



Perspectives on Social Interaction Science: From a Multilevel Multi-timescale Computational Architecture for Synchrony-Induced and Homophily-Induced Attunement to Designing Bonding Bots

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Abstract. In this paper a generic computational architecture for social interaction adaptivity and attunement is presented that was developed based on unification of a number of specific case studies addressed earlier. This architecture describes a generic multilevel multi-timescale adaptive dynamical system and is formalised and represented as a multi-order self-modeling network. It is shown how this architecture covers different earlier case studies addressing social interaction adaptivity and attunement subsuming synchrony- or homophily-induced adaptivity. Moreover, it is shown how based on it a new application to the design of bonding bots is realised that supports interpersonal emotion regulation via adaptive human-bot interaction and attunement.

Keywords: Social interaction · homophily · synchrony · adaptivity · similarity · connectedness · computational architecture · multilevel · multi-timescale · bonding bot

1 Introduction: Social Interaction Adaptivity

A central focus in this paper is on unification of the contributions in our research line on computational methods for social interaction science. The emphasis is on modeling and analysis of multimodal mental and social interaction dynamics adaptivity and attunement as occurs in affiliation and bonding from underlying causal mechanisms and pathways. The paper will contribute a unified computational architecture that covers several case studies analysed in the past and was also evaluated based on a new analysis to design bonding bots that interact with humans in order to obtain interpersonal emotion regulation.

The processes where people mutually coordinate their behavior have been studied under various labels, including alignment (Shamay-Tsoory et al., 2019), mimicry (Bourgeois & Hess, 2008), interpersonal coordination (dynamics), coregulation (Butler & Randall, 2013), concordance (Bilodeau-Houle et al., 2023), coupling (Goldstein et al., 2017), matching (Bernieri & Rosenthal, 1991), and mirroring (Gorman et al., 2017). We use the term ‘interpersonal synchrony’ or simply ‘synchrony’, to refer to mutually coordinated behavioral patterns over time displayed by two or more agents (AtzilSlonim et al., 2023; Basso et al., 2021; Cirelli, 2018; Czeszumski et al., 2022; Feldman, 2012; Koole and Tschacher, 2016; Palumbo et al., 2017; Semin, 2007; Shamay-Toory et al., 2019). Also in the area referred as ‘bonding by homophily’, it has been studied how during social interaction people can form bonds, e.g., (McPherson, Smith-Lovin, Cook, 2001). The term ‘homophily’ is used here: it concerns states or characteristics of two persons that are (approximately) the same at a given point in time, such as an emotion, opinion or a preference (McPherson et al, 2001).

The computational architecture proposed in the current paper provides a form of unification of the types of processes and phenomena mentioned. Throughout this work, we have sought to allow computational modeling and empirical science to mutually benefit from each other. More specifically, we used the causal relationships and pathways described in empirical literature to explain certain phenomena as the foundation for a programmatic series of computational adaptive dynamical system models. These were designed as higher-order adaptive network models based on the self-modeling or reification principle introduced in (Treur, 2018) and extended to multiple levels in (Treur, 2019; Treur 2020a), see also (Treur, 2020b; 2020c).

Such empirical literature usually has an emphasis on showing that these mechanisms and pathways are necessary for the phenomenon to be explained: if these mechanisms are (made) disfunctional, the phenomenon does not occur. But whether the presumed mechanisms on their own are sufficient to let the phenomenon emerge is another, much harder question to answer empirically due to the high extent of contextuality. Contributions from other mechanisms than the presumed ones that are left implicit but are present in the context cannot be excluded empirically in an easy manner as many of such mechanisms naturally occur in all real humans that act in experiments.

One of the major advantages of computational modeling is that it can test whether proposed correlations between such mechanisms and phenomena indeed can be confirmed computationally by *in silico* experiments (experiments through computer simulations), both in the necessary and sufficiency sense. This allows researchers to verify whether what leads to the emergence of certain observed phenomena are indeed the presumed causal relationships and not other mechanisms left implicit. Moreover, in specific cases where there is doubt on the mechanisms involved it means that researchers can ask themselves whether any additional mechanisms that are tacitly assumed are needed explicitly and check this computationally. Furthermore, in cases where the empirical literature does not show all necessary specific mechanisms in detail, assumptions can be made about the missing details and based on that it can be verified computationally whether and to what extent they lead to the phenomena of interest. Consequently, in the research we have sought to achieve a mutual exchange between empirical science and computational science.

2 Coevolution of Similarity and Induced Connectedness

During social interaction different forms of ‘becoming connected’ may develop. This may concern shorter term forms such as affiliation during a meeting or therapy session or a joint action that is undertaken. But also longer term forms often develop indicated, for example, by friendships, lifelong relationships or bonding. In this paper we will use the term ‘connectedness’ to subsume all such different types of becoming connected in one way or the other (Fig. 1).

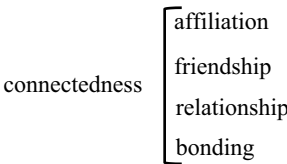


Fig. 1. Different forms of becoming connected: shorter-term and longer-term

There are two areas that particularly address how such connectedness may develop: homophily-induced connectedness and (interpersonal) synchrony-induced connectedness. The first area was developed mostly from sociology and social science (see Sect. 2.1), the second mostly from social and clinical psychology (see Sect. 2.2).

2.1 Homophily-Induced Connectedness

Already in early research in the area of social networks an important focus was on the relationship between connectedness between persons and the extent of similarity of them. For example in (McPherson et al, 2001) it is put forward that the relationship between connectedness and similarity is mentioned by Aristotle by writing that people ‘love those who are like themselves’ (Aristotle, 1934, p. 1371) and Plato writing ‘similarity begets friendship’ (Plato, 1968, p. 837). Systematic observations of group formation and network ties by social scientists began in the 1920s and 1930s. For example, (Bott, 1928; Wellman, 1929; Hubbard, 1929) reported that school children formed friendships and play groups at higher rates if they were similar on demographic characteristics (McPherson et al, 2001). An important contribution to the sociological literature is (Lazarsfeld & Merton, 1954) about forming friendships. They use the term ‘homophily’ and to describe the process they also quoted the metaphoric expression

‘Birds of a feather flock together’ (Lazarsfeld & Merton, 1954)

which has often been used in the literature since then (McPherson et al, 2001). For a further historical review, see (Freeman 1996). Although in such literature often the emphasis may seem on the causal effect that the extent of homophily has on (strengthened) connectedness such as friendship, usually there is still a causal effect in the opposite direction as well. By social contagion, persons that have strong connectedness can strengthen their extent of homophily. Unfortunately, the above metaphor is not applicable to describe this

opposite causal effect: it is very unlikely that feathers of birds can change due to flocking together. Nevertheless, for many cases a bidirectional causal mechanism is considered realistic and sometimes described by the term coevolution which means that over time:

- connectedness evolves via adaptation under influence of the extent of homophily
- homophily evolves via social contagion under influence of the extent of connectedness

Especially when homophily is considered for personal characteristics or states that can change over time, such as opinions, emotions, or preferences for types of movies or music, it is assumed that these can become attuned to each other due to social contagion. In turn, social contagion depends on strength of connectedness, so in this way you indeed get the above circular feedback loop.

