Developing a Safety and Security AI Coach: A Second-Order Adaptive Network Model of Shared Mental Models in Hospital Teamwork

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Abstract This chapter describes a second-order adaptive network model for mental processes making use of shared mental models (SMM) for team performance. The chapter illustrates on the one hand the value of adequate SMM's for safe and efficient team performance and on the other hand in cases of imperfections of such shared team models how this complicates the team performance. To this end, the adaptive network model covers use, adaptation and control of the shared mental model. It is illustrated for an application context of a medical team performing a tracheal intubation, executed by a nurse and a medical specialist. Simulations illustrate how the adaptive network model is able to address the type of complications that can occur in realistic scenarios.

Keywords Shared mental model · Second-order network model · Hospital · Team performance · Healthcare safety

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P. H. M. P. Roelofsma et al. (eds.), *Using Shared Mental Models and Organisational Learning to Support Safety and Security Through Cyberspace: A Computational Analysis Approach*, Studies in Systems, Decision and Control 570,
https://doi.org/10.1007/978-3-031-72075-8_2

1 Introduction

The concept of a shared mental model (SMM) has recently received increased attention in medical team performance literature as well as in other domains. SMM's are often brought in relation to the quality of team performance and safety (Burthscher et al. 2011; Wilson 2019; Todd 2018; Higgs et al. 2018; Seo et al. 2021). A team has a shared mental model when relevant knowledge structures concerning how reality works or should work are held by all team members and when there is sufficient alignment in the internal representations of these knowledge structures (Fischhof and Johnson 1997; Jones and Roelofsma 2000; Mathieu et al. 2000). Like mental models in general, shared mental models are used in mental processes for internal mental simulation and decision making based on their outcomes; e.g., Craik (1943). Moreover, they often are adaptive in the sense that they can be learnt or forgotten, and for such adaptation usually a form of control is applied. These aspects of shared mental models are all addressed in the current chapter.

In this chapter, it is shown how the adaptive network-oriented modeling approach from Treur (2020) and the three-level cognitive architecture for mental models described in Van Ments and Treur (2021c) can be used to model second-order adaptive mental processes involving shared mental models. It is illustrated in particular for the mental processes of members of a medical team. The real-world challenge addressed here is to cover (1) the errors and other imperfections that are daily practice in such teams and (2) the way in which such teams handle them.

In Sect. 2, a general introduction and background is described. This section also describes the domain specifics of the example scenario: the use case. This use case is a tracheal intubation performed by a medical team consisting of a specialist and a nurse. In Sect. 3 the design of the adaptive network model for this type of shared mental model is presented. Section 4, then, describes the illustrative simulation examples. Section 5 gives the chapter's main conclusions and provides a discussion for further extensions of the adaptive network model using SMM to support team performance and healthcare safety.

2 Background

The second-order adaptive network model introduced here integrates knowledge of mental models from psychology, team mental models from social sciences, hospital protocols from medical- and safety sciences, and the AI-domain of network-oriented modeling.

2.1 Mental Models

For the history of the mental model area, often Kenneth Craik is mentioned as a central person. In his book (Craik 1943), he describes a mental model as a *small-scale model* that is carried by an organism within its head as follows; see also Williams (2018):

> If the organism carries a "small-scale model" of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it. (Craik 1943, p. 61)

Note that this quote covers both the usage of a mental model based on so-called internal mental simulation ('try out various alternatives') and the learning of it ('utilize the knowledge of past events'). Other authors also have formulated what mental models are. For example, with an emphasis on causal relations, Shih and Alessi (1993, p. 157) explain that

> By a mental model we mean a person's understanding of the environment. It can represent different states of the problem and the causal relationships among states.

De Kleer and Brown (1983) describe a mental model as the envisioning of a system, including a topological representation of the system components, the possible states of each of the components, and the structural relations between these components, the running or execution of the causal model based on basic operational rules and on general scientific principles.

2.2 Shared Mental Models

Team errors have often been linked to inadequacies of the shared mental model and the lack of adaptivity of it Fisschoff and Johnson (1997), Jones and Roelofsma (2000), Mathieu et al. (2000), Burthscher et al. (2011), Wilson (2019), Todd (2018). This has major implications for health care and patent safety in the operation room, e.g., concerning open heart operation and tracheal intubation (Higgs et al. 2018; Seo et al. 2021). Jones and Roelofsma (2000) discuss four types of team errors resulting from inadequate shared mental models.

The first is called 'false consensus'. The false consensus effect (Ross et al. 1977; Krueger 1998) refers to the tendency to overestimate the degree of similarity between self and others team members and this may result in biased judgements or team decisions. It is often described as people's tendency to 'see their own behavioural choices and judgements as relatively common and appropriate to existing circumstances while viewing alternative responses as uncommon, deviant, or inappropriate'.

A second type of team error and perhaps the most well-known is 'groupthink'; e.g., Janis (1972), Kleindorfer et al. (1993). It is often described as a mode of thinking that people engage in when they are deeply involved in a cohesive in-group, when the members' striving for unanimity overrides their motivation to realistically appraise alternative courses of action. Groupthink refers to a deterioration of mental efficiency and reality testing that results from in-group pressures.

A third type of team error resulting from inadequate shared mental model is group polarization; e.g., Isenberg (1986). This refers to the phenomenon that occurs when the position that is held on an issue by the majority of the group members is intensified as a result of discussion. For example, if group members are initially generally in favour of a particular preference of action, then group discussion will further enhance the favorability of this preference at an individual level. There are two special cases of group polarization. One is termed risky shift and occurs when a group, overall, becomes more risk seeking than the initial average risk seeking tendencies of the individual members. The other is termed cautious shift and occurs when groups become more risk averse than the initial average risk averse tendencies of the individual members. In both cases the average response of the individual group members is more extreme after discussion. Such shifts in preference have been demonstrated by an overwhelming number of studies.

A fourth team error is labelled escalation of commitment; e.g., Bazerman et al. (1984), Staw (1976). This refers to the tendency for individuals or groups to continue to support a course of action despite evidence that it is failing. In other words, it is the tendency for a decision to support a previous decision for which there was a negative outcome. The specific concern is with non-rational escalation of commitment with a degree to which an individual escalates commitment to a previously selected course of action beyond that which a rational.

2.3 Case Description

The general setting of the addressed case is an emergency department where an emergency team is coming together for preparing to intubate a critically ill patient with deteriorating conscious state. The airway has been assessed as being normal and there is no expectation that there are going to be any difficulties with intubation. A doctor (D) is called in to perform a tracheal intubation in collaboration with a nurse (N). In general, a tracheal intubation induces stress for D and A. The call of the doctor triggers the activation of the initial state of a shared mental model with separate roles and activities for the tracheal intubation for the D and N. The roles and activities are unique for D and N. The roles for the doctor are:

- team leader
- prepare team
- prepare for difficulties
- intubator.

The roles for the nurse are:

- intubator's assistant
- prepare patient
- prepare equipment
- prepare drugs
- give drugs
- monitoring the patient
- cricoid force
- runner for help and/or additional equipment.

In addition to the allocation of roles, the shared mental model contains the corresponding (temporal) sequence of activities for D and N. For the chosen example scenario based on an imperfect shared mental model considered here, this consists of the following sequence.

- The nurse prepares the patient.
- According to the protocol she should then have performed the preparation of the equipment; but she forgets this and goes on to perform the preparation of the drugs.
- The doctor executes pre oxygenation and
- starts with the preparation of the team and
- the preparation for difficulties.
- The nurse listens to and observes the doctor's team preparation.
- The nurse gives drugs to the patient and
- applies cricoid to the patient.
- Then the doctor initiates the executing of plan A Larynscopy and
- starts the first intubation attempt.
- The nurse assists the doctor in the intubation attempt.
- The nurse monitors the patient.
- When the first attempt is finished, the nurse seeks confirmation of its success by monitoring the capnograph. Then N realizes the earlier omission and sees that the capnograph is not active.

The intubation attempt is repeated with the exclusion of the preparation and the giving of the drugs to the patient by N. Also the preparation of the team for the intubation and for difficulties are not performed anymore by D. All other tasks are repeated in a second round and when this is not successful also in a third attempt. According to the protocol the doctor should have asked for help when the third attempt is not successful. But she does not do this.

2.4 Network-Oriented Modeling

The Network-Oriented Modelling approach based on temporal-causal networks from Treur (2016, 2020) is a suitable modeling approach to represent causal relations and the way they can be processed to generate mental processes, as needed for the use of shared mental models as described above. In particular, in Treur (2020) it is described how adaptive networks of different orders can be modelled relatively easily. Therefore, this approach was used to design a second-order adaptive network model for using shared mental models in a team member's mental processing and acting.

Network nodes X have state values indicated by real numbers $X(t)$ that vary over time t; nodes are also called states. The characteristics defining a network model are:

- **Connectivity characteristics**:
  Connections from states X to Y, having *connection weights* $\boldsymbol{\omega}_{X,Y}$ specifying their strengths
- **Aggregation characteristics**:
  Each state Y has a *combination function* $\mathbf{c}_Y$ that specifies how impact from all incoming connections on Y is aggregated. Based on a list of basic combination functions $\mathbf{bcf}_i$ (each with some parameters) provided by an available library, such a combination function can be specified by weights $\boldsymbol{\gamma}_i$ and parameters $\boldsymbol{\pi}_{i,j}$ for these basic combination functions $\mathbf{bcf}_i$
- **Timing characteristics**:
  Each state Y has a *speed factor* $\boldsymbol{\eta}_Y$ specifying how fast Y changes.

The numerical representation created by the available dedicated software environment is based on the following equations based on the above network characteristics (where $X_1, \ldots, X_k$ are the states from which state Y gets incoming connections):

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

A computational network engine developed within this software environment based on the generic Eq. (1) takes care for the processing of all network states thereby using their connections and other network characteristics.

