n}$ = 357.

Note that this difference equation (2) is not exactly in the standard format of a temporal-causal network, as $\mathbf{H}_Y$ is not a constant speed factor and also the **P**- and **W**-values are not constant. However, it can be rewritten into the temporal-causal network format when the following general combination function $\mathbf{c}^*_Y(..)$ is defined:

$$\mathbf{c}^*_Y(H, P_{1,Y}, \ldots, P_{m,Y}, W_1, \ldots, W_k, V_1, \ldots, V_k, V) = H\, \mathbf{c}_{P_Y,Y}(W_1V_1, \ldots, W_kV_k) + (1\text{-}H)\, V \qquad (3)$$

where $P_Y = (P_{1,Y}, \ldots, P_{m,Y})$ are variables for adaptive parameters of the combination function, H is a variable for adaptive speed factors, W_i are variables for adaptive connection weights, and V_i and V are variables for state activations. Based on this universal combination function, consider the following difference equation:

$$Y(t+\Delta t) = Y(t) + [\mathbf{c}^*_Y(\mathbf{H}_Y(t), \mathbf{P}_{1,Y}(t), \ldots, \mathbf{P}_{m,Y}(t), \mathbf{W}_{X_1,Y}(t), \ldots, \mathbf{W}_{X_k,Y}(t), X_1(t), \ldots, X_k(t), Y(t)) - Y(t)]\, \Delta t \quad (4)$$

This is indeed in temporal-causal network format (with speed factor 1) defined by (1). Now note that using (3), equation (4) can be rewritten as follows:

$$\begin{aligned} Y(t+\Delta t) &= Y(t) + [\mathbf{H}_Y(t)\, \mathbf{c}_{\mathbf{P}_Y(t),Y}(\mathbf{W}_{X_1,Y}(t)X_1(t), \ldots, \mathbf{W}_{X_k,Y}(t)X_k(t)) + (1\text{-}\,\mathbf{H}_Y(t))\, Y(t) - Y(t)]\, \Delta t \\ &= Y(t) + [\mathbf{H}_Y(t)\, \mathbf{c}_{\mathbf{P}_Y(t),Y}(\mathbf{W}_{X_1,Y}(t)X_1(t), \ldots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - \mathbf{H}_Y(t)Y(t)\,]\, \Delta t \\ &= Y(t) + \mathbf{H}_Y(t)[\, \mathbf{c}_{\mathbf{P}_Y(t),Y}(\mathbf{W}_{X_1,Y}(t)X_1(t), \ldots, \mathbf{W}_{X_k,Y}(t)X_k(t)) - Y(t)\,]\, \Delta t \qquad (5) \\ &\qquad \text{where } \mathbf{P}_Y(t) = (\mathbf{P}_{1,Y}(t), \ldots, \mathbf{P}_{m,Y}(t)). \end{aligned}$$

This (5) shows exactly difference equation (2) above; this confirms that the chosen combination function $\mathbf{c}^*_Y(..)$ in (3) to show that the self-modelling network has a temporal-causal network format like (1) indeed works.

As the above shows that a self-modelling network is also a temporal-causal network model itself, this self-modelling network construction can easily be applied iteratively to obtain multiple orders of self-models at multiple (first-order, second-order, …) self-model levels. For example, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{W}_{X,Y}}$ representing the speed factor $\boldsymbol{\eta}_{\mathbf{W}_{X,Y}}$ for the dynamics of first-order self-model state $\mathbf{W}_{X,Y}$ which in turn represents the adaptation of connection weight $\boldsymbol{\omega}_{X,Y}$. So, this second-order self-model state $\mathbf{H}_{\mathbf{W}_{X,Y}}$ represents the adaptation speed (or learning rate) for that connection weight. Similarly, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{T}_Y}$ representing the speed factor $\boldsymbol{\eta}_{\mathbf{T}_Y}$ for the dynamics of first-order self-model state $\mathbf{T}_Y$ which in turn represents the adaptation of excitability threshold $\boldsymbol{\tau}_Y$ for Y, so this second-order self-model state $\mathbf{H}_{\mathbf{T}_Y}$ represents the adaptation speed for that excitability threshold. Moreover, also higher-order **W**-states can be used of the form $\mathbf{W}_{Z,\mathbf{W}_{X,Y}}$ representing the weight of the connection from a given state Z to state $\mathbf{W}_{X,Y}$ or of the form $\mathbf{W}_{Z,\mathbf{T}_Y}$ representing the weight of the connection from a given state Z to state $\mathbf{T}_Y$. All such second-order self-model states can be used to modulate an adaptation process for $\mathbf{W}_{X,Y}$ or $\mathbf{T}_Y$ over time. Therefore, these second-order self-model states as indicated can be used to exert control over different aspects of first-order adaptation processes, in line with the notion of metaplasticity from neuroscience to control plasticity in a context-sensitive manner, e.g., (Abraham and Bear, 1996). In this way such second-order adaptation effects contribute to (the speed and strength of) first-order adaptation.

In the current paper, this multi-level self-modelling network perspective will be applied to obtain a second-order adaptive network architecture addressing both first- and second-order adaptation. As an example, the adaptation control level can be used to make the adaptation speed context-sensitive as addressed by metaplasticity literature such as (Abraham and Bear, 1996; Robinson et al, 2016). This indeed has been done for the introduced model, as will be discussed in Section 5.

5. The Multi-Adaptive Dynamical Systems Model

In this section, the agent model (modelled through multi-adaptive dynamical systems) is introduced (Fig. 2 for the base level). First, the conceptual assumptions underlying the model are discussed (Section 5.1). Next, an overview of the model is presented (Section 5.2). After this, the states used in the model are discussed in more detail, together with the related network characteristics, subsequently for the base level (Section 5.3), the first-order self-model level (Section 5.4), and the second-order self-model level (Section 5.5).

5.1 Conceptual assumptions behind the introduced adaptive dynamical system model

The aim of this paper is to analyse in which ways agents change their behaviour during social interactions with multiple others over time and how these changes can be related to internal mental learning mechanisms. The chosen mental learning mechanisms are based on what is known from neuroscience, in particular on synaptic and nonsynaptic plasticity (Bear and Malenka, 1994; Chandra and Barkai, 2016; Debanne, Inglebert, Russier, 2019; Stanton, 1996) and metaplasticity (Abraham and Bear, 1996). Overall, the following assumptions were made on adaptive changes that can take place during social interaction:

(a) Changes in the way others are perceived
(b) Changes in the way of responding to other persons
(c) Changes in the way of executing or expressing certain behaviours to other persons

As discussed in Section 4, first-order self-model states can be used to model adaptation. In particular, $\mathbf{W}_{X,Y}$-states and $\mathbf{T}_Y$-states can be applied to model synaptic and nonsynaptic types of adaptation of connections from states X to Y and excitability thresholds for states Y used to model the mental processes perceiving, responding and executing or expressing (a) to (c) mentioned above. Thus, stronger and more sensitive activation of states used to model the three types of mental processes (a) to (c) can be obtained.

More specifically, if sensor states and sensory representation states for others are used to model the way how someone else is perceived, then strengthening the connections from sensor states and representation states and lowering the excitability thresholds for representation states can lead to stronger and more sensitive forms of perceiving (a). Furthermore, if in addition preparation states and connections from representation states to them are used to model the basis of the responding process, then strengthening these connections and lowering the excitability thresholds for these preparation states will lead to stronger and more sensitive responding (b). Finally, if in addition (action) execution states and connections from preparation states to them are used to model the execution process, then strengthening these connections and lowering the excitability thresholds for these execution states will lead to stronger and more sensitive acting and expressing (c). We assume here that synaptic plasticity is used to model long-term changes (over multiple episodes) like in bonding, whereas nonsynaptic adaptation of excitability thresholds is used to model short-term changes like in affiliation (within one episode).

For all of the above forms of adaptations, it has been considered in how far they are relationship-specific or relationship-independent. For example, when an agent learns to respond stronger to an agent within an interaction, will that only change the behaviour in interaction with that specific agent, or also when interacting with other agents? In terms of the model to be designed, which (adaptive) state and connection characteristics play only a role when interacting with one and the same agent and which (adaptive) state and connection characteristics play a role when interacting with any other agent? Below we will make these distinctions for the different forms of learning addressed.

Still other assumptions are made about second-order adaptivity. Within neuroscience this is described by metaplasticity which can control plasticity in a context-sensitive manner (Abraham and Bear, 1996). In the first place, this concept is used to address adaptation of the adaptation strength for $\mathbf{W}_{X,Y}$ and $\mathbf{T}_Y$. As discussed in Section 3, second-order self-model states $\mathbf{W}_{Z,\mathbf{W}_{X,Y}}$ and $\mathbf{W}_{Z,\mathbf{T}_Y}$ can be used to make the strength of adaptation of $\mathbf{W}_{X,Y}$ and $\mathbf{T}_Y$ adaptive. This can be used to model how over time a person learns to adapt stronger. Secondly, the concept of metaplasticity is used to address adaptation of the adaptation speed for $\mathbf{W}_{X,Y}$ and $\mathbf{T}_Y$. Again, as discussed in Section 3, second-order self-model states $\mathbf{H}_{\mathbf{W}_{X,Y}}$ and $\mathbf{H}_{\mathbf{T}_Y}$ can be used to make the speed of adaptation of $\mathbf{W}_{X,Y}$ and $\mathbf{T}_Y$ adaptive. This can be used to model how over time a person learns to adapt faster. In this way, in the model both stronger adaptation and faster adaptation over time are modelled by these second-order self-model states. This second-order adaptation effect can substantially contribute to first-order adaptation.

In total two first-order adaptation mechanisms have been identified, modelled through **W**-states for long-term adaptation and **T**-states for short-term adaptation. Moreover, these two learning mechanisms have been applied to the different types of mental processes (a) to (c) mentioned above, which makes six types of first-order adaptation. In addition, four second-order adaptation mechanisms have been identified modelled through $\mathbf{W}_{Z,\mathbf{W}_{X,Y}}$-, $\mathbf{W}_{Z,\mathbf{T}_Y}$-, $\mathbf{H}_{\mathbf{W}_{X,Y}}$-, and $\mathbf{H}_{\mathbf{T}_Y}$-states. Further assumptions have been made about which of these 10 learning types work within a given episode and which ones over multiple episodes, and which are other-agent-specific and which relationship-independent, see Table 2 for an overview of this. Here, in the first four rows (in purple) the assumptions are indicated that all four types of second-order adaptivity are relationship-independent and long-term. So, their influence on the first-order adaptation is a long-term relationship-independent influence. Furthermore, in rows 5 to 7 (in blue) the assumptions are indicated that synaptic plasticity is used as a form of long-term learning, for representing and responding relationship-specific, and for executing actions relationship-independent. In contrast, in the last three rows (in blue) the assumptions are indicated that nonsynaptic plasticity of excitability thresholds is used as a form of short-term learning, again for representing and responding relationship-specific, and for executing actions relationship-independent. Note that the second-order adaptation also provides long-term relationship-independent effects, even on the relationship-specific short-term first-order adaptation modelled by the **T**-states for the representation states.

Table 1 Overview of the assumptions on first-order and second-order relationship-specific and relationship-independent adaptivity and short-term and long-term learning adaptivity

	Relationship-independent	Long-term	Order and type of adaptivity
$\mathbf{W}_\mathbf{W}$-states for connectivity of **W**-states	+	+	Second-order, relationship-independent adaptivity
$\mathbf{W}_\mathbf{T}$-states for connectivity of **T**-states	+	+	Second-order, relationship-independent adaptivity
$\mathbf{H}_\mathbf{W}$-states for timing of **W**-states	+	+	Second-order, relationship-independent adaptivity
$\mathbf{H}_\mathbf{T}$-states for timing of **T**-states	+	+	Second-order, relationship-independent adaptivity
W-states for representing	-	+	First-order, relationship-specific adaptivity
W-states for responding	-	+	First-order, relationship-specific adaptivity
W-states for executing	+	+	First-order, relationship-independent adaptivity
T-states for representing	-	-	First-order, relationship-specific adaptivity
T-states for responding	-	-	First-order, relationship-specific adaptivity
T-states for executing	+	-	First-order, relationship-independent adaptivity

5.2 Overview of the model

The designed adaptive dynamical systems model takes actions of agents for three different modalities into account: for moving *m*, expressing affect *b* and talking *v*. In total, the model covers four agents and their interactions and adaptivity, modelled according to a second-order adaptive dynamical system and represented in a network-oriented format. Overall, it has 357 states X_i, which in view of Section 4 means that its dynamics is based on a system of 357 difference or differential equations which are instantiations of (1) for the chosen network characteristics including the specific combination functions shown in Table 3. Within the overall model, each of the four agents A to D is modelled by 79 states:

- From these 79 states per agent, 35 states are at the base level and model the base processes of perceiving other persons, responding to them and executing actions. These 35 states are sensor and execution states, representation and preparation states and synchrony detector states, all for different modalities.
- Furthermore, 33 states are at the first-order self-model level and model the agent's first-order adaptivity: **W**-states and **T**-states representing connectivity and aggregation characteristics of the

base-level network. They model respectively synaptic plasticity (adaptivity of connection weights) and nonsynaptic plasticity (adaptivity of excitability thresholds).
- Finally, 11 states are at the second-order self-model level and model the agent's second-order adaptivity for control over its adaptivity: aggregation states, $\mathbf{H}_{\mathbf{W}}$- and $\mathbf{H}_{\mathbf{T}}$-states, $\mathbf{W}_{\mathbf{W}}$-, and $\mathbf{W}_{\mathbf{T}}$-states representing timing and connectivity network characteristics for first-order self-model **W**- and **T**-states. Here, the $\mathbf{H}_{\mathbf{W}}$- and $\mathbf{H}_{\mathbf{T}}$-states represent the adaptive speed factors for the **W**-states and **T**-states and the $\mathbf{W}_{\mathbf{W}}$- and $\mathbf{W}_{\mathbf{T}}$-states represent the weights of the incoming connections for the **W**-states and **T**-states.

Table 2 Overall overview of the adaptive dynamical system model

Type	States	Explanation
Base world states: 5	X_1 X_2-X_5	• World state for stimulus *s* • Context states for excitability thresholds for the agent states
Base agent states: 35 base states per agent	agent A X_6-X_{40} agent B X_{41}-X_{75} agent C X_{76}-X_{110} agent D X_{111}-X_{145}	• Sensor states sense$_{-,-,-}$ for stimulus *s* and observed multimodal actions • Representation states rep$_{-,-,-}$ for stimulus and actions in different modalities • Preparation states prep$_{-,-}$ for actions move, express, talk in different modalities. • Interpersonal synchrony detection states intersyncdet$_{-,-,-}$ for different modalities • Execution states move, express, talk for actions in different modalities.
First-order self-model agent states: 33 per agent	agent A X_{146}-X_{178} agent B X_{179}-X_{211} agent C X_{212}-X_{244} agent D X_{245}-X_{278}	• First-order self-model **W**-states for weights of connections *within* agents: ○ States $\mathbf{W}_{\text{sense-rep-},-,-}$ for connections from sensing to representation states ○ States $\mathbf{W}_{\text{rep-prep-},-,-}$ for connections from representation to preparation states ○ States $\mathbf{W}_{\text{prep-exec-},-,-}$ for connections from preparation to execution states • First-order self model **T**-states for excitability thresholds: ○ States $\mathbf{T}_{\text{rep-},-,-}$ for excitability thresholds of representation states ○ States $\mathbf{T}_{\text{exec-},-,-}$ for excitability thresholds of execution states
First-order self-model interaction states: 35	X_{279}-X_{313}	• First-order self-model **W**-states for weights of connections *between* agents: ○ States $\mathbf{W}_{z,X,Y}$ for weights of connections from agent *X* to agent *Y* for modality *z*
Second-order self-model agent aggregation states: 7 per agent	agent A X_{314}-X_{320} agent B X_{321}-X_{327} agent C X_{328}-X_{334} agent D X_{335}-X_{341}	• Aggregation states agg$_{-,-,-}$ for aggregation of: ○ Sensing, execution, and for synchrony states ○ **W**-states for weights of connections from sensing to representation, from representation to preparation, and from preparation to execution
Second-order self-model agent states for adaptation speed and adaptation strength: 4 per agent	agent A X_{342}-X_{345} agent B X_{346}-X_{329} agent C X_{350}-X_{353} agent D X_{354}-X_{357}	• Second-order self-model $\mathbf{H}_{\mathbf{W}}$- and $\mathbf{H}_{\mathbf{T}}$-states representing the speed factors of the first-order self-model **W**-states and **T**-states of the agent. • Second-order self-model $\mathbf{W}_{\mathbf{W}}$- and $\mathbf{W}_{\mathbf{T}}$-states representing the weights of the incoming connections of the first-order self-model **W**-states and **T**-states of the agent.

5.3 Network Characteristics for the Base Level

At this point, some more details are discussed of the network model's (connectivity, aggregation, timing) characteristics, starting with the base level states.

Connectivity characteristics for base states

- Connectivity for base agent states:
  - Within-agent connections for representing, responding, and executing have adaptive weights modelled by within-agent first-order self-model **W**-states.
  - Within-agent connections for representing stimulus *s* and from representation states of *s* to preparation states have weights 1.
  - Within-agent connections to synchrony detection have weights 1.
  - Within-agent connections from preparation states to representation states for predicting have weights 1.
  - Between-agents connections from execution states of one agent *X* to sensing states of another agent *Y* have adaptive weights modelled by between-agents first-order self-model **W**-states.
  - Connections from world state ws$_s$ to agent sensor states for *s* have weights 1.
- Connectivity for base world states:
  - Base world states have no connections from other states. Instead, they have circular persistence connections to themselves (not depicted in the model pictures) with weight 1 which makes them persistent over time.

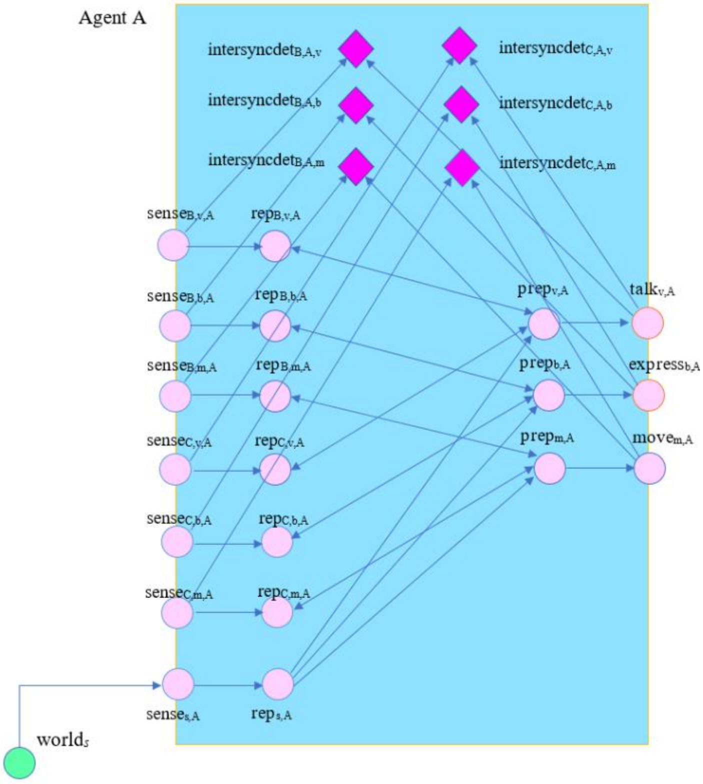

Fig. 2 Base level connectivity for one agent A: states and within-agent connections. With three modalities and (in dark pink) six synchrony detection states for interpersonal synchrony

Aggregation characteristics for base states

- Aggregation for base agent states:
  - Sensing states use the Euclidean function **eucl** from Table 3 of order $\boldsymbol{n}$ = 1 and scaling factor $\boldsymbol{\lambda}$ = 1.1.
  - Interpersonal synchrony detector states use the synchrony detection function **compdiff** from Table 3.
  - All other base agent states use the logistic function **alogistic** from Table 3 with steepness $\boldsymbol{\sigma}$ = 5 and adaptive thresholds modelled by within-agent first-order self-model **T**-states.
- Aggregation for base world states:
  - World state ws$_s$ uses the stimulus repetition function **stepmod** from Table 3 with repetition $\boldsymbol{\rho}$ = 80 time units and step time $\boldsymbol{\delta}$ = 40 time units.
  - Context states use the identity function via Euclidean function **eucl** from Table 3 of order $\boldsymbol{n}$ = 1 and scaling factor $\boldsymbol{\lambda}$ = 1.

