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From Conceptual to Computational Mechanisms

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Computational Modeling of Multilevel Organizational Learning: From Conceptual to Computational Mechanisms

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Abstract This paper addresses formalization and computational modeling of multi-level organizational learning, which is one of the major challenges for the area of organizational learning. It is discussed how various conceptual mechanisms in multi-level organizational learning as identified in the literature, can be formalized by computational mechanisms which provide mathematical formalizations that enable computer simulation. The formalizations have been expressed using a self-modeling network modeling approach.

Keywords Organizational learning · Mechanisms · Computational modeling · Self-modeling networks

1 Introduction

Multilevel organizational learning is a complex adaptive process with multiple levels and nested cycles between them. Much literature is available analyzing and describing in a conceptual manner the different conceptual mechanisms involved, e.g., [18, 9,

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26, 27, 16]. However, mathematical or computational formalization of organizational learning in a systematic manner is a serious challenge. Successfully addressing this challenge requires:

- An overall mathematical and computational modeling approach able to handle the interplay of the different levels, adaptations and mechanisms involved
- For the conceptual mechanisms involved mathematical and computational formalization as computational mechanisms.

In this paper, for the first bullet, the self-modeling network modeling approach described in [20] is chosen, this approach has successfully been applied to the use, adaptation and control of mental models in [21]. For the second bullet, for many of the identified conceptual mechanisms from the literature, it is discussed how they can be modeled mathematically and computationally as computational mechanisms within a self-modeling network format.

In Sect. 2, an overview is given of conceptual mechanisms and how they can be related to computational mechanisms. Section 3 briefly describes the self-modeling network modeling approach used for computational formalization. In Sect. 4, a few examples of computational mechanisms for the level of individuals are described more in detail. Section 5 discusses more complex examples of computational models for feedforward and feedback learning that form bridges between the levels.

2 Overview: From Conceptual to Computational Mechanisms

In this section, a global overview of conceptual organizational learning mechanisms is described and supported by relevant references. Some of these conceptual mechanisms do not have pointers yet to computational mechanisms and can be considered items for a research agenda. Organizations operate as a system or organism of interconnected parts. Similarly, organizational learning is considered a multilevel phenomenon involving dynamic connections between individuals, teams and organization [12, 9], see Fig. 1. Due to the complex and changing environment within which organizations operate, the learning constantly evolves, and some learning may become obsolete. Organizational learning is a vital means of achieving strategic renewal and continuous improvement, as it allows an organization to explore new possibilities as well as exploit what they have already learned (March, 1991). Organizational learning is a dynamic process that occurs in feedforward and feedback directions. Feedforward learning assists in exploring new knowledge by individuals and teams and institutionalizing this knowledge at the organizational level [9]. Feedback learning helps in exploiting existing and institutionalized knowledge, making it available for teams and individuals. The essence of organizational learning is best captured in the following quote:

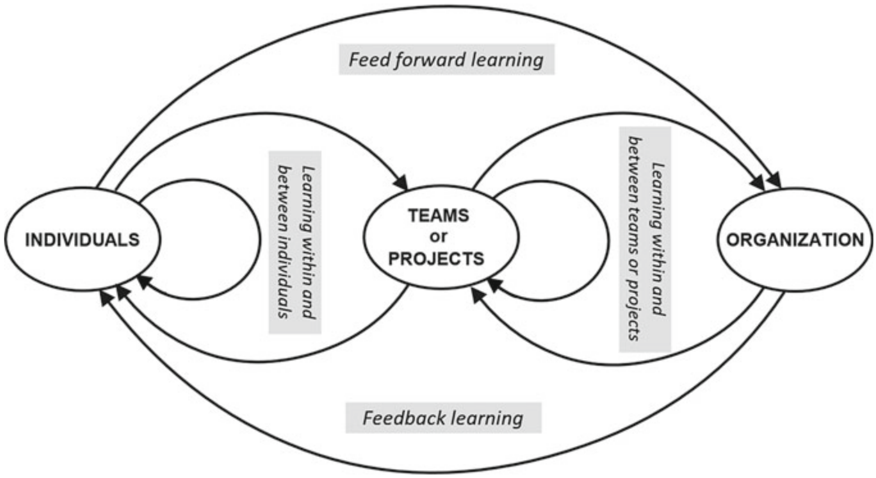

Fig. 1 Organizational learning: multiple levels and nested cycles (with depth 3) of interactions