2.5 Self-modeling Networks to Model Adaptivity and Control

First-order adaptation (also called plasticity) will be applied to the strength of the relations (connections) within a mental model: by Hebbian learning (Hebb 1949) they can become stronger and by extinction (forgetting) they can become weaker. In addition, second-order adaptation will be applied to model as a form of meta-plasticity (Abraham and Bear 1996; Garcia 2002), for the control effect of the contextual stress on the first-order adaptation process of learning and forgetting. To design network models that are adaptive, the concept *self-modeling network* (also called reified network) introduced in Treur (2020) has turned out very useful. A self-modeling network is obtained if for some of the network characteristics $\boldsymbol{\omega}$, $\mathbf{c}$, $\boldsymbol{\eta}$ as introduced above, network states are added to the network that represent their value. For example, for a connection weight $\boldsymbol{\omega}_{X,Y}$ an additional state $\mathbf{W}_{X,Y}$ (called *self-model state*) is added to the network that represents this weight and is used for that weight in the processing. Also, notations such as **IW**, **LW** and **RW** can be used instead of **W**, to distinguish different types of connection weights (see Sect. 3 for examples). For such an additional network **W**-state, also additional network characteristics are added to get an adequate embedding in the obtained self-modeling network. Next, as another example, for the combination function of a self-model state $\mathbf{W}_{X,Y}$, a persistence parameter $\boldsymbol{\mu}_{\mathbf{W}_{X,Y}}$ can be used that is represented by another self-model state $\mathbf{M}_{\mathbf{W}_{X,Y}}$. The latter network state is a *second-order self-model state* as it represents a network characteristic related to (first-order) self-model state $\mathbf{W}_{X,Y}$. These two types of self-model states will be used in the adaptive network model introduced in Sect. 3 to model learning of (shared) mental models and forgetting them under stressful circumstances.

3 The Adaptive Network Model Using a Shared Mental Model

As also indicated in the quote from Craik (1943) in Sect. 2, mental models are not only used by a form of internal mental simulation, but are also adaptive in that over time they are learned and can be forgotten. Moreover, cognitive control is exerted over these processes. To cover these three types of mental processes, the second-order adaptive network model introduced here follows the generic three-level cognitive architecture depicted in Fig. 1, as described in Van Ments and Treur (2021c). For more details and several case studies, see (Treur and Van Ments, 2022) and for applications to multilevel organisational learning, see (Canbaloğlu et al. 2023). Here the base level (lower, pink plane) models the use of a mental model by internal simulation, the adaptation level (middle, blue plane) the learning (and forgetting) of a mental model, and the control level (upper, purple plane) models the control of these processes.

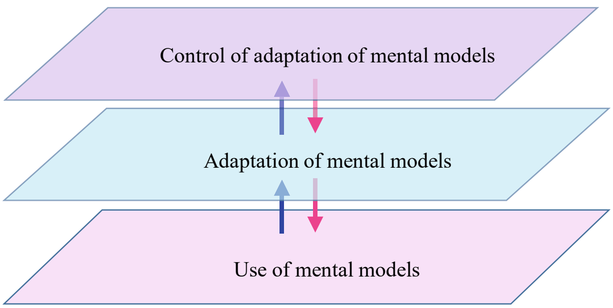

Fig. 1 Cognitive architecture with three levels of mental processing for usage (by internal mental simulation), adaptation (by learning and forgetting), and (cognitive) control of mental model adaptation

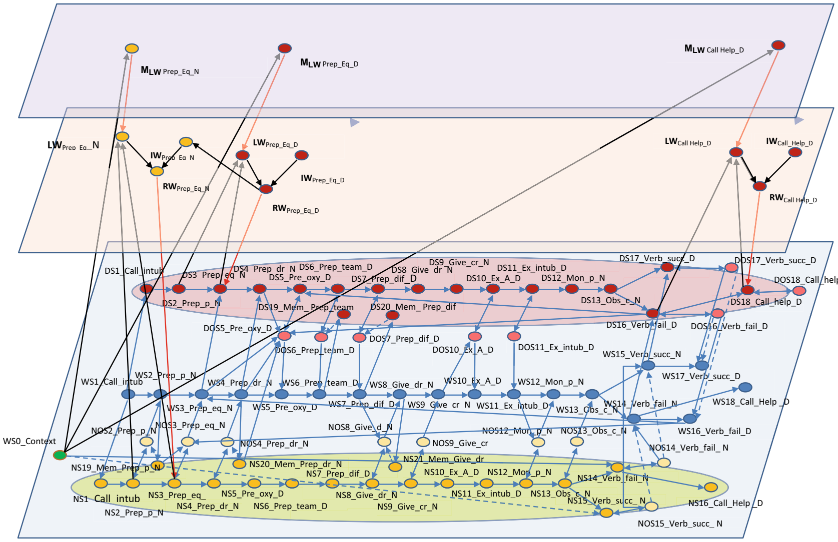

Fig. 2 Connectivity of the designed adaptive network model for the shared mental model. It includes the two mental models of the nurse (long yellow oval) and of the doctor (long red oval) and the self-models for the first-order (the pink plane) and second-order (the purple plane) adaptation. Dashed connections indicate connections with negative weights

The adaptive network model introduced here is a refinement and instantiation of this generic architecture for the scenario described in Sect. 2. It has connectivity as depicted in Fig. 2; for an explanation of the most important states, see Tables 1, 2 and 3. The scenario concerns a sequence of actions with actors assigned performing them and their temporal order, according to the realistic example scenario as described in Sect. 2.

3.1 Base Level: Overview

Within the base plane, the world states indicating the actual steps in the world for this scenario are depicted in Fig. 2 by the blue nodes with their connections in the middle area of the base plane. A contextual stress factor is represented by the green node on the left. The actor is indicated within a world state name by D for doctor or N for nurse. The shared mental model consists of two individual mental models for the doctor and the nurse. These mental models of the doctor and the nurse are shown in the base level plane and reflect the ordered structure specified in the use case discussed in Sect. 2. They are depicted by the red nodes (in the long light-red oval) and yellow nodes (in the yellow-green oval) in the base plane and their connections, respectively.

Table 1 Overview of the world states (WS) and the mental model states for the doctor (DS) and nurse (NS) reflecting these world states

World, Doctor and Nurse				Explanation
WS0			Context	Contextual stress factor
WS1	DS1	NS1	Call_intub	External call for intubation
WS2	DS2	NS2	Prep_p_N	Preparation of the patient by the nurse
WS3	DS3	NS3	Prep_eq_N	Preparation of the intubation equipment by the nurse
WS4	DS4	NS4	Prep_dr_N	Nurse prepares drugs for the patient
WS5	DS5	NS5	Pre_oxy_D	Doctor executes pre oxygenation
WS6	DS6	NS6	Prep_team_D	Doctor prepares the team for intubation
WS7	DS7	NS7	Prep_dif_D	Doctor prepares the team for difficulties
WS8	DS8	NS8	Give_dr_N	Nurse gives the patient drugs
WS9	DS9	NS9	Give_cr_N	Nurse applies cricoid to the patient
WS10	DS10	NS10	E_A_D	Doctor executes plan A Laryngoscopy
WS11	DS11	NS11	E_intub_D	Doctor intubates the patient
WS12	DS12	NS12	Mon_p_N	Nurse monitors patient
WS13	DS13	NS13	Obs_c_N	Nurse observes capnograph
WS14		NS14	Verb_fail_N	Nurse verbalizes failure of intubation
WS15		NS15	Verb_succ_N	Nurse verbalizes success of intubation
WS16	DS16		Verb_fail_D	Doctor verbalizes failure of intubation
WS17	DS17		Verb_succ_D	Doctor verbalizes success of intubation
WS18	DS18	NS18	Call_help_D	Doctor calls for help

Table 2 Overview of the memory states and ownership states for the doctor and nurse

Name		Explanation
DS19	Mem for Prep team D	Memory state of Doctor for the action of preparing the team
DS20	Mem for Prep dif D	Memory state of Doctor for the action of preparing the team for difficulties
DOS5	DOS for Pre_oxy_D	Ownership state for the action of preoxygenation
DOS6	DOS for Prep_team_D	Ownership state for the action of preparing the team
DOS7	DOS for Prep_dif_D	Ownership state for the action of preparing the team for difficulties
DOS10	DOS for E_A_D	Ownership state for the action of plan A Laryngoscopy by doctor
DOS11	DOS for E_intub_D	Ownership state for the action of intubating first attempt by doctor
DOS16	DOS for Verb_fail_D	Ownership state for the action of verbalizing that attempt has failed by doctor
DOS17	DOS for Verb_succ_D	Ownership state for the action of verbalizing that attempt has succeeded by doctor
DOS18	DOS for Call_help_D	Ownership state for the action of call for help, by doctor
NS19	Mem for Prep_p N	Memory state of Nurse for the action of preparing the patient
NS20	Mem for Prep_dr N	Memory state of Nurse for the action of preparing the drugs
NS21	Mem for Give_dr N	Memory state of Nurse for the action of giving the drugs
NOS2	NOS for Prep_N	Nurse Ownership State for Preparation patient
NOS3	NOS for Prep_eq_N	Nurse Ownership State for Preparation equipment
NOS4	NOS for Prep_dr_N	Nurse Ownership State for preparing drugs
NOS8	NOS for Give_d_N	Nurse Ownership State for Nurse gives drugs
NOS9	NOS for Give_cr_N	Nurse Ownership State for Nurse gives cricoid
NOS12	NOS for Mon_p_N	Nurse Ownership State for Nurse monitors patient
NOS13	NOS for Obs_c_N	Nurse Ownership State for observing capnograph
NOS14	NOS for Verb_fail_N	Nurse Ownership State for verbalizing that attempt has failed
NOS15	NOS for Verb_succ_N	Nurse Ownership State for verbalizing that attempt has succeeded

Table 3 Overview of the first-and second-order self-model states

Name		Explanation
W1	$\mathbf{LW}_{\text{Prep p Nurse} \rightarrow \text{Prep eq Nurse}}$	First-order self-model state for the Nurse's weight of the connection from the preparing the patient mental model state to the preparing the equipment mental model state as learnt by Hebbian learning
W2	$\mathbf{IW}_{\text{Prep p Nurse} \rightarrow \text{Prep eq Nurse}}$	First-order self-model state for the Nurse's weight of the connection from preparing the patient mental model state to preparing the equipment mental model state as learnt from instruction by the doctor
W3	$\mathbf{RW}_{\text{Prep p Nurse} \rightarrow \text{Prep eq Nurse}}$	First-order self-model state for the Nurse's overall weight of the connection from preparing the patient mental model state to preparing the equipment mental model state
W4	$\mathbf{LW}_{\text{Prep p N D} \rightarrow \text{Prep eq N D}}$	First-order self-model state for the Doctor's weight of the connection from preparing the patient by the Nurse mental model state to preparing the equipment by the Nurse mental model state as learnt by Hebbian learning
W5	$\mathbf{IW}_{\text{Prep p N D} \rightarrow \text{Prep eq N D}}$	First-order self-model state for the Doctor's weight of the connection from preparing the patient by the Nurse mental model state to preparing the equipment by the Nurse mental model state as known to the Doctor
W6	$\mathbf{RW}_{\text{Prep p N D} \rightarrow \text{Prep eq N D}}$	First-order self-model state for the Doctor's overall weight of the connection from preparing the patient by the Nurse mental model state to preparing the equipment by the Nurse mental model state
W7	$\mathbf{LW}_{\text{Verb fail D} \rightarrow \text{Call help D}}$	First-order self-model state for the Doctor's weight of the connection from verbalisation of failure mental model state to call for help mental model state as learnt by Hebbian learning
W8	$\mathbf{IW}_{\text{Verb fail D} \rightarrow \text{Call help D}}$	First-order self-model state for the Doctor's weight of the connection from verbalisation of failure mental model state to call for help mental model state as known to the Doctor
W9	$\mathbf{RW}_{\text{Verb fail D} \rightarrow \text{Call help D}}$	First-order self-model state for the Doctor's overall weight of the connection from verbalisation of failure mental model state to call for help mental model state
M1	$\mathbf{M}_{\mathbf{LW}_{\text{Prep p Nurse} \rightarrow \text{Prep eq Nurse}}}$	Second-order self-model state for the persistence factor of the Nurse's weight of the connection from preparing the patient mental model state to preparing the equipment mental model state as learnt by Hebbian learning
M2	$\mathbf{M}_{\mathbf{LW}_{\text{Prep p N D} \rightarrow \text{Prep eq N D}}}$	Second-order self-model state for the persistence factor of the Doctor's weight of the connection from preparing the patient by the Nurse mental model state to preparing the equipment by the Nurse mental model state as learnt by Hebbian learning
M3	$\mathbf{M}_{\mathbf{LW}_{\text{Verb fail D} \rightarrow \text{Call help D}}}$	Second-order self-model state for the persistence factor of the Doctor's weight of the connection from preparing the patient by the Nurse mental model state to preparing the equipment by the Nurse mental model state as learnt by Hebbian learning