In recent years this circular coevolution process in relation to homophily has been modeled from an adaptive dynamical system perspective (Port and van Gelder, 1995), often in a network-oriented manner, see, for example, (Blankendaal, Parinussa, Treur, 2016; Luo, Du, Liu, Xuan, Wang, 2015; Hsieh, König, Liu, 2022; King, Smith, Webb, 2024; Liu, Huang, Aden, Johnson, Song, 2023; Sharpanskykh and Treur, 2014; Snijders, Steglich, Schweinberger, 2017; Su, Liu, Li, Ma, 2014; Treur, 2019; Van den Beukel, Goos, Treur, 2019). Simulations based on such adaptive computational network models have demonstrated how such a circular coevolution process can explain, for example, the emergence of clusters or communities, or segregation in society, e.g., (Kappert, Rus, Treur, 2018; Heijmans, Van Stijn, Treur, 2020).

Perhaps because homophily-induced connectedness often has been addressed from a social science or sociology perspective, in computational models for coevolution as indicated in the previous paragraph usually no internal mental states are taken into account. In particular, the underlying criterion of homophily is usually based on objective states in the social world as considered from an external observer perspective. However, in reality, for one of the persons to notice a form of homophily, a process of perception and interpretation plays an important role. For example, are you sure that the other person really prefers the same type of music? Therefore, in some work on homophily-induced connectedness this subjective perspective is addressed. Here, the connectedness is induced by subjective homophily detection, not by objective homophily (Treur, 2022; Mukeriia, Treur, Hendrikse, 2023; Mukeriia, Treur, Hendrikse, 2024), see also (Treur, 2025; Mukeriia, Treur, Hendrikse, 2025a; Mukeriia, Treur, Hendrikse, 2025b). In such a case also manipulation of homophily can be modelled, for example, by faking that you like the same type of movies as your friend does (Bössenecker, Mreijen, Treur, 2022), see also (Bössenecker, Mreijen, Treur, 2025).

2.2 Synchrony-Induced Connectedness

In the analysis in Sect. 2.1, the term homophily can also be generalised so that also the notion interpersonal synchrony is covered. The concept ‘synchrony-induced connectedness’, has been explored extensively in literature such as (Hove and Risen, 2009; Tarr, Launay, Dunbar, 2016; Vacharkulksemsuk and Fredrickson, 2012; Valdesolo and DeSteno, 2011; Valdesolo, Ouyang, DeSteno, 2010; Wiltermuth and Heath, 2009).

Within the area focusing on synchrony, research has documented how people spontaneously synchronize their activities in a variety of ways, including their movements (Bernieri, 1988; Cirelli, 2018; Oullier et al., 2007), vocal pitch (Schoenherr et al., 2021; Tomprou et al., 2021; Yokozuka, Miyamoto, Kasai, Miyake, Nozawa, 2021), linguistic expressions (Doré and Morris, 2018; Goode and Robinson, 2013; Shapira et al., 2022), their physiological responses (Palumbo et al., 2017) and neural responses (Shamay-Toory et al., 2019). These interpersonal dynamics play a role in many relationships over the lifetime. Already in utero, infants synchronize their heart beats with their mother's heart beats (Ivanov, Ma, Bartsch, 2009; Van Leeuwen et al., 2009). After birth, children develop autonomous emotion regulation from physiological synchrony that they exhibit with their caretaker (Feldman, 2007). Moreover, when adults form close relationships, they are prone to synchronize their physiological responses (Palumbo et al., 2017). Neural synchrony can also elevate within parent-child relationships (Reindl, Gerloff, Scharke, Konrad, 2018), romantic relationships (Kinreich, Djalovski, Kraus, Louzoun, & Feldman, 2017) or persons who play together guitar (Müller, Sängler, Lindenberger, 2018). Strangers may even synchronize their physiological responses by merely watching the same event (Konvalinka et al., 2011). Interpersonal synchrony is thus a pervasive pattern in social life.

Importantly, interpersonal synchrony has been shown to have important psychological consequences concerning adaptation of the social interaction behaviour. For instance, it has been found that people bond more with each other after they were experimentally induced to synchronize their movements (Tarr, Launay, Dunbar, 2016). Furthermore, leading people to synchronize by singing or laughing together has been shown to stimulate more cooperative behavior (Wiltermuth and Heath, 2009). Perhaps most impressively, experimentally inducing synchrony in brain-to-brain activity has been found to improve joint performance on cognitive tasks (Pan, Novembre, Song, Zhu, Hu, 2021). These and related studies demonstrate that interpersonal synchrony is not merely an epiphenomenon, but that it actually shapes interpersonal dynamics in an adaptive manner. Consequently, it seems important to learn more about the nature of interpersonal synchrony.

Given the above, like for homophily as discussed in Sect. 2.1, from a dynamical system perspective also for synchrony an overall circular pattern of coevolution over time has been found:

- connectedness evolves via adaptation under influence of the extent of synchrony
- synchrony evolves via social contagion under influence of the extent of connectedness

Recently, this type of coevolution processes have been analysed computationally in (Hendrikse, Treur, Koole, 2023; Hendrikse, Treur, Koole, 2024; Hendrikse, Treur, Wilderjans, Dikker, Koole, 2022a, 2022b, 2022c, 2022d; Hendrikse, Treur, Wilderjans, Dikker, Koole, 2023); see also (Hendrikse, Treur, Koole, 2025a; Hendrikse, Treur, Koole, 2025b; Hendrikse, Treur, Wilderjans, Dikker, Koole, 2025a, 2025b, 2025c, 2025d, 2025e). To achieve this, based on the temporal factorisation principle from (Treur, 2007a, 2007b), the notion of subjective synchrony detection was postulated to indicate how a person can actually notice being in synchrony with someone else.

Adaptive self-modeling network models were very useful to address the complexity of this type of adaptive dynamical systems. This developed adaptive dynamical system

modeling approach to synchrony-based connectedness has been successfully applied to model complex social phenomena such as adaptive interpersonal emotion regulation and adaptive collective phenomena involving elderly in (Eler, Treur, Hendrikse, Donker, Koole, 2024; Vervoordeldonk, Treur, Hendrikse, Roelofsma, 2024; Xu, Treur, Hendrikse, Roelofsma, 2024); see also (Eler, Treur, Hendrikse, Donker, Koole, 2024; Vervoordeldonk, Treur, Hendrikse, Roelofsma, 2025; Xu, Treur, Hendrikse, Roelofsma, 2025).

2.3 A Unified View on Coevolution: Similarity-Induced Connectedness

To unify the two types of coevolution discussed in Sects. 2.2.2 and 2.2.2, in this paper, we will use the term similarity as generalisation subsuming different forms of both homophily and synchrony (Fig. 2).

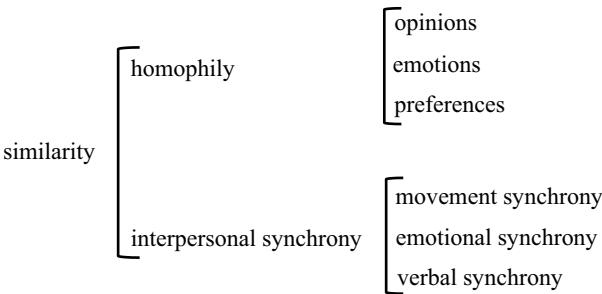


Fig. 2. Different forms of similarity subsuming homophily and interpersonal synchrony

The two co-evolution patterns indicated here then can be unified as a more general circular coevolution pattern as shown in Fig. 3.