Table 3 The combination functions used in the introduced network model

	Notation	Formula	Parameters
Advanced logistic sum	$\mathbf{alogistic}_{\sigma,\tau}(V_1, \dots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\dots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right](1+e^{-\sigma\tau})$	Steepness σ Excitability threshold τ
Complemental difference	$\mathbf{compdiff}(V_1, V_2)$	0 if $V_1 = V_2 = 0$ $1 - \frac{\lvert V_1 - V_2\rvert}{\max(V_1, V_2)}$ else	-
Stepmod	$\mathbf{stepmod}_{\rho,\delta}(V)$	0 if $0 \leq t$ **mod** $\rho \leq \delta$ 1 else	Time t Repetition ρ Step time δ
Euclidean	$\mathbf{eucl}_{n,\lambda}(V_1, \dots, V_k)$	$\sqrt[n]{\frac{V_1^{\,n} + \dots + V_k^{\,n}}{\lambda}}$	Order $\boldsymbol{n}$ Scaling factor λ

The four functions in Table 1 are all used in the introduced model. To obtain stochastic generation of runs, in addition a fifth function is used, called **scenario-generation**. Over time this function determines in a stochastic manner environmental circumstances: which pairs of agents can interact with each other over which time periods and for which modalities.

Timing characteristics for base states

- Timing for base agent states:
  - All interpersonal synchrony detector states have speed factor 0.5.
  - All other agent states have speed factor 1.
- Timing for base world states:
  - World state ws_s has speed factor 0.5.
  - The context states have speed factor 0, which makes them constant.

An overview of explanations of all base states for agent A can be found in Table 4.

Table 4 Base states of the adaptive dynamical systems model for agent A. For the other agents, similar base states are used: X_{41} to X_{75} for B, X_{76} to X_{110} for C, X_{111} to X_{145} for D.

state	name	Explanation
X_1	ws_s	World state for stimulus *s*
X_2	$con_{th,A}$	Context state for excitability thresholds for *A*
X_3	$con_{th,B}$	Context state for excitability thresholds for *B*
X_4	$con_{th,C}$	Context state for excitability thresholds for *C*
X_5	$con_{th,D}$	Context state for excitability thresholds for *D*
X_6	$sense_{s,A}$	Sensor state of *A* for stimulus *s* for *A*
X_7	$sense_{B,m,A}$	Sensor state of *A* for movement *m* of *B*
X_8	$sense_{B,b,A}$	Sensor state of *A* for expressed affective response *b* of *B*
X_9	$sense_{B,v,A}$	Sensor state of *A* for verbal action *v* of *B*
X_{10}	$sense_{C,m,A}$	Sensor state of *A* for movement *m* of *C*
X_{11}	$sense_{C,b,A}$	Sensor state of *A* for expressed affective response *b* of *C*
X_{12}	$sense_{C,v,A}$	Sensor state of *A* for verbal action *v* of *C*
X_{13}	$sense_{D,m,A}$	Sensor state of *A* for movement *m* of *D*
X_{14}	$sense_{D,b,A}$	Sensor state of *A* for expressed affective response *b* of *D*
X_{15}	$sense_{D,v,A}$	Sensor state of *A* for verbal action *v* of *D*
X_{16}	$rep_{s,A}$	Sensory representation state of *A* for stimulus *s* for *A*
X_{17}	$rep_{B,m,A}$	Sensory representation state of *A* for movement *m* of *B*
X_{18}	$rep_{B,b,A}$	Sensory representation state of *A* for expressed affective response *b* of *B*
X_{19}	$rep_{B,v,A}$	Sensory representation state of *A* for verbal action *v* of *B*
X_{20}	$rep_{C,m,A}$	Sensory representation state of *A* for movement *m* of *C*
X_{21}	$rep_{C,b,A}$	Sensory representation state of *A* for expressed affective response *b* of *C*
X_{22}	$rep_{C,v,A}$	Sensory representation state of *A* for verbal action *v* of *C*
X_{23}	$rep_{D,m,A}$	Sensory representation state of *A* for movement *m* of *D*
X_{24}	$rep_{D,b,A}$	Sensory representation state of *A* for expressed affective response *b* of *D*
X_{25}	$rep_{D,v,A}$	Sensory representation state of *A* for verbal action *v* of *D*
X_{26}	$prep_{m,A}$	Preparation state for movement *m* of *A*
X_{27}	$prep_{b,A}$	Preparation state for affective response *b* of *A*
X_{28}	$prep_{v,A}$	Preparation state for verbal action *v* of *A*
X_{29}	$intersyncdet_{B,A,m}$	Interpersonal synchrony detection of *A* for executing *m* by *B* and *A*
X_{30}	$intersyncdet_{B,A,b}$	Interpersonal synchrony detection of *A* for executing *b* by *B* and *A*
X_{31}	$intersyncdet_{B,A,v}$	Interpersonal synchrony detection of *A* for executing *v* by *B* and *A*
X_{32}	$intersyncdet_{C,A,m}$	Interpersonal synchrony detection of *A* for executing *m* by *C* and *A*
X_{33}	$intersyncdet_{C,A,b}$	Interpersonal synchrony detection of *A* for executing *b* by *C* and *A*
X_{34}	$intersyncdet_{C,A,v}$	Interpersonal synchrony detection of *A* for executing *v* by *C* and *A*
X_{35}	$intersyncdet_{D,A,m}$	Interpersonal synchrony detection of *A* for executing *m* by *D* and *A*
X_{36}	$intersyncdet_{D,A,b}$	Interpersonal synchrony detection of *A* for executing *b* by *D* and *A*
X_{37}	$intersyncdet_{D,A,v}$	Interpersonal synchrony detection of *A* for executing *v* by *D* and *A*
X_{38}	$move_{m,A}$	Executing movement *m* by *A*
X_{39}	$express_{b,A}$	Executing expression of *b* by *A*
X_{40}	$talk_{A,B,v}$	Executing verbal action *v* by *A*

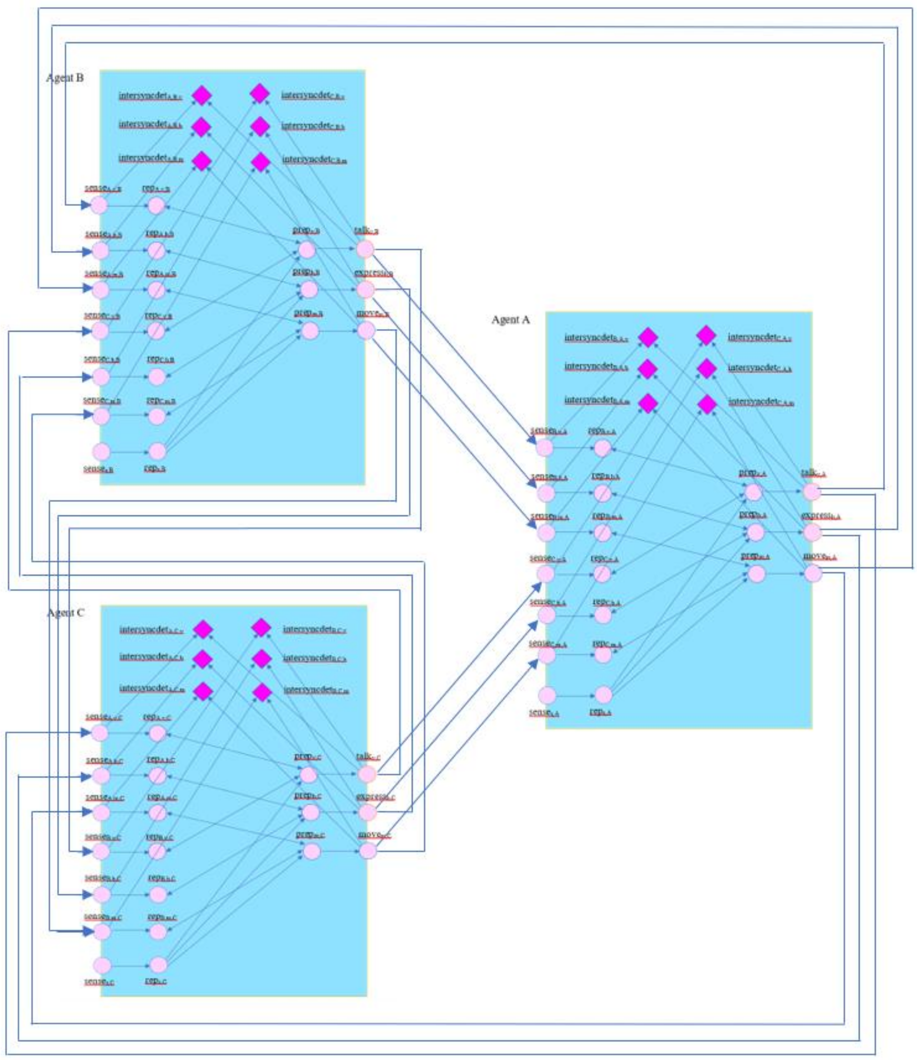

Fig. 3 Base level connectivity for three agents A, B, C: within-agent connections and between-agents connections

5.4 Network Characteristics for the First-Order Self-Model Level

Next, some more details are discussed of the network model's (connectivity, aggregation, and timing) characteristics for the first-order self-model level states.

Connectivity characteristics for first-order self-model states

- **Connectivity for within-agent first-order self-model states**
  - Within-agent connections from synchrony detector states to **T**-states for representation, preparation and execution states have (negative) adaptive weights that are represented by second-order self-model states $\mathbf{W_T}$.
  - Within-agent connections from context states to all **T**-states have weight 1.
  - Within-agent connections from synchrony detector states to **W**-states for representing and responding have adaptive weights represented by second-order self-model states $\mathbf{W_W}$. In addition, these **W**-states have circular persistence connections to themselves with weight 1.
  - Within-agent connections from preparation and execution states to **W**-states for execution have adaptive weights represented by second-order self-model states $\mathbf{W_W}$. In addition, these **W**-states have circular persistence connections to themselves with weight 1.

- **Connectivity for between-agents first-order self-model states**
    - Between-agents **W**-states have no connections from other states. However, these **W**-states have circular persistence connections to themselves with weight 1.

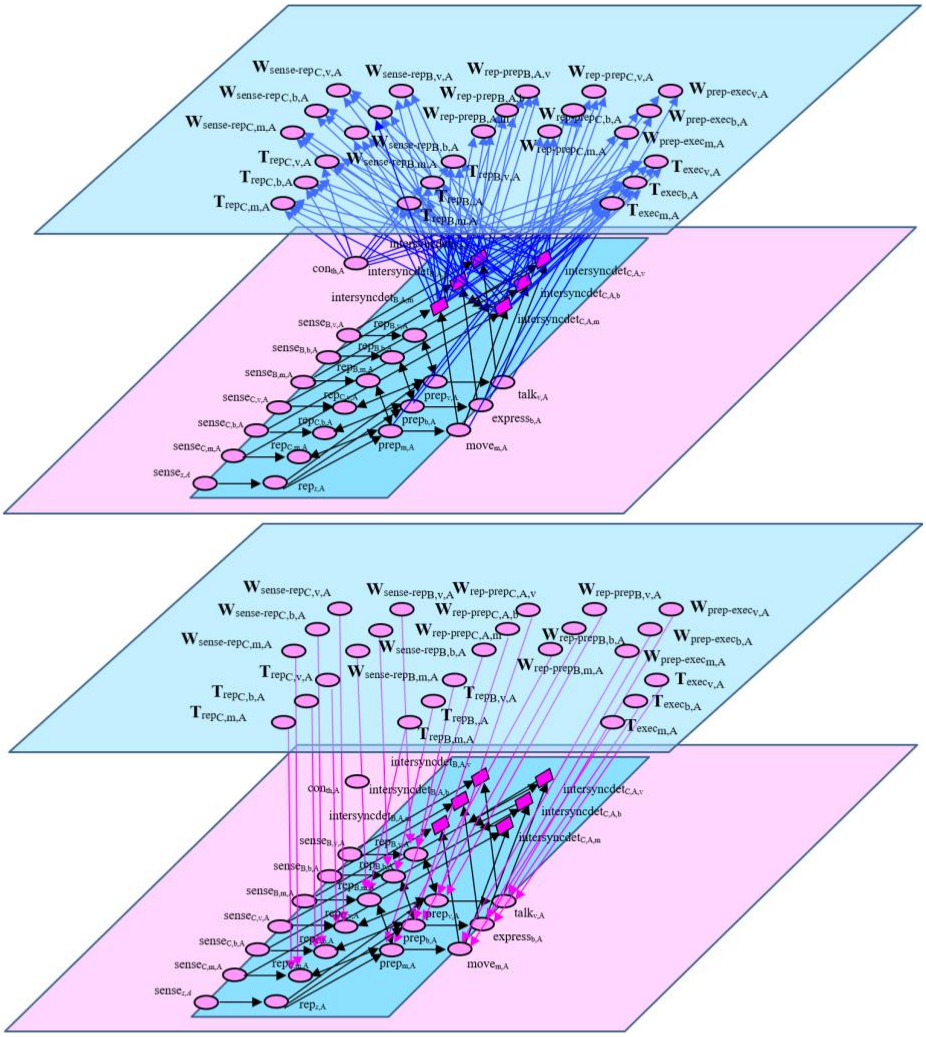

Fig. 4 The adaptive agent model: the base level and first-order self-model level with in the upper picture their upward interaction links (in blue) and in the lower picture their downward interaction links (in pink)

Aggregation characteristics for first-order self-model states

- **Aggregation for within-agent first-order self-model states**
    - All first-order self-model within-agent **W**-states use the logistic function **alogistic** from Table 3 with steepness $\boldsymbol{\sigma}$ = 5 and threshold $\boldsymbol{\tau}$ = 0.5 and **T**-states with steepness $\boldsymbol{\sigma}$ = 5 and threshold $\boldsymbol{\tau}$ = 0.6.
- **Aggregation for between-agents first-order self-model states**
    - All first-order self-model between-agents **W**-states use stochastic generation of interaction episodes for dyads via combination function **scenario-generation**.

Timing characteristics for first-order self-model states

- **Timing for within-agent first-order self-model states**
    - All first-order self-model within-agent **W**-states and **T**-states use adaptive speed factors represented by second-order self-model states $\mathbf{H_W}$ and $\mathbf{H_T}$, respectively.

- **Timing for between-agents first-order self-model states**
  - All first-order self-model between-agents **W**-states have timing specified by speed factor 2.

An overview of explanations of all first-order self-model states for agent A can be found in Table 5.

Table 5 First-order self-model **T**-states and **W**-states of agent A in the adaptive dynamical systems model: modelling excitability thresholds and connection weights. For the other agents, similar first-order self-model states are used: X_{179} to X_{211} for B, X_{212} to X_{244} for C, X_{245} to X_{278} for D.

State	Name	Explanation
X_{146}	$\mathbf{W}_{\text{sense-rep\_}m,B,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing movement *m* of *B*
X_{147}	$\mathbf{W}_{\text{sense-rep\_}b,B,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing affective response *b* of *B*
X_{148}	$\mathbf{W}_{\text{sense-rep\_}v,B,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing verbal action *v* of *B*
X_{149}	$\mathbf{W}_{\text{sense-rep\_}m,C,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing movement *m* of *B*
X_{150}	$\mathbf{W}_{\text{sense-rep\_}b,C,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing affective response *b* of *B*
X_{151}	$\mathbf{W}_{\text{sense-rep\_}v,C,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing verbal action *v* of *B*
X_{152}	$\mathbf{W}_{\text{sense-rep\_}m,D,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing movement *m* of *B*
X_{153}	$\mathbf{W}_{\text{sense-rep\_}b,D,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing affective response *b* of *B*
X_{154}	$\mathbf{W}_{\text{sense-rep\_}v,D,A}$	First-order self-model state for the weight of *A*'s internal connection from sensing to representing verbal action *v* of *B*
X_{155}	$\mathbf{W}_{\text{rep-prep\_}m,B,A}$	First-order self-model state for the weight of *A*'s internal connection from representing movement *m* of *B* to preparing for movement *m*
X_{156}	$\mathbf{W}_{\text{rep-prep\_}b,B,A}$	First-order self-model state for the weight of *A*'s internal connection from representing affective response *b* of *B* to preparing for affective response *b*
X_{157}	$\mathbf{W}_{\text{rep-prep\_}v,B,A}$	First-order self-model state for the weight of *A*'s internal connection from representing verbal action *v* of *B* to preparing for verbal action *v*
X_{158}	$\mathbf{W}_{\text{rep-prep\_}m,C,A}$	First-order self-model state for the weight of *A*'s internal connection from representing movement *m* of *C* to preparing for movement *m*
X_{159}	$\mathbf{W}_{\text{rep-prep\_}b,C,A}$	First-order self-model state for the weight of *A*'s internal connection from representing affective response *b* of *C* to preparing for affective response *b*
X_{160}	$\mathbf{W}_{\text{rep-prep\_}v,C,A}$	First-order self-model state for the weight of *A*'s internal connection from representing verbal action *v* of *C* to preparing for verbal action *v*
X_{161}	$\mathbf{W}_{\text{rep-prep\_}m,D,A}$	First-order self-model state for the weight of *A*'s internal connection from representing movement *m* of *D* to preparing for movement *m*
X_{162}	$\mathbf{W}_{\text{rep-prep\_}b,D,A}$	First-order self-model state for the weight of *A*'s internal connection from representing affective response *b* of *D* to preparing for affective response *b*
X_{163}	$\mathbf{W}_{\text{rep-prep\_}v,D,A}$	First-order self-model state for the weight of *A*'s internal connection from representing verbal action *v* of *D* to preparing for verbal action *v*
X_{164}	$\mathbf{W}_{\text{prep-exec\_}m,A}$	First-order self-model state for the weight of *A*'s internal connection from preparing to executing movement *m*
X_{165}	$\mathbf{W}_{\text{prep-exec\_}b,A}$	First-order self-model state for the weight of *A*'s internal connection from preparing to expressing affective response *b*
X_{166}	$\mathbf{W}_{\text{prep-exec\_}v,A}$	First-order self-model state for the weight of *A*'s internal connection from preparing to executing verbal action *v*
X_{167}	$\mathbf{T}_{\text{rep\_}B,m,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{m,A}$ for movement *m* of *B*
X_{168}	$\mathbf{T}_{\text{rep\_ }B,b,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{b,A}$ for affective response *b* of *B*
X_{169}	$\mathbf{T}_{\text{rep\_ }B,v,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{v,A}$ for verbal response *v* of *B*
X_{170}	$\mathbf{T}_{\text{rep\_}C,m,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{m,A}$ for movement *m* of *C*
X_{171}	$\mathbf{T}_{\text{rep\_ }C,b,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{b,A}$ for affective response *b* of *C*
X_{172}	$\mathbf{T}_{\text{rep\_ }C,v,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{v,A}$ for verbal response *v* of *C*
X_{173}	$\mathbf{T}_{\text{rep\_}D,m,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{m,A}$ for movement *m* of *D*
X_{174}	$\mathbf{T}_{\text{rep\_ }D,b,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{b,A}$ for affective response *b* of *D*
X_{175}	$\mathbf{T}_{\text{rep\_ }D,v,A}$	First-order self-model state for the excitability threshold of *A*'s sensory representation state $\text{rep}_{v,A}$ for verbal response *v* of *D*

X_{176}	$\mathbf{T}_{exec\_m,A}$	First-order self-model state for the excitability threshold of *A*'s execution state $move_{m,A}$ for movement *m*
X_{177}	$\mathbf{T}_{exec\_b,A}$	First-order self-model state for the excitability threshold of *A*'s execution state state $express_{b,A}$ for affective response *b*
X_{178}	$\mathbf{T}_{exec\_v,A}$	First-order self-model state for the excitability threshold of *A*'s execution state state $talk_{v,A}$ for verbal response *v*

5.5 Network Characteristics for the Second-Order Self-Model Level

Finally, more details are discussed of the network model's (connectivity, aggregation, timing) characteristics for the second-order self-model level states.

Connectivity characteristics for second-order self-model states

- **Connectivity for within-agent second-order self-model states**
  - Within-agent connections from base-level within-agent states for sensing, execution and synchrony detection to respective aggregation states have weights 0.1.
  - Within-agent connections from within-agent first-order self-model **W**-states for representing, responding and executing to respective aggregation states have weight 0.1.
  - Within-agent connections from second-order within-agent self-model aggregation states for representing, responding and executing to overall **W**-aggregation states have weight 0.1.
  - Within-agent connections from aggregation states for sensing, execution and synchrony detection and from overall **W**-aggregation states to $\mathbf{H_W}$-, $\mathbf{H_T}$-, $\mathbf{W_W}$-, $\mathbf{W_T}$-states have weight 1 for the first three $\mathbf{H_W}$, $\mathbf{H_T}$, $\mathbf{W_W}$, and weight -0.35 for the $\mathbf{W_T}$-states. In addition, these $\mathbf{H_W}$-, $\mathbf{H_T}$-, $\mathbf{W_W}$-, $\mathbf{W_T}$-states have circular persistence connections to themselves with weight 1 for $\mathbf{H_W}$- and $\mathbf{H_T}$-states, 0.15 for $\mathbf{W_W}$-states, and -1 for $\mathbf{W_T}$-states.