The states within the mental models refer to the world states they model and like these world states they also specify an actor, indicated by D for doctor or N for nurse. The two individual mental models are two instances of an overall team mental model incorporating both the course of actions and the roles of the different team members for these actions. These individual instances of the team mental model can have differences, as in general not all team members will possess one and the same perfect team mental model.

3.2 Base Level: Memory States in the Mental Models

Within the mental models some specific states enable to take into account what has occurred in the past; these mental model states are called *memory states*. These are particularly useful if parts of the processes have to be repeated because of failures. Usually then only some of the actions have to be redone, while other actions can be skipped, as is illustrated in the addressed scenario. For example, preparation of the patient does not need to be redone, but preparation of the equipment has to be redone when the process has to be repeated. The memory states within the mental models are a crucial element to obtain this form of flexibility as they enable to model such issues in a context-sensitive manner taking into account the history of the process.

3.3 Base Level: Action Ownership States

By each of the two team members, their own mental model is used to determine their actions in the world. This goes through the member's action ownership states (indicated in light red for the doctor and in light yellow for the nurse). These ownership states are mental states but are not considered to be part of the mental models. Instead, they use input from the mental models and realise a form mediation from mental model to the real world by initiating the execution of the indicated actions, which leads to affecting the related world states. In this way, the mental models affect the decisions for actions activating the world states. Conversely, connections from world states to corresponding mental model states are (at some points) used to feed information about the world into the mental models.

3.4 Middle Level: Adaptation of the Mental Models (Plasticity)

The middle (blue) plane addresses the mental processes for learning and forgetting of the mental models. In particular, this addresses the connection within the nurse's mental model from the mental model state for preparation of the patient to the mental model state for preparation of the equipment. Inspired by Bhalwankar and Treur (2021a, b), where it was shown how instructional learning and observational learning of mental models can be integrated, in a similar manner two types of learning are covered here:

- Learning by instruction from the Doctor (modelled by the Nurse's **IW**-state and its incoming connection from the Doctor's **RW**-state)
- Hebbian learning (Hebb 1949) based on running the own internal simulation, among others triggered by observation (modelled by the Nurse's **LW**-state with its incoming connections from the two relevant Nurse's mental model states)

Table 4 Combination functions from the library used in the introduced network model

	Notation	Formula	Parameters
Steponce	$\mathbf{steponce}(V)$	1 if $\boldsymbol{\alpha} \leq t \leq \boldsymbol{\beta}$, else 0	$\boldsymbol{\alpha}$ start, $\boldsymbol{\beta}$ end time
Scalemap	$\mathbf{scalemap}_{\boldsymbol{\lambda},\boldsymbol{\upsilon}}(V)$	$\boldsymbol{\lambda} + (\boldsymbol{\upsilon}-\boldsymbol{\lambda})\ V$	Lower bound $\boldsymbol{\lambda}$; Upper bound $\boldsymbol{\upsilon}$
Advanced logistic sum	$\mathbf{alogistic}_{\boldsymbol{\sigma},\boldsymbol{\tau}}(V_1, \ldots, V_k)$	$[\frac{1}{1+e^{-\boldsymbol{\sigma}(V_1+\cdots+V_k-\boldsymbol{\tau})}} - \frac{1}{1+e^{\boldsymbol{\sigma}\boldsymbol{\tau}}}]\ (1 + e^{-\boldsymbol{\sigma}\boldsymbol{\tau}})$	Steepness $\boldsymbol{\sigma} > 0$ Excitability threshold $\boldsymbol{\tau}$
Hebbian learning	$\mathbf{hebb}_{\boldsymbol{\mu}}(V_1, V_1, W)$	$V_1 V_2\ (1-W) + \boldsymbol{\mu}\ W$	V_1,V_2 activation levels of the connected states; W activation level of the self-model state for the connection weight $\boldsymbol{\mu}$ persistence factor

The values of these two states are integrated in the **RW**-state, which represents the overall value that is actually used as connection weight in the internal simulation at the base level. The Hebbian learning applied for the **LW**-state is modeled by applying combination function $\mathbf{hebb}_{\boldsymbol{\mu}}$ (shown in Table 4) for aggregation for the **LW**-states; this learning is not fully persistent as this combination function $\mathbf{hebb}_{\boldsymbol{\mu}}$ used includes a persistence factor $\boldsymbol{\mu}$ that represents the fraction (of the learnt value) that persists per time unit. For example, if $\boldsymbol{\mu}$ is 0.9, then every time unit 10% of the learnt value is lost (forgotten). In this way, the Hebbian learning also covers extinction or forgetting. This combination function parameter $\boldsymbol{\mu}$ is one of the aggregation network characteristics of the (first-order) self-model represented in the middle plane.

3.5 Upper Level: Control of the Adaptation of Mental Models (Metaplasticity)

Within the adaptive network model introduced here, the extent $\boldsymbol{\mu}$ of persistence is not assumed constant but depends on circumstances. This means that this network characteristic of the first-order self-model is adaptive, which is modelled by including a second-order self-model **M**-state within the upper-level plane that represents the adaptive value of $\boldsymbol{\mu}$. This enables modelling metaplasticity (Abraham and Bear 1996; Garcia 2002) of mental processes, which is plasticity of the plasticity. For the considered scenario, it is assumed that in particular a high stress level leads to a decreased value of the **M**-state; in this way forgetting due to stressful circumstances is modelled, in line with (Garcia 2002). This is specified by the (suppressing) upward connections from the stressful context state in the base level to the **M**-states.

The combination functions from the combination function library available within the software environment used here are shown in Table 4.

4 Simulation for the Example Scenario

Recall from the introduction that the main real-world challenge addressed for the designed adaptive network model is that it is able to cover.

(1) the errors and other imperfections that are daily practice in medical teams and
(2) the way in which such teams handle them.

This can be considered a performance indicator against which the model can be validated. In this section, it will be shown by the realistic example simulation scenario from Sect. 2 how the model indeed satisfies this performance indicator. In this simulation, a repeatedly unsuccessful intubation process is shown.

The network characteristics defining the network model introduced above have been specified in a standard table format (called role matrices) that can be used as input for the available dedicated software environment; see also the Appendix Sect. 6. When transferred to this software environment, these tables with network characteristics are automatically used by the incorporated generic differential Eq. (1) when running simulations. The example simulation discussed here was run over a time interval of 0 to 180 with step size $\Delta t = 0.5$. This provides us with graphs of simulations based on the values chosen for the network characteristics. In this simulation, a repeatedly unsuccessful intubation process is shown. The contextual stress level has been set relatively high (0.5). For reasons of clarity, the figures have split the world states (Fig. 3), the nurse's states (Fig. 5), the doctor's states (Fig. 4), and the adaptivity states (Fig. 6), but they all happen in the same simulation at the indicated time points.

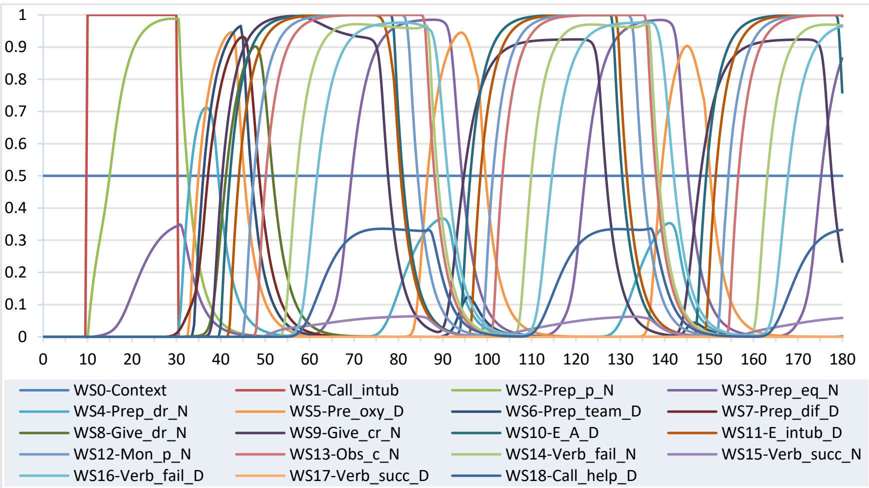

Fig. 3 World states of a repeated failing intubation process

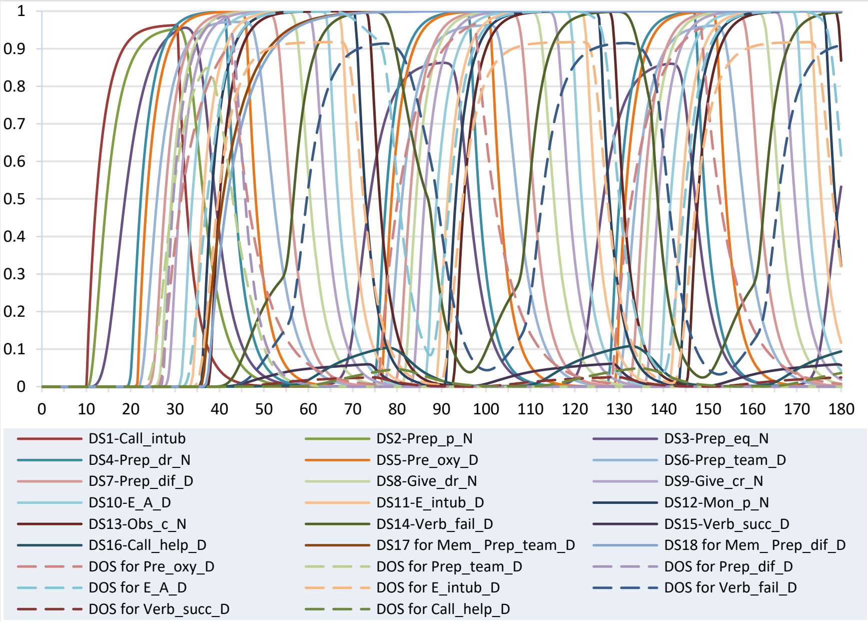

Fig. 4 The doctor's mental model states (solid lines) and ownership states (dashed lines) for a repeated failing process