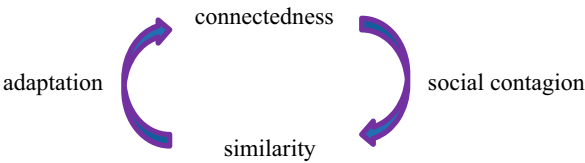


Fig. 3. Coevolution of similarity and connectedness as unified view

This perspective provides a conceptual basis for the unified computational view based on multilevel multi-timescale dynamical system modeling that is developed in the current paper.

In Fig. 4 an informal global conceptual architecture is shown for adaptive (multimodal) social interaction for coevolution processes as depicted in Fig. 3. This is used as point of departure for the computational architecture proposed in this paper. It considers base level mechanisms, multimodal interaction and different types of social interaction adaptivity. This conceptual architecture generalises and refines what is depicted in (Górriz et al, 2023, Fig. 13), by this time subsuming both homophily-induced connectedness and synchrony-induced connectedness (using the more abstract term similarity for homophily and synchrony) and by distinguishing different levels of adaptivity, in particular, first-order and second-order adaptivity, see Fig. 4.

At the base level, basic mechanisms are covered (see the pink boxes in Fig. 4), for example, for representing based on (multimodal) sensory processing, for responding by preparing for actions, and for executing by performing prepared actions. As part of the base level, also some form of (subjective) similarity detection is assumed by which each of the persons can subjectively notice similarity, for example, in terms of homophily or synchrony. At this base level, also the actual multimodal interaction between two agents takes place, indicated by the green boxes and green arrows in Fig. 4.

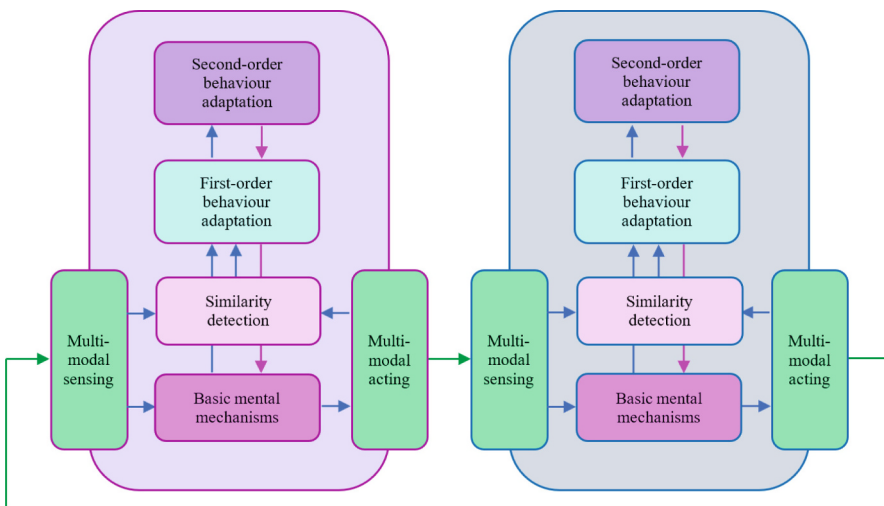


Fig. 4. Informal overall conceptual architecture for adaptive multimodal social interaction; generalised and refined version of Fig. 13 contributed by the current authors to (Góriz et al, 2023).

First-order adaptivity is indicated by the light-blue boxes in Fig. 4. It can cover, for example, plasticity of structures in the brain such as connectivity adaptation by Bainian or Hebbian learning (Bain, 1873; Hebb, 1949) or intrinsic excitability adaptation as described in (Chandra and Barkai, 2018; Debanne, Inglebert, Russier, 2019).

Second-order adaptivity is indicated by the purple boxes in Fig. 4. This provides context-sensitive control over first-order adaptivity, also called metaplasticity; see for example (Abraham and Bear, 1996; Robinson, Harper, McAlpine, 2016; Sjöström, Rancz, Roth, Häusser, 2008). These forms of adaptivity and their interaction will be discussed in more detail in Sect. 4 and formalised in a proposed computational architecture Sect. 6.

In this paper, we consider connectedness concepts such as affiliation and bonding in an operational manner from the perspective of changing mental and social interaction processes. Hereby we consider different time scales. For example, affiliation can happen on a short-term time scale (like one 45 min therapy session), bonding on a longer-term time scale (like a longer series of therapy sessions). These time scales are both much slower in comparison to the very fast time scale of milliseconds or seconds of the direct responses on the base level. For some literature on computational modeling at different time scales, see (Geiser, 2016; Radhakrishnan, 2021).

4 Neural Mechanisms for Brain Plasticity and Metaplasticity

In this section an overview is given of the different forms of first-order (plasticity) and second-order (metaplasticity) adaptivity considered in neuroscience that form a foundation for the proposed computational architecture.

4.1 Neural Mechanisms for First-Order Adaptivity: Brain Plasticity

In this section a number of mechanisms for first-order adaptivity (plasticity of the brain) are discussed. For second-order adaptivity (metaplasticity), see Sect. 4.2. In this section, two examples of first-order adaptation principles are considered: Bainian (1873) or Hebbian (1949) learning for connectivity adaptation and intrinsic excitability modulation (Chandra and Barkai, 2018; Debanne, Inglebert, Russier, 2019).

Neural Mechanisms for Connectivity Adaptation: Synaptic Plasticity

Some early work on connectivity adaptation can be found, for example, in contributions by Beale (1864) and Bain (1873) who as a first step have put forward the cyclic structure of networks ('circuits') in the brain:

'I venture to conclude that the typical anatomical arrangement of a nervous mechanism is not a cord with two ends— a point of origin and terminal extremity, but a cord without an end—a continuous circuit.' (Beale, 1864, p. 392)

Bain (1873) commented on this and points at the role of connection ('cell-crossing') points:

'He couples with this appearance the doctrine (maintained by him, although disputed by others) that the nerves terminate in loops, and consequently form an unbroken nervous circuit. He then suggests that the cell-crossing is the place where the inner bendings of a great many independent circuits come into close neighbourhood, and affect one another by a process of the nature of electrical induction.

Any one of the circuits being active, or excited, would impart excitement to all that came near it in the same cell.’ (Bain, 1873, p. 118-119)

As one step further, also plasticity of brain networks was discussed in (Bain, 1873):

‘Now to each impression, each sensation or thought, there corresponds physically a group or series of nerve-currents; when two impressions concur, or closely succeed one another, the nerve currents find some bridge or place of continuity, better or worse, according to the abundance of nerve matter available for the transition. In the cells or corpuscles where the currents meet and join, there is, in consequence of the meeting, a *strengthened connexion* or *diminished obstruction*—a preference track for that line over lines where no continuity has been established.’ (Bain, 1873, p. 117, original italics)

He continues in more detail in:

‘This is merely a hypothetical rendering of the facts: yet it is a very probable rendering. In the nature and number of the nerve elements, and their mode of connexion, there is nothing hypothetical; and there is no departure from fact or strong probability, in assigning special and distinct tracks for the currents connected with each separate sensation, idea, emotion, or other conscious state. As to the precise mode of the plastic growth that unites separate impressions into trains and aggregates in the memory,—we know that the corpuscles or crossings are the points that must be operated upon; that a flow of healthy blood must co-operate to the effect; and that the process takes time. It is evidently a species of growth: but the precise molecular change effected in the lines of strengthened communication, or diminished obstruction, we can describe only as increasing the conducting tendency in those lines, as compared with the collateral openings where no such operation has taken place.’ (Bain, 1873, pp. 117-118)