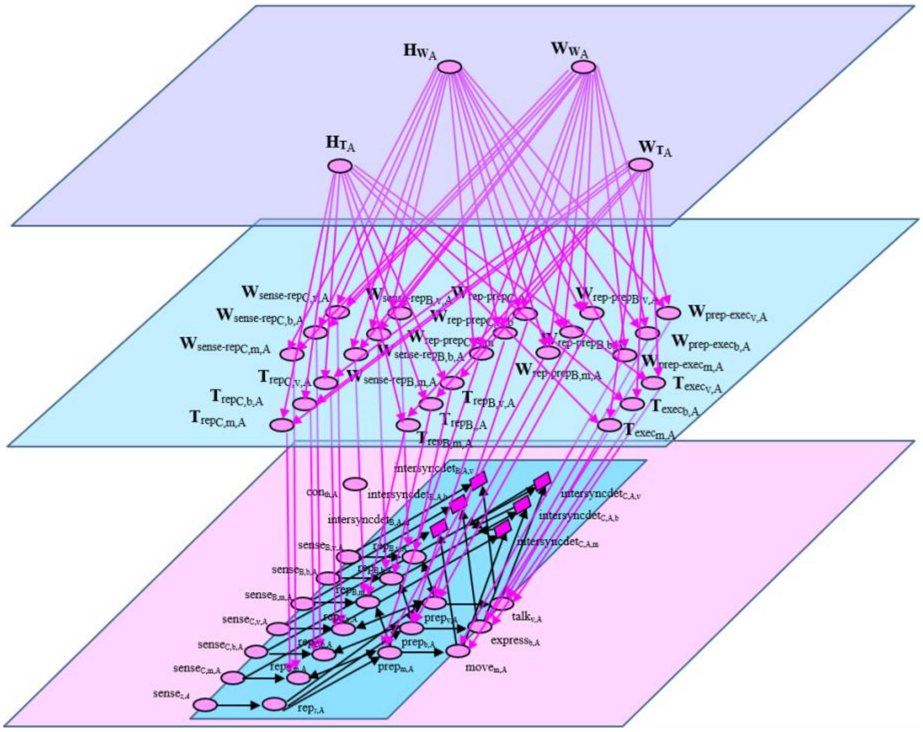

Fig. 5 The ada

Aggregation characteristics for second-order self-model states

- **Aggregation for within-agent second-order self-model states**
  - All second-order self-model aggregation states use the Euclidean function **eucl** from Table 3 of order $\boldsymbol{n} = 1$ with a normalising scaling factor $\boldsymbol{\lambda}$ = the sum of the weights of the incoming connections.

- All second-order self-model states $\mathbf{H_W}$-, $\mathbf{H_T}$-, $\mathbf{W_W}$-states use the logistic function **alogistic** from Table 3 with steepness σ = 5, threshold τ = 0.8 for $\mathbf{H_W}$- and $\mathbf{H_T}$-states and threshold τ = 0.2 for $\mathbf{W_W}$-states.
- All second-order self-model states $\mathbf{W_T}$-states use the logistic function **alogistic** for negative values with steepness σ = 2 and threshold τ = 0.

Timing characteristics for second-order self-model states

- **Timing for within-agent second-order self-model states**
  - All second-order self-model aggregation states use speed factor 1.
  - All second-order self-model $\mathbf{H_W}$-, $\mathbf{H_T}$-, $\mathbf{W_W}$-, $\mathbf{W_T}$-states use speed factors 0.005, 0.1, 0.005, and 0.009, respectively.

An overview of explanations of all second-order self-model states for agent A can be found in Table 6.

Table 6 Second-order self-model $\mathbf{H_W}$-, $\mathbf{H_T}$-, $\mathbf{W_W}$- and $\mathbf{W_T}$-states for agent A in the adaptive dynamical systems model: modelling the adaptation speed of the **T**-states and **W**-states and the connection weights of their incoming connections. For the other agents, similar second-order self-model states are used: X_{346} to X_{349} for B, X_{350} to X_{353} for C, X_{354} to X_{357} for D.

State	Name	Explanation
X_{342}	$\mathbf{H}_{\mathbf{W}_A}$	Second-order self-model state for the speed factors of the first-order self-model **W**-states for *A*
X_{343}	$\mathbf{H}_{\mathbf{T}_A}$	Second-order self-model state for the speed factors of the first-order self-model **T**-states for *A*
X_{344}	$\mathbf{W}_{\mathbf{W}_A}$	Second-order self-model state for the weights of the incoming connections of the first-order self-model **W**-states for *A* (from the respective synchrony detector states for the $\mathbf{W}_{\text{sense-rep}}$-states and $\mathbf{W}_{\text{rep-prep}}$-states and from the preparation and execution states for the $\mathbf{W}_{\text{prep-exec}}$-states)
X_{345}	$\mathbf{W}_{\mathbf{T}_A}$	Second-order self-model state for the weights of the incoming connections of the first-order self-model **T**-states for *A* (from the respective synchrony detector states)

6. Operationalization of the Research Question and Hypotheses for the Introduced Model

Recall the main research question and hypotheses A. to F. introduced in Section 3. Now the model has been described, these hypotheses can be operationalised by relating them to the states of the model. We go through them one by one.

A. Adaptation in basic interaction behaviour can be observed for
   (a) Representing the other agent
   (b) Responding to the representations of the other agent
   (c) Expressing (executing) interaction actions
   (d) Emergence of synchrony shown by its detection

B. The adaptation can be considered for multiple modalities (movement *m*, express *b*, verbal *v*).

The base states for representing, responding and executing are the rep-, prep-, and exec-states (note that the (inter)action execution states move_m, express_b, talk_v are also indicated by exec_m, exec_b, exec_v). Their activation values over time will be analysed to verify to what extent behaviour is adapted; see Table 7.

Table 7 The interaction-related base states that are examined to analyse behaviour adaptation.

Interaction-related base processes		Modalities		
Type of processes	**Type of states**	**Movement** ***m***	**Affect** ***b***	**Verbal action** ***v***
representing	rep-states	rep_m	rep_b	rep_v
responding	prep-states	$prep_m$	$prep_b$	$prep_v$
expressing	exec-states	$move_m$	$express_b$	$talk_v$

C. Two types of adaptation will occur, (i) other-agent specific and (ii) other-agent independent:
   (i) More experiences with interactions with a given agent A lead to faster and stronger adaptation in interactions with A in the future.
   (ii) More experiences with interactions with any agent A lead to faster and stronger adaptation in interactions with any agent B in the future (transference).

D. Such adaptation occurs both (i) in the short-term and (ii) in the long-term:
   (i) Interaction within episodes
   (ii) Interaction over multiple episodes

E. The relation between the extents of interaction and adaptation can be observed in two ways:
   (i) Within a given simulation run over time adaptation becomes stronger after more interaction has taken place
   (ii) In a comparative manner, simulation runs that show longer interaction durations will also show more adaptation compared to simulation runs with shorter interaction durations

F. More experiences with interactions will in general not only lead to adaptations in interaction behaviour (first-order adaptation effect) but also to faster and stronger adaptation in interactions in the future (second-order adaptation effect). This happens (i) within a given simulation and (ii) more in simulations where more interaction occurs.

First-order self-model **T**- and **W**-states and second-order self-model $\mathbf{W_T}$-, $\mathbf{H_T}$-, $\mathbf{W_W}$-, $\mathbf{H_W}$-states are indicative for the different types of adaptations that occur. The above hypotheses can be observed at the first-order and second-order self-model level as follows (see also Table 8).

Table 8 The first-order and second-order self-model states that are examined to analyse adaptation.

	First-order adaptation		Second-order adaptation
	Relationship-specific	**Relationship-independent**	**Relationship-independent**
Short term	**T**-states for all representation and preparation states for each dyad separately for 3 modalities *m, b, v*	**T**-states for all dyads and all execution states for 3 modalities *m, b, v*	
Long Term	**W**-states for all sense-rep and rep-prep connections for each dyad separately for 3 modalities *m, b, v*	**W**-states for all dyads and all prep-exec connections for 3 modalities *m, b, v*	$\mathbf{W_T}$- and $\mathbf{W_W}$-states for the strengths of **T**- and **W**-states activation $\mathbf{H_T}$- and $\mathbf{H_W}$-states for the speeds of **T**- and **W**-states activation

First-order self-model **T**-states represent the adaptive excitability thresholds for certain base states within the model: the rep-, prep-, and exec-states. Lower thresholds imply that a state can get stronger activation (more sensitive, higher extent of excitability). First-order self-model **W**-states represent adaptive connection weights between two states, e.g., between sense and representation states. Higher connection weights imply that a connection between two states is stronger, resulting in a stronger activation of the target state. Globally, for these first-order self-model states we expect that

- Within a given simulation run, the activation values of the **T**-states will become lower within each interaction episode, and higher when no interaction episode for a specific relationship occurs; in contrast, the activation values of the **W**-states will become higher over time in general. For the **W**-states for prep-exec connections this will be irrespective of which are the relationships that have interactions. For the other **W**-states this will be relationship-specific.
- In a comparative manner, on the average, the activation values of the **T**-states will be lower and of the **W**-states will be higher in simulation runs with longer interaction durations. For the

W-states for prep-exec connections this will be irrespective of which are the relationships that have interactions. For the other **W**-states this will be relationship-specific.

Second-order self-model $\mathbf{H}_\mathbf{T}$- and $\mathbf{H}_\mathbf{W}$-states control the speed of adaptivity for the **T**-states and **W**-states. Second-order self-model $\mathbf{W}_\mathbf{W}$-states and $\mathbf{W}_\mathbf{T}$-states control the strength of the incoming connections to the **T**-states and **W**-states and through that the strengths of the activations of the **T**-states and **W**-states. For the second-order self-model states we expect that

- Within a given simulation run, for all relationships the activation values of all second-order self-model states will increase over time, irrespective of which are the relationships that have interactions, except those of the $\mathbf{W}_\mathbf{T}$-states which instead will decrease over time.
- In a comparative manner, on the average the activation values of all second-order self-model states will be higher in simulation runs with longer interaction durations irrespective of which relationships it concerns, except those of the $\mathbf{W}_\mathbf{T}$-states which instead will be lower.

7. Simulation Setup and Example

In this section, the setup of the simulation experiments and one illustrative example simulation run is discussed. In Section 8 an extensive analysis is presented for a collection of 20 simulation runs performed according to this setup.

7.1 Design of the simulation experiments

A stimulus occurs regularly during certain periods: 40 time units without the stimulus followed by 40 time units with the stimulus and this pattern is repeated every 80 time units. Moreover, in a random manner interaction-enabled periods happen for certain modalities for randomly chosen pairs of agents. After each interaction-enabled period for two agents, a new pair of agents is chosen at random from A, B, C and D for the next interaction-enabled period (see Fig. 6). In addition, the duration until the next interaction-enabled period (interaction break length: the durations of the intervals between the purple boxes in Fig. 6) and the duration of the next interaction-enabled period (interaction length: the lengths of the purple boxes in Fig. 6) are both chosen at random from the interval [0, 50].

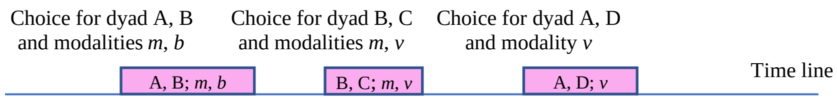

Fig. 6 Example of a timeline with interaction episodes based on randomly chosen dyads from {A, B, C, D}, up to three modalities from {*m*, *b*, *v*}, interaction durations from the interval [0, 50] and durations between interactions from the interval [0, 50].

Furthermore, the enabled modalities for the interaction in the next interaction-enabled period are chosen. Each modality has a 5/6 = 0.83 independent probability to be available. In other words, for each interaction-enabled period there is 0.58 chance that all three modalities are available and 0.42 chance that only one or two modalities are available (and 0.005 chance that none is available, in which case the agents in principle would be able to interact during some time, but actually do not have any of the three modalities available for it). The formulas within MATLAB to randomly select each of the three interaction modalities *m* (cmm), *b* (cma) and *v* (cmv) are:

```
cmm = round(0.4+0.6*rand(1,1));
cma = round(0.4+0.6*rand(1,1));
cmv = round(0.4+0.6*rand(1,1));
```

We have conducted 20 independent runs, each of them with a total time duration of 4000 time units and step size $\Delta t = 0.5$. We chose this approach because of the stochastic set up of the experiment, to evaluate the consistency of behaviour under multiple circumstances.

7.2 Evaluation of a simulation run

First, we zoom in on how agents' states develop over time. Therefore, we evaluate the patterns of the activation values of the states of an agent A from simulation 1. In the other 19 simulations (available on request), we have seen that the patterns of adaptivity are roughly the same over simulations. This means that, overall, the described findings from simulation 1 are representative for all simulations.

Base level states

The sensing states are only activated during interaction episodes, and their activation values become generally higher within interaction episodes later in time (Fig. 7). The representation states get already activated within the stimulus intervals; regardless interaction is enabled (Fig. 7). During the interaction episodes, when no stimulus is present, the representation states do not become higher, because both agents do not have enough input to trigger their actions then. However, later in time, for example around time unit 800, the representation states are extra activated during interaction and common stimulus episodes, when the sensing states are activated as well. This highlights the role interaction plays in combination with the stimulus regarding increased activation of the representation states. The patterns of the preparation and the execution states tend in general to be the same: they align with the activations of the common stimulus and when on top of this common stimulus interaction between agents A and C happens, their activation levels elevate further (Fig. 8). The interpersonal synchrony states only get activated through the interaction episodes and seem to achieve higher peaks over time, indicating agents A and C become more attuned towards each other. These findings are in line with **hypotheses A and B**: adaptation of representing (rep-states), responding (prep-states) and expressing (exec-states) occurs for the three modalities. This adaptation is shown through the elevated activation values of the relevant states over the simulation when interaction between agents A and C (in combination with a common stimulus) happened.

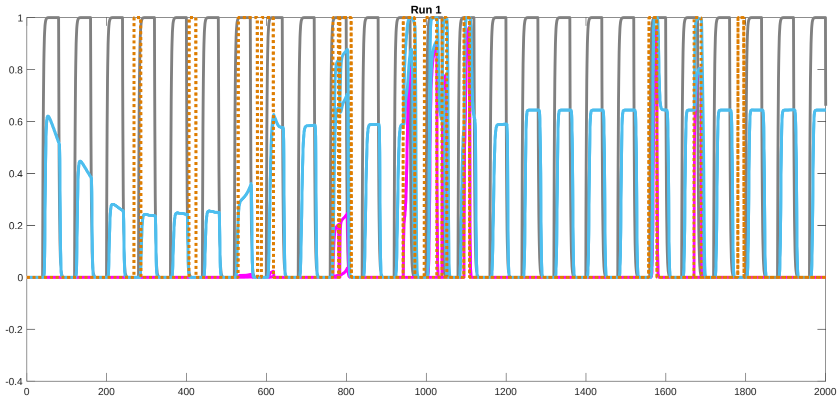

Fig. 7 The grey solid line is the common stimulus. The orange dashed lines are interaction episodes of agent A and C. The pink lines are the sensing states from agent A of agent's C *m*, *b* and *v*. The blue lines are agent A's representation states of agent C's actions.

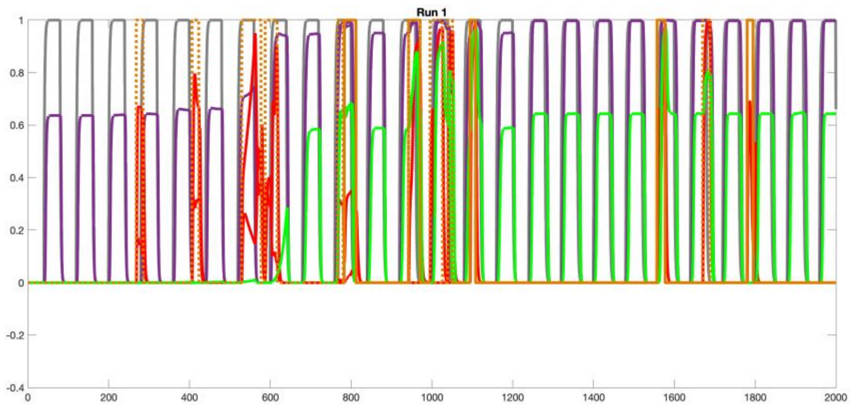

Fig. 8 The grey solid line is the common stimulus. The orange dashed lines are interaction episodes of agent A and C. The purple lines are the preparation states, the green lines the execution states and the red lines the interpersonal synchrony detection states for the three modalities (*m*, *b* and *v*) of A towards agent C.

First-order adaptation: T-states

The two types of first-order **T**-states are roughly following the same patterns for all modalities: they show downwards jumps during the interaction episodes of agents A and C and these jumps are becoming larger over time until time 1600 (Fig. 9). Not similarly, the $\mathbf{T}_{\text{exec}}$ states sometimes display small downwards jumps when no interaction between A and C occurs, for example around time 1950. An explanation for this might be that not only the interpersonal synchrony states of agents C and A influence the $\mathbf{T}_{\text{exec}}$ states of agent A, but also the detected interpersonal synchrony states from agent A towards agents B and D ($\mathbf{T}_{\mathbf{exec}}$-states are other-agent independent). These findings are in line with the expectations that within simulations the activation values of **T**-states will become lower during interaction episodes with a specific agent and higher when the interaction episode is finished, meaning that during interaction with a specific agent the relationship-specific adaptivity emerges. This is in accordance with **hypotheses D(i) and E(i)** from Section 6.

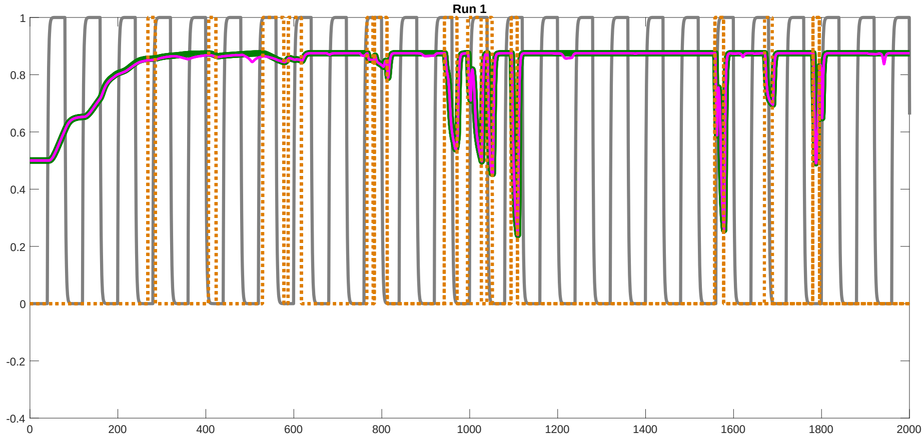

Fig. 9 The grey solid line is the common stimulus. The orange dashed lines are interaction episodes of agents A and C. The pink lines are the $\mathbf{T}_{\text{exec}}$ states and the green lines the $\mathbf{T}_{\text{rep}_{C,x,A}}$ states.

First-order adaptation: W-states

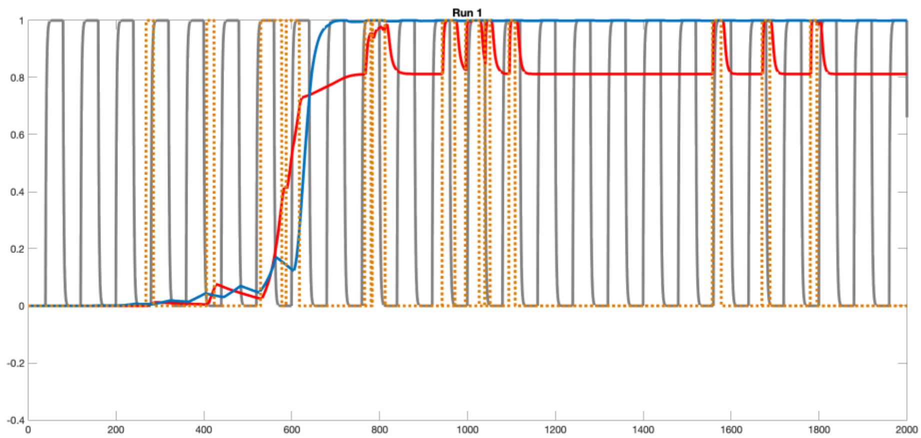

Fig. 10 The grey solid line is the common stimulus. The orange dashed lines are interaction episodes of agent A and C. The overlapping red lines are the $\mathbf{W}_{\text{sense-rep}_{x,C,A}}$ and $\mathbf{W}_{\text{rep-prep}_{x,C,A}}$ states and the overlapping blue lines the $\mathbf{W}_{\text{prep-exec}_{x,C,A}}$.