> 'organizations are more than simply a collection of individuals; organizational learning is different from the simple sum of the learning of its members. Although individuals may come and go, what they have learned as individuals or in groups does not necessarily leave with them. Some learning is embedded in the systems, structures, strategy, routines, prescribed practices of the organization, and investments in information systems and infrastructure.'Crossan et al. [9], p. 529).

Individuals can learn by reflecting on their own past experiences, learn on the job (learning by doing), by observing others and from others, or by exploiting existing knowledge and applying that knowledge to other situations and contexts. Individuals can also learn by exploring new insights through pattern recognition, deep evaluation of a problem at hand, materialized in the 'aha' moment, when a new discovery is made. It is highly subjective and deeply rooted in individual experiences [9]. Teams learn by interpreting and integrating individual learnings by interpreting and sharing knowledge through the use of language, mind maps, images, or metaphors and thus jointly developing new shared mental models [9]. Team-level learning encompasses integration of possibly diverse, conflicting meanings, in order to obtain a shared understanding of a state or a situation. The developed shared understanding results in taking coordinated action by the team members [9]. Eventually, these shared actions by individuals and teams are turned into established routines, deeply embedded into organizational cultures, and/or captured in new processes or norms. From a computational perspective, such a process of shared mental model formation out of a number of individual mental models may be considered to relate to some specific form of knowledge integration or (feedforward) aggregation of the individual mental models.

In order for the organizational learning to occur, it has to be triggered by learning mechanisms, which are defined as apparatus for enabling learning. A recent review by

Wiewiora et al. [26] and their subsequent empirical investigation [27] identified organizational and situational mechanisms affecting project learning in a project-based context. Organizational learning mechanisms include culture, practices, systems, leadership and structure. From the organizational learning perspective, *organizational systems* are designed to capture knowledge, which was developed locally by teams or projects and captured into manuals or guidelines. These can represent knowledge management systems such as centralized knowledge repositories or specialized software used to collect, store and access organizational knowledge. Future learnings of individuals based on this in general may be considered another specific form of (feedback) aggregation, this time of the organization-level mental model with the already available individual mental model,an extreme form of this is fully replacing the own mental model by the organization mental model.

Organizational practices include *coaching and mentoring* sessions for building competencies. Coaching and mentoring occurs on individual level, where individuals have opportunities to learn from more experienced peers or teachers. Coaching and mentoring can also facilitate organizational to individual-level learning. These experts have often accumulated, through the years, a vast of organizational knowledge and experiences, in which case they can be also sharing organizational learnings. Furthermore, *training sessions* provide opportunities for developing soft and technical skills. During the sessions, a facilitator shares their own soft or technical skills or organizational knowledge with individuals or teams. *Leaders* have been described as social architects and orchestrators of learning processes (Hannah and Lester 2009). Leaders who limit power distances and encourage input and debate promote an environment conducive to openness and sharing, hence facilitating individual to team learning [10]. Meanwhile, self-protected leaders are more likely to use their position of power and impose control, hence restricting collective learning opportunities. When it comes to the *organizational structure*, decentralized structures promote rapid diffusion of ideas and encourage the exploration of a more diverse range of solutions [1]. The ideal structure appears to be the one that is loosely coupled, providing some degree of team separation, while ensuring weak connections between teams and the organization [11]. A situational mechanism affecting multilevel learning is *occurrence of major events* [26]: significant situations, positive or negative, that trigger immediate reaction (Madsen 2009).

There is limited research that systematically and empirically investigates mechanisms that trigger learning flows within and between levels. Tables 1, 2 and 3 synthesize existing research into multilevel learning and offers (in the first three columns of Tables 1, 2 and 3) a list of learning mechanisms facilitating multilevel learning flows. This paper demonstrates one of the first attempts to translate these (conceptual) mechanisms into computational mechanisms (in the last three columns of Tables 1, 2 and 3) and proposes a new computational modeling approach (briefly summarized in Sect. 3) that can handle the interplay between the levels and consider learning mechanisms that trigger learning flows between the levels.