‘I can suppose that, at first, each one of the circuits would affect all others indiscriminately; but that, in consequence of two of them being independently made active at the same moment (which is the fact in acquisition), a strengthened connexion or diminished obstruction would arise between these two, by a change wrought in the intervening cell-substance; and that, afterwards, the induction from one of these circuits would not be indiscriminate, but select; being comparatively strong towards one, and weaker towards the rest.’ (Bain, 1873, p. 119)

Much later, this perspective on connectivity adaptation has been presented as well by Hebb (1949). For example, in this form:

‘When an axon of cell A is near enough to excite B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A’s efficiency, as one of the cells firing B, is increased.’ (Hebb, 1949, p. 62)

This type of connectivity adaptation is often referred as Hebbian learning, but considering the above, might as well or even better be called Bainian learning. For more on

this issue, see also (Wilkes and Wade, 1997). To indicate this type of adaptation, often the following summarised phrasing is used:

‘What fires together, wires together’ (Shatz, 1992; Keyser and Gazzola, 2014)

Neural Mechanisms for Intrinsic Excitability Adaptation: Nonsynaptic Plasticity

The brain network does not only show connectivity adaptation (synaptic plasticity). More recently, in the neuroscientific literature, a distinction was made between synaptic and nonsynaptic (or intrinsic) plasticity. Intrinsic nonsynaptic adaptation of (neural) states has been addressed in more detail more recently in literature such as (Chandra and Barkai, 2016; Debanne, Inglebert, & Russier, 2019; Zhang, Li, Gao, Niu, 2021). For example:

‘Learning-related cellular changes can be divided into two general groups: modifications that occur at synapses and modifications in the intrinsic properties of the neurons. While it is commonly agreed that changes in strength of connections between neurons in the relevant networks underlie memory storage, ample evidence suggests that modifications in intrinsic neuronal properties may also account for learning related behavioral changes. (Chandra and Barkai, 2018, p. 30)

The following quote indicates that long-lasting modifications in excitability of neurons can evolve over time:

‘Long-lasting modifications in intrinsic excitability are manifested in changes in the neuron’s response to a given extrinsic current (generated by synaptic activity or applied via the recording electrode).’ (Chandra and Barkai, 2018, p. 30)

Intrinsic excitability adaptation has been related, for example, to homeostatic regulation (Williams, O’Leary, & Marder, 2013) and also to how deviant dopamine levels during sleep make that dreams can make use of more associations due to easier excitable neurons; e.g., (Budding, Doornkamp, Treur, 2023).

The Interplay of Connectivity Adaptation and Intrinsic Excitability Adaptation

Both synaptic and nonsynaptic forms of adaptation can work together, e.g., (Alejandre-García, Kim, Pérez-Ortega, Yuste, 2022; Budding, Doornkamp, Treur, 2023; Lisman, Cooper, Sehgal, Silva, 2018; Hansel and Yuste, 2024), see for example:

‘So, circuit plasticity could be due to the interplay of synaptic and intrinsic mechanisms and this balance could be different for short and long-term plasticity. In this view, ensembles could be quickly formed by fast intrinsic mechanisms but then be modified by slower synaptic plasticity, perhaps in relation with learning.’ (Alejandre-García et al, 2022, p. 18/25)

‘To explain how neuronal ensembles are generated, we propose an “iceberg” model, by which the increased neuronal excitability that results from repeated input stimulation makes subthreshold connections become suprathreshold, enhancing the postsynaptic effect of already existing synapses, and generating a neuronal ensemble.’ (Hansel and Yuste, 2024, p. 4/10)

Note that here it is assumed that intrinsic plasticity works on a faster timescale than synaptic plasticity. Based on this perspective, the model proposed in (Budding et al, 2023) explains how creativity can be based on dopamine-induced (DA) enhanced associativity during dreaming that is ‘exported’ to the awake life. More specifically, the model uses dopamine-induced enhanced intrinsic excitability by lowering so-called T-states for adaptive excitability thresholds (see also Sect. 20.4) as short-term adaptation during dreaming (only short-lived) which in turn boosts longer-term adaptation based on Hebbian learning that can cross the border from dreaming to being awake:

‘The longer-term adaptation of connection weights by Hebbian learning creates the plasticity that is needed, as it has the potential to cross the border from sleeping to being awake (depending also on dream recall). This is in contrast to the DA-dependent T-state suppression which is a short-term adaptation that will not cross this border.’ (Budding et al, 2023, p. 42)

In a different context, a similar perspective on short-term adaptation boosting long-term adaptation is used in (Hendrikse, Treur, Koole, 2023), see also (Hendrikse, Treur, Koole, 2025, Ch 12). Here, induced by detected emerging synchrony, also different time scales for short-term affiliation and long-term bonding are used where repeated episodes of nonsynaptic short-term adaptation (intrinsic excitability modulation) can boost the synaptic long-term adaptation (connectivity adaptation).

4.2 Neural Mechanisms for Second-Order Adaptivity: Metaplasticity

The two types of first-order adaptation principles discussed above refer to what in neuroscientific literature is called plasticity. However, this is usually not a constant feature. For an organism, in some circumstances it is better to learn (and change) fast, but in other circumstances, it is better to stay stable and let what has been learnt in the past persist: ‘The Plasticity Versus Stability Conundrum’ (Sjöström, Rancz, Roth, Hausser, 2008, p. 773). Under which circumstances and to which extent such plasticity actually takes place is controlled by a form of so-called *metaplasticity*; e.g., (Abraham and Bear, 1996; Garcia, 2002; Magerl, Hansen, Treede, Klein, 2018; Robinson, Harper, McAlpine, 2016; Sjöström, Rancz, Roth, Hausser, 2008). Such control can address ‘The Plasticity Versus Stability Conundrum’ by only making plasticity happen in contextual circumstances when it is important for the person to change, and otherwise stabilize it. In literature as mentioned, various studies show how adaptation (for example, connectivity adaptation), is modulated depending on contextual circumstances by accelerating the adaptation process or decelerating or even blocking it. Among the reported factors affecting plasticity in such a way are stimulus exposure, activation, previous experiences, and stress. For example, in (Robinson et al., 2016) the following compact quote can be found summarizing that increasing stimulus exposure makes that the adaptation speed increases:

‘Adaptation accelerates with increasing stimulus exposure’ (Robinson et al., 2016, p. 2).

Also, for learning of mental models by individuals or for learning within or of organisations such context-sensitive control of adaptation is a crucial concept, e.g., (Treur and Van Ments, 2022; Canbaloglu, Treur, Wiewiora, 2023). For example, depending on the context, a manager can decide to organise organisational processes where individuals learn from other individuals. In (Mukeriia, Treur, Hendrikse, 2024; Treur, 2020b, Ch 6) different variants of second-order adaptation to control bonding by adaptive homophily are addressed; see also (Hendrikse, Treur, Koole, 2025, Ch 8).

5 Modeling Adaptive Dynamical Systems by Self-modeling Networks

The type of computational modeling considered here is based on a computational architecture of multilevel adaptive dynamical system models. Such an architecture can cover well the concept of multiple control levels for mechanisms in biological and mental processes as from a philosophical and biological perspective put forward, for example, in (Bechtel and Bich, 2024; Bevilacqua et al, 2008; Bich and Bechtel, 2022a, 2022b; Treur, 2024a, 2024b). In this paper two of such adaptation or control levels are used: first-order and second-order. The second-order adaptation level exerts control over the first-order adaptation in a context-sensitive manner. For more details of underlying neural mechanisms addressing brain plasticity and metaplasticity, see Sect. 4.