All first-order self-model **W**-states show a kind of breakthrough around time 600: a sharp increase, when two relatively long interaction episodes follow closely on each other (Fig. 10). After that sharp increase, the $\mathbf{W}_{\text{sense-rep}_{x,C,A}}$ and $\mathbf{W}_{\text{rep-prep}_{x,C,A}}$ states balance around an activation level of 0.8, with jumps towards 1 during interaction episodes. More extremely, the $\mathbf{W}_{\text{prep-exec}_{x,C,A}}$-states already reach an activation level around 1 at time 700 at the end of the sharp increase, meaning its maximum is already achieved and effects of interaction episodes cannot cause an extra effect anymore. These results are in line with the **hypotheses C, D(ii), and E(i)**. But note that this is not a gradual monotonous development in which the **W**-states become higher over time, but the main increase is rather suddenly (tipping points that are reached around time 600) and the $\mathbf{W}_{\text{sense-rep}_{x,C,A}}$ and $\mathbf{W}_{\text{rep-prep}_{x,C,A}}$ states are not completely monotonous during the non-interaction episodes, as observed by the drops in activation values from the moment interaction ends (especially from time 800 onwards).

Second-order adaptation

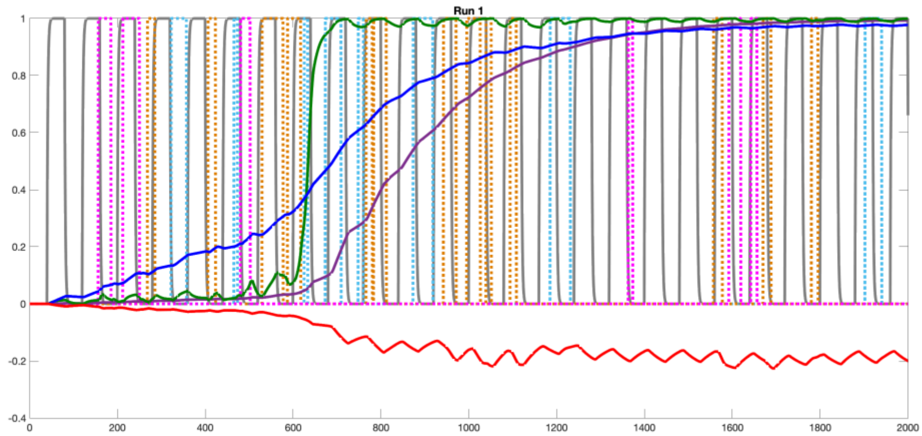

Fig. 11 The grey solid line is the common stimulus. The pink dotted lines are the interactions between A and D, the light blue dotted lines these between A and B and the orange dotted lines these between A and C. $\mathbf{H}_{\mathbf{W}_A}$ is the purple line, $\mathbf{H}_{\mathbf{T}_A}$ the dark green line, $\mathbf{W}_{\mathbf{WA}}$ the dark blue line and $\mathbf{W}_{\mathbf{T}_A}$ the red line.

The $\mathbf{H}_{\mathbf{T}_A}$-state from agent A increases during each interaction episode with any other agent, and drops again when no interaction with any agent occurs. Around time 650, there is a sharp incline in the activation values, and thereafter there are again fluctuations that show the same trend between interaction and no interaction episodes (Fig. 11). The patterns for the $\mathbf{H}_{\mathbf{W}_A}$-states and the $\mathbf{W}_{\mathbf{W}_A}$-states are roughly similar, although the oscillations are less pronounced and their inclines are more gradual. The $\mathbf{W}_{\mathbf{T}_A}$-state is declining over time, towards negative activation levels around -0.2. All these patterns are in line with the **hypothesis F(i)** that within a given simulation run, the activation values of all second-order self-model states will increase over time, except those of the $\mathbf{W}_\mathbf{T}$-states which instead will decrease over time. This indicates that relationship-independent adaptivity can emerge from interactions with specific agents. Namely, each of these second-order self-model states from agent A adapt during the simulation, regardless the other agent with whom agent A interacts and all second-order self-model states have their effect in a relationship-independent manner. Moreover, these second-order effects induce relationship-independent influences on first-order adaptivity.

8. Statistical Analysis of the Simulation Outcomes

In Sect. 7, we have evaluated the adaptation patterns of one typical simulation run at the base level, first-order level and second-order level. Within that simulation run it can be observed how over time more and more adaptations take place, based on the social interaction episodes and emerging synchronies within them. Although this run was claimed to be typical, a single run cannot show in how far the adaptations indeed depend on the extent to which social interaction takes place as that extent is fixed. Therefore, as an additional step, in the current section we quantify the main patterns for all 20 generated simulation runs in a statistical manner. These 20 runs do have variation in the extent of social interaction. In this way some more evidence is obtained about the behaviour of the model in relation to the hypotheses formulated in Section 3 and related to the model in Section 6, in particular, for example, also **E(ii) and F(ii)**. This can be done especially in a comparative manner by comparing runs with more interaction to runs with less interaction, so that the extent of interaction can be considered an independent variable over the 20 runs and it can be analysed how other factors depend on this.

8.1 Variation in total interaction durations

The 80 agents in the 20 simulation runs had on average a total individual interaction duration of 2512 time units (diameter: 1580 time units), with a standard deviation of 345 time units, and their individual interaction durations seemed to be normally distributed, see Fig. 12. The smallest and largest interaction durations from an agent from the 80 agents equalled 1650 and 3230 time units, respectively. These results indicate that there was enough variation in the interaction durations, and that the average of 2512 of their total interaction durations over the whole simulation runs of 4000 time units was only slightly above the 2000 time units. These results enable a further evaluation of the agents' mechanisms performances in relation to their total interaction durations (see Sect. 8.3).

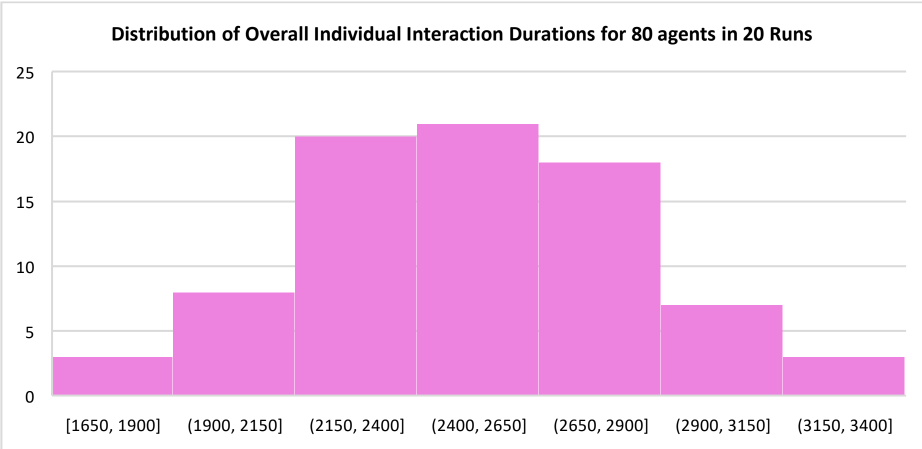

Fig. 12 The distribution of individual total interaction durations over the whole population of 80 agents

8.2 Averaged learning effects between two phases

To evaluate the hypotheses, in all runs we zoom in on the first half (time 0-2000, Phase 1) and second half (time 2000-4000, Phase 2), see Figure 13. All activation levels of the different types of states were averaged over time and over the three modalities *m*, *b* and *v*. Additionally, the synchrony detection activation levels are averaged over all interpersonal synchrony states. Regarding the states (rep, prep, exec and sync) from the base level, it appears that their activation levels have on average increased from Phase 1 to Phase 2 by a factor more than 2.5 (see Table 5). Although the average activation values of synchrony detection states are generally low in both phases (because each dyad only interacts only a small part of the time) and the differences are hardly seen in Figure 13, the synchrony activation levels still have increased with a factor around 2, from 0.026 to 0.054. These results at the base level are in line with **hypothesis A** from Sections 3 and 6 that the activation values (between 0 and 1) of the base states will increase over time within simulations.

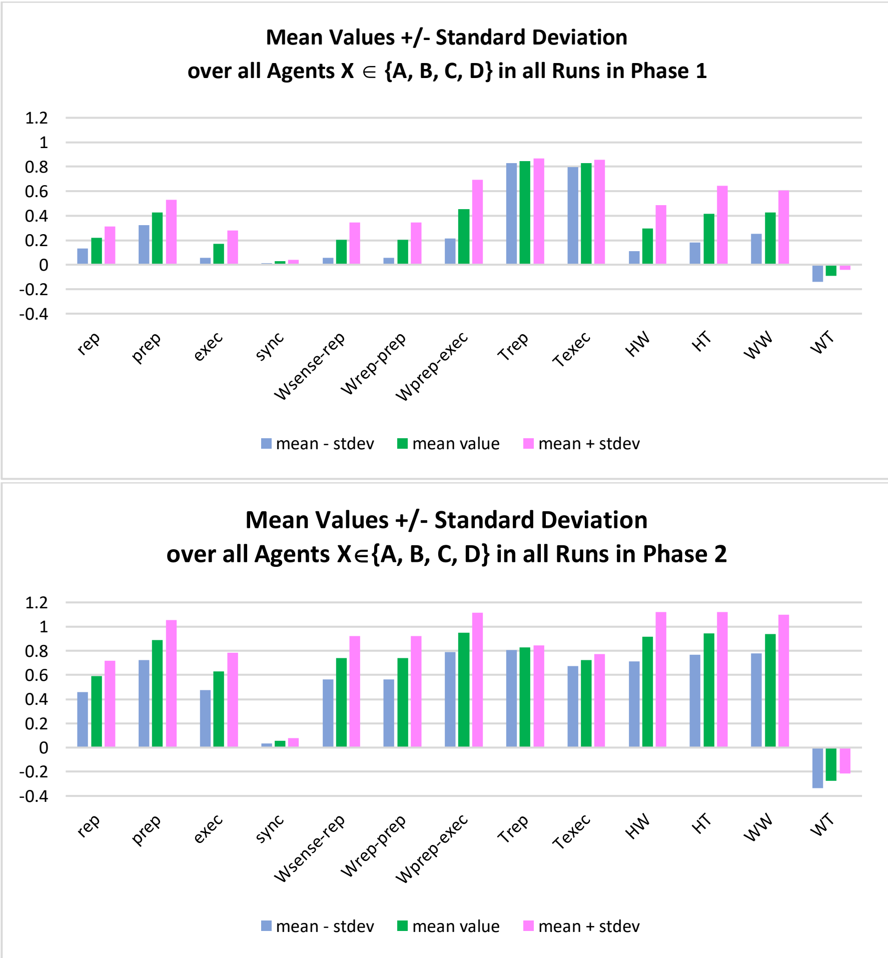

Fig. 13 Mean values and standard deviations for all types of states in comparison for Phase 1 (upper graph) for time 0-2000 and Phase 2 for time 2000-4000 (lower graph)

Concerning the first-order self-model **W**- and **T**-states, the activation levels of all **W**-states display an increasing pattern and those of all **T**-states a decreasing pattern from Phase 1 to 2, see Fig. 13. The overall factors are approximately 3 and 0.9, respectively, see Table 5. These results are overall in line with our expectations formulated in **hypotheses C to E**. Higher activation levels of **W**-states demonstrate that the adaptive connection weights became stronger, and lower activation levels of **T**-states that the target states can get a stronger activation (more sensitive target states: enhanced excitability). Although the overall decrease with a factor of 0.92 for the **T**-states does not seem that high, it fits perfectly within the hypothesis. We expected that the values of the **T**-states of given agents would decline when they interact, but would become higher when they are not interacting, because this type of adaptation works in the short-term only within interaction episodes. Since the values of the **T**-states are computed over all episodes (interaction episodes and no interaction episodes) and in the non-interaction periods they stay high as they should, in the averaging process the adaptation effects are flattened out.

The outcomes of all second-order self-model $\mathbf{W}_{\mathbf{W}}$-, $\mathbf{H}_{\mathbf{W}}$-, $\mathbf{W}_{\mathbf{T}}$-, $\mathbf{H}_{\mathbf{T}}$-states are in line with the **hypothesis F(ii)** as well. The activation values of the $\mathbf{W}_{\mathbf{W}}$-, $\mathbf{H}_{\mathbf{W}}$-, $\mathbf{H}_{\mathbf{T}}$-states are all elevated in Phase 2 compared to Phase 1, with factors ranging from 2.19 to 3.09. In contrast, the mean (negative) values of the $\mathbf{W}_{\mathbf{T}}$-states are dropped by a factor of 3.07 from Phase 1 to Phase 2, so decreasing over time. These results for the second-order self-model states have the second-order adaptive effect that independent of the relationship:

- the speeds of adaptivity for the **W**-states and **T**-states increase over time,
- the strengths of the connections from the synchrony detection states to the **W**-states increase, and
- the strengths of the connections from the synchrony detection states to the **T**-states decrease over time.

This shows both second-order relationship-independent adaptivity and the relationship-independent influences on first-order adaptivity induced by it.

Note that all described differences between activation levels of states between Phase 1 and 2 do not only hold for the mean values, but as well for the mean values minus and plus the standard deviation (see Figure 13). This is an extra indication that the hypotheses are confirmed.

Table 5 Comparisons of mean values for types of states over all 80 individuals for Phase 1 and Phase 2

	Phase 1	Phase 2	Factor	Geometric mean of factors	Arithmetic mean of factors
Representation	0.222	0.589	2.65		
Preparation	0.426	0.889	2.09		
Execution	0.169	0.631	3.74		
Synchrony	0.026	0.054	2.04	2.55 for all base level states	2.63 for all base level states
$\mathbf{W}_{\text{sense-rep}}$	0.203	0.742	3.67		
$\mathbf{W}_{\text{rep-prep}}$	0.203	0.742	3.67		
$\mathbf{W}_{\text{prep-exec}}$	0.455	0.952	2.09	3.04 for all **W**-states	3.14 for all **W**-states
$\mathbf{T}_{\text{rep}}$	0.848	0.826	0.97		
$\mathbf{T}_{\text{exec}}$	0.828	0.723	0.87	0.92 for all **T**-states	0.92 for all **T**-states
$\mathbf{H}_{\mathbf{W}}$	0.297	0.917	3.09		
$\mathbf{H}_{\mathbf{T}}$	0.415	0.944	2.27		
$\mathbf{W}_{\mathbf{W}}$	0.428	0.939	2.19		
$\mathbf{W}_{\mathbf{T}}$	-0.090	-0.277	3.07	2.62 for all second-order states	2.66 for all second-order states

8.3 Averaged learning effects versus overall interaction duration

Next, we want to more explicitly relate the adaptive effects to the extent of interaction during a simulation run. Therefore, we created scatterplots for the 80 agents of the 20 runs with for each of them their total interaction duration on the horizontal axis and for the different types of states their average activation levels on the vertical axis. Within each of the scatterplots we added the trendline and determined its slope and the R^2 coefficient.

Effects of the learning on the base states

First, we analyse how the adaptive effects on the base level states relate to the interaction duration. For each of the four considered types of base states, scatterplots were created: in Figure 14 for representation and preparation states and in Figure 15 for execution and interpersonal synchrony states. Indeed, they all show positive slopes for the trendlines. The R^2 coefficients are between 0.19 and 0.27. Moreover, as listed in Table 6, Pearson correlation coefficients were determined which varied from 0.44 to 0.51. This shows that the way how adaptivity results in changes for the base states strongly depends on the extent of interaction.

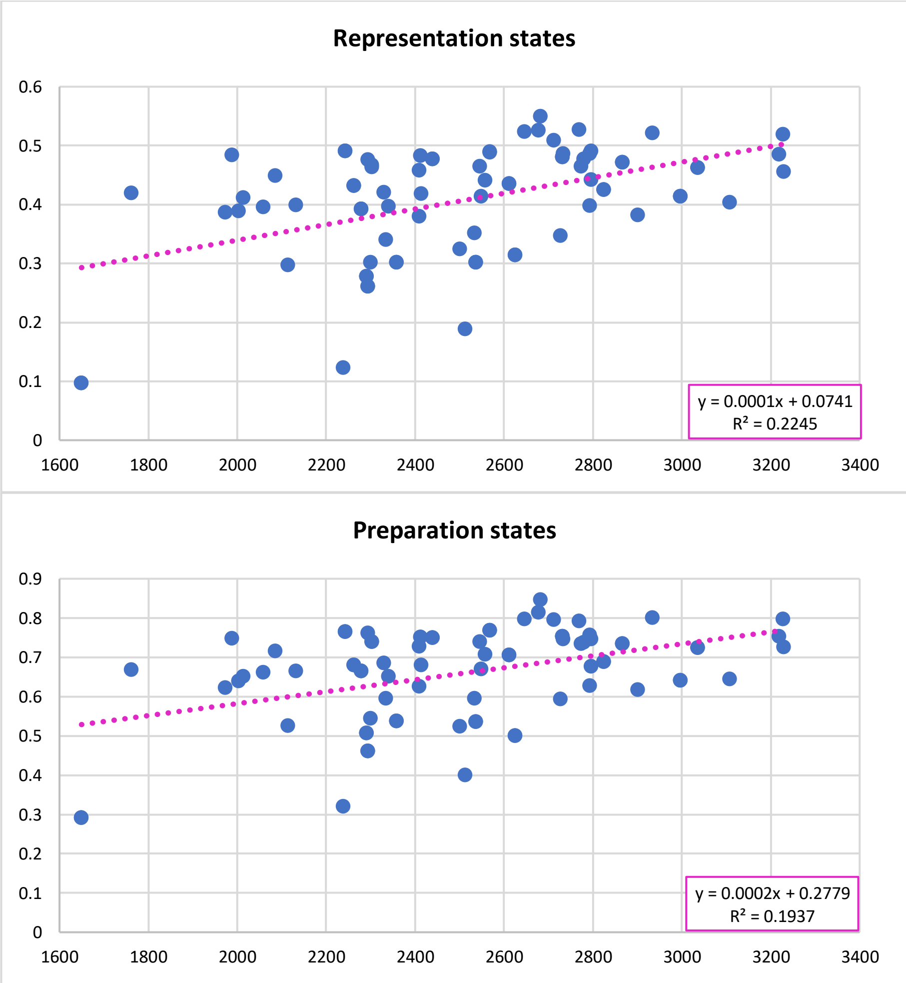

Fig. 14 The base level effects for the mean values for representation states (upper graph) and preparation states (lower graph) against the interaction durations (both for times 0-4000) over all 80 agents.

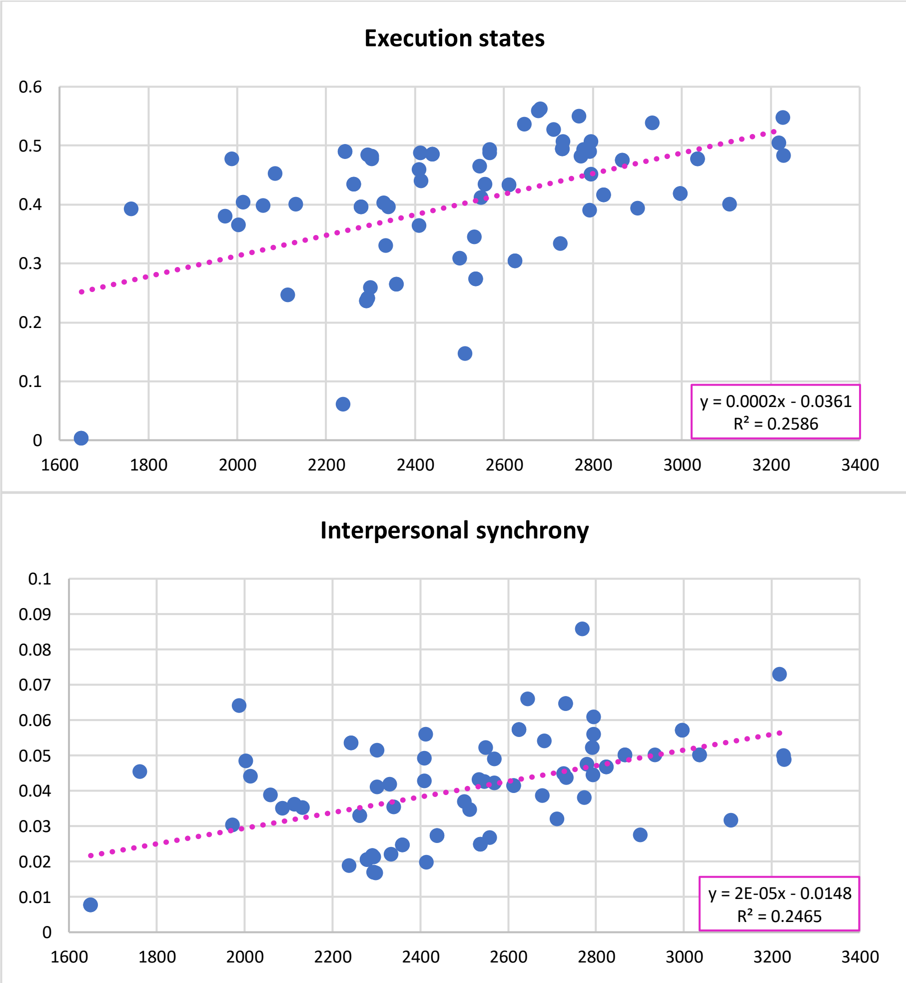

Fig. 15 The base level effects for the mean values for execution states (upper graph) and interpersonal synchrony detection states (lower graph) against the interaction durations (both for times 0-4000) over all 80 individuals.