Table 1 addresses the learning at the individual level, in Fig. 1 indicated by the circular arrow from individuals to individuals. A number of examples of conceptual mechanisms are shown in the different rows, and for each of them, it is indicated

Table 1 Conceptual and computational mechanisms for learning at the level of individuals

Conceptual mechanisms	Examples	Relevant references	Computational mechanisms	Examples	Relevant references
Individual: within persons					
Learning by internal simulational	Mental simulation (sometimes called visualization) of individual mental models to memorize them better		Hebbian learning during internal simulation of an individual mental model	Mental simulation of individual mental models for surgery in a hospital before shared mental model formation and after learning from a shared mental model	[6, 7]
Learning by observing oneself during own task execution	Individuals are observing themselves while they are performing a task	Iftikhar and Wiewiora (2020)	Hebbian learning for mirroring and internal simulation of an individual mental model	Observation of own task execution by nurses and doctors in a hospital operation room	[2, 24, 25]
Learning from past experiences	Individuals are learning by reflecting on their own past experiences	Iftikhar and Wiewiora (2020)	Learning based on counterfactual thinking	Counterfactual internal what-if simulation of nearest alternative scenarios	[3]
Individual: between persons					
Learning by observing others during their task execution	Individuals are observing how their peers are performing a task	Iftikhar and Wiewiora (2020)	Hebbian learning for mirroring and internal simulation of an individual mental model	Observation of each other's task execution by nurses and doctors in a hospital operation room	[2, 24, 25]
Coaching and mentoring	Learning from more senior and experienced people their individual 'tricks of the trade' via coaching and mentoring	[26, 27]	Learning from internal communication channels and aggregation	Doctor explains own mental model to nurse as preparation for surgery	[2, 24]

(continued)

Table 1 (continued)

Conceptual mechanisms	Examples	Relevant references	Computational mechanisms	Examples	Relevant references
Training sessions	Training sessions in which a facilitator shares their own soft and technical skills with individuals	[26, 27]	Learning from internal communication channels and aggregation	Experienced doctor explains own mental model to team	[2, 24]

Table 2 Conceptual and computational mechanisms for feedforward learning: from individual to teams or projects or to the organization and from teams or projects to the organization

Conceptual mechanisms	Examples	Relevant references	Computational mechanisms	Examples	Relevant references
Feedforward learning					
From individuals to organization					
Shared organization mental model formation and improvement based on individual mental models	Individuals share their mental models and institutionalize a shared mental model for the organization	[26, 27]	Feedforward aggregation of individual mental models for formation or improvement of shared mental models	Aggregating individual mental models from a nurse and a doctor to form a shared mental model of an intubation	[4, 5], Canbaloğlu et al. (2021a)
Occurrence of major events	Individuals mobilize to react and find solutions to major events. The best solution is selected and institutionalized by the organization	[26]	Feedforward aggregation of individual mental models for formation or improvement of shared mental models	Aggregating individual mental models from a nurse and a doctor to form a shared mental model of an intubation	[4, 5], Canbaloğlu et al. (2021a)
From individuals to teams or projects					
Training sessions	Training sessions in which a facilitator shares their own soft and technical skills with teams or projects	[26, 27]	Feedforward aggregation of individual mental models (and perhaps an existing shared organization mental model)	Aggregating individual mental models for surgery by hospital teams to form a shared team or project mental model	Canbaloğlu et al. (2021b)

(continued)

Table 2 (continued)