To design multilevel adaptive dynamical systems for social interaction adaptivity, a network-oriented modeling format based on self-modeling networks can be useful. In (Hendrikse, Treur, Koole, 2023; Treur, 2021) it has been shown how any smooth multilevel adaptive dynamical system can be represented as a multilevel temporal-causal self-modeling network. Therefore, this network-oriented format does not introduce any fundamental limitation. A brief introduction to this modeling format is as follows.

In this approach *nodes* Y in a temporal-causal network have activation values $Y(t)$ that are dynamic over time t ; therefore, they serve as state variables and will usually be called *states*. To specify these state dynamics, the states are considered to causally affect each other by the connections within the network. Following (Treur, 2016), a basic *network structure* is characterised by:

- **connectivity characteristics**

Connections from a state X to a state Y and their *weights* $\omega_{X,Y}$

- **aggregation characteristics**

For any node Y , some *combination function* $c_Y(\dots)$ defines aggregation that is applied to the *single impacts* $\mathbf{impact}_{X_i,Y}(t) = \omega_{X_i,Y} X_i(t)$ on Y from its incoming connections from states $X_1, \dots, X_k$:

$$\mathbf{aggimpact}_Y(t) = c_Y(\mathbf{impact}_{X_1,Y}(t), \dots, \mathbf{impact}_{X_k,Y}(t)) = c_Y(\omega_{X_1,Y} X_1(t), \dots, \omega_{X_k,Y} X_k(t)) \quad (1)$$

- **timing characteristics**

- Each state Y has a *speed factor* η_Y defining how fast it changes upon given impact. This is an important feature enabling different time scales within one network model.

Here, the states X_i and Y have activation levels $X_i(t)$ and $Y(t)$ that vary (often within the $[0, 1]$ interval) over time, described by real numbers t . Note that speed factors can be used to design network models where different states change on different time scales.

The dynamics of such networks are described by the following difference (or differential) equations that via (1) incorporate in a canonical manner the network characteristics $\omega_{X,Y}$, $c_Y(\cdot)$, η_Y :

$$Y(t + t) = Y(t) + \eta_Y[\text{aggimpact}_Y(t) - Y(t)]t \quad (2)$$

for any state Y .

The concept of self-modeling networks (or reified networks) was introduced in (Treur, 2018) to model adaptation for a network by adding *self-model states* to it. This modeling approach was extended by introducing higher-order self-models in (Treur, 2019a; Treur, 2020a) and further extended by illustrations for case studies and mathematical analysis in (Treur, 2020b; Treur, 2020c), resulting in multilevel or higher-order *self-modeling networks*, also called *reified networks*.

The idea is that self-model states represent network characteristics by network states, e.g., a self-model state $\mathbf{W}_{X,Y}$ is used to represent connection weight $\omega_{X,Y}$ or a self-model state $\mathbf{T}_Y$ is used to represent excitability threshold τ_Y . Such states are also called in general **W**-states or **T**-states. Then the impacts of the self-modeled characteristics $\omega_{X,Y}$ or τ_Y on a state Y at time t can be modelled as impacts from the state values $\mathbf{W}_{X,Y}(t)$ or $\mathbf{T}_Y(t)$ of such self-model states $\mathbf{W}_{X,Y}$ or $\mathbf{T}_Y$ on Y . In this way, the dynamics of these self-model states can model the adaptation processes for connectivity learning and modulation of excitability as discussed in Sect. 4.1. This brings the impacts from the adaptive characteristics on a state Y in the standard form of a network model where via connections node activations affect activations of other nodes.

For example, if all connection weights $\omega_{X_i,Y}$ in (1) are represented by self-model states $\mathbf{W}_{X_i,Y}$, then $\text{impact}_{X_i,Y}(t) = \mathbf{W}_{X_i,Y}(t)X_i(t)$ for all i and therefore (1) becomes:

$$\begin{aligned} \text{aggimpact}_Y(t) &= c_Y(\text{impact}_{X_1,Y}(t), \dots, \text{impact}_{X_k,Y}(t)) \\ &= c_Y(\mathbf{W}_{X_1,Y}(t)X_1(t), \dots, \mathbf{W}_{X_k,Y}(t)X_k(t)) \end{aligned}$$

Within a self-modeling network model, such self-model states have their own network characteristics. For instance, **W**-states $\mathbf{W}_{X,Y}$ have their own speed factor $\eta_{\mathbf{W}_{X,Y}}$, and their own connection weights $\omega_{Z,\mathbf{W}_{X,Y}}$ of a connection from a state Z to $\mathbf{W}_{X,Y}$. As adaptation processes modeled by the dynamics of such self-model states in general take place on a much slower time scale than for the base states X and Y , the values of such speed factors $\eta_{\mathbf{W}_{X,Y}}$ or $\eta_{\mathbf{T}_Y}$ will be much lower than for those of these X and Y . This feature is then used to enable different time scales for base dynamics and for adaptivity.

As a base network model extended by self-model states is also a temporal-causal network model itself, as has been shown in detail (Treur, 2020b, Ch 10), this self-modeling construction can easily be applied iteratively to include self-models of multiple self-modeling (or reification) levels. For example:

- a second-order self-model state $\mathbf{H}\mathbf{W}_{X,Y}$ can represent the speed factor of first-order self-model state $\mathbf{W}_{X,Y}$ so that the adaptation speed of $\mathbf{W}_{X,Y}$ becomes adaptive
- a second-order self-model state $\mathbf{H}\mathbf{T}_Y$ can represent the speed factor of first-order self-model state $\mathbf{T}_Y$ so that the adaptation speed of $\mathbf{T}_Y$ becomes adaptive

- a second-order self-model state $\mathbf{W}_{Z, \mathbf{W}_{X,Y}}$ can represent the weight $\omega_{Z, \mathbf{W}_{X,Y}}$ of the connection from Z to first-order self-model state $\mathbf{W}_{X,Y}$ so that the adaptation speed of $\mathbf{W}_{X,Y}$ becomes adaptive
- a second-order self-model state $\mathbf{W}_{Z, \mathbf{T}_Y}$ can represent the weight $\omega_{Z, \mathbf{T}_Y}$ of the connection from Z to first-order self-model state $\mathbf{T}_Y$ so that the adaptation speed of $\mathbf{T}_Y$ becomes adaptive

This can model higher-order adaptive dynamical systems by network models and has turned out quite useful to model metaplasticity in a unified form by a second-order self-model: context-sensitive control of adaptation, as discussed in Sect. 4.2. Such second-order self-model states can use yet other timescales by assigning proper values to their own speed factors $\eta H_{\mathbf{W}_{X,Y}}$, $\eta H_{\mathbf{T}_Y}$, $\eta W_{Z, \mathbf{W}_{X,Y}}$, and $\eta W_{Z, \mathbf{T}_Y}$.

In other, more biologically oriented research the role of environment-induced epigenetic changes for the development of mental disorders is addressed, such as Schizophrenia, ASPD, Binge eating, Insomnia, Psychopathy, SUD. In that case, a fifth-order control architecture turned out useful; e.g., (Augustinus, Hendrikse, Treur, 2024; Blei, Hendrikse, Treur, 2024; Călin, Hendrikse, Treur, 2024; Hassouna, Hendrikse, Treur, 2024; Jaganjac, Hendrikse, Treur, 2024; Schlöder, Hendrikse, Treur, 2024).