Table 6 Trendline slopes, R^2 coefficients, and correlation coefficients for the mean values for all types of states against the interaction durations (both for times 0-4000) over all 80 individuals

	Trendline slope	**R^2**	**Correlation coefficient**	**Averages slopes**	**R^2 coefficients**	**Correlation coefficients**
Representation	0.000133	0.225	0.474			
Preparation	0.000152	0.194	0.440			
Execution	0.000175	0.259	0.509	for base states		
Interpersonal Synchrony	0.000022	0.247	0.497	0.000120	0.231	0.480
$\mathbf{W}_{\text{sense-rep}}$	0.000213	0.259	0.509			
$\mathbf{W}_{\text{rep-prep}}$	0.000213	0.259	0.509	for **W**-states		
$\mathbf{W}_{\text{prep-exec}}$	0.000260	0.267	0.517	0.000229	0.261	0.511
$\mathbf{T}_{\text{rep}}$	-0.000019	0.169	-0.411	for **T**-states		
$\mathbf{T}_{\text{exec}}$	-0.000056	0.313	-0.559	-0.000037	0.241	-0.485
$\mathbf{H}_{\text{W}}$	0.000268	0.282	0.531			
$\mathbf{H}_{\text{T}}$	0.000273	0.278	0.528	for $\mathbf{H}_{\text{W}}$, $\mathbf{H}_{\text{T}}$, $\mathbf{W}_{\text{W}}$		
$\mathbf{W}_{\text{W}}$	0.000230	0.283	0.532	0.000257	0.280	0.529
$\mathbf{W}_{\text{T}}$	-0.000074	0.278	-0.527			

First-order adaptation: W-states

Next, the adaptivity shown in the first-order self-model states were addressed: see the scatterplots for the **W**-states in Figure 16 and for the **T**-states in Figure 17. All **W**-states show increasing trendlines. The R^2 coefficients are around 0.25-0.27. Note that de results for the $\mathbf{W}_{sense\text{-}rep}$-states and $\mathbf{W}_{rep\text{-}prep}$-states are the same because for all four agents we have used a uniform structure for this with only slight differences in the way they sense as indicated in Section 10. The correlation coefficients are around 0.51-0.52, see Table 6. This shows also a clear dependence of the adaptations of the **W**-states on the extent of interaction.

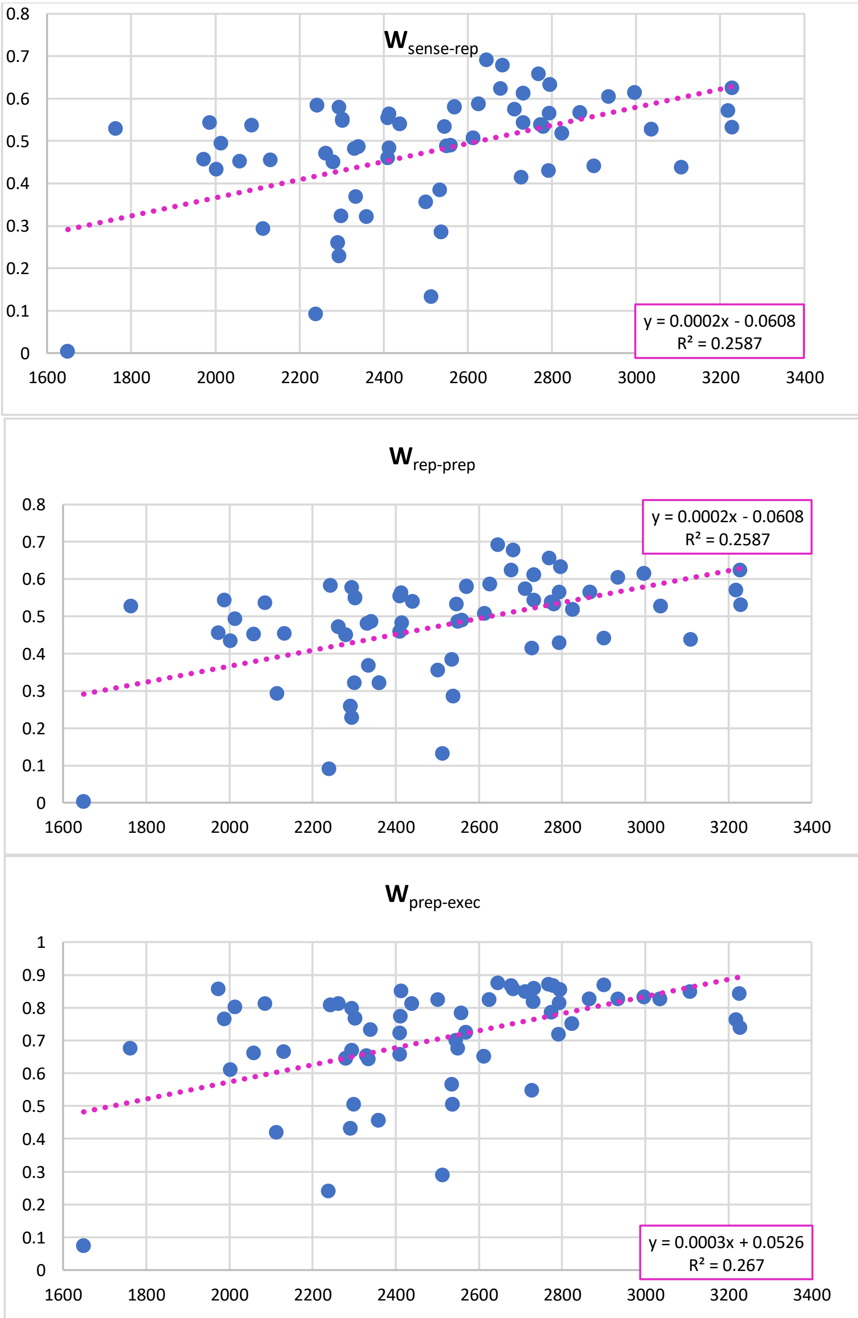

Fig. 16 The first-order learning effects for the mean values for the **W**-states against the interaction durations (both for times 0-4000) over all 80 individuals: $\mathbf{W}_{sense\text{-}rep}$ (upper graph), $\mathbf{W}_{rep\text{-}prep}$ (middle graph), $\mathbf{W}_{prep\text{-}exec}$ (lower graph).

First-order adaptation: T-states

Similarly, we analysed the **T**-states. Here the trendlines in Figure 17 have negative slopes. But these trends should indeed be negative as the adaptive effect concerns lowering the **T**-values during interactions so that more sensitive responses can be generated. In this case the R^2 values vary from 0.17 to 0.31. Moreover, the correlation coefficients vary from -0.41 to -0.56. So, also here a strong dependence of the adaptivity on the extent of interaction is found.

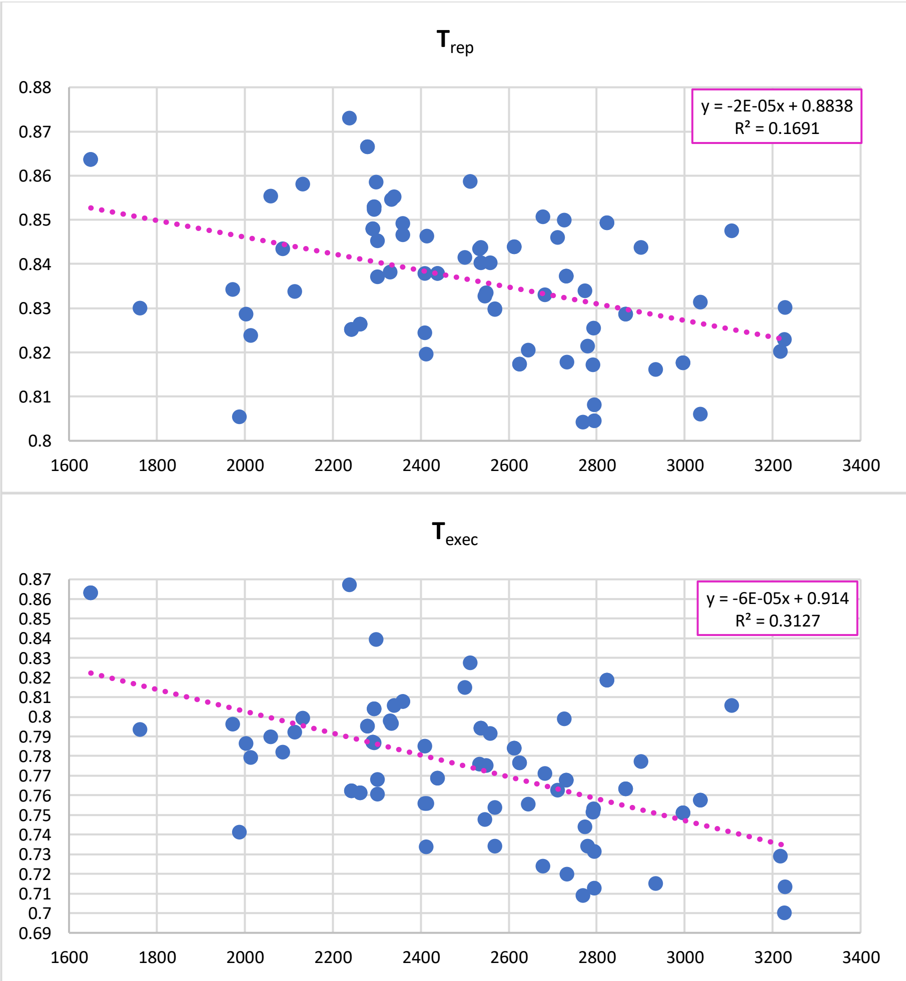

Fig. 17 The first-order learning effects for the mean values for the **T**-states against the interaction durations (both for times 0-4000) over all 80 individuals: $\mathbf{T}_{rep}$ (upper graph), $\mathbf{T}_{exec}$ (lower graph).

Second-order adaptive effects

Finally, we analysed how the states for second-order adaptation depend on interaction duration. For the scatterplots of the $\mathbf{H}_{\mathbf{W}}$- and $\mathbf{H}_{\mathbf{T}}$-states, see Figure 18, for the $\mathbf{W}_{\mathbf{W}}$- and $\mathbf{W}_{\mathbf{T}}$-states, see Figure 19. It is also found here that for the $\mathbf{H}_{\mathbf{W}}$-, $\mathbf{H}_{\mathbf{T}}$- and $\mathbf{W}_{\mathbf{W}}$- states the trendlines are positive. The R^2 coefficients are around 0.28 and the correlation coefficients are around 0.53, see Table 6. Indeed, for these second-order adaptivity states, a strong dependence is found on the extent of interaction as well. However, regarding the fourth type of states, the $\mathbf{W}_{\mathbf{T}}$-states show a negative trend, which is also what it is supposed to display as these activation values are negative and adaptation makes them more negative. Here the R^2-coefficient is 0.28 and the correlation coefficient is -0.53. These findings highlight how second-order relationship-independent adaptivity depends on the extent of social interaction and thus also the relationship-independent influences on first-order adaptivity induced by it depend on this extent of social interaction.

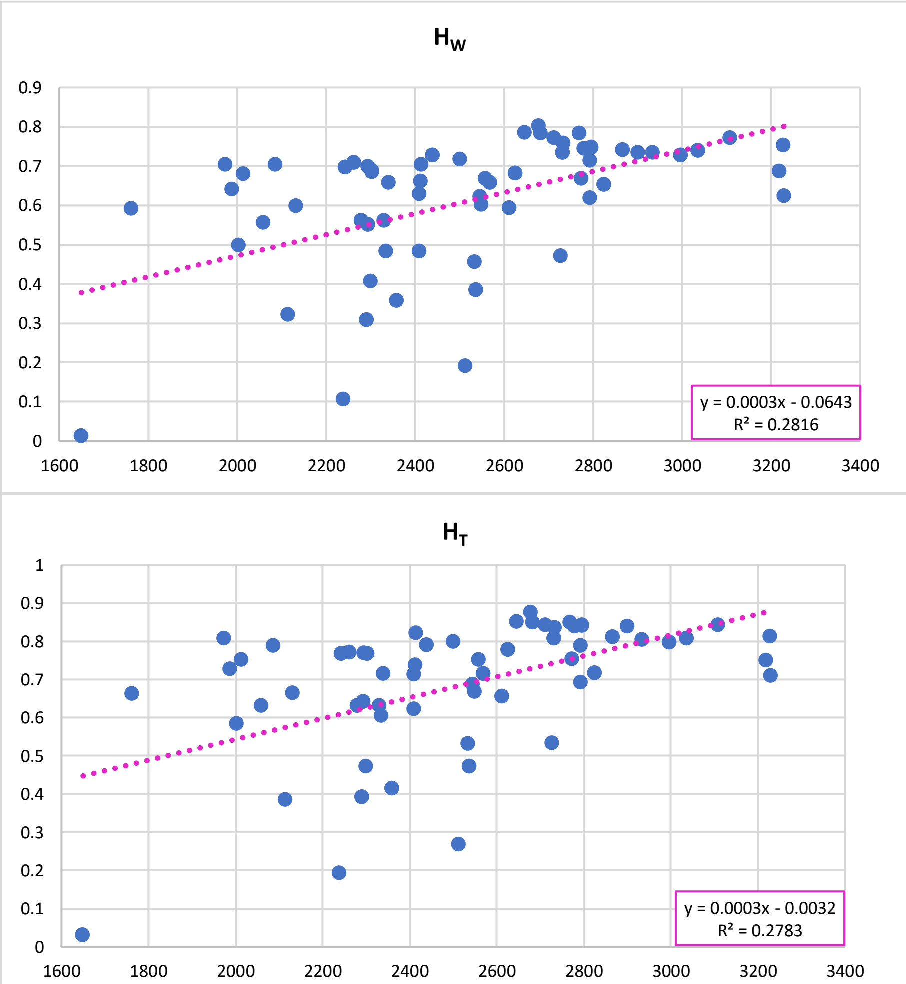

Fig. 18 The second-order learning effects for the mean values for the $\mathbf{H_W}$ and $\mathbf{H_T}$-states against the interaction durations (both for times 0-4000) over all 80 individuals: $\mathbf{H_W}$ (upper graph), $\mathbf{H_T}$ (lower graph).

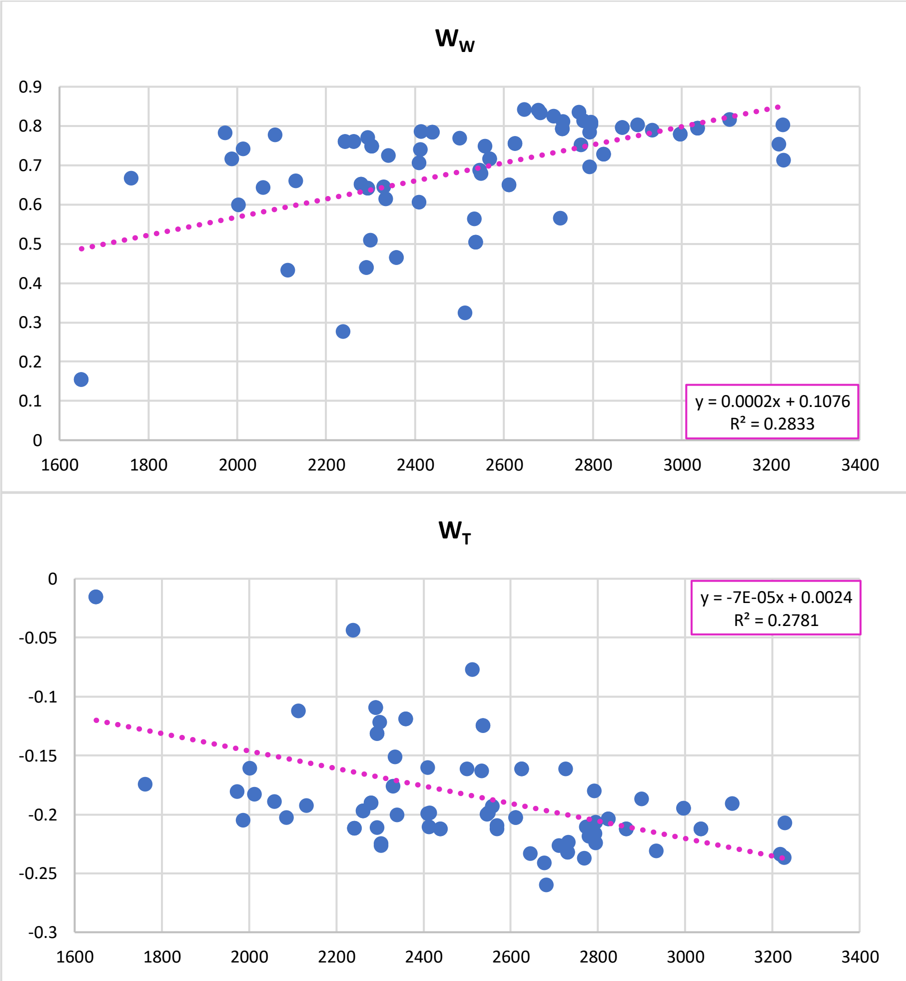

Fig. 19 The second-order learning effects for the mean values for the $\mathbf{W_W}$- and $\mathbf{W_T}$-states against the interaction durations (both for times 0-4000) over all 80 individuals: $\mathbf{W_W}$ (upper graph), $\mathbf{W_T}$ (lower graph).

Overall findings

We conclude that the adaptive changes in activation values for the **T**-states for first-order adaptation and corresponding $\mathbf{W_T}$-states for second-order adaptation may seem relatively low as the **T**-states concern short-term adaptation to contextual circumstances that only occasionally occur. This implies that there are long periods covered in the averages in which no adaptation takes place as the context does not ask for that. Moreover, for threshold values (represented by these **T**-states) small differences often already have a substantial effect. Therefore, most indicative are the three **W**-states for first-order adaptation and the first three states $\mathbf{H_W}$, $\mathbf{H_T}$, $\mathbf{W_W}$ for second-order adaptation. For the Pearson correlation coefficients, these correlation coefficients show convincing numbers around 0.51 for the first-order adaptation **W**-states, around -0.49 for the first-order adaptation **T**-states, and around 0.53 resp. -0.53 for the second-order adaptation states $\mathbf{H_W}$, $\mathbf{H_T}$, $\mathbf{W_W}$, $\mathbf{W_T}$. Similarly, the R^2 numbers are around 0.26 for the first-order adaptation **W**-states, around 0.24 for the first-order adaptation **T**-states, and around 0.28 resp. -0.28 for the second-order adaptation states $\mathbf{H_W}$, $\mathbf{H_T}$, $\mathbf{W_W}$, $\mathbf{W_T}$. All these data indicate a strong dependence of the different forms of adaptivity on the durations of the social interaction episodes. In particular this holds for the second-order adaptation states which have their effects on first-order adaptation in a relationship-independent manner.

9. Discussion

9.1 Research findings and conclusion

In this paper, an adaptive agent-based dynamical system model was introduced for how persons develop during the social interaction they have. It incorporates how interaction behaviour changes on the short term during interaction episodes and on the long term over multiple interaction episodes. Furthermore, it addresses social interaction in multiple relationships and transference between them: how behaviour learned in one relationship can also be carried over to other relationships, like described, for example, in attachment theory developed by Mary Salter Ainsworth and John Bowlby (Salter Ainsworth and Bowlby, 1965; Salter Ainsworth, 1967; Salter Ainsworth, Blehar, Waters, and Wall, 1978; Salter Ainsworth and Bowlby, 1991; Bowlby, 2008). Moreover, it distinguishes first-order adaptation from second-order adaptation and to model them applies mechanisms known from neuroscience: synaptic plasticity (Bear and Malenka, 1994) for long-term first-order adaptation, nonsynaptic plasticity (Debanne, Inglebert, Russier, 2019) for short-term first-order adaptation and metaplasticity (Abraham and Bear, 1996) for second-order adaptation.

The model was developed for four agents as an adaptive dynamical system specified by its canonical self-modelling network representation (Hendrikse, Treur, Koole, 2023b). The four agents do not interact all the time but only during episodes separated by periods without interaction. In each interaction episode only one dyad interacts, selected at random, while also the modalities used, the durations of the interaction episodes, and the times between episodes are chosen at random. In this way, we generated 20 simulation runs and statistically analysed, among others, the dependence of the different types of adaptivity on the extent of social interaction. The outcomes of the analysis indeed show a strong dependence: more social interaction leads to more adaptation of the interaction behaviour, both for the short-term and long-term first-order adaptation and for the second-order adaptation, which is long-term.

The extent of adaptation of the agents can be observed in a most clear manner in their three **W**-states for first-order adaptation and the first three states $\mathbf{H_W}$, $\mathbf{H_T}$, $\mathbf{W_W}$ for second-order adaptation. It was found that the degree of adaptation of an agent depends in a significant manner on the overall duration of the interaction episodes of this agent. In more detail, the collected simulation data indicate a strong dependence of the different forms of adaptivity on the durations of the social interaction episodes. This does not only hold for the first-order adaptation states but also for the second-order adaptation states which have their effects on first-order adaptation in a relationship-independent manner.