Conceptual mechanisms	Examples	Relevant references	Computational mechanisms	Examples	Relevant references
Learning by working together and joint-problem solving	Individuals of a team while working together are sharing their individual mental models and creating a new shared mental model by discussing and jointly solving a problem in hand	[18] Iftikhar and Wiewiora, (2020)	Feedforward aggregation of individual mental models (and perhaps an existing shared organization mental model)	Aggregating individual mental models for surgery by hospital teams to form a shared organization mental model	Canbaloğlu et al. (2021b)
From teams or projects to organization					
Formalizing team learnings	Teams capture their learnings into manuals or guidelines, which then inform new organizational practices	[9], Iftikhar and Wiewiora (2020)	Feedforward aggregation of team or project mental models to obtain a shared organization mental model	Aggregating team or project mental models for surgery by hospital teams to form a shared team or project mental model	Canbaloğlu et al. (2021b)
Occurrence of major events	Teams mobilize to react and find solutions to major events. The best solution is selected and institutionalized by the organization	[26]	Feedforward aggregation of team or project mental models to obtain a shared organization mental model	Aggregating team or project mental models for surgery by hospital teams to form a shared organization mental model	Canbaloğlu et al. (2021b)

which computational mechanisms have been found that can be associated to them. These computational mechanisms are based on findings from neuroscience, such as Hebbian learning [13] and mirroring, e.g., [15, 17, 19, 22]. Tables 2 and 3 address the mechanisms behind the arrows from left to right and vice versa connecting different levels in Fig. 1. Here, the arrows from left to right indicate feedforward learning (see Table 2), and the arrows from right to left indicate feedback learning (Table 3). The three different sections in Table 2 relate to arrows from individuals to teams or projects, from teams or projects to the organization, and from individuals directly to the organization level. Similarly, the three different sections in Table 3 relate to the

Table 3 Conceptual and computational mechanisms for feedback learning: from the organization to individuals and to teams or projects and from teams or projects to individuals

Conceptual mechanisms	Examples	Relevant references	Computational mechanisms	Examples	Relevant references
Feedback learning					
From organization to individuals					
Instructional learning from a shared organization mental model					
Coaching and mentoring	Learning from experienced people who have through years accumulated organizational knowledge	[26, 27]	Learning from internal communication channels and feedback aggregation	Individuals (doctors and nurses) learning an own mental model from a shared organization mental model for intubation	Canbaloğlu et al. (2021a)
Organizational systems	Individuals access organizational knowledge management systems, policies and procedures to inform their practices	[9], Iftikhar and Wiewiora (2020)	Learning from internal communication channels and feedback aggregation	Individuals (doctors and nurses) learning an own mental model from a shared organization mental model for intubation	Canbaloğlu et al. (2021a)
Training sessions	Provision of courses during which a facilitator shares organizational knowledge to individuals	[26, 27]	Learning from internal communication channels and feedback aggregation	Individuals (doctors and nurses) learning an own mental model from a shared organization mental model for intubation	Canbaloğlu et al. (2021a)
From organization to teams or projects					
Training sessions	Provision of courses during which a facilitator shares organizational knowledge to teams or projects	[26, 27)	Learning from internal communication channels and feedback aggregation	Teams of doctors and nurses learning a team mental model from a shared organization mental model for intubation	Canbaloğlu et al. (2021b)

(continued)

Table 3 (continued)

Conceptual mechanisms	Examples	Relevant references	Computational mechanisms	Examples	Relevant references
From teams or projects to individuals					
Learning by working together and joint-problem solving	Individuals of a team while working together are sharing their individual mental models and creating a new shared mental model by discussing and jointly solving a problem in hand	[18] Iftikhar and Wiewiora (2020)	Learning from internal communication channels and feedback aggregation	Individuals (doctors and nurses) learning an own mental model from a shared team mental model for intubation	Canbaloğlu et al. (2021b)
Training sessions	Provision of courses during which a facilitator shares team knowledge to individuals	[26, 27]	Learning from internal communication channels and feedback aggregation	Individuals (doctors and nurses) learning an own mental model from a shared team mental model for intubation	Canbaloğlu et al. (2021a)

arrows in Fig. 1 from the organization to teams or projects, from teams or projects to individuals and from the organization level directly to individuals. After introducing the computational modeling approach based on self-modeling networks in Sect. 3, in the subsequent Sects. 4 and 5 for a number of the computational mechanisms indicated in Tables 1, 2 and 3. more details will be given.