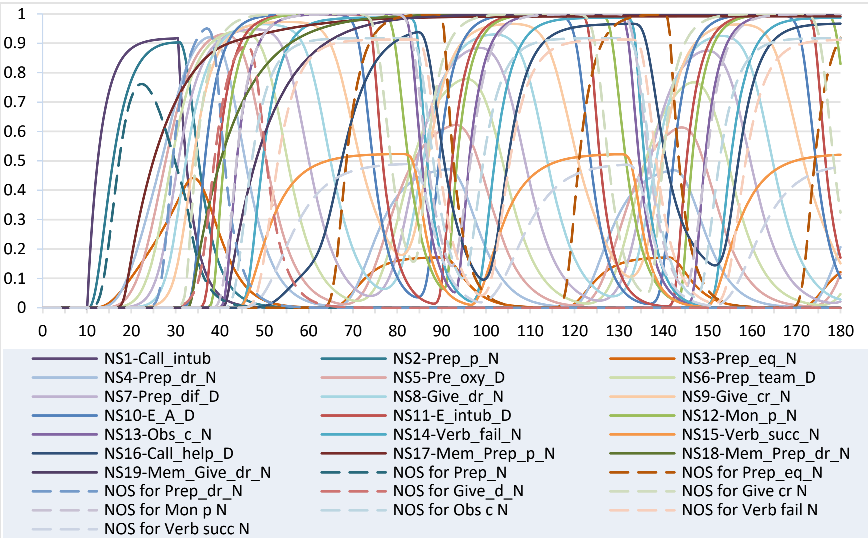

Fig. 5 The nurse's mental model states (solid lines) and ownership states (dashed lines) for a repeated failing intubation process

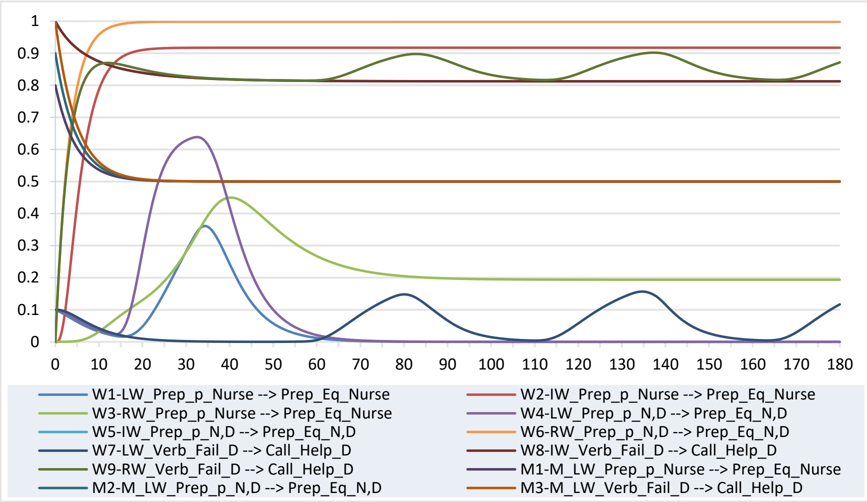

Fig. 6 The first- and second-order self-model states for adaptation (learning and forgetting) and control of it (stress leading to forgetting)

4.1 The World States

Figure 3 shows the simulation output for the world states. This shows how the actual process in the world proceeds. In time period t = 10–30 a call for intubation takes place, which sets in motion the intubation sequence for the scenario indicated by the use case described in Sect. 2. A bit after the call for intubation, the Nurse starts preparing the patient (the light green line). In this scenario, the purple line indicating the preparation of the equipment starting at time $t = 15$ does not reach an adequate level of activation, only around 0.375, meaning that this preparation of equipment is not (sufficiently) executed in the world. However, the next step in the scenario of preparing the drugs becomes active around $t = 33$ and does get activated enough. Subsequently, also the rest of the steps in the scenario continue as prescribed by the shared mental model. Between $t = 40$ and $t = 45$, the doctor's first actions all become activated: the pre-oxygenation of the patient, the preparation of the team and the preparation for difficulties. After this, the nurse continues with giving the drugs to the patient (dark green around $t = 47$), and applies the cricoid force right after. Now, the execution of the attempt laryngoscopy A, and the intubation action itself both become activated between $t = 47$ and $t = 50$. This also activates the nurse's actions to monitor the patient, around $t = 55$, and to observe the capnograph equipment around $t = 60$. Around this time point, the nurse will realize she did not prepare the equipment (remember the non-activated prepare equipment state), and verbalize the failed intubation attempt as a result, around $t = 67$. Soon after, around $t = 69$, the doctor confirms this by also verbalizing the failed intubation attempt.

After this verbalization of failure, the doctor and nurse will start their second attempt. This time, this starts with the nurse preparing the equipment; see how the light purple prepare equipment line now does reach activation around $t = 77$. Now, the preparation of the patient and drugs are skipped by the nurse because they do not need to happen more than once. These states do not get activated in the simulation and there is a slight gap, until the pre-oxygenation gets activated around $t = 93$: the orange line. After this, the doctor skips the preparation of the team and for difficulties, because these steps already happened and do not need to be repeated. Around $t = 100$, the nurse gives cricoid force, and the doctor starts the second intubation attempt. Again, the nurse monitors the patient, and the capnograph, but unfortunately also this intubation attempt fails. The nurse verbalizes this failed attempt around $t = 120$, and the doctor verbalizes the failure around $t = 125$. The team now continues with a third intubation attempt, see the activation of the preparation of the equipment at $t = 133$. The third pre-oxygenation becomes activated around $t = 145$, and the nurse applies the cricoid around $t = 155$. This activates the third intubation attempt and intubation action, and the monitoring of the patient and the capnograph by the nurse. Note that also in this attempt the same actions are skipped as in the second attempt, because they do not need to happen again. This attempt fails too and this is verbalized by the nurse at $t = 170$, and right after by the doctor as well. In the simulation the same pattern keeps on repeating after this time point. Note that after the failure verbalisations the 'call for help' state (the dark blue line) gets a small level of activation, up to around 0.35, but this is not enough to actually happen, so no help is called in this simulation scenario.

Figures 4 and 5 show for the addressed intubation scenario, what precedes the world state activations described above: respectively the internal simulations by the doctor and nurse of their own mental model and activating accordingly their ownership states for the actions they execute in the world.

4.2 The Doctor's Mental Processes Based on Her Mental Model

Figure 4 shows the doctor's mental model states and the doctor's ownership states simulated over time. At $t = 10$, the world state for the call for intubation becomes activated, hereby activating the sequence of events in the mental model of intubation of the doctor. Right after the call for intubation, the doctor's mental model for the nurse preparing the patient, equipment and drugs get activated at $t = 15$ (note that at this point this action only happens in the doctor's mental model, but not in the real world). Then the mental model states for the doctors first 'own' actions get activated: to pre oxygenate the patient, prepare the team and for difficulties, around $t = 20$. Now, the doctor's ownership states for the doctors' actions (pre oxygenate, preparing the team and for difficulties) get activated at $t = 30$, which will ultimately lead to the corresponding real-world actions. Around $t = 32$ some mental model states of actions the nurse has to do become activated, namely, to give the patient drugs and to apply cricoid force. This triggers the doctor's mental model state of starting plan A of intubation, and the actual intubation, also around $t = 32$, and slightly after that around $t = 35$ the ownership states for these actions. At around $t = 37$, the nurse's actions activate in the doctor's mental model: to monitor the patient and to observe the capnograph. This leads to the doctor to verbalize failure in her mental model around $t = 50$, and to develop activation of ownership of this verbalisation action a bit after that. The call for help does not get proper activation. This round ends around $t = 75$, after which the next round starts immediately (as an emergent process; there is no round information or control of rounds in the model).

4.3 The Nurse's Mental Processes Based on Her Mental Model

Figure 5 shows the nurse's mental model states and the nurse's ownership states simulated over time. At $t = 10$, the world state for the call for intubation becomes activated, hereby activating the sequence of events in the mental model of intubation of the nurse. Right after the call for intubation, the nurse's mental model for herself preparing the patient gets activated at $t = 15$, and right after also the ownership state for the first action gets activated, meaning the nurse executes the preparation of the patient. At around $t = 25$, the memory state of the nurse for preparing the patient reaches activation, meaning that the nurse can remember that she did this and does not have to repeat this action. Around this time, the prepare equipment mental model state reaches partial activation, but not enough to activate the ownership state for this action. From $t = 24$ until around $t = 37$, the mental model states for the preparation and execution actions of the intubation get activated, with the mental model state for the intubation reaching activation around $t = 39$. Also, the ownership states for most actions become activated in this time period, although the ownership state for 'prepare equipment' does not become activated, indicating that the nurse does not execute this action. At $t = 40$, the mental model state for monitoring the patient, and around $t = 44$ the mental model state for observing the capnograph become activated. At $t = 49$ the nurse's mental model state for verbalizing failure gets activation, and interestingly at $t = 69$, the nurse's mental model state for calling for help gets activated, even though this does not get executed by the doctor in the real world.

Note how also the memory states for preparing the patient, preparing the drugs and giving the drugs become activated at respectively $t = 25$, $t = 45$ and $t = 54$, after the ownership states for the same actions, causing the nurse to remember and not execute these actions in following rounds. At $t = 70$, the ownership state for preparing the equipment becomes activated, indicating the start of the second attempt at intubation. Note that the mental model state for the equipment preparation does not reach activation, showing that the nurse gets this input from an external source (the verbalization of failure of the intubation, by the doctor).