6 A Computational Architecture for Social Interaction Adaptivity

In this section, in addition to the informal conceptual architecture in Sect. 3, a formalised multilevel multi-timescale computational dynamical system architecture is discussed, represented via the self-modeling networks modeling approach briefly introduced in Sect. 5. This computational architecture refines and formalises the informal conceptual architecture from Fig. 4.

6.1 Base Level of the Computational Architecture

The architecture for the base level for three modalities (movement m , affect b , and verbal modality v) can be seen in Fig. 5 with states indicated by pink (within person) and green (external) circles and connections by blue arrows.

Here perception by sensory processing and representing takes place via the sense (for sensing) and rep (for representing) states and the connections between them. Moreover, the connections from rep states to prep (for preparation) states indicate responding, and the connections from prep states to talk, express and move state indicate executing. This refines and formalises what is in the lower pink boxes in Fig. 4. Moreover, subjective similarity detection states for the different modalities are included (pink diamond shapes). In this way, this picture refines and formalises what is in both the lower and upper pink boxes in Fig. 4.

6.2 First-Order Adaptation Level of the Computational Architecture

For the computational architecture, at the first-order adaptation level, the agents make use of one or two types of first-order self-model states, called $\mathbf{W}$ -states and $\mathbf{T}$ -states; see the blue area of Table 1:

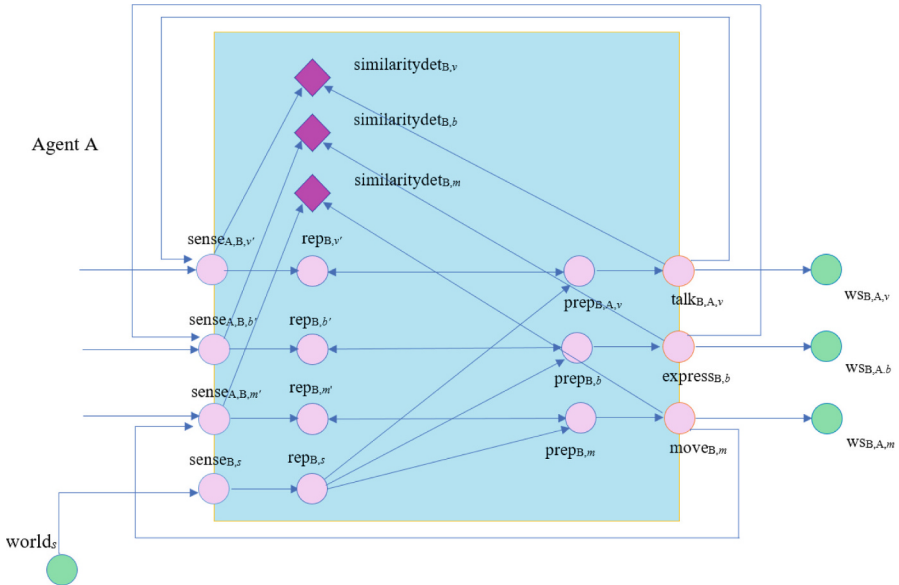


Fig. 5. Base level of the computational architecture with states and connectivity for basic mechanisms including subjective similarity detection states (pink diamond shapes)

- self-model **T**-states T_Y control adaptive excitability thresholds for the base level states Y indicated in their subscripts. This is a form of (nonsynaptic) adaptation at a relatively fast adaptation timescale, but slower than the timescales for the base level.
- self-model **W**-states $W_{X,Y}$ control adaptive connection weights of connections $X \rightarrow Y$ for the base level states X, Y indicated in their subscripts. This is a form of (synaptic) adaptation at a relatively slow adaptation timescale.

In Table 1 more details can be found of these different types of first-order self-models states of the computational architecture for the different types of base states and base connections for representing, responding, executing and connecting. Within the computational architecture, the connections for these first-order self-model states are as follows; see also Table 2 for an overview of the connectivity of all self-model states:

- Upward connections from similarity detector base states to the self-model **T**-states and **W**-states to model the similarity-induced adaptation principle
- Downward connections for each self-model **T**-state T_Y to base state Y and from each self-model **W**-state to base state Y to effectuate the adaptivity

Figure 6 shows a 3D visualisation of the nodes and connections of the base level (pink plane) and first-order adaptivity level (blue plane) of the computational architecture. Here for the sake of transparency the downward connections have been left out. However, these downward connections are shown in Fig. 7. Note that this concerns agent A that has interaction with and senses two other agents B and C.

Table 1. Overview of the first- and second-order self-model states in the computational architecture for social interaction adaptivity.

	Representing		Responding		Executing		Connecting	
First-order adaptation								
Adaptive activation timing								
Ultra short term	H-states for speed of representing base states		H-states for speed of responding base states		H-states for speed of executing base states		H-states for speed of connecting base states	
Adaptive activation strength								
	connectivity	excitability	connectivity	excitability	connectivity	excitability	connectivity	excitability
Short term	T-states for excitability of representing base states		T-states for excitability of responding base states		T-states for excitability of executing base states		T-states for excitability of connecting base states	
Long term	W-states for weights for representing base states		W-states for weights for responding base states		W-states for weights for executing base states		W-states for weights for connecting base states	
Second-order adaptation								
Adaptive adaptation timing								
	connectivity	excitability	connectivity	excitability	connectivity	excitability	connectivity	excitability
Short term	H _T -states for excitability adaptation speed for representing base states		H _T -states for excitability adaptation speed for responding base states		H _T -states for excitability adaptation speed for executing base states		H _T -states for excitability adaptation speed for connecting base states	
Long term	H _W -states for weights adaptation speed for representing base states		H _W -states for weights adaptation speed for responding base states		H _W -states for weights adaptation speed for executing base states		H _W -states for weights adaptation speed for connecting base states	
Adaptive adaptation strength								
	connectivity	excitability	connectivity	excitability	connectivity	excitability	connectivity	excitability
Short term	W _T -states for excitability adaptation strength for representing base states		W _T -states for excitability adaptation strength for responding base states		W _T -states for excitability adaptation strength for executing base states		W _T -states for excitability adaptation strength for connecting base states	
Long term	W _W -states for weights adaptation strength of representing base states		W _W -states for weights adaptation strength of responding base states		W _W -states for weights adaptation strength of executing base states		W _W -states for weights adaptation strength of connecting base states	

6.3 Second-Order Adaptation Level of the Computational Architecture

In Table 1 also the second-order self-model level (purple area and purple plane) is shown, with four types of second-order self-model states:

- **H_T-states H_{T_Y}** control the adaptation speed of **T-state T_Y**
- **H_W-states H_{W_{X,Y}}** control the adaptation speed of **W-state W_{X,Y}**
- **W_T-states W_{Z,T_Y}** control the adaptation strength of **T-state T_Y**
- **W_W-states W_{Z,W_{X,Y}}** control the adaptation strength of **W-state W_{X,Y}**

In the purple area in Table 1 more details of the different second-order self-model states of the computational architecture as shown for the different types of base states and base connections for representing, responding, executing and connecting.