9.2 Comparison to prior work

The work presented here has adopted some elements of earlier work. For example, modelling of the emergence of synchrony during social interaction between agents was addressed in earlier work such as (Hendrikse et al, 2022a; Hendrikse et al, 2023a). However, in these models no (subjective) internal detection of synchrony was incorporated and in (Hendrikse et al., 2022a) no adaptivity was modelled, whereas in (Hendrikse et al., 2023a) another type of adaptivity was captured: of internal responding connections from representation to preparation. The idea of subjective synchrony detection in an agent-based model was introduced in (Hendrikse et al, 2023c) and subsequently the distinction between short-term and long-term behavioural adaptivity was introduced in (Hendrikse, Treur, Wilderjans, Dikker, Koole, 2022b) and (Hendrikse, Treur, Koole, 2023b). However, these papers did not distinguish between relationship-specific and relationship-independent adaptation and were limited to a fixed dyad as they did not include a context of interaction with multiple agents as studied here.

A specific computational model for attachment theory has been contributed in (Hermans, Muhammad, Treur, 2021; Hermans, Muhammad, Treur, 2022). This model is based on the internal working models for the self and the other, following (Bartholomew and Horowitz, 1991). It does not address the distinction between short-term and long-term adaptivity and also not the differentiation between relationship-specific and relationship-independent adaptivity as in the current paper. Moreover, there the second-order adaptation is limited to the speed of adaptation, whereas here also second-order adaptation for the strength of adaptation is addressed.

9.3 Limitations

Regardless the novelty of this work, multiple limitations are also present. First, we have now developed a general adaptive agent model, which we have evaluated through simulation experiments. However, it would be very helpful to evaluate the transfer learning behaviour of agents on real data sets to see if the observed learning patterns hold there as well. Second, agents were now only able to randomly interact in dyads. It is likely that transfer learning is a useful ability in groups of agents as well. It would be good to conduct simulations in which agents interact with multiple agents simultaneously to verify if the transfer learning then happens as well. Third, all agents were designed with a network model that consists of states with values between 0 and 1 that change over time. It would be valuable to add both before the sensory states and after the execution states an extra user-interface level to suit the agent models for real time interaction with humans. Such a user-interface before the sensory level can, as an example for the verbal sensory state, be a speech-to-text algorithm combined with a large language model. From this large language model, a state value is obtained for the verbal sensory state. The addition of user-interfaces would enable the agent-models to interact with humans, to investigate whether the transfer learning adaptation for the agent model also works in interaction with different humans.

9.4 Future work

For future work, note that in the model only few variations for individual differences between the agents have been addressed. As follow-up research it can be interesting to study such differences in much more detail. Furthermore, as mentioned, mechanisms for plasticity and metaplasticity from neuroscience have been used as a basis for the adaptive agent model. However, more work on the neuroscientific mechanisms behind attachment theory exists, for example, in (Beckes and Coan, 2015; Beckes, IJzerman, Tops, 2015; Coan, 2016; White, Kungl, Vrticka, 2023). This work can provide input for refinement of the presented models. As an example, Coan (2016) mentions that topics concerning neural systems supporting emotion and motivation and emotion-regulation, filial bonding, familiarity, proximity seeking, and individual differences are important. Moreover, Beckes and Coan (2015) put forward processes such as person perception, familiarity, anticipatory motivation, behavioural organisation, consummatory behaviour, emotion regulation, and aversive motivation. Another perspective that might be interesting for further work is the multidimensional model for attachment proposed by Gagliardi (2022). So, these literatures can provide many forms of inspiration to extend the current model. Our current adaptive agent model provides a solid base to model further refinements of relationship-specific and relationship-independent social behaviour development.

10. Conclusion

We conclude that we successfully created an adaptive agent-based dynamical system model for how social interaction behaviour of persons develops over time. This adaptive agent-based dynamical system model includes how interaction behaviour changes during interaction episodes (short-term adaptivity) and across multiple interaction episodes (long-term adaptivity). Furthermore, it addresses social interaction in multiple relationships and transference between them: how behaviour learned in one relationship can also be carried over to other relationships Moreover, this model distinguishes first-order adaptivity from second-order adaptivity through modelled mechanisms known from neuroscience: synaptic plasticity (Bear and Malenka, 1994) for long-term first-order adaptivity, nonsynaptic plasticity (Debanne, Inglebert, Russier, 2019) for short-term first-order adaptivity and metaplasticity (Abraham and Bear, 1996) for second-order adaptivity. The model was evaluated by a number of explored simulations where within a group of four agents, each agent randomly has episodes of interaction with one of the three other agents. The outcomes of the simulations show that more social interaction leads to more adaptation of the interaction behaviour. This holds for both relationship-specific and relationship-independent adaptivity, and for both short-term adaptivity and long-term adaptivity.

11. Appendix Specifications by Role Matrices

In Figures 20 to 39, parts of the different role matrices are shown that provide a specification of the network characteristics defining the adaptive network model in a standardised table format. In each role matrix, each state has its row where it is listed which are the impacts on it from the role addressed by that role matrix. The entire model has 357 states, but the parts for the four different agents are in principle similar, so mostly we show only the specifications for agent A.

The base connectivity characteristics are specified by role matrices **mb** and **mcw**. The parts for role matrix **mb** are shown in Fig. 20 to Fig. 23. Role matrix **mb** specifies for each row the other states at the same or lower level from which the indicated state gets its incoming connections.

mb	**base connectivity**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
X_1	ws_s	X_1									
X_2	$con_{th,A}$	X_2									
X_3	$con_{th,B}$	X_3									
X_4	$con_{th,C}$	X_4									
X_5	$con_{th,D}$	X_5									
X_6	$sense_{s,A}$	X_1									
X_7	$sense_{B,m,A}$	X_{73}									
X_8	$sense_{B,b,A}$	X_{74}									
X_9	$sense_{B,v,A}$	X_{75}									
X_{10}	$sense_{C,m,A}$	X_{108}									
X_{11}	$sense_{C,b,A}$	X_{109}									
X_{12}	$sense_{C,v,A}$	X_{110}									
X_{13}	$sense_{D,m,A}$	X_{143}									
X_{14}	$sense_{D,b,A}$	X_{144}									
X_{15}	$sense_{D,v,A}$	X_{145}									
X_{16}	$rep_{s,A}$	X_6									
X_{17}	$rep_{B,m,A}$	X_7	X_{26}								
X_{18}	$rep_{B,b,A}$	X_8	X_{27}								
X_{19}	$rep_{B,v,A}$	X_9	X_{28}								
X_{20}	$rep_{C,m,A}$	X_{10}	X_{26}								
X_{21}	$rep_{C,b,A}$	X_{11}	X_{27}								
X_{22}	$rep_{C,v,A}$	X_{12}	X_{28}								
X_{23}	$rep_{D,m,A}$	X_{13}	X_{26}								
X_{24}	$rep_{D,b,A}$	X_{14}	X_{27}								
X_{25}	$rep_{D,v,A}$	X_{15}	X_{28}								
X_{26}	$prep_{m,A}$	X_{16}	X_{17}	X_{20}	X_{23}						
X_{27}	$prep_{b,A}$	X_{16}	X_{18}	X_{21}	X_{24}						
X_{28}	$prep_{v,A}$	X_{16}	X_{19}	X_{22}	X_{25}						
X_{29}	$intersyncdet_{B,A,m}$	X_7	X_{38}								
X_{30}	$intersyncdet_{B,A,b}$	X_8	X_{39}								
X_{31}	$intersyncdet_{B,A,v}$	X_9	X_{40}								
X_{32}	$intersyncdet_{C,A,m}$	X_{10}	X_{38}								
X_{33}	$intersyncdet_{C,A,b}$	X_{11}	X_{39}								
X_{34}	$intersyncdet_{C,A,v}$	X_{12}	X_{40}								
X_{35}	$intersyncdet_{D,A,m}$	X_{13}	X_{38}								
X_{36}	$intersyncdet_{D,A,b}$	X_{14}	X_{39}								
X_{37}	$intersyncdet_{D,A,v}$	X_{15}	X_{40}								
X_{38}	$move_{m,A}$	X_{26}									
X_{39}	$express_{b,A}$	X_{27}									
X_{40}	$talk_{A,B,v}$	X_{28}									

Fig. 20 The part of role matrix **mb** of the connectivity characteristics for the base states of Agent A.

mb	base connectivity	1	2	3	4	5	6	7	8	9	10
X_{146}	$\mathbf{W}_{\text{sense-rep\_}m,B,A}$	X_{29}	X_{30}	X_{31}	X_{146}						
X_{147}	$\mathbf{W}_{\text{sense-rep\_}b,B,A}$	X_{29}	X_{30}	X_{31}	X_{147}						
X_{148}	$\mathbf{W}_{\text{sense-rep\_}v,B,A}$	X_{29}	X_{30}	X_{31}	X_{148}						
X_{149}	$\mathbf{W}_{\text{sense-rep\_}m,C,A}$	X_{32}	X_{33}	X_{34}	X_{149}						
X_{150}	$\mathbf{W}_{\text{sense-rep\_}b,C,A}$	X_{32}	X_{33}	X_{34}	X_{150}						
X_{151}	$\mathbf{W}_{\text{sense-rep\_}v,C,A}$	X_{32}	X_{33}	X_{34}	X_{151}						
X_{152}	$\mathbf{W}_{\text{sense-rep\_}m,D,A}$	X_{35}	X_{36}	X_{37}	X_{152}						
X_{153}	$\mathbf{W}_{\text{sense-rep\_}b,D,A}$	X_{35}	X_{36}	X_{37}	X_{153}						
X_{154}	$\mathbf{W}_{\text{sense-rep\_}v,D,A}$	X_{35}	X_{36}	X_{37}	X_{154}						
X_{155}	$\mathbf{W}_{\text{rep-prep\_}m,B,A}$	X_{29}	X_{30}	X_{31}	X_{155}						
X_{156}	$\mathbf{W}_{\text{rep-prep\_}b,B,A}$	X_{29}	X_{30}	X_{31}	X_{156}						
X_{157}	$\mathbf{W}_{\text{rep-prep\_}v,B,A}$	X_{29}	X_{30}	X_{31}	X_{157}						
X_{158}	$\mathbf{W}_{\text{rep-prep\_}m,C,A}$	X_{32}	X_{33}	X_{34}	X_{158}						
X_{159}	$\mathbf{W}_{\text{rep-prep\_}b,C,A}$	X_{32}	X_{33}	X_{34}	X_{159}						
X_{160}	$\mathbf{W}_{\text{rep-prep\_}v,C,A}$	X_{32}	X_{33}	X_{34}	X_{160}						
X_{161}	$\mathbf{W}_{\text{rep-prep\_}m,D,A}$	X_{35}	X_{36}	X_{37}	X_{161}						
X_{162}	$\mathbf{W}_{\text{rep-prep\_}b,D,A}$	X_{35}	X_{36}	X_{37}	X_{162}						
X_{163}	$\mathbf{W}_{\text{rep-prep\_}v,D,A}$	X_{35}	X_{36}	X_{37}	X_{163}						
X_{164}	$\mathbf{W}_{\text{prep-exec\_}m,A}$	X_{26}	X_{38}	X_{164}	X_{164}						
X_{165}	$\mathbf{W}_{\text{prep-exec\_}b,A}$	X_{27}	X_{39}	X_{165}	X_{165}						
X_{166}	$\mathbf{W}_{\text{prep-exec\_}v,A}$	X_{28}	X_{40}	X_{166}	X_{166}						
X_{167}	$\mathbf{T}_{\text{rep\_}B,m,A}$	X_{2}	X_{29}	X_{30}	X_{31}						
X_{168}	$\mathbf{T}_{\text{rep\_}B,b,A}$	X_{2}	X_{29}	X_{30}	X_{31}						
X_{169}	$\mathbf{T}_{\text{rep\_}B,v,A}$	X_{2}	X_{29}	X_{30}	X_{31}						
X_{170}	$\mathbf{T}_{\text{rep\_}C,m,A}$	X_{2}	X_{32}	X_{33}	X_{34}						
X_{171}	$\mathbf{T}_{\text{rep\_}C,b,A}$	X_{2}	X_{32}	X_{33}	X_{34}						
X_{172}	$\mathbf{T}_{\text{rep\_}C,v,A}$	X_{2}	X_{32}	X_{33}	X_{34}						
X_{173}	$\mathbf{T}_{\text{rep\_}D,m,A}$	X_{2}	X_{35}	X_{36}	X_{37}						
X_{174}	$\mathbf{T}_{\text{rep\_}D,b,A}$	X_{2}	X_{35}	X_{36}	X_{37}						
X_{175}	$\mathbf{T}_{\text{rep\_}D,v,A}$	X_{2}	X_{35}	X_{36}	X_{37}						
X_{176}	$\mathbf{T}_{\text{exec\_}m,A}$	X_{2}	X_{29}	X_{30}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}
X_{177}	$\mathbf{T}_{\text{exec\_}b,A}$	X_{2}	X_{29}	X_{30}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}
X_{178}	$\mathbf{T}_{\text{exec\_}v,A}$	X_{2}	X_{29}	X_{30}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}

Fig. 21 The part of role matrix **mb** of the connectivity characteristics for the first-order adaptation states of Agent A: the **W**-states and the **T**-states.

mb	base connectivity	1	2	3	4	5	6	7	8	9	10
X_{278}	$\mathbf{W}_{m,A,B}$	X_{278}									
X_{279}	$\mathbf{W}_{b,A,B}$	X_{279}									
X_{280}	$\mathbf{W}_{v,A,B}$	X_{280}									
X_{281}	$\mathbf{W}_{m,A,C}$	X_{281}									
X_{282}	$\mathbf{W}_{b,A,C}$	X_{282}									
X_{283}	$\mathbf{W}_{v,A,C}$	X_{283}									
X_{284}	$\mathbf{W}_{m,A,D}$	X_{284}									
X_{285}	$\mathbf{W}_{b,A,D}$	X_{285}									
X_{286}	$\mathbf{W}_{v,A,D}$	X_{286}									
X_{287}	$\mathbf{W}_{m,B,A}$	X_{287}									
X_{288}	$\mathbf{W}_{b,B,A}$	X_{288}									
X_{289}	$\mathbf{W}_{v,B,A}$	X_{289}									
X_{290}	$\mathbf{W}_{m,B,C}$	X_{290}									
X_{291}	$\mathbf{W}_{b,B,C}$	X_{291}									
X_{292}	$\mathbf{W}_{v,B,C}$	X_{292}									
X_{293}	$\mathbf{W}_{m,B,D}$	X_{293}									
X_{294}	$\mathbf{W}_{b,B,D}$	X_{294}									
X_{295}	$\mathbf{W}_{v,B,D}$	X_{295}									
X_{296}	$\mathbf{W}_{m,C,A}$	X_{296}									
X_{297}	$\mathbf{W}_{b,C,A}$	X_{297}									
X_{298}	$\mathbf{W}_{v,C,A}$	X_{298}									
X_{299}	$\mathbf{W}_{m,C,B}$	X_{299}									
X_{300}	$\mathbf{W}_{b,C,B}$	X_{300}									
X_{301}	$\mathbf{W}_{v,C,B}$	X_{301}									

		1	2	3	4	5	6	7	8	9	10
X_{302}	$\mathbf{W}_{m,C,D}$	X_{302}									
X_{303}	$\mathbf{W}_{b,C,D}$	X_{303}									
X_{304}	$\mathbf{W}_{v,C,D}$	X_{304}									
X_{305}	$\mathbf{W}_{m,D,A}$	X_{305}									
X_{306}	$\mathbf{W}_{b,D,A}$	X_{306}									
X_{307}	$\mathbf{W}_{v,D,A}$	X_{307}									
X_{308}	$\mathbf{W}_{m,D,B}$	X_{308}									
X_{309}	$\mathbf{W}_{b,D,B}$	X_{309}									
X_{310}	$\mathbf{W}_{v,D,B}$	X_{310}									
X_{311}	$\mathbf{W}_{m,D,C}$	X_{311}									
X_{312}	$\mathbf{W}_{b,D,C}$	X_{312}									
X_{313}	$\mathbf{W}_{v,D,C}$	X_{313}									

Fig. 22 The part of role matrix **mb** of the connectivity characteristics for the first-order adaptation **W**-states for interaction enabling for the interactions between all four agents.

mb	**base connectivity**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
X_{314}	$\mathbf{agg}_{sensA}$	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
X_{315}	$\mathbf{agg}_{execA}$	X_{38}	X_{39}	X_{40}							
X_{316}	$\mathbf{agg}_{syncA}$	X_{29}	X_{30}	X_{31}	X_{32}	X_{33}	X_{34}	X_{35}	X_{36}	X_{37}	
X_{317}	$\mathbf{aggw}_{sense\text{-}repA}$	X_{146}	X_{147}	X_{148}	X_{149}	X_{150}	X_{151}	X_{152}	X_{153}	X_{154}	
X_{318}	$\mathbf{aggw}_{rep\text{-}prepA}$	X_{155}	X_{156}	X_{157}	X_{158}	X_{159}	X_{160}	X_{161}	X_{162}	X_{163}	
X_{319}	$\mathbf{aggw}_{prep\text{-}execA}$	X_{164}	X_{165}	X_{166}							
X_{320}	$\mathbf{aggw}_{A}$	X_{317}	X_{318}	X_{319}							

mb	**base connectivity**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
X_{342}	$\mathbf{H}_{\mathbf{W_A}}$	X_{314}	X_{315}	X_{316}	X_{320}	X_{342}					
X_{343}	$\mathbf{H}_{\mathbf{T_A}}$	X_{314}	X_{315}	X_{316}	X_{320}	X_{343}					
X_{344}	$\mathbf{W}_{\mathbf{W_A}}$	X_{314}	X_{315}	X_{316}	X_{320}	X_{344}					
X_{345}	$\mathbf{W}_{\mathbf{T_A}}$	X_{314}	X_{315}	X_{316}	X_{320}	X_{345}					

Fig. 23 The part of role matrix **mb** of the connectivity characteristics for the second-order adaptation states of Agent A: the $\mathbf{H}_{\mathbf{W_A}}$-, $\mathbf{H}_{\mathbf{T_A}}$-, $\mathbf{W}_{\mathbf{W_A}}$-, and $\mathbf{W}_{\mathbf{T_A}}$-states controlling speed and strength for first-order adaptation **W**-states and **T**-states.

In role matrix **mcw** the connection weights are specified for the base connections, see Fig. 24 to 27. Here nonadaptive connection weights are indicated in **mcw** by a number in a green shaded cell. In contrast, (first-order) adaptive connection weights are indicated in pink-red shaded cells by a reference to the (self-model) adaptation state representing the adaptive value. In Fig. 24, this is shown for base states X_7 to X_{15} (with references to first-order adaptation states X_{287} to X_{289}, X_{296} to X_{298}, and X_{305} to X_{307}), base states X_{17} to X_{28} (with references to first-order adaptation states X_{146} to X_{163}), and base states X_{38} to X_{40} (with references to first-order adaptation states X_{164} to X_{166}).

mcw	**connection weights**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
X_1	ws_s	1									
X_2	$con_{th,A}$	1									
X_3	$con_{th,B}$	1									
X_4	$con_{th,C}$	1									
X_5	$con_{th,D}$	1									
X_6	$sense_{s,A}$	1									
X_7	$sense_{B,m,A}$	X_{287}									
X_8	$sense_{B,b,A}$	X_{288}									
X_9	$sense_{B,v,A}$	X_{289}									
X_{10}	$sense_{C,m,A}$	X_{296}									
X_{11}	$sense_{C,b,A}$	X_{297}									

X_{12}	sense$_{C,v,A}$	X_{298}									
X_{13}	sense$_{D,m,A}$	X_{305}									
X_{14}	sense$_{D,b,A}$	X_{306}									
X_{15}	sense$_{D,v,A}$	X_{307}									
X_{16}	rep$_{s,A}$	1									
X_{17}	rep$_{B,m,A}$	X_{146}	1								
X_{18}	rep$_{B,b,A}$	X_{147}	1								
X_{19}	rep$_{B,v,A}$	X_{148}	1								
X_{20}	rep$_{C,m,A}$	X_{149}	1								
X_{21}	rep$_{C,b,A}$	X_{150}	1								
X_{22}	rep$_{C,v,A}$	X_{151}	1								
X_{23}	rep$_{D,m,A}$	X_{152}	1								
X_{24}	rep$_{D,b,A}$	X_{153}	1								
X_{25}	rep$_{D,v,A}$	X_{154}	1								
X_{26}	prep$_{m,A}$	1	X_{155}	X_{158}	X_{161}						
X_{27}	prep$_{b,A}$	1	X_{156}	X_{159}	X_{162}						
X_{28}	prep$_{v,A}$	1	X_{157}	X_{160}	X_{163}						
X_{29}	intersyncdet$_{B,A,m}$	1	1								
X_{30}	intersyncdet$_{B,A,b}$	1	1								
X_{31}	intersyncdet$_{B,A,v}$	1	1								
X_{32}	intersyncdet$_{C,A,m}$	1	1								
X_{33}	intersyncdet$_{C,A,b}$	1	1								
X_{34}	intersyncdet$_{C,A,v}$	1	1								
X_{35}	intersyncdet$_{D,A,m}$	1	1								
X_{36}	intersyncdet$_{D,A,b}$	1	1								
X_{37}	intersyncdet$_{D,A,v}$	1	1								
X_{38}	move$_{m,A}$	X_{164}									
X_{39}	express$_{b,A}$	X_{165}									
X_{40}	talk$_{A,B,v}$	X_{166}									

Fig. 24 Role matrix **mcw** of the connectivity characteristics specifying connection weights for the base states of agent A.