3 The Self-modeling Network Modeling Approach Used

In this section, the network-oriented modeling approach used is briefly introduced. A temporal-causal network model is characterized by the following; here X and Y denote nodes of the network that have activation levels that can change over time, also called states [20]:

- *Connectivity characteristics*: Connections from a state X to a state Y and their weights $\boldsymbol{\omega}_{X,Y}$
- *Aggregation characteristics*: For any state Y, some combination function $\mathbf{c}_Y(..)$ defines the aggregation that is applied to the impacts $\boldsymbol{\omega}_{X,Y}X(t)$ on Y by its incoming connections from states X
- *Timing characteristics*: Each state Y has a speed factor $\boldsymbol{\eta}_Y$ defining how fast it changes for given causal impact.

The following canonical difference (or related differential) equations are used for simulation; they incorporate these network characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, $\boldsymbol{\eta}_Y$ in a standard numerical format:

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

for any state Y, where X_1 to X_k are the states from which Y gets incoming connections.

Modeling and simulation are supported by a dedicated software environment described in [20], it comes with a combination function library with currently around 65 combination functions. Some examples of these combination functions that are used here can be found in Table 4.

Applying the concept of *self-modeling network*, the network-oriented approach can also be used to model *adaptive* networks; see (Treur 2020a, b). By the addition of new states to the network which represent certain network characteristics, such characteristics become adaptive. These additional states are called self-model states, and they are depicted at the next level, distinguished from the base level of the network. For instance, the weight $\boldsymbol{\omega}_{X,Y}$ of a connection from one state X to another state Y is represented by an additional self-model state $\mathbf{W}_{X,Y}$. In such a way, by including self-model states, any network characteristic can be made adaptive. An adaptive speed factor $\boldsymbol{\eta}_Y$ can be modeled by a self-model state $\mathbf{H}_Y$. The self-modeling network

Table 4 Examples of combination functions for aggregation available in the library

Name	Formula	Parameters
Advanced logistic sum **alogistic**$_{\sigma,\tau}(V_1, \ldots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\ldots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau})}\right](1+e^{-\sigma\tau})$	Steepness $\boldsymbol{\sigma} > 0$; excitability threshold $\boldsymbol{\tau}$
Scaled maximum **smax**$_{\lambda}(V_1, \ldots, V_k)$	$\max(V_1, \ldots, V_k)/\boldsymbol{\lambda}$	Scaling factor $\boldsymbol{\lambda}$
Euclidean **eucl**$_{n,\lambda}(V_1, \ldots, V_k)$	$\sqrt[n]{\frac{V_1^n+\ldots+V_k^n}{\boldsymbol{\lambda}}}$	Order $\boldsymbol{n}$; scaling factor $\boldsymbol{\lambda}$
Scaled geometric mean **sgeomean**$_{\lambda}(V_1, \ldots, V_k)$	$\sqrt[k]{\frac{V_1*\ldots*V_k}{\boldsymbol{\lambda}}}$	Scaling factor $\boldsymbol{\lambda}$
Hebbian learning **hebb**$_{\mu}(V_1, V_2, V_3)$	$V_1 * V_2(1 - V_3) + V_3$	V_1,V_2 activation levels of the connected states; V_3 activation level of the self-model state for the connection weight; persistence factor $\boldsymbol{\mu}$
Maximum composed with Hebbian learning **max-hebb**$_{\mu}(V_1, \ldots, V_k)$	$\max(\mathbf{hebb}(V_1, V_2, V_3), V_4, \ldots, V_k)$	V_1,V_2 activation levels of the connected states; V_3 activation level of the self-model state for the connection weight; persistence factor $\boldsymbol{\mu}$

concept can be applied iteratively thus creating multiple orders of self-models (Treur 2020b). A second-order self-model can model an adaptive speed factor $\boldsymbol{\eta}\mathbf{W}_{X,Y}$ by a second-order self-model state $\mathbf{HW}_{X,Y}$. Moreover, a persistence factor $\boldsymbol{\mu}\mathbf{W}_{X,Y}$ of a first-order self-model state $\mathbf{W}_{X,Y}$ used for Hebbian learning can be modeled by a second-order self-model state $\mathbf{MW}_{X,Y}$.