Within the computational architecture, the connections for these second-order self-model states are as follows; see also Figs. 6 and 7 and Table 2 for a visualisation and concise overview of the connectivity of all self-model states:

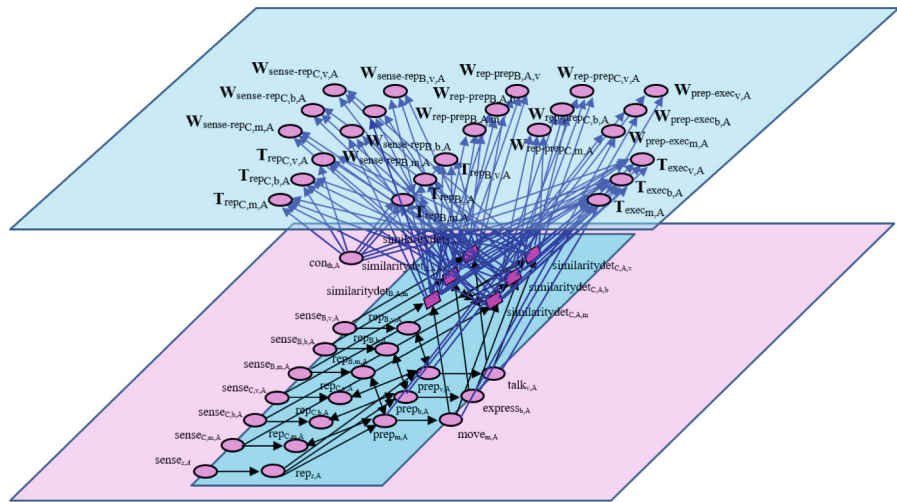


Fig. 6. A 3D visualisation of the lower two levels of the computational architecture; for the downward connections, see Fig. 7.

Table 2. Concise overview of the connectivity for the self-model states by upward and downward connections in the computational architecture

Upward connections		Downward connections	
For first-order self-model states			
Similarity detector base states	→	T-state $\mathbf{T}_Y$	→ Base state Y
Similarity detector base states	→	W-state $\mathbf{W}_{X,Y}$	→ Base state Y
For second-order self-model states			
Relevant context indicators from lower levels	→	H_T-state $\mathbf{H}_{T_Y}$	→ T-state $\mathbf{T}_Y$
Relevant context indicators from lower levels	→	H_w-state $\mathbf{H}_{w_{X,Y}}$	→ W-state $\mathbf{W}_{X,Y}$
Relevant context indicators from lower levels	→	W_T-state $\mathbf{W}_{Z,T_Y}$	→ T-state $\mathbf{T}_Y$
Relevant context indicators from lower levels	→	W_w-state $\mathbf{W}_{Z,w_{X,Y}}$	→ W-state $\mathbf{W}_{X,Y}$

- To model context-sensitive control over the adaptivity, upward connections to the second-order self-model states are included from all base states and first-order self-model states that are considered indicators for the relevant context considered. For example, to model the second-order adaptation principle ‘Adaptation accelerates with increasing stimulus exposure’ from (Chandra and Barkai, 2016) by H_T -states or H_W -states, the (sensory) representation states from the base level can be used as such context indicators.
- To effectuate the adaptivity, downward connections from the second-order self-model states to the first-order self-model level are included:
 - o for each second-order self-model H_T -state H_{T_Y} a downward connection to first-order self-model T-state T_Y

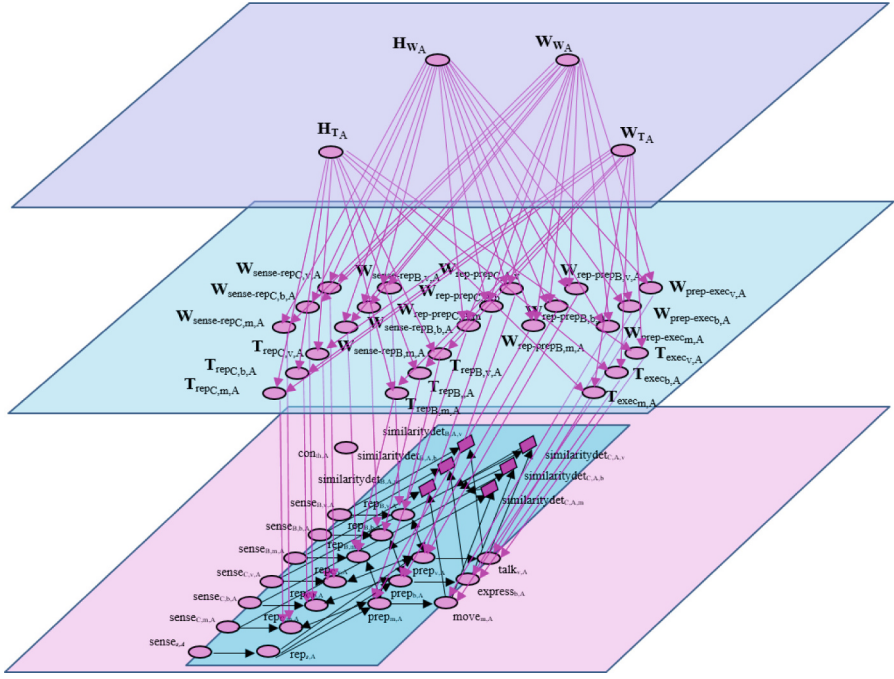


Fig. 7. A 3D visualisation of all three levels of the computational architecture with all nodes and their within-level and downward connections.

- o for each second-order self-model H_W -state $H_{W,X,Y}$ a downward connection to first-order self-model W -state $W_{X,Y}$
- o for each second-order self-model W_T -state $W_{T,Y}$ a downward connection to first-order self-model T -state T_Y
- o for each second-order self-model W_W -state $W_{Z,W,X,Y}$ a downward connection to first-order self-model W -state $W_{X,Y}$.

Note that in Fig. 7, for the sake of transparency at the second-order self-model level, a form of abstraction is applied. There is not a specific second-order self-model state for each specific first-order self-model state but one for all specific first-order self-model states of the same type, for example one H_T -state for all T -states of a given person A and one H_W -state for all W -states of person A, so no state H_{T_Y} for each state T_Y and no state $H_{W_{X,Y}}$ for each state $T_{X,Y}$.

7 The Computational Architecture Illustrated in Case Studies

Two case studies used as inspiration in particular for the computational architecture proposed here are briefly discussed in this section. Case study 1 addresses the distinction between and interplay of short-term affiliation and long-term bonding (Hendrikse, Treur, Koole, 2023) and Case study 2 transference between different relationships (Hendrikse,

Treur, Koole, 2024). In these two case studies different forms of synchrony-induced adaptivity are addressed:

- Some forms of adaptivity have a relatively fast timescale (e.g., within an episode of 45 min), modeled by self-model **T**-states for excitability adaptation, and some have a slower timescale (e.g., over tens of episodes of 45 min), modeled by self-model **W**-states for connectivity adaptation, in accordance with Sect. 4.1, last part.
- In Case study 1 in addition to (subjective) interpersonal synchrony detection, als intrapersonal synchrony detection is addressed and used for the adaptivity and for conscious emotion (Grandjean, Sander, Scherer, 2008)
- In Case study 2, some forms of adaptivity are relationship-specific and some are relationship-independent so that transference takes place (Andersen and Berk, 1998; Andersen and Przybylinski, 2012; Chen and Andersen, 1999)

For examples of simulation experiments performed for these case studies, see (Hendrikse et al., 2023; 2024).

In Fig. 8 the base level for Case study 1 is shown, with added states for intrapersonal synchrony detection and conscious emotion based on them (Grandjean, Sander, Scherer, 2008). In Fig. 9 all levels are shown with the within-level connections (black arrows) and the downward interlevel connections (pink arrows) from first- and second-order self-model states. These downward connections indicate the control effects of the different types of adaptation.