4.4 The Learning and Forgetting States

Figure 6 shows the activation levels of the states involved in adaptation (learning and forgetting) of the mental models, as shown in the first- and second-order self-model levels in Fig. 2. In the current model, for the sake of simplicity there are only three places in the model where learning and forgetting have been incorporated: in the nurse's mental model between the 'prepare equipment' state and the 'prepare drugs' state, in the doctor's mental model between the 'prepare equipment' state and the 'prepare drugs' state and finally in the doctor's mental model between the 'verbalization of failure' state and the 'call for help' state. As also discussed in Sect. 3, in each of these cases, the applied adaptation mechanism was built upon three sub-mechanisms, modelled in a network-oriented manner by additional states and connections:

- **LW**-states, representing the Hebbian learning. This means that the person learns by activation of connected states of the mental model, for example by using the mental model for internal simulation or triggered by observing the corresponding states in the real world. In the model, an **LW**-state is activated from the source and destination mental model states of the learnt connection. The persistence involved in the adaptation represented by an **LW**-state is controlled by an **M**-state in the second-order adaptation level (which represents the persistence factor $\boldsymbol{\mu}$).
- **IW**-states, representing instructional learning. This means that the agent learns by getting some sort of instruction, either during the process or before. In the model, the nurse learns from the doctor's instructions. The doctor applies previously acquired knowledge for this.
- **RW**-states, which models just a combination of the above two states.

In Fig. 6, the above three mechanisms are shown in a simulation graph. All three **M**-states start at a high level (0.8, 0.9 or 1) and due to the high stress level drop to 0.5 around $t = 10$. There are a few states that get activated around $t = 15$: **RW** for preparing the equipment in the doctor's mental model (W6), **RW** for the verbalization of failure by the doctor (W9) and **IW** for calling for help by the doctor (W8).

Besides that, none of the learning states really reach proper activation. Therefore, while the learning mechanisms in principle are working as can be seen from the changing activation levels, they do not have a strong enough positive learning impact but instead an overall negative impact, due to the forgetting that is induced by the high stress level (Garcia 2002), making the persistence factor representations **M** low. This negative effect contributes to the omission of the preparation of the equipment by the nurse in the first round and also to not calling for help after each failed round.

5 Discussion

In this chapter, a quite flexible and second-order adaptive computational network model was introduced enabling simulation of mental processes involving a shared mental model for teams, illustrated for a doctor and a nurse performing tracheal intubation of a patient. It is mainly based on material from Van Ments et al. (2021b). The model allows for the representation and processing of the actions in the world, the preceding internal simulation of the two mental models of the nurse and doctor and the dynamics of the interactions between them via the ownership states that represent how the actors actually decide based on the internal simulation and perform the actions. A contextual stress factor is included that determines the effects of stress on these mental processes, in particular forgetting parts of a mental model as a negative effect of metaplasticity (Abraham and Bear 1996) as described in more detail in Garcia (2002). Accordingly, in simulation experiments it was shown how learning and forgetting of shared mental models can happen and how failing team processes and redoing them can be modelled in a context-sensitive and flexible manner.

The computational model was developed based on the network-oriented modeling approach described in Treur (2016, 2020) and its dedicated software environment described in Treur (2020, Chap. 9). In earlier work it has been shown how this modeling approach enables modeling of different types of mental models, for example, for mental models representing flashback experiences in PTSD (van Ments and Treur 2021a), for joint decision making based on certain metaphors (Van Ments and Treur 2021b), and for how a mental God-model can affect empathic and disempathic human behaviour (Van Ments et al. 2016, 2018, 2022). Other computational approaches such as described in Dionne et al. (2010), Outland (2019), Scheutz (2013), use agent-based models (which usually brings more added complexity), dynamical system models or program code. This lacks a well-defined description at a modelling level and makes it hard if not impossible to incorporate second-order adaptation in a transparent manner in the model, as needed here. Otherwise it is hard to cover the positive and negative effects of metaplasticity as described in Garcia (2002). In contrast, the current chapter describes at a modelling level a very flexible second-order adaptive network model. It addressing shared mental models for teamwork and illustrates this by a hospital teamwork scenario.

A less flexible precursor of the second-order adaptive network model introduced in the current chapter was described in Van Ments et al. (2021a, b). The latter network model only addressed parts (not including memory states) of the base level. Therefore, it was nonadaptive and also did not cover errors and other imperfections of the team members occurring in their daily practice. For example, it was shown that the adaptive network model introduced here is able to model forgetting part of a shared mental model as illustrated in the simulated scenario, failure of the action and redoing the process in a context-sensitive manner after it has turned out to fail. In this way as a form of validation, the current model has be shown to be much closer to real-world team processes.

To achieve this, the two levels of self-models for first-order and second-order adaptation are new in the current model; this enabled modelling the positive and negative effects of metaplasticity as described in Garcia (2002) in the form of learning and forgetting parts of a mental model. In addition, also the use of memory states to be able to redo a failed attempt in a history-context-sensitive manner is new, providing a mechanism for only redoing the actions that are needed and skipping the ones that are not needed again as can be observed naturally in practice; the precursor model from Van Ments et al. (2021a, b) is much more rigid and lacks also this type of flexibility.

A next step will be to model the occurrence of a wider variety of errors and incidents—and their solutions—that are specific for team and group performance. Examples are: false consensus, group think, escalation of commitment and group polarization (Jones and Roelofsma 2000). Another relevant issue would be to examine the effect of group dynamics as a function of the team size. Often it is suggested that increasing the team, would lead to more safety and efficiency (Higgs et al. 2018) but increasing group size also leads to new group dynamics with corresponding potential problems. As mentioned, shared mental models are used in a variety of safety-related situations such as aviation, firefighting teams, dealing rooms, shipping control, etc. An important line for future research is to examine the descriptive validity of our model and further extensions of it for such domains.

Appendix: Specification of the Network Model

In this section the full specification of the adaptive network model is given by role matrices as explained in Treur (2020, Chap. 9) and the initial values used are listed. The role matrices provide a good basis for communication between modellers, and they can be used as input for the software environment to run simulations based on them.

Role matrices provide a compact standardised and structured table format that can be used to specify the network charactistics $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{j,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$ that define a design of a (self-modeling) network model. As discussed in Sect. 4, the three types of characteristics are:

Connectivity specified in role matrices **mb** (for base connections $X \rightarrow Y$) and **mcw** (for connection weights $\boldsymbol{\omega}_{X,Y}$).

Aggregation specified by role matrices **mcfw** (for combination function weights $\boldsymbol{\gamma}_{j,Y}$) and **mcfp** (for combination function parameters $\boldsymbol{\pi}_{i,j,Y}$).

Timing specified by role matrix **ms** (for speed factors $\boldsymbol{\eta}_Y$).

Role matrices have rows for all of the states in the network model, indicated by the state names X_i on the left side (which is also followed by a more informative name).

For *connectivity* characteristics, in role matrix **mb**, in each row it is listed which are the states X_j from which X_i has incoming connections. For example in the row for X_8 it is indicated that state X_8 (which is also named WS3-Prep_eq_N) has incoming connections from states X_7, X_{70} and X_{21}. In role matrix **mcw**, for each of these connections weights are specified in the corresponding cell. For example, in the row for X_8, in the first column it is indicated that the the weights from all connections to X_8 are 1. In this way, a compact overview is obtained for all connection weights $\boldsymbol{\omega}_{X,Y}$ of the network model. Note that in some of the (peach-red shaded) cells of **mcw** no numbers are specified but state names X_k. This is the way in which it is indicated that that X_k is a self-model state which plays the role of the connection weight for the cell in which it is specified. In a computational sense, this means that at any time in computations the value of that state is used for the concerning connection weight. This makes the adaptation of the connection weights happen. Similarly, for *timing* characteristics, in role matrix **ms** a list of speed factors for all states is given.

For *aggregation* characteristics, in role matrix **mcfw** the combination function weights are specified. In addition, in role matrix **mcfp** the parameters for the combination functions are specified. For example, in **mcfw** it is indicated that state X_8 uses the advanced logistic sum function **alogistic** (see Table 4) with steepness parameter $\boldsymbol{\sigma} = 5$ and threshold parameter $\boldsymbol{\tau} = 1.1$ indicated in **mcfp**. Also in some of the (peach-red shaded) cells of **mcfp**, no numbers are specified but state names X_k. In particular, this holds for the first-order self-model **LW**-states X_{78}, X_{81}, and X_{84} which model Hebbian learning; it is indicated in **mcfp** that their persistence factors are adaptive and represented by second-order self-model $\mathbf{M_{LW}}$-states X_{87}, X_{88}, and X_{89}, respectively.

Finally, also a list of initial values is given (Figs. 7, 8, 9, 10, 11 and 12).

mb	base-connectivity	1	2	3	4	5
X_1						
X_2						
X_3						
X_4						
X_5	WS0-Context	X_5				
X_6	WS1-Call_intub	X_6				
X_7	WS2-Prep_p_N	X_6	X_{69}			
X_8	WS3-Prep_eq_N	X_7	X_{70}	X_{21}		
X_9	WS4-Prep_dr_N	X_8	X_{71}			
X_{10}	WS5-Pre_oxy_D	X_9	X_{42}			
X_{11}	WS6-Prep_team_D	X_{10}	X_{43}			
X_{12}	WS7-Prep_dif_D	X_{11}	X_{44}			
X_{13}	WS8-Give_dr_N	X_{12}	X_{72}			
X_{14}	WS9-Give_cr_N	X_{13}	X_{73}			
X_{15}	WS10-E_A_D	X_{14}	X_{45}			
X_{16}	WS11-E_intub_D	X_{15}	X_{46}			
X_{17}	WS12-Mon_p_N	X_{16}	X_{74}			
X_{18}	WS13-Obs_c_N	X_{17}	X_{75}			
X_{19}	WS14-Verb_fail_N	X_{18}	X_{76}	X_{77}		
X_{20}	WS15-Verb_succ_N	X_{18}	X_{77}	X_{76}		
X_{21}	WS16-Verb_fail_D	X_{19}	X_{47}	X_{48}		
X_{22}	WS17-Verb_succ_D	X_{20}	X_{48}	X_{47}		
X_{23}	WS18-Call_help_D	X_{19}				
X_{24}	DS1-Call_intub	X_6				
X_{25}	DS2-Prep_p_N	X_{24}				
X_{26}	DS3-Prep_eq_N	X_{25}	X_8			
X_{27}	DS4-Prep_dr_N	X_{26}	X_9			
X_{28}	DS5-Pre_oxy_D	X_{27}	X_{42}			
X_{29}	DS6-Prep_team_D	X_{28}	X_{43}			
X_{30}	DS7-Prep_dif_D	X_{29}	X_{44}			
X_{31}	DS8-Give_dr_N	X_{30}				
X_{32}	DS9-Give_cr_N	X_{31}				
X_{33}	DS10-E_A_D	X_{32}	X_{45}			
X_{34}	DS11-E_intub_D	X_{33}	X_{46}			
X_{35}	DS12-Mon_p_N	X_{34}				
X_{36}	DS13-Obs_c_N	X_{35}				