In Fig. 25, the second-order connectivity adaptation for the first-order adaptation states is shown for first-order adaptation states X_{146} to X_{178} with references to second-order adaptation states X_{344} and X_{345} for the adaptive weights for most of the incoming connections for the **W**-states and **T**-states, respectively.

mcw	connection weights	1	2	3	4	5	6	7	8	9	10
X_{146}	$\mathbf{W}_{\text{sense-rep\_}m,B,A}$	X_{344}	X_{344}	X_{344}	1						
X_{147}	$\mathbf{W}_{\text{sense-rep\_}b,B,A}$	X_{344}	X_{344}	X_{344}	1						
X_{148}	$\mathbf{W}_{\text{sense-rep\_}v,B,A}$	X_{344}	X_{344}	X_{344}	1						
X_{149}	$\mathbf{W}_{\text{sense-rep\_}m,C,A}$	X_{344}	X_{344}	X_{344}	1						
X_{150}	$\mathbf{W}_{\text{sense-rep\_}b,C,A}$	X_{344}	X_{344}	X_{344}	1						
X_{151}	$\mathbf{W}_{\text{sense-rep\_}v,C,A}$	X_{344}	X_{344}	X_{344}	1						
X_{152}	$\mathbf{W}_{\text{sense-rep\_}m,D,A}$	X_{344}	X_{344}	X_{344}	1						
X_{153}	$\mathbf{W}_{\text{sense-rep\_}b,D,A}$	X_{344}	X_{344}	X_{344}	1						
X_{154}	$\mathbf{W}_{\text{sense-rep\_}v,D,A}$	X_{344}	X_{344}	X_{344}	1						
X_{155}	$\mathbf{W}_{\text{rep-prep\_}m,B,A}$	X_{344}	X_{344}	X_{344}	1						
X_{156}	$\mathbf{W}_{\text{rep-prep\_}b,B,A}$	X_{344}	X_{344}	X_{344}	1						
X_{157}	$\mathbf{W}_{\text{rep-prep\_}v,B,A}$	X_{344}	X_{344}	X_{344}	1						
X_{158}	$\mathbf{W}_{\text{rep-prep\_}m,C,A}$	X_{344}	X_{344}	X_{344}	1						
X_{159}	$\mathbf{W}_{\text{rep-prep\_}b,C,A}$	X_{344}	X_{344}	X_{344}	1						
X_{160}	$\mathbf{W}_{\text{rep-prep\_}v,C,A}$	X_{344}	X_{344}	X_{344}	1						
X_{161}	$\mathbf{W}_{\text{rep-prep\_}m,D,A}$	X_{344}	X_{344}	X_{344}	1						
X_{162}	$\mathbf{W}_{\text{rep-prep\_}b,D,A}$	X_{344}	X_{344}	X_{344}	1						
X_{163}	$\mathbf{W}_{\text{rep-prep\_}v,D,A}$	X_{344}	X_{344}	X_{344}	1						
X_{164}	$\mathbf{W}_{\text{prep-exec\_}m,A}$	X_{344}	X_{344}	X_{344}	1						
X_{165}	$\mathbf{W}_{\text{prep-exec\_}b,A}$	X_{344}	X_{344}	X_{344}	1						
X_{166}	$\mathbf{W}_{\text{prep-exec\_}v,A}$	X_{344}	X_{344}	X_{344}	1						
X_{167}	$\mathbf{T}_{\text{rep\_}B,m,A}$	1	X_{345}	X_{345}	X_{345}						
X_{168}	$\mathbf{T}_{\text{rep\_ }B,b,A}$	1	X_{345}	X_{345}	X_{345}						
X_{169}	$\mathbf{T}_{\text{rep\_ }B,v,A}$	1	X_{345}	X_{345}	X_{345}						

X_{170}	$\mathbf{T}_{rep\_C,m,A}$	1	X_{345}	X_{345}	X_{345}						
X_{171}	$\mathbf{T}_{rep\_C,b,A}$	1	X_{345}	X_{345}	X_{345}						
X_{172}	$\mathbf{T}_{rep\_C,v,A}$	1	X_{345}	X_{345}	X_{345}						
X_{173}	$\mathbf{T}_{rep\_D,m,A}$	1	X_{345}	X_{345}	X_{345}						
X_{174}	$\mathbf{T}_{rep\_D,b,A}$	1	X_{345}	X_{345}	X_{345}						
X_{175}	$\mathbf{T}_{rep\_D,v,A}$	1	X_{345}	X_{345}	X_{345}						
X_{176}	$\mathbf{T}_{exec\_m,A}$	1	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}
X_{177}	$\mathbf{T}_{exec\_b,A}$	1	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}
X_{178}	$\mathbf{T}_{exec\_v,A}$	1	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}	X_{345}

Fig. 25 Role matrix **mcw** of the connectivity characteristics specifying the connection weights for the first-order adaptation **W**-states and **T**-states of agent A.

mcw	connection weights	1	2	3	4	5	6	7	8	9	10
X_{278}	$\mathbf{W}_{m,A,B}$	1									
X_{279}	$\mathbf{W}_{b,A,B}$	1									
X_{280}	$\mathbf{W}_{v,A,B}$	1									
X_{281}	$\mathbf{W}_{m,A,C}$	1									
X_{282}	$\mathbf{W}_{b,A,C}$	1									
X_{283}	$\mathbf{W}_{v,A,C}$	1									
X_{284}	$\mathbf{W}_{m,A,D}$	1									
X_{285}	$\mathbf{W}_{b,A,D}$	1									
X_{286}	$\mathbf{W}_{v,A,D}$	1									
X_{287}	$\mathbf{W}_{m,B,A}$	1									
X_{288}	$\mathbf{W}_{b,B,A}$	1									
X_{289}	$\mathbf{W}_{v,B,A}$	1									
X_{290}	$\mathbf{W}_{m,B,C}$	1									
X_{291}	$\mathbf{W}_{b,B,C}$	1									
X_{292}	$\mathbf{W}_{v,B,C}$	1									
X_{293}	$\mathbf{W}_{m,B,D}$	1									
X_{294}	$\mathbf{W}_{b,B,D}$	1									
X_{295}	$\mathbf{W}_{v,B,D}$	1									
X_{296}	$\mathbf{W}_{m,C,A}$	1									
X_{297}	$\mathbf{W}_{b,C,A}$	1									
X_{298}	$\mathbf{W}_{v,C,A}$	1									
X_{299}	$\mathbf{W}_{m,C,B}$	1									
X_{300}	$\mathbf{W}_{b,C,B}$	1									
X_{301}	$\mathbf{W}_{v,C,B}$	1									
X_{302}	$\mathbf{W}_{m,C,D}$	1									
X_{303}	$\mathbf{W}_{b,C,D}$	1									
X_{304}	$\mathbf{W}_{v,C,D}$	1									
X_{305}	$\mathbf{W}_{m,D,A}$	1									
X_{306}	$\mathbf{W}_{b,D,A}$	1									
X_{307}	$\mathbf{W}_{v,D,A}$	1									
X_{308}	$\mathbf{W}_{m,D,B}$	1									
X_{309}	$\mathbf{W}_{b,D,B}$	1									
X_{310}	$\mathbf{W}_{v,D,B}$	1									
X_{311}	$\mathbf{W}_{m,D,C}$	1									
X_{312}	$\mathbf{W}_{b,D,C}$	1									
X_{313}	$\mathbf{W}_{v,D,C}$	1									

Fig. 26 Role matrix **mcw** of the connectivity characteristics specifying the connection weights for the first-order adaptation **W**-states for interaction enabling.

mcw	connection weights	1	2	3	4	5	6	7	8	9	10
X_{314}	$\mathbf{agg}_{sensA}$	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
X_{315}	$\mathbf{agg}_{execA}$	0.1	0.1	0.1							
X_{316}	$\mathbf{agg}_{syncA}$	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	
X_{317}	$\mathbf{agg}_{\mathbf{W}_{sense\text{-}repA}}$	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	
X_{318}	$\mathbf{agg}_{\mathbf{W}_{rep\text{-}prepA}}$	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	
X_{319}	$\mathbf{agg}_{\mathbf{W}_{prep\text{-}execA}}$	0.1	0.1	0.1							
X_{320}	$\mathbf{agg}_{\mathbf{W}_A}$	0.1	0.1	0.1							

mcw	connection weights	1	2	3	4	5	6	7	8	9	10
X_{342}	$\mathbf{H}_{\mathbf{W}_\mathbf{A}}$	1	1	1	1	1					
X_{343}	$\mathbf{H}_{\mathbf{T}_\mathbf{A}}$	1	1	1	1	1					
X_{344}	$\mathbf{W}_{\mathbf{W}_\mathbf{A}}$	1	1	1	1	0.15					
X_{345}	$\mathbf{W}_{\mathbf{T}_\mathbf{A}}$	-0.35	-0.35	-0.35	-0.35	-1					

Fig. 27 Role matrix **mcw** of the connectivity characteristics specifying the connection weights for the second-order adaptation states of agent A: the $\mathbf{H}_{\mathbf{W}_\mathbf{A}}$-, $\mathbf{H}_{\mathbf{T}_\mathbf{A}}$-, $\mathbf{W}_{\mathbf{W}_\mathbf{A}}$-, and $\mathbf{W}_{\mathbf{T}_\mathbf{A}}$-states.

In Figures 28 to 31 the role matrices for speed factors and initial values are shown. For the base states all speed factors are nonadaptive as shown in Fig. 28.

ms	speed factors	1	iv	1
X_1	ws_s	0.5		0
X_2	$con_{th,A}$	0		1
X_3	$con_{th,B}$	0		1
X_4	$con_{th,C}$	0		1
X_5	$con_{th,D}$	0		1
X_6	$sense_{s,A}$	1		0
X_7	$sense_{B,m,A}$	1		0
X_8	$sense_{B,b,A}$	1		0
X_9	$sense_{B,v,A}$	1		0
X_{10}	$sense_{C,m,A}$	1		0
X_{11}	$sense_{C,b,A}$	1		0
X_{12}	$sense_{C,v,A}$	1		0
X_{13}	$sense_{D,m,A}$	1		0
X_{14}	$sense_{D,b,A}$	1		0
X_{15}	$sense_{D,v,A}$	1		0
X_{16}	$rep_{s,A}$	1		0
X_{17}	$rep_{B,m,A}$	1		0
X_{18}	$rep_{B,b,A}$	1		0
X_{19}	$rep_{B,v,A}$	1		0
X_{20}	$rep_{C,m,A}$	1		0
X_{21}	$rep_{C,b,A}$	1		0
X_{22}	$rep_{C,v,A}$	1		0
X_{23}	$rep_{D,m,A}$	1		0
X_{24}	$rep_{D,b,A}$	1		0
X_{25}	$rep_{D,v,A}$	1		0
X_{26}	$prep_{m,A}$	1		0
X_{27}	$prep_{b,A}$	1		0
X_{28}	$prep_{v,A}$	1		0
X_{29}	$intersyncdet_{B,A,m}$	0.5		0
X_{30}	$intersyncdet_{B,A,b}$	0.5		0
X_{31}	$intersyncdet_{B,A,v}$	0.5		0
X_{32}	$intersyncdet_{C,A,m}$	0.5		0
X_{33}	$intersyncdet_{C,A,b}$	0.5		0
X_{34}	$intersyncdet_{C,A,v}$	0.5		0
X_{35}	$intersyncdet_{D,A,m}$	0.5		0
X_{36}	$intersyncdet_{D,A,b}$	0.5		0
X_{37}	$intersyncdet_{D,A,v}$	0.5		0
X_{38}	$move_{m,A}$	1		0
X_{39}	$express_{b,A}$	1		0
X_{40}	$talk_{A,B,v}$	1		0

Fig. 28 Role matrix **ms** of the timing characteristics for speed factors and initial values **iv** for the base states of agent A.

However, In Fig. 29 it is shown that all first-order adaptation **W**-states and **T**-states have adaptive speed factors. For each agent, there is one common speed adaptation state $\mathbf{H}_{\mathbf{W}_\mathbf{A}}$ for all **W**-states (represented by X_{342}) and one common speed adaptation state $\mathbf{H}_{\mathbf{T}_\mathbf{A}}$ for all **T**-states (represented by X_{343}).

ms	speed factors	1	iv	1
X_{146}	$\mathbf{W}_{\text{sense-rep\_}m,B,A}$	X_{342}		0
X_{147}	$\mathbf{W}_{\text{sense-rep\_}b,B,A}$	X_{342}		0
X_{148}	$\mathbf{W}_{\text{sense-rep\_}v,B,A}$	X_{342}		0
X_{149}	$\mathbf{W}_{\text{sense-rep\_}m,C,A}$	X_{342}		0
X_{150}	$\mathbf{W}_{\text{sense-rep\_}b,C,A}$	X_{342}		0
X_{151}	$\mathbf{W}_{\text{sense-rep\_}v,C,A}$	X_{342}		0
X_{152}	$\mathbf{W}_{\text{sense-rep\_}m,D,A}$	X_{342}		0
X_{153}	$\mathbf{W}_{\text{sense-rep\_}b,D,A}$	X_{342}		0
X_{154}	$\mathbf{W}_{\text{sense-rep\_}v,D,A}$	X_{342}		0
X_{155}	$\mathbf{W}_{\text{rep-prep\_}m,B,A}$	X_{342}		0
X_{156}	$\mathbf{W}_{\text{rep-prep\_}b,B,A}$	X_{342}		0
X_{157}	$\mathbf{W}_{\text{rep-prep\_}v,B,A}$	X_{342}		0
X_{158}	$\mathbf{W}_{\text{rep-prep\_}m,C,A}$	X_{342}		0
X_{159}	$\mathbf{W}_{\text{rep-prep\_}b,C,A}$	X_{342}		0
X_{160}	$\mathbf{W}_{\text{rep-prep\_}v,C,A}$	X_{342}		0
X_{161}	$\mathbf{W}_{\text{rep-prep\_}m,D,A}$	X_{342}		0
X_{162}	$\mathbf{W}_{\text{rep-prep\_}b,D,A}$	X_{342}		0
X_{163}	$\mathbf{W}_{\text{rep-prep\_}v,D,A}$	X_{342}		0
X_{164}	$\mathbf{W}_{\text{prep-exec\_}m,A}$	X_{342}		0
X_{165}	$\mathbf{W}_{\text{prep-exec\_}b,A}$	X_{342}		0
X_{166}	$\mathbf{W}_{\text{prep-exec\_}v,A}$	X_{342}		0
X_{167}	$\mathbf{T}_{\text{rep\_}B,m,A}$	X_{343}		0.5
X_{168}	$\mathbf{T}_{\text{rep\_ }B,b,A}$	X_{343}		0.5
X_{169}	$\mathbf{T}_{\text{rep\_ }B,v,A}$	X_{343}		0.5
X_{170}	$\mathbf{T}_{\text{rep\_}C,m,A}$	X_{343}		0.5
X_{171}	$\mathbf{T}_{\text{rep\_ }C,b,A}$	X_{343}		0.5
X_{172}	$\mathbf{T}_{\text{rep\_ }C,v,A}$	X_{343}		0.5
X_{173}	$\mathbf{T}_{\text{rep\_}D,m,A}$	X_{343}		0.5
X_{174}	$\mathbf{T}_{\text{rep\_ }D,b,A}$	X_{343}		0.5
X_{175}	$\mathbf{T}_{\text{rep\_ }D,v,A}$	X_{343}		0.5
X_{176}	$\mathbf{T}_{\text{exec\_}m,A}$	X_{343}		0.5
X_{177}	$\mathbf{T}_{\text{exec\_}b,A}$	X_{343}		0.5
X_{178}	$\mathbf{T}_{\text{exec\_}v,A}$	X_{343}		0.5

Fig. 29 Role matrix **ms** of the timing characteristics for the first-order adaptation **W**-states and **T**-states showing how their adaptation speed is adaptive, represented by second-order adaptation states X_{342} and X_{343} ($\mathbf{H}_{\mathbf{W_A}}$ and $\mathbf{H}_{\mathbf{T_A}}$) and showing their initial values.

ms	speed factors	1	iv	1
X_{278}	$\mathbf{W}_{m,A,B}$	2		0
X_{279}	$\mathbf{W}_{b,A,B}$	2		0
X_{280}	$\mathbf{W}_{v,A,B}$	2		0
X_{281}	$\mathbf{W}_{m,A,C}$	2		0
X_{282}	$\mathbf{W}_{b,A,C}$	2		0
X_{283}	$\mathbf{W}_{v,A,C}$	2		0
X_{284}	$\mathbf{W}_{m,A,D}$	2		0
X_{285}	$\mathbf{W}_{b,A,D}$	2		0
X_{286}	$\mathbf{W}_{v,A,D}$	2		0
X_{287}	$\mathbf{W}_{m,B,A}$	2		0
X_{288}	$\mathbf{W}_{b,B,A}$	2		0
X_{289}	$\mathbf{W}_{v,B,A}$	2		0
X_{290}	$\mathbf{W}_{m,B,C}$	2		0
X_{291}	$\mathbf{W}_{b,B,C}$	2		0
X_{292}	$\mathbf{W}_{v,B,C}$	2		0
X_{293}	$\mathbf{W}_{m,B,D}$	2		0
X_{294}	$\mathbf{W}_{b,B,D}$	2		0
X_{295}	$\mathbf{W}_{v,B,D}$	2		0
X_{296}	$\mathbf{W}_{m,C,A}$	2		0
X_{297}	$\mathbf{W}_{b,C,A}$	2		0

X_{298}	$\mathbf{W}_{v,C,A}$	2		0
X_{299}	$\mathbf{W}_{m,C,B}$	2		0
X_{300}	$\mathbf{W}_{b,C,B}$	2		0
X_{301}	$\mathbf{W}_{v,C,B}$	2		0
X_{302}	$\mathbf{W}_{m,C,D}$	2		0
X_{303}	$\mathbf{W}_{b,C,D}$	2		0
X_{304}	$\mathbf{W}_{v,C,D}$	2		0
X_{305}	$\mathbf{W}_{m,D,A}$	2		0
X_{306}	$\mathbf{W}_{b,D,A}$	2		0
X_{307}	$\mathbf{W}_{v,D,A}$	2		0
X_{308}	$\mathbf{W}_{m,D,B}$	2		0
X_{309}	$\mathbf{W}_{b,D,B}$	2		0
X_{310}	$\mathbf{W}_{v,D,B}$	2		0
X_{311}	$\mathbf{W}_{m,D,C}$	2		0
X_{312}	$\mathbf{W}_{b,D,C}$	2		0
X_{313}	$\mathbf{W}_{v,D,C}$	2		0

Fig. 30 Role matrix **ms** of the timing characteristics for the first-order adaptation **W**-states for interaction enabling showing that their speed factors all are 2 and initial values 0.

ms	**speed factors**	**1**	**iv**	**1**
X_{314}	$\mathbf{agg}_{\text{sensA}}$	1		0
X_{315}	$\mathbf{agg}_{\text{execA}}$	1		0
X_{316}	$\mathbf{agg}_{\text{syncA}}$	1		0
X_{317}	$\mathbf{agg}_{\mathbf{W}_{\text{sense-repA}}}$	1		0
X_{318}	$\mathbf{agg}_{\mathbf{W}_{\text{rep-prepA}}}$	1		0
X_{319}	$\mathbf{agg}_{\mathbf{W}_{\text{prep-execA}}}$	1		0
X_{320}	$\mathbf{agg}_{\mathbf{W}_{\text{A}}}$	1		0

ms	**speed factors**	**1**	**iv**	**1**
X_{342}	$\mathbf{H}_{\mathbf{W_A}}$	0.005		0
X_{343}	$\mathbf{H}_{\mathbf{T_A}}$	0.1		0
X_{344}	$\mathbf{W}_{\mathbf{W_A}}$	0.005		0
X_{345}	$\mathbf{W}_{\mathbf{T_A}}$	0.009		0

Fig. 31 Role matrix **ms** of the timing characteristics for the second-order adaptation states showing their speed factors and initial values.