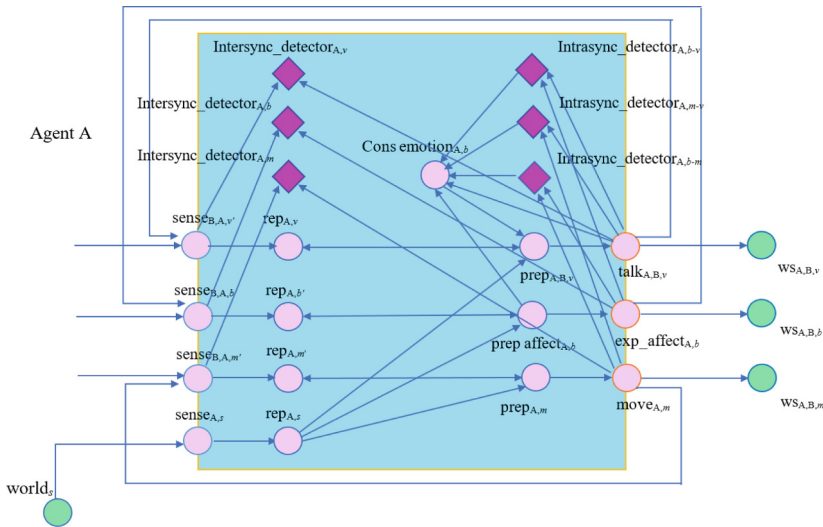
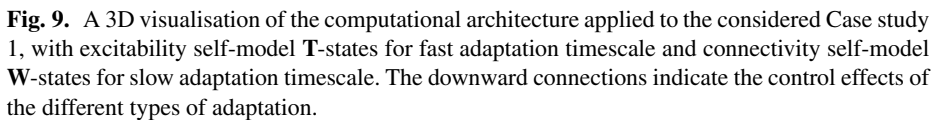


Fig. 8. Base level for Case study 1.

In accordance with the connectivity summarised in Table 2, at the first-order adaptation level **W**-states $W_{X,Y}$ control connection weights of connections $X \rightarrow Y$ for base level states X,Y indicated in their subscripts, and **T**-states T_Y control excitability thresholds for base level states Y indicated in their subscripts. At the second-order adaptation



8 The Computational Architecture Applied for Bonding Bots

To incorporate emotion regulation, in this case a feeling state (e.g., for a negative feeling) and an emotion control state to suppress the feeling state has been added. This control state gets incoming connections from the feeling and preparation states so that a form of monitoring occurs by which it gets activated when these activation levels are too high. If so, in turn the emotion control state suppresses these states by negative connections to them. Weaker or stronger forms of emotion regulation can be modeled by weaker or stronger links to this emotion control state: if these links are too weak, the control state will not get activated when needed. If the human has weak emotion regulation, the emotion levels can stay high.

However, if the bot has strong emotion regulation while the human has weak emotion regulation, then due to proper social contagion between the two based on mirroring

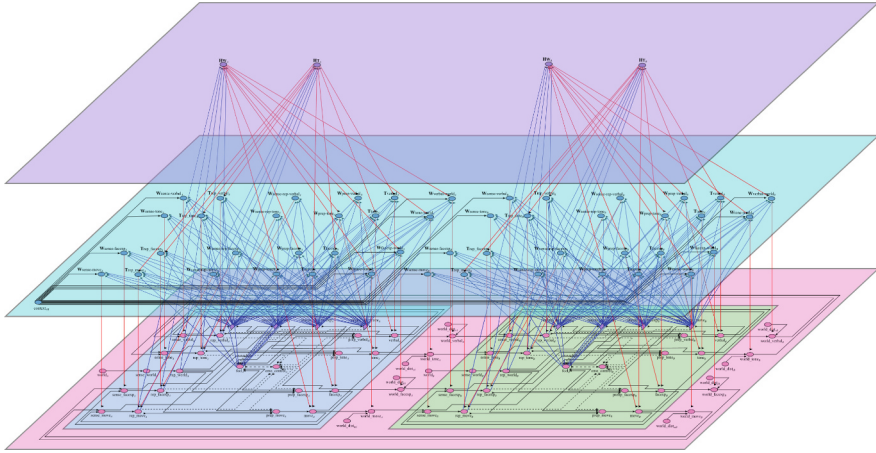


Fig. 10. The computational architecture applied to design bonding bots. Base level (pink plane), of the human (blue area) and the bot (green area), and first- and second-order adaptation level for both of them (blue and purple plane). Adopted from (Eler et al, 2024, Fig. 1).

(which also depends on how strong their bond is), interpersonal emotion regulation can emerge by which the human's emotion will still be downregulated. By the adaptivity built-in in the bonding bot according to the computation architecture, the bond can become stronger over time so that the interpersonal emotion regulation will become more and more effective. For more details, including example simulations, see (Eler et al, 2024).

9 Discussion

The generic computational architecture for social interaction adaptivity and attunement proposed in this paper was developed based on unification of a number of specific case studies addressed earlier. The proposed architecture concerns a generic multilevel multi-timescale adaptive dynamical system. It is formalised and represented as a multi-order self-modeling network (Treur, 2020a, 2020b, 2020c). In the paper it was discussed how this architecture covers earlier case studies addressing social interaction adaptivity and attunement subsuming synchrony- or homophily-induced adaptivity. It was also shown how based on it a new application to the design of bonding bots is realised that supports interpersonal emotion regulation via adaptive human-bot interaction and attunement.

The presented computational architecture for adaptive social interaction was based on a variety of case studies and related evaluations, some of which for synchrony-induced social interaction adaptivity already have been discussed in Sect. 7 and 8. Overall, the following case studies in the area of synchrony-induced social interaction adaptivity were an important source of inspiration: (Hendrikse, Kluiver, Treur, Wilderjans, Dikker, Koole, 2022; Hendrikse, Treur, Koole, 2023; Hendrikse, Treur, Koole, 2024; Hendrikse, Treur, Wilderjans, Dikker, Koole, 2022a; 2022b; 2023). Case studies in the area of homophily-induced social interaction adaptivity were equally well an important source

of inspiration, in particular those described in (Bössenecker, Mreijen, Treur, 2022; Mukerria, Treur, Hendrikse, 2023; 2024; Tichelaar and Treur, 2024; Treur, 2022). Finally, recent case studies that had a more evaluative role can be found in (Eler et al, 2024; Vervoordeldonk, Treur, Hendrikse, Roelofsma, 2024; Xu, Treur, Hendrikse, Roelofsma, 2024). All these case studies provide an indication of how the presented computational architecture has a wide applicability to various adaptive social interaction phenomena. These will be covered as well in (Hendrikse, Treur, Koole, 2025).

More background from biological and philosophical perspectives on the use of a multilevel dynamical system architecture with multiple adaptation or control levels at different timescales can be found in (Bechtel and Bich, 2024; Bevilacqua et al., 2009; Bich and Bechtel, 2022a, 2022b; Treur, 2024a, 2024b). Although in this paper only two adaptation or control levels are used, in other research where the role of environment-induced epigenetic changes for the development of mental disorders such as Schizophrenia, ASPD, Binge eating, Insomnia, Psychopathy, SUD is analysed, a fifth-order computational control architecture turned out useful; e.g., (Augustinus, Hendrikse, Treur, 2024; Blei, Hendrikse, Treur, 2024; Călin, Hendrikse, Treur, 2024; Hassouna, Hendrikse, Treur, 2024; Jaganjac, Hendrikse, Treur, 2024; Schlöder, Hendrikse, Treur, 2024).

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