Fig. 7 Connectivity characteristics: role matrix **mb**

X_{37}	DS16-Verb_fail_D	X_{36}	X_{47}	X_{19}		
X_{38}	DS17-Verb_succ_D	X_{36}	X_{48}	X_{20}		
X_{39}	DS18-Call_help_D	X_{37}	X_{49}			
X_{40}	DS19-Mem-Prep_team_D	X_{11}	X_{40}			
X_{41}	DS20-Mem-Prep_dif_D	X_{12}	X_{41}			
X_{42}	DOS5-Pre_oxy_D	X_{9}	X_{28}	X_{37}	X_{27}	X_{8}
X_{43}	DOS6-Prep_team_D	X_{29}	X_{40}			
X_{44}	DOS7-Prep_dif_D	X_{30}	X_{41}			
X_{45}	DOS10-E_A_D	X_{14}	X_{33}			
X_{46}	DOS11-E_intub_D	X_{34}				
X_{47}	DOS16-Verb_fail_D	X_{37}				
X_{48}	DOS17-Verb_succ_D	X_{38}				
X_{49}	DOS18-Call_help_D	X_{39}				
X_{50}	NS1-Call_intub	X_{6}				
X_{51}	NS2-Prep_p_N	X_{50}	X_{69}			
X_{52}	NS3-Prep_eq_N	X_{51}	X_{70}			
X_{53}	NS4-Prep_dr_N	X_{52}	X_{71}			
X_{54}	NS5-Pre_oxy_D	X_{53}				
X_{55}	NS6-Prep_team_D	X_{54}				
X_{56}	NS7-Prep_dif_D	X_{55}				
X_{57}	NS8-Give_dr_N	X_{56}	X_{72}			
X_{58}	NS9-Give_cr_N	X_{57}	X_{73}			
X_{59}	NS10-E_A_D	X_{58}				
X_{60}	NS11-E_intub_D	X_{59}				
X_{61}	NS12-Mon_p_N	X_{60}	X_{74}			
X_{62}	NS13-Obs_c_N	X_{61}	X_{75}			
X_{63}	NS14-Verb_fail_N	X_{62}	X_{5}	X_{76}		
X_{64}	NS15-Verb_succ_N	X_{62}	X_{5}	X_{77}		
X_{65}	NS18-Call_help_D	X_{63}	X_{3}			
X_{66}	NS19-Mem_Prep_p_N	X_{7}	X_{66}			
X_{67}	NS20-Mem_Prep_dr_N	X_{9}	X_{67}			
X_{68}	NS21-Mem_Give_dr_N	X_{13}	X_{68}			
X_{69}	NOS2-Prep_p_N	X_{51}	X_{66}			
X_{70}	NOS3-Prep_eq_N	X_{52}	X_{21}	X_{66}		
X_{71}	NOS4-Prep_dr_N	X_{53}	X_{67}			
X_{72}	NOS8-Give_dr_N	X_{12}	X_{57}	X_{68}		
X_{73}	NOS9-Give_cr_N	X_{58}				
X_{74}	NOS12-Mon_p_N	X_{16}	X_{61}			
X_{75}	NOS13-Obs_c_N	X_{62}				
X_{76}	NOS14-Verb_fail_N	X_{63}				
X_{77}	NOS15-Verb_succ_N	X_{64}				
X_{78}	W1-**LW**_Prep_p_Nurse→Prep_eq_Nurse	X_{51}	X_{52}	X_{78}		
X_{79}	W2-**IW**_Prep_p_Nurse→Prep_eq_Nurse	X_{83}				
X_{80}	W3-**RW**_Prep_p_Nurse→Prep_eq_Nurse	X_{78}	X_{79}			
X_{81}	W4-**LW**_Prep_p_N,D→Prep_eq_N,D	X_{25}	X_{26}	X_{81}		
X_{82}	W5-**IW**_Prep_p_N,D→Prep_eq_N,D	X_{82}				
X_{83}	W6-**RW**_Prep_p_N,D→Prep_eq_N,D	X_{81}	X_{82}			
X_{84}	W7-**LW**_Verb_fail_D→Call_help_D	X_{37}	X_{39}	X_{84}		
X_{85}	W8-**IW**_Verb_fail_D→Call_help_D	X_{85}				
X_{86}	W9-**RW**_Verb_fail_D→Call_help_D	X_{84}	X_{85}			
X_{87}	M1-**M_LW**_Prep_p_Nurse→Prep_eq_Nurse	X_{5}				
X_{88}	M2-**M_LW**_Prep_p_N,D→Prep_eq_N,D	X_{5}				
X_{89}	M3-**M_LW**_Verb_fail_D→Call_help_D	X_{5}				

Fig. 7 (continued)

mcw	connection weights	1	2	3	4	5
X_1						
X_2						
X_3						
X_4						
X_5	WS0-Context	1				
X_6	WS1-Call_intub	1				
X_7	WS2-Prep_p_N	1	1			
X_8	WS3-Prep_eq_N	1	1	1		
X_9	WS4-Prep_d_N	1	1			
X_{10}	WS5-Pre_oxy_D	1	1			
X_{11}	WS6-Prep_team_D	1	1			
X_{12}	WS7-Prep_dif_D	1	1			
X_{13}	WS8-Give_d_N	1	1			
X_{14}	WS9-Give_cr_N	1	1			
X_{15}	WS10-E_A_D	1	1			
X_{16}	WS11-E_intub_D	1	1			
X_{17}	WS12-Mon_p_N	1	1			
X_{18}	WS13-Obs_c_N	1	1			
X_{19}	WS14-Verb_fail_N	1	1	-1		
X_{20}	WS15-Verb_succ_N	1	1	-1		
X_{21}	WS16-Verb_fail_D	1	1	-1		
X_{22}	WS17-Verb_succ_D	1	1	-1		
X_{23}	WS18-Call_help_D	1				
X_{24}	DS1-Call_intub	1				
X_{25}	DS2-Prep_p_N	1				
X_{26}	DS3-Prep_eq_N	X_{83}	1			
X_{27}	DS4-Prep_d_N	1	1			
X_{28}	DS5-Pre_oxy_D	1	0.1			
X_{29}	DS6-Prep_team_D	1	0.1			
X_{30}	DS7-Prep_dif_D	1	0.1			
X_{31}	DS8-Give_d_N	1				
X_{32}	DS9-Give_cr_N	1				
X_{33}	DS10-E_A_D	1	0.1			
X_{34}	DS11-E_intub_D	1	0.1			
X_{35}	DS12-Mon_p_N	1				
X_{36}	DS13-Obs_c_N	1				
X_{37}	DS16-Verb_fail_D	1	0.1	1		
X_{38}	DS17-Verb_succ_D	1	0.1	1		
X_{39}	DS18-Call_help_D	X_{86}	0.1			
X_{40}	DS19-Mem-Prep_team_D	1	1			
X_{41}	DS20-Mem-Prep_dif_D	1	1			
X_{42}	DOS5-Pre_oxy_D	1	1	1	1	1

Fig. 8 Connectivity characteristics: role matrix **mcw** for connection weights

X_{43}	DOS6-Prep_team_D	1	-1	
X_{44}	DOS7-Prep_dif_D	1	-1	
X_{45}	DOS10-E_A_D	1	1	
X_{46}	DOS11-E_intub_D	1		
X_{47}	DOS16-Verb_fail_D	1		
X_{48}	DOS17-Verb_succ_D	1		
X_{49}	DOS18-Call_help_D	1		
X_{50}	NS1-Call_intub	1		
X_{51}	NS2-Prep_p_N	1	0.1	
X_{52}	NS3-Prep_eq_N	X_{80}	0.1	
X_{53}	NS4-Prep_d_N	1	0.1	
X_{54}	NS5-Pre_oxy_D	1		
X_{55}	NS6-Prep_team_D	1		
X_{56}	NS7-Prep_dif_D	1		
X_{57}	NS8-Give_d_N	1	0.1	
X_{58}	NS9-Give_cr_N	1	0.1	
X_{59}	NS10-E_A_D	1		
X_{60}	NS11-E_intub_D	1		
X_{61}	NS12-Mon_p_N	1	0.1	
X_{62}	NS13-Obs_c_N	1	0.1	
X_{63}	NS14-Verb_fail_N	1	1	0.1
X_{64}	NS15-Verb_succ_N	1	-1	0.1
X_{65}	NS18-Call_help_D	1	1	
X_{66}	NS19-Mem_Prep_p_N	1	1	
X_{67}	NS20-Mem_Prep_dr_N	1	1	
X_{68}	NS21-Mem_Give_dr_N	1	1	
X_{69}	NOS2-Prep_p_N	1	-1	
X_{70}	NOS3-Prep_eq_N	1	1	1
X_{71}	NOS4-Prep_dr_N	1	-1	
X_{72}	NOS8-Give_d_N	1	1	-1
X_{73}	NOS9-Give_cr_N	1		
X_{74}	NOS12-Mon_p_N	1	1	
X_{75}	NOS13-Obs_c_N	1		
X_{76}	NOS14-Verb_fail_N	1		
X_{77}	NOS15-Verb_succ_N	1		
X_{78}	W1-**LW**_Prep_p_Nurse→Prep_eq_Nurse	1	1	1
X_{79}	W2-**IW**_Prep_p_Nurse→Prep_eq_Nurse	1		
X_{80}	W3-**RW**_Prep_p_Nurse→Prep_eq_Nurse	1	1	
X_{81}	W4-**LW**_Prep_p_N,D→Prep_eq_N,D	1	1	1
X_{82}	W5-**IW**_Prep_p_N,D→Prep_eq_N,D	1		
X_{83}	W6-**RW**_Prep_p_N,D→Prep_eq_N,D	1	1	
X_{84}	W7-**LW**_Verb_fail_D→Call_help_D	1	1	1
X_{85}	W8-**IW**_Verb_fail_D→Call_help_D	1		
X_{86}	W9-**RW**_Verb_fail_D→Call_help_D	1	1	
X_{87}	M1-**M_LW**_Prep_p_Nurse→Prep_eq_Nurse	1		
X_{88}	M2-**M_LW**_Prep_p_N,D→Prep_eq_N,D	1		
X_{89}	M3-**M_LW**_Verb_fail_D→Call_help_D	1		

Fig. 8 (continued)