4 Some Examples of Computational Mechanisms

In this section and the next one, for a number of conceptual mechanisms, it will be shown in more detail how they can be related to computational mechanisms in terms of the self-modeling network format. Some examples from (Canbaloğlu and Treur 2021a, b; Canbaloğlu et al. 2021a, b) will be briefly discussed, e.g., (see also Fig. 1 and Tables 1, 2 and 3):

- Learning by internal simulation: individual mental model learning based on internal simulation (conceptual) modeled by Hebbian learning (computational)
- Learning by observation: individual mental model learning based on observation (conceptual) and mirroring combined with Hebbian learning (computational)
- Learning by communication: individual mental model learning based on communication with another individual (conceptual) modeled by aggregation of communicated information with already available information (computational)
- Feedforward learning: shared team or organization mental model learning based on an individual or shared team mental model (conceptual) modeled by aggregation of multiple individual mental models
- Feedback learning: individual mental model learning based on a shared team or organization mental model (conceptual) modeled by aggregation of multiple shared team mental models.

In the current section, the first three bullets (all relating to Table 1) are addressed as mechanisms. In Sect. 5, the last two bullets (relating to Tables 2 and 3, respectively) are addressed, and it is also shown how the mechanisms involved can play their role in an overall multilevel organizational learning process. The mental models used as examples are kept simple; they concern tasks a, b, c, d which are assumed to be linearly connected.

Learning by internal simulation: Hebbian learning for an individual mental model

In Fig. 2a (see also Table 1) it is shown how internal simulation of a mental model by person B (triggered by context state con_1) activates subsequently the mental model states a_B to d_B of B and these activations in turn activate Hebbian learning of their mutual conection weights. Here for the Hebbian learning [13], the self-model state $\mathbf{W}_{X,Y}$ for the weight of the connection from X to Y uses the combination function $\mathbf{hebb}_{\boldsymbol{\mu}}(V_1, V_2, W)$ shown in Table 4. More specifically, this function $\mathbf{hebb}_{\boldsymbol{\mu}}(V_1, V_2, W)$ is applied to the activation values V_1, V_2 of X and Y and the current value

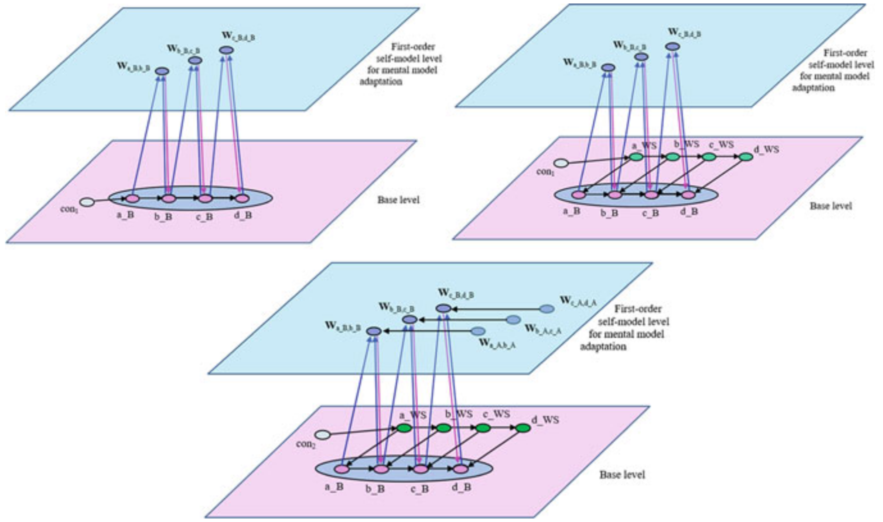

Fig. 2 **a** Upper, left. Learning by internal simulation: Hebbian learning during internal simulation. **b** Upper, right. Learning by observation: Hebbian learning after mirroring of the world states, **c** Lower. Learning by communication and by observation combined: learning by communication from person A to person B combined with Hebbian learning based on mirroring within person B

W of $\mathbf{W}_{X,Y}$. To this end upward (blue) connections are included in Fig. 2a (also a connection to $\mathbf{W}_{X,Y}$ itself is assumed but usually such connections are not depicted). The (pink) downward arrow from $\mathbf{W}_{X,Y}$ to Y depicts how the obtained value of $\mathbf{W}_{X,Y}$ is actually used in activation of Y. Thus, the mental model is learnt. If the persistence parameter $\boldsymbol{\mu}$ is 1, the learning result persists forever,if $\boldsymbol{\mu} < 1$, then forgetting takes place. For example, when $\boldsymbol{\mu} = 0.9$, per time unit 10% of the learnt result is lost.