Role matrix **mcfw** defines part of the network characteristics for aggregation by indicating the selection of combination functions; see Fig. 32 to 35. Another part of the network characteristics for aggregation is specified by matrix **mcfp** for parameter values of selected combination functions.

mcfw	**combination function weights**	**1 alogistic**	**2 sync detector compdiff**	**3 stepmod**	**4 eucl**	**5 scenario generation**	**6 alogisticneg**
X_1	ws_s			1			
X_2	$\text{con}_{th,A}$				1		
X_3	$\text{con}_{th,B}$				1		
X_4	$\text{con}_{th,C}$				1		
X_5	$\text{con}_{th,D}$				1		
X_6	$\text{sense}_{s,A}$				1		
X_7	$\text{sense}_{B,m,A}$				1		
X_8	$\text{sense}_{B,b,A}$				1		
X_9	$\text{sense}_{B,v,A}$				1		
X_{10}	$\text{sense}_{C,m,A}$				1		
X_{11}	$\text{sense}_{C,b,A}$				1		
X_{12}	$\text{sense}_{C,v,A}$				1		
X_{13}	$\text{sense}_{D,m,A}$				1		
X_{14}	$\text{sense}_{D,b,A}$				1		
X_{15}	$\text{sense}_{D,v,A}$				1		
X_{16}	$\text{rep}_{s,A}$	1					
X_{17}	$\text{rep}_{B,m,A}$	1					
X_{18}	$\text{rep}_{B,b,A}$	1					

X_{19}	$rep_{B,v,A}$	1					
X_{20}	$rep_{C,m,A}$	1					
X_{21}	$rep_{C,b,A}$	1					
X_{22}	$rep_{C,v,A}$	1					
X_{23}	$rep_{D,m,A}$	1					
X_{24}	$rep_{D,b,A}$	1					
X_{25}	$rep_{D,v,A}$	1					
X_{26}	$prep_{m,A}$	1					
X_{27}	$prep_{b,A}$	1					
X_{28}	$prep_{v,A}$	1					
X_{29}	$intersyncdet_{B,A,m}$		1				
X_{30}	$intersyncdet_{B,A,b}$		1				
X_{31}	$intersyncdet_{B,A,v}$		1				
X_{32}	$intersyncdet_{C,A,m}$		1				
X_{33}	$intersyncdet_{C,A,b}$		1				
X_{34}	$intersyncdet_{C,A,v}$		1				
X_{35}	$intersyncdet_{D,A,m}$		1				
X_{36}	$intersyncdet_{D,A,b}$		1				
X_{37}	$intersyncdet_{D,A,v}$		1				
X_{38}	$move_{m,A}$	1					
X_{39}	$express_{b,A}$	1					
X_{40}	$talk_{A,B,v}$	1					

Fig. 32 Role matrix **mcfw** of the aggregation characteristics for the base states of agent A specifying the combination functions used for them.

mcfw	combination function weights	1 alogistic	2 sync detector compdiff	3 stepmod	4 eucl	5 scenario generation	6 alogisticneg
X_{146}	$\mathbf{W}_{sense\text{-}rep\_m,B,A}$	1					
X_{147}	$\mathbf{W}_{sense\text{-}rep\_b,B,A}$	1					
X_{148}	$\mathbf{W}_{sense\text{-}rep\_v,B,A}$	1					
X_{149}	$\mathbf{W}_{sense\text{-}rep\_m,C,A}$	1					
X_{150}	$\mathbf{W}_{sense\text{-}rep\_b,C,A}$	1					
X_{151}	$\mathbf{W}_{sense\text{-}rep\_v,C,A}$	1					
X_{152}	$\mathbf{W}_{sense\text{-}rep\_m,D,A}$	1					
X_{153}	$\mathbf{W}_{sense\text{-}rep\_b,D,A}$	1					
X_{154}	$\mathbf{W}_{sense\text{-}rep\_v,D,A}$	1					
X_{155}	$\mathbf{W}_{rep\text{-}prep\_m,B,A}$	1					
X_{156}	$\mathbf{W}_{rep\text{-}prep\_b,B,A}$	1					
X_{157}	$\mathbf{W}_{rep\text{-}prep\_v,B,A}$	1					
X_{158}	$\mathbf{W}_{rep\text{-}prep\_m,C,A}$	1					
X_{159}	$\mathbf{W}_{rep\text{-}prep\_b,C,A}$	1					
X_{160}	$\mathbf{W}_{rep\text{-}prep\_v,C,A}$	1					
X_{161}	$\mathbf{W}_{rep\text{-}prep\_m,D,A}$	1					
X_{162}	$\mathbf{W}_{rep\text{-}prep\_b,D,A}$	1					
X_{163}	$\mathbf{W}_{rep\text{-}prep\_v,D,A}$	1					
X_{164}	$\mathbf{W}_{prep\text{-}exec\_m,A}$	1					
X_{165}	$\mathbf{W}_{prep\text{-}exec\_b,A}$	1					
X_{166}	$\mathbf{W}_{prep\text{-}exec\_v,A}$	1					
X_{167}	$\mathbf{T}_{rep\_B,m,A}$	1					
X_{168}	$\mathbf{T}_{rep\_B,b,A}$	1					
X_{169}	$\mathbf{T}_{rep\_B,v,A}$	1					
X_{170}	$\mathbf{T}_{rep\_C,m,A}$	1					
X_{171}	$\mathbf{T}_{rep\_C,b,A}$	1					
X_{172}	$\mathbf{T}_{rep\_C,v,A}$	1					
X_{173}	$\mathbf{T}_{rep\_D,m,A}$	1					
X_{174}	$\mathbf{T}_{rep\_D,b,A}$	1					
X_{175}	$\mathbf{T}_{rep\_D,v,A}$	1					
X_{176}	$\mathbf{T}_{exec\_m,A}$	1					
X_{177}	$\mathbf{T}_{exec\_b,A}$	1					
X_{178}	$\mathbf{T}_{exec\_v,A}$	1					

Fig. 33 Role matrix **mcfw** of the aggregation characteristics for the first-order adaptation **W**-states and **T**-states of agent A specifying that all of them use the combination function **alogistic**.

mcfw	combination function weights	1 alogistic	2 sync detector compdiff	3 stepmod	4 eucl	5 scenario generation	6 alogisticneg
X_{278}	$\mathbf{W}_{m,A,B}$					1	
X_{279}	$\mathbf{W}_{b,A,B}$					1	
X_{280}	$\mathbf{W}_{v,A,B}$					1	
X_{281}	$\mathbf{W}_{m,A,C}$					1	
X_{282}	$\mathbf{W}_{b,A,C}$					1	
X_{283}	$\mathbf{W}_{v,A,C}$					1	
X_{284}	$\mathbf{W}_{m,A,D}$					1	
X_{285}	$\mathbf{W}_{b,A,D}$					1	
X_{286}	$\mathbf{W}_{v,A,D}$					1	
X_{287}	$\mathbf{W}_{m,B,A}$					1	
X_{288}	$\mathbf{W}_{b,B,A}$					1	
X_{289}	$\mathbf{W}_{v,B,A}$					1	
X_{290}	$\mathbf{W}_{m,B,C}$					1	
X_{291}	$\mathbf{W}_{b,B,C}$					1	
X_{292}	$\mathbf{W}_{v,B,C}$					1	
X_{293}	$\mathbf{W}_{m,B,D}$					1	
X_{294}	$\mathbf{W}_{b,B,D}$					1	
X_{295}	$\mathbf{W}_{v,B,D}$					1	
X_{296}	$\mathbf{W}_{m,C,A}$					1	
X_{297}	$\mathbf{W}_{b,C,A}$					1	
X_{298}	$\mathbf{W}_{v,C,A}$					1	
X_{299}	$\mathbf{W}_{m,C,B}$					1	
X_{300}	$\mathbf{W}_{b,C,B}$					1	
X_{301}	$\mathbf{W}_{v,C,B}$					1	
X_{302}	$\mathbf{W}_{m,C,D}$					1	
X_{303}	$\mathbf{W}_{b,C,D}$					1	
X_{304}	$\mathbf{W}_{v,C,D}$					1	
X_{305}	$\mathbf{W}_{m,D,A}$					1	
X_{306}	$\mathbf{W}_{b,D,A}$					1	
X_{307}	$\mathbf{W}_{v,D,A}$					1	
X_{308}	$\mathbf{W}_{m,D,B}$					1	
X_{309}	$\mathbf{W}_{b,D,B}$					1	
X_{310}	$\mathbf{W}_{v,D,B}$					1	
X_{311}	$\mathbf{W}_{m,D,C}$					1	
X_{312}	$\mathbf{W}_{b,D,C}$					1	
X_{313}	$\mathbf{W}_{v,D,C}$					1	

Fig. 34 Role matrix **mcfw** of the aggregation characteristics for the first-order adaptation **W**-states for interaction enabling specifying that all of them use the combination function called **scenario generation**.

mcfw	combination function weights	1 alogistic	2 sync detector compdiff	3 stepmod	4 eucl	5 scenario generation	6 alogisticneg
X_{314}	$\mathbf{agg}_{sensA}$				1		
X_{315}	$\mathbf{agg}_{execA}$				1		
X_{316}	$\mathbf{agg}_{syncA}$				1		
X_{317}	$\mathbf{agg}\mathbf{w}_{sense\text{-}repA}$				1		
X_{318}	$\mathbf{agg}\mathbf{w}_{rep\text{-}prepA}$				1		
X_{319}	$\mathbf{agg}\mathbf{w}_{prep\text{-}execA}$				1		
X_{320}	$\mathbf{agg}\mathbf{w}_{A}$				1		

mcfw	combination function weights	1 alogistic	2 sync detector compdiff	3 stepmod	4 eucl	5 scenario generation	6 alogisticneg
X_{342}	$\mathbf{H}_{\mathbf{W}_\mathbf{A}}$	1					
X_{343}	$\mathbf{H}_{\mathbf{T}_\mathbf{A}}$	1					
X_{344}	$\mathbf{W}_{\mathbf{W}_\mathbf{A}}$	1					
X_{345}	$\mathbf{W}_{\mathbf{T}_\mathbf{A}}$						1

Fig. 35 Role matrix **mcfw** of the aggregation characteristics for the second-order adaptation states of agent A specifying the combination functions used for them.

In role matrix **mcfp** the parameters of the chosen combination functions are shown, see Figures 36 to 39. In Fig. 36 it is shown that the representation states and execution states of agent A have adaptive excitability thresholds represented by first-order adaptation **W**-states X_{167} to X_{175} and **T**-states X_{176} to X_{178}.

mcfp	combination function parameters	1 alogistic		2 sync detector compdiff		3 stepmod		4 eucl		5 scenario generation		6 alogisticneg	
X_1	ws_s					80	40						
X_2	$con_{th,A}$							1	1				
X_3	$con_{th,B}$							1	1				
X_4	$con_{th,C}$							1	1				
X_5	$con_{th,D}$							1	1				
X_6	$sense_{s,A}$							1	1				
X_7	$sense_{B,m,A}$							1	1				
X_8	$sense_{B,b,A}$							1	1				
X_9	$sense_{B,v,A}$							1	1				
X_{10}	$sense_{C,m,A}$							1	1				
X_{11}	$sense_{C,b,A}$							1	1				
X_{12}	$sense_{C,v,A}$							1	1				
X_{13}	$sense_{D,m,A}$							1	1				
X_{14}	$sense_{D,b,A}$							1	1				
X_{15}	$sense_{D,v,A}$							1	1				
X_{16}	$rep_{s,A}$	5	0.5										
X_{17}	$rep_{B,m,A}$	5	X_{167}										
X_{18}	$rep_{B,b,A}$	5	X_{168}										
X_{19}	$rep_{B,v,A}$	5	X_{169}										
X_{20}	$rep_{C,m,A}$	5	X_{170}										
X_{21}	$rep_{C,b,A}$	5	X_{171}										
X_{22}	$rep_{C,v,A}$	5	X_{172}										
X_{23}	$rep_{D,m,A}$	5	X_{173}										
X_{24}	$rep_{D,b,A}$	5	X_{174}										
X_{25}	$rep_{D,v,A}$	5	X_{175}										
X_{26}	$prep_{m,A}$	5	0.8										
X_{27}	$prep_{b,A}$	5	0.8										
X_{28}	$prep_{v,A}$	5	0.8										
X_{29}	$intersyncdet_{B,A,m}$												
X_{30}	$intersyncdet_{B,A,b}$												
X_{31}	$intersyncdet_{B,A,v}$												
X_{32}	$intersyncdet_{C,A,m}$												
X_{33}	$intersyncdet_{C,A,b}$												

X_{34}	$\text{intersyncdet}_{C,A,v}$												
X_{35}	$\text{intersyncdet}_{D,A,m}$												
X_{36}	$\text{intersyncdet}_{D,A,b}$												
X_{37}	$\text{intersyncdet}_{D,A,v}$												
X_{38}	$\text{move}_{m,A}$	5	X_{176}										
X_{39}	$\text{express}_{b,A}$	5	X_{177}										
X_{40}	$\text{talk}_{A,B,v}$	5	X_{178}										

Fig. 36 Role matrix **mcfp** of the aggregation characteristics for the base states of agent A specifying the parameters of the combination functions used.

Concerning Figure 36, note that in order to have some small differences slight variations in the scaling factors for the Euclidean function between the agents have been made:

- Agent A has scaling factors 1 for all sensing states
- Agent B has scaling factors 1.05 instead of 1 for all sensing states
- Agent C has same scaling factors 1 like agent A for all sensing states
- Agent D has scaling factors 1.1 instead of 1 for all sensing states

mcfp	combination function parameters	1 alogistic		2 sync detector compdiff		3 stepmod		4 eucl		5 scenario generation		6 alogisticneg	
X_{146}	$\mathbf{W}_{\text{sense-rep\_}m,B,A}$	5	0.5										
X_{147}	$\mathbf{W}_{\text{sense-rep\_}b,B,A}$	5	0.5										
X_{148}	$\mathbf{W}_{\text{sense-rep\_}v,B,A}$	5	0.5										
X_{149}	$\mathbf{W}_{\text{sense-rep\_}m,C,A}$	5	0.5										
X_{150}	$\mathbf{W}_{\text{sense-rep\_}b,C,A}$	5	0.5										
X_{151}	$\mathbf{W}_{\text{sense-rep\_}v,C,A}$	5	0.5										
X_{152}	$\mathbf{W}_{\text{sense-rep\_}m,D,A}$	5	0.5										
X_{153}	$\mathbf{W}_{\text{sense-rep\_}b,D,A}$	5	0.5										
X_{154}	$\mathbf{W}_{\text{sense-rep\_}v,D,A}$	5	0.5										
X_{155}	$\mathbf{W}_{\text{rep-prep\_}m,B,A}$	5	0.5										
X_{156}	$\mathbf{W}_{\text{rep-prep\_}b,B,A}$	5	0.5										
X_{157}	$\mathbf{W}_{\text{rep-prep\_}v,B,A}$	5	0.5										
X_{158}	$\mathbf{W}_{\text{rep-prep\_}m,C,A}$	5	0.5										
X_{159}	$\mathbf{W}_{\text{rep-prep\_}b,C,A}$	5	0.5										
X_{160}	$\mathbf{W}_{\text{rep-prep\_}v,C,A}$	5	0.5										
X_{161}	$\mathbf{W}_{\text{rep-prep\_}m,D,A}$	5	0.5										
X_{162}	$\mathbf{W}_{\text{rep-prep\_}b,D,A}$	5	0.5										
X_{163}	$\mathbf{W}_{\text{rep-prep\_}v,D,A}$	5	0.5										
X_{164}	$\mathbf{W}_{\text{prep-exec\_}m,A}$	5	0.5										
X_{165}	$\mathbf{W}_{\text{prep-exec\_}b,A}$	5	0.5										
X_{166}	$\mathbf{W}_{\text{prep-exec\_}v,A}$	5	0.5										
X_{167}	$\mathbf{T}_{\text{rep\_}B,m,A}$	5	0.6										
X_{168}	$\mathbf{T}_{\text{rep\_ }B,b,A}$	5	0.6										
X_{169}	$\mathbf{T}_{\text{rep\_ }B,v,A}$	5	0.6										
X_{170}	$\mathbf{T}_{\text{rep\_}C,m,A}$	5	0.6										
X_{171}	$\mathbf{T}_{\text{rep\_ }C,b,A}$	5	0.6										
X_{172}	$\mathbf{T}_{\text{rep\_ }C,v,A}$	5	0.6										
X_{173}	$\mathbf{T}_{\text{rep\_}D,m,A}$	5	0.6										
X_{174}	$\mathbf{T}_{\text{rep\_ }D,b,A}$	5	0.6										
X_{175}	$\mathbf{T}_{\text{rep\_ }D,v,A}$	5	0.6										
X_{176}	$\mathbf{T}_{\text{exec\_}m,A}$	5	0.6										
X_{177}	$\mathbf{T}_{\text{exec\_}b,A}$	5	0.6										
X_{178}	$\mathbf{T}_{\text{exec\_}v,A}$	5	0.6										

Fig. 37 Role matrix **mcfp** of the aggregation characteristics for the first-order adaptation **W**-states and **T**-states of agent A specifying the steepness and threshold parameters of the combination function **alogistic** used for them.

mcfp	combination function parameters	1 alogistic		2 sync detector compdiff		3 stepmod		4 eucl		5 scenario generation		6 alogisticneg	
X_{278}	$\mathbf{W}_{m,A,B}$									1			
X_{279}	$\mathbf{W}_{b,A,B}$									2			
X_{280}	$\mathbf{W}_{v,A,B}$									3			
X_{281}	$\mathbf{W}_{m,A,C}$									4			
X_{282}	$\mathbf{W}_{b,A,C}$									5			
X_{283}	$\mathbf{W}_{v,A,C}$									6			
X_{284}	$\mathbf{W}_{m,A,D}$									7			
X_{285}	$\mathbf{W}_{b,A,D}$									8			
X_{286}	$\mathbf{W}_{v,A,D}$									9			
X_{287}	$\mathbf{W}_{m,B,A}$									10			
X_{288}	$\mathbf{W}_{b,B,A}$									11			
X_{289}	$\mathbf{W}_{v,B,A}$									12			
X_{290}	$\mathbf{W}_{m,B,C}$									13			
X_{291}	$\mathbf{W}_{b,B,C}$									14			
X_{292}	$\mathbf{W}_{v,B,C}$									15			
X_{293}	$\mathbf{W}_{m,B,D}$									16			
X_{294}	$\mathbf{W}_{b,B,D}$									17			
X_{295}	$\mathbf{W}_{v,B,D}$									18			
X_{296}	$\mathbf{W}_{m,C,A}$									19			
X_{297}	$\mathbf{W}_{b,C,A}$									20			
X_{298}	$\mathbf{W}_{v,C,A}$									21			
X_{299}	$\mathbf{W}_{m,C,B}$									22			
X_{300}	$\mathbf{W}_{b,C,B}$									23			
X_{301}	$\mathbf{W}_{v,C,B}$									24			
X_{302}	$\mathbf{W}_{m,C,D}$									25			
X_{303}	$\mathbf{W}_{b,C,D}$									26			
X_{304}	$\mathbf{W}_{v,C,D}$									27			
X_{305}	$\mathbf{W}_{m,D,A}$									28			
X_{306}	$\mathbf{W}_{b,D,A}$									29			
X_{307}	$\mathbf{W}_{v,D,A}$									30			
X_{308}	$\mathbf{W}_{m,D,B}$									31			
X_{309}	$\mathbf{W}_{b,D,B}$									32			
X_{310}	$\mathbf{W}_{v,D,B}$									33			
X_{311}	$\mathbf{W}_{m,D,C}$									34			
X_{312}	$\mathbf{W}_{b,D,C}$									35			
X_{313}	$\mathbf{W}_{v,D,C}$									36			

Fig. 38 Role matrix **mcfp** of the aggregation characteristics for the first-order adaptation **W**-states for interaction enabling specifying the parameter of the combination function **scenario generation** used; this parameter represents a state identifier, to distinguish the different states for which this function is used.

mcfp	combination function parameters	1 alogistic		2 sync detector compdiff		3 stepmod		4 eucl		5 scenario generation		6 alogisticneg	
X_{314}	$\mathbf{agg}_{\text{sensA}}$							1	1				
X_{315}	$\mathbf{agg}_{\text{execA}}$							1	0.3				
X_{316}	$\mathbf{agg}_{\text{syncA}}$							1	0.9				
X_{317}	$\mathbf{aggW}_{\text{sense-repA}}$							1	0.9				
X_{318}	$\mathbf{aggW}_{\text{rep-prepA}}$							1	0.9				
X_{319}	$\mathbf{aggW}_{\text{prep-execA}}$							1	0.3				
X_{320}	$\mathbf{aggW}_{\text{A}}$							1	0.3				

mcfp	combination function parameters	1 alogistic		2 sync detector compdiff		3 stepmod		4 eucl		5 scenario generation		6 alogisticneg	
X_{342}	$\mathbf{H}_{\mathbf{W}_{\mathbf{A}}}$	5	0.8										
X_{343}	$\mathbf{H}_{\mathbf{T}_{\mathbf{A}}}$	5	0.8										
X_{344}	$\mathbf{W}_{\mathbf{W}_{\mathbf{A}}}$	5	0.2										
X_{345}	$\mathbf{W}_{\mathbf{T}_{\mathbf{A}}}$											2	0

Fig. 39 Role matrix **mcfp** of the aggregation characteristics for the second-order adaptation states of agent A specifying the parameters of the combination functions used.

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