Fig. 9 Timing characteristics: role matrix **ms** for speed factors

ms	speed factors	1
X_1		
X_2		
X_3		
X_4		
X_5	WS0-Context	0
X_6	WS1-Call_intub	2
X_7	WS2-Prep_p_N	0.3
X_8	WS3-Prep_eq_N	0.3
X_9	WS4-Prep_d_N	0.3
X_{10}	WS5-Pre_oxy_D	0.3
X_{11}	WS6-Prep_team_D	0.3
X_{12}	WS7-Prep_dif_D	0.3
X_{13}	WS8-Give_d_N	0.3
X_{14}	WS9-Give_cr_N	0.3
X_{15}	WS10-E_A_D	0.3
X_{16}	WS11-E_intub_D	0.3
X_{17}	WS12-Mon_p_N	0.3
X_{18}	WS13-Obs_c_N	0.3
X_{19}	WS14-Verb_fail_N	0.3
X_{20}	WS15-Verb_succ_N	0.3
X_{21}	WS16-Verb_fail_D	0.3
X_{22}	WS17-Verb_succ_D	0.3
X_{23}	WS18-Call_help_D	0.3
X_{24}	DS1-Call_intub	0.3
X_{25}	DS2-Prep_p_N	0.3
X_{26}	DS3-Prep_eq_N	0.3
X_{27}	DS4-Prep_d_N	0.3
X_{28}	DS5-Pre_oxy_D	0.3
X_{29}	DS6-Prep_team_D	0.3
X_{30}	DS7-Prep_dif_D	0.3
X_{31}	DS8-Give_d_N	0.3
X_{32}	DS9-Give_cr_N	0.3
X_{33}	DS10-E_A_D	0.3
X_{34}	DS11-E_intub_D	0.3
X_{35}	DS12-Mon_p_N	0.3
X_{36}	DS13-Obs_c_N	0.3
X_{37}	DS16-Verb_fail_D	0.3
X_{38}	DS17-Verb_succ_D	0.3
X_{39}	DS18-Call_help_D	0.3
X_{40}	DS19-Mem-Prep_team_D	0.15
X_{41}	DS20-Mem-Prep_dif_D	0.15
X_{42}	DOS5-Pre_oxy_D	0.15
X_{43}	DOS6-Prep_team_D	0.3
X_{44}	DOS7-Prep_dif_D	0.3
X_{45}	DOS10-E_A_D	0.3
X_{46}	DOS11-E_intub_D	0.3
X_{47}	DOS16-Verb_fail_D	0.3

Fig. 9 (continued)

X_{48}	DOS17-Verb_succ_D	0.3
X_{49}	DOS18-Call_help_D	0.3
X_{50}	NS1-Call_intub	0.3
X_{51}	NS2-Prep_p_N	0.3
X_{52}	NS3-Prep_eq_N	0.3
X_{53}	NS4-Prep_d_N	0.3
X_{54}	NS5-Pre_oxy_D	0.3
X_{55}	NS6-Prep_team_D	0.3
X_{56}	NS7-Prep_dif_D	0.3
X_{57}	NS8-Give_d_N	0.3
X_{58}	NS9-Give_cr_N	0.3
X_{59}	NS10-E_A_D	0.3
X_{60}	NS11-E_intub_D	0.3
X_{61}	NS12-Mon_p_N	0.3
X_{62}	NS13-Obs_c_N	0.3
X_{63}	NS14-Verb_fail_N	0.3
X_{64}	NS15-Verb_succ_N	0.3
X_{65}	NS18-Call_help_D	0.3
X_{66}	NS19-Mem_Prep_p_N	0.1
X_{67}	NS20-Mem_Prep_dr_N	0.1
X_{68}	NS21-Mem_Give_dr_N	0.1
X_{69}	NOS2-Prep_p_N	0.3
X_{70}	NOS3-Prep_eq_N	0.3
X_{71}	NOS4-Prep_dr_N	0.3
X_{72}	NOS8-Give_d_N	0.3
X_{73}	NOS9-Give_cr_N	0.3
X_{74}	NOS12-Mon_p_N	0.3
X_{75}	NOS13-Obs_c_N	0.3
X_{76}	NOS14-Verb_fail_N	0.3
X_{77}	NOS15-Verb_succ_N	0.3
X_{78}	W1-**LW**_Prep_p_Nurse→Prep_eq_Nurse	0.3
X_{79}	W2-**IW**_Prep_p_Nurse→Prep_eq_Nurse	0.3
X_{80}	W3-**RW**_Prep_p_Nurse→Prep_eq_Nurse	0.1
X_{81}	W4-**LW**_Prep_p_N,D→Prep_eq_N,D	0.3
X_{82}	W5-**IW**_Prep_p_N,D→Prep_eq_N,D	0.3
X_{83}	W6-**RW**_Prep_p_N,D→Prep_eq_N,D	0.3
X_{84}	W7-**LW**_Verb_fail_D→Call_help_D	0.3
X_{85}	W8-**IW**_Verb_fail_D→Call_help_D	0.3
X_{86}	W9-**RW**_Verb_fail_D→Call_help_D	0.3
X_{87}	M1-**M_LW**_Prep_p_Nurse→Prep_eq_Nurse	0.7
X_{88}	M2-**M_LW**_Prep_p_N,D→Prep_eq_N,D	0.3
X_{89}	M3-**M_LW**_Verb_fail_D→Call_help_D	0.3

mcfw	combination function weights	1 alogistic	2 hebb	3 scalemap	4 steponce
X_1					
X_2					
X_3					
X_4					
X_5	WS0-Context	1			
X_6	WS1-Call_intub				1
X_7	WS2-Prep_p_N	1			
X_8	WS3-Prep_eq_N	1			
X_9	WS4-Prep_d_N	1			
X_{10}	WS5-Pre_oxy_D	1			
X_{11}	WS6-Prep_team_D	1			
X_{12}	WS7-Prep_dif_D	1			
X_{13}	WS8-Give_d_N	1			
X_{14}	WS9-Give_cr_N	1			
X_{15}	WS10-E_A_D	1			
X_{16}	WS11-E_intub_D	1			
X_{17}	WS12-Mon_p_N	1			
X_{18}	WS13-Obs_c_N	1			
X_{19}	WS14-Verb_fail_N	1			
X_{20}	WS15-Verb_succ_N	1			
X_{21}	WS16-Verb_fail_D	1			
X_{22}	WS17-Verb_succ_D	1			
X_{23}	WS18-Call_help_D	1			
X_{24}	DS1-Call_intub	1			
X_{25}	DS2-Prep_p_N	1			
X_{26}	DS3-Prep_eq_N	1			
X_{27}	DS4-Prep_d_N	1			
X_{28}	DS5-Pre_oxy_D	1			
X_{29}	DS6-Prep_team_D	1			
X_{30}	DS7-Prep_dif_D	1			
X_{31}	DS8-Give_d_N	1			
X_{32}	DS9-Give_cr_N	1			
X_{33}	DS10-E_A_D	1			
X_{34}	DS11-E_intub_D	1			
X_{35}	DS12-Mon_p_N	1			
X_{36}	DS13-Obs_c_N	1			
X_{37}	DS16-Verb_fail_D	1			
X_{38}	DS17-Verb_succ_D	1			
X_{39}	DS18-Call_help_D	1			
X_{40}	DS19-Mem-Prep_team_D	1			
X_{41}	DS20-Mem-Prep_dif_D	1			
X_{42}	DOS5-Pre_oxy_D	1			
X_{43}	DOS6-Prep_team_D	1			
X_{44}	DOS7-Prep_dif_D	1			
X_{45}	DOS10-E_A_D	1			
X_{46}	DOS11-E_intub_D	1			
X_{47}	DOS16-Verb_fail_D	1			

Fig. 10 Aggregation characteristics: role matrix **mcfw** for combination function weights

X_{48}	DOS17-Verb_succ_D	1			
X_{49}	DOS18-Call_help_D	1			
X_{50}	NS1-Call_intub	1			
X_{51}	NS2-Prep_p_N	1			
X_{52}	NS3-Prep_eq_N	1			
X_{53}	NS4-Prep_d_N	1			
X_{54}	NS5-Pre_oxy_D	1			
X_{55}	NS6-Prep_team_D	1			
X_{56}	NS7-Prep_dif_D	1			
X_{57}	NS8-Give_d_N	1			
X_{58}	NS9-Give_cr_N	1			
X_{59}	NS10-E_A_D	1			
X_{60}	NS11-E_intub_D	1			
X_{61}	NS12-Mon_p_N	1			
X_{62}	NS13-Obs_c_N	1			
X_{63}	NS14-Verb_fail_N	1			
X_{64}	NS15-Verb_succ_N	1			
X_{65}	NS18-Call_help_D	1			
X_{66}	NS19-Mem_Prep_p_N	1			
X_{67}	NS20-Mem_Prep_dr_N	1			
X_{68}	NS21-Mem_Give_dr_N	1			
X_{69}	NOS2-Prep_p_N	1			
X_{70}	NOS3-Prep_eq_N	1			
X_{71}	NOS4-Prep_dr_N	1			
X_{72}	NOS8-Give_d_N	1			
X_{73}	NOS9-Give_cr_N	1			
X_{74}	NOS12-Mon_p_N	1			
X_{75}	NOS13-Obs_c_N	1			
X_{76}	NOS14-Verb_fail_N	1			
X_{77}	NOS15-Verb_succ_N	1			
X_{78}	W1-**LW**_Prep_p_Nurse→Prep_eq_Nurse		1		
X_{79}	W2-**IW**_Prep_p_Nurse→Prep_eq_Nurse	1			
X_{80}	W3-**RW**_Prep_p_Nurse→Prep_eq_Nurse	1			
X_{81}	W4-**LW**_Prep_p_N,D→Prep_eq_N,D		1		
X_{82}	W5-**IW**_Prep_p_N,D→Prep_eq_N,D	1			
X_{83}	W6-**RW**_Prep_p_N,D→Prep_eq_N,D	1			
X_{84}	W7-**LW**_Verb_fail_D→Call_help_D		1		
X_{85}	W8-**IW**_Verb_fail_D→Call_help_D	1			
X_{86}	W9-**RW**_Verb_fail_D→Call_help_D	1			
X_{87}	M1-**M_LW**_Prep_p_Nurse→Prep_eq_Nurse			1	
X_{88}	M2-**M_LW**_Prep_p_N,D→Prep_eq_N,D			1	
X_{89}	M3-**M_LW**_Verb_fail_D→Call_help_D			1	