Learning by observation: observing, mirroring and Hebbian learning of an individual mental model

For learning by observation, see Fig. 2b (see also Table 1). Here, mirror links are included: the (black) horizontal links from World States a_WS to d_WS to mental model states a_B to d_B within the base (pink) plane. When the world states are activated, through these mirror links, they in turn activate B's mental model states which in their turn activate Hebbian learning like above; this is modeled, e.g., in [2].

Learning by communication: receiving communication and aggregation in an individual mental model

See Fig. 2c for a combined form of learning by communication and by observation as modeled, e.g., in [2]; see also Table 1. The horizontal links within the upper (blue) plane model communication from A to B. This communication provides input from the mental model self-model states $\mathbf{W}_{\text{a\_A,b\_A}}$ to $\mathbf{W}_{\text{a\_A,b\_A}}$ of A to the mental model self-model states $\mathbf{W}_{\text{a\_B,b\_B}}$ to $\mathbf{W}_{\text{a\_B,b\_B}}$ of B; this input is aggregated within these self-model states of B's mental model using the $\mathbf{max\text{-}hebb}_{\boldsymbol{\mu}}$ combination function (see Table 4). This function takes the maximum of the communicated value originating from $\mathbf{W}_{x\_A,y\_A}$ and the current value of $\mathbf{W}_{x\_B,y\_B}$ that is being learnt by B through Hebbian learning.

More complex examples covering multiple mechanisms for feedforward and feedback learning relating to Table 2 and 3 are shown in Sect. 5.

5 Computational Models for Feedforward and Feedback Learning

In this section, feedforward and feedback learning mechanisms (see also Fig. 1) in computational models in self-modeling network format will be explained with two examples from (Canbaloğlu et al. 2021b) and [5]; see the network pictures in Fig. 3 and Fig. 4. These are the mechanisms listed as the last two bullets of the list of building blocks of organizational learning process in the first paragraph of the Sect. 4.

Feedforward learning: formation of a shared mental model by individuals or teams

In Fig. 3, self-model **W**-states representing the weights of connections between mental model states at the base level and horizontal **W**-to-**W** connections between them are depicted in the first-order self-model level (blue plane). The rightward connections from **W**-states of individuals' mental models to **W**-states of teams'

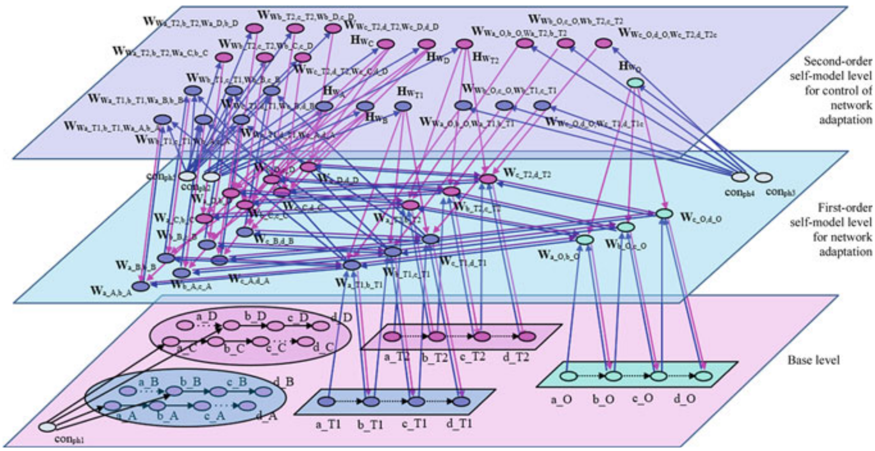

Fig. 3 Connectivity within the first-order self-model level for the adaptation of the mental models by formation of shared team and organization mental models (links from left to right: feedforward learning) and by instructional learning of individual mental models and shared team mental models from these shared mental models (links from right to left: feedback learning). (Canbaloğlu et al. 2021b)

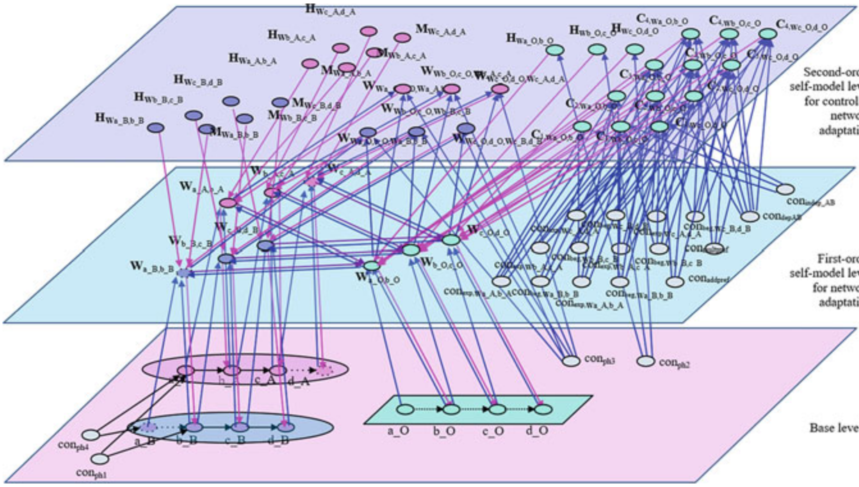

Fig. 4 Example involving context-sensitive control of aggregation in the process of shared mental model formation based on 16 context states (gray ovals) and four options of combination functions for aggregation [5]

shared mental models and from **W**-states of teams' shared mental models to **W**-states of the organization's shared mental model trigger the formation (by a form of aggregation) of shared mental models for teams and for the organization by feedforward learning.

Feedback learning: learning of individuals from shared mental models

In Fig. 3, self-model **W**-states of individuals' mental models (on the left) have connections coming from self-model **W**-states of their corresponding teams' shared mental models, and these team **W**-states have connections coming from self-model **W**-states of the organization's shared mental model. These leftward connections are used for individuals' improvements on their knowledge with the help of the shared mental models: the aggregated knowledge returns to the individuals by feedback learning.

Feedforward learning requires a combination function for aggregation of separate individual mental models to form a team's shared mental model, and a combination function for aggregation of different teams' mental models to form the organization's shared mental model. This aggregation can take place always according to one and the same method (modeled by one combination function), like in Fig. 3, or it can be adaptive according to the context. For real-life cases, the formation of a shared mental model is not same for different scenarios. Thus, making the aggregation adaptive improves the model in terms of applicability and accuracy.

In Fig. 4, context factors placed in the first-order self-model level (gray ovals in the blue plane) determine the choice of combination function during the aggregation of different mental models. Here, the combination function is dynamically chosen according to the activation status of the context factors that by their activation values characterize the context. In the second-order self-model level, **C**-states represent the choice of combination function for different mental model connections (between tasks a to d). Each **C**-state has (1) an incoming connection from each of the relevant context factors for the corresponding task connection it addresses (upward connections), and (2) one (downward) outward connection to the corresponding **W**-state. Thus, the control of the selection of the combination function is realized by the connections between context factors and **C**-states. Therefore, this approach makes the choice of combination function for the aggregation context sensitive. This makes the aggregation adaptive.

6 Discussion

Formalization and computational modeling of multilevel organizational learning is one of the major challenges for the area of organizational learning. The current paper addresses this challenge. Various conceptual mechanisms in multilevel organizational learning as identified in the literature were discussed. Moreover, it was shown how they can be formalized by computational mechanisms. For example, it has been discussed how formation of a shared mental model on the basis of a number of individual mental models, from a computational perspective can be considered a form of (feedforward) aggregation of these individual mental models.

The formalizations have been expressed using the self-modeling network modeling approach introduced in [20] and used as