Fig. 10 (continued)

mcfp	combination function parameters	1 alogistic		2 hebb	3 scalemap	4 steponce	
X_1							
X_2							
X_3							
X_4							
X_5	WS0-Context	5	0.5				
X_6	WS1-Call_intub					10	30
X_7	WS2-Prep_p_N	8	1				
X_8	WS3-Prep_eq_N	5	1.1				
X_9	WS4-Prep_d_N	30	1				
X_{10}	WS5-Pre_oxy_D	25	1				
X_{11}	WS6-Prep_team_D	25	1				
X_{12}	WS7-Prep_dif_D	5	1.1				
X_{13}	WS8-Give_d_N	5	1.1				
X_{14}	WS9-Give_cr_N	25	0.9				
X_{15}	WS10-E_A_D	25	1.1				
X_{16}	WS11-E_intub_D	25	1.1				
X_{17}	WS12-Mon_p_N	25	1.3				
X_{18}	WS13-Obs_c_N	25	1.1				
X_{19}	WS14-Verb_fail_N	25	1.3				
X_{20}	WS15-Verb_succ_N	5	1.1				
X_{21}	WS16-Verb_fail_D	5	1.1				
X_{22}	WS17-Verb_succ_D	5	1.1				
X_{23}	WS18-Call_help_D	5	1.1				
X_{24}	DS1-Call_intub	5	0.3				
X_{25}	DS2-Prep_p_N	5	0.3				
X_{26}	DS3-Prep_eq_N	5	0.6				
X_{27}	DS4-Prep_d_N	50	0.6				
X_{28}	DS5-Pre_oxy_D	50	0.3				
X_{29}	DS6-Prep_team_D	5	0.3				
X_{30}	DS7-Prep_dif_D	15	0.4				
X_{31}	DS8-Give_d_N	15	0.3				
X_{32}	DS9-Give_cr_N	15	0.4				
X_{33}	DS10-E_A_D	25	0.55				
X_{34}	DS11-E_intub_D	25	0.5				
X_{35}	DS12-Mon_p_N	40	0.4				
X_{36}	DS13-Obs_c_N	25	0.4				
X_{37}	DS16-Verb_fail_D	8	1.1				
X_{38}	DS17-Verb_succ_D	8	1.4				
X_{39}	DS18-Call_help_D	5	1.3				
X_{40}	DS19-Mem-Prep_team_D	25	0.5				
X_{41}	DS20-Mem-Prep_dif_D	25	0.5				
X_{42}	DOS5-Pre_oxy_D	45	2				
X_{43}	DOS6-Prep_team_D	5	0.5				
X_{44}	DOS7-Prep_dif_D	25	0.4				

Fig. 11 Aggregation characteristics: role matrix **mcfp** for combination function parameters

X_{45}	DOS10-E_A_D	5	0.5			
X_{46}	DOS11-E_intub_D	5	0.5			
X_{47}	DOS16-Verb_fail_D	5	0.5			
X_{48}	DOS17-Verb_succ_D	5	0.5			
X_{49}	DOS18-Call_help_D	5	0.5			
X_{50}	NS1-Call_intub	5	0.5			
X_{51}	NS2-Prep_p_N	5	0.5			
X_{52}	NS3-Prep_eq_N	5	0.15			
X_{53}	NS4-Prep_d_N	8	0.1			
X_{54}	NS5-Pre_oxy_D	5	0.3			
X_{55}	NS6-Prep_team_D	5	0.3			
X_{56}	NS7-Prep_dif_D	5	0.3			
X_{57}	NS8-Give_d_N	5	0.3			
X_{58}	NS9-Give_cr_N	5	0.3			
X_{59}	NS10-E_A_D	15	0.5			
X_{60}	NS11-E_intub_D	15	0.55			
X_{61}	NS12-Mon_p_N	15	0.3			
X_{62}	NS13-Obs_c_N	15	0.55			
X_{63}	NS14-Verb_fail_N	15	1.3			
X_{64}	NS15-Verb_succ_N	5	0.5			
X_{65}	NS18-Call_help_D	5	1.3			
X_{66}	NS19-Mem_Prep_p_N	25	0.8			
X_{67}	NS20-Mem_Prep_dr_N	25	0.5			
X_{68}	NS21-Mem_Give_dr_N	25	0.5			
X_{69}	NOS2-Prep_p_N	5	0.2			
X_{70}	NOS3-Prep_eq_N	25	1.8			
X_{71}	NOS4-Prep_dr_N	25	0.5			
X_{72}	NOS8-Give_d_N	5	1.1			
X_{73}	NOS9-Give_cr_N	25	0.3			
X_{74}	NOS12-Mon_p_N	5	0.5			
X_{75}	NOS13-Obs_c_N	5	0.5			
X_{76}	NOS14-Verb_fail_N	5	0.5			
X_{77}	NOS15-Verb_succ_N	5	0.5			
X_{78}	W1-**LW**_Prep_p_Nurse→Prep_eq_Nurse			X_{87}		
X_{79}	W2-**IW**_Prep_p_Nurse→Prep_eq_Nurse	5	0.5			
X_{80}	W3-**RW**_Prep_p_Nurse→Prep_eq_Nurse	5	1.2			
X_{81}	W4-**LW**_Prep_p_N,D→Prep_eq_N,D			X_{88}		
X_{82}	W5-**IW**_Prep_p_N,D→Prep_eq_N,D	5	0.5			
X_{83}	W6-**RW**_Prep_p_N,D→Prep_eq_N,D	5	0.5			
X_{84}	W7-**LW**_Verb_fail_D→Call_help_D			X_{89}		
X_{85}	W8-**IW**_Verb_fail_D→Call_help_D	5	0.5			
X_{86}	W9-**RW**_Verb_fail_D→Call_help_D	5	0.5			
X_{87}	M1-**M_LW**_Prep_p_Nurse→Prep_eq_Nurse				1	0
X_{88}	M2-**M_LW**_Prep_p_N,D→Prep_eq_N,D				1	0
X_{89}	M3-**M_LW**_Verb_fail_D→Call_help_D				1	0

Fig. 11 (continued)

Fig. 12 Initial values list **iv**

iv	initial values	1
X_1		
X_2		
X_3		
X_4		
X_5	WS0-Context	0.5
X_6	WS1-Call_intub	0
X_7	WS2-Prep_p_N	0
X_8	WS3-Prep_eq_N	0
X_9	WS4-Prep_d_N	0
X_{10}	WS5-Pre_oxy_D	0
X_{11}	WS6-Prep_team_D	0
X_{12}	WS7-Prep_dif_D	0
X_{13}	WS8-Give_d_N	0
X_{14}	WS9-Give_cr_N	0
X_{15}	WS10-E_A_D	0
X_{16}	WS11-E_intub_D	0
X_{17}	WS12-Mon_p_N	0
X_{18}	WS13-Obs_c_N	0
X_{19}	WS14-Verb_fail_N	0
X_{20}	WS15-Verb_succ_N	0
X_{21}	WS16-Verb_fail_D	0
X_{22}	WS17-Verb_succ_D	0
X_{23}	WS18-Call_help_D	0
X_{24}	DS1-Call_intub	0
X_{25}	DS2-Prep_p_N	0
X_{26}	DS3-Prep_eq_N	0
X_{27}	DS4-Prep_d_N	0
X_{28}	DS5-Pre_oxy_D	0
X_{29}	DS6-Prep_team_D	0
X_{30}	DS7-Prep_dif_D	0
X_{31}	DS8-Give_d_N	0
X_{32}	DS9-Give_cr_N	0
X_{33}	DS10-E_A_D	0
X_{34}	DS11-E_intub_D	0
X_{35}	DS12-Mon_p_N	0
X_{36}	DS13-Obs_c_N	0
X_{37}	DS16-Verb_fail_D	0
X_{38}	DS17-Verb_succ_D	0
X_{39}	DS18-Call_help_D	0
X_{40}	DS19-Mem-Prep_team_D	0
X_{41}	DS20-Mem-Prep_dif_D	0
X_{42}	DOS5-Pre_oxy_D	0
X_{43}	DOS6-Prep_team_D	0
X_{44}	DOS7-Prep_dif_D	0
X_{45}	DOS10-E_A_D	0
X_{46}	DOS11-E_intub_D	0
X_{47}	DOS16-Verb_fail_D	0
X_{48}	DOS17-Verb_succ_D	0
X_{49}	DOS18-Call_help_D	0

Fig. 12 (continued)

X_{50}	NS1-Call_intub	0
X_{51}	NS2-Prep_p_N	0
X_{52}	NS3-Prep_eq_N	0
X_{53}	NS4-Prep_d_N	0
X_{54}	NS5-Pre_oxy_D	0
X_{55}	NS6-Prep_team_D	0
X_{56}	NS7-Prep_dif_D	0
X_{57}	NS8-Give_d_N	0
X_{58}	NS9-Give_cr_N	0
X_{59}	NS10-E_A_D	0
X_{60}	NS11-E_intub_D	0
X_{61}	NS12-Mon_p_N	0
X_{62}	NS13-Obs_c_N	0
X_{63}	NS14-Verb_fail_N	0
X_{64}	NS15-Verb_succ_N	0
X_{65}	NS18-Call_help_D	0
X_{66}	NS19-Mem_Prep_p_N	0
X_{67}	NS20-Mem_Prep_dr_N	0
X_{68}	NS21-Mem_Give_dr_N	0
X_{69}	NOS2-Prep_p_N	0
X_{70}	NOS3-Prep_eq_N	0
X_{71}	NOS4-Prep_dr_N	0
X_{72}	NOS8-Give_d_N	0
X_{73}	NOS9-Give_cr_N	0
X_{74}	NOS12-Mon_p_N	0
X_{75}	NOS13-Obs_c_N	0
X_{76}	NOS14-Verb_fail_N	0
X_{77}	NOS15-Verb_succ_N	0
X_{78}	W1-**LW**_Prep_p_Nurse→Prep_eq_Nurse	0.1
X_{79}	W2-**IW**_Prep_p_Nurse→Prep_eq_Nurse	0
X_{80}	W3-**RW**_Prep_p_Nurse→Prep_eq_Nurse	0
X_{81}	W4-**LW**_Prep_p_N,D→Prep_eq_N,D	0.1
X_{82}	W5-**IW**_Prep_p_N,D→Prep_eq_N,D	1
X_{83}	W6-**RW**_Prep_p_N,D→Prep_eq_N,D	0
X_{84}	W7-**LW**_Verb_fail_D→Call_help_D	0.1
X_{85}	W8-**IW**_Verb_fail_D→Call_help_D	1
X_{86}	W9-**RW**_Verb_fail_D→Call_help_D	0
X_{87}	M1-**M_LW**_Prep_p_Nurse→Prep_eq_Nurse	0.8
X_{88}	M2-**M_LW**_Prep_p_N,D→Prep_eq_N,D	0.9
X_{89}	M3-**M_LW**_Verb_fail_D→Call_help_D	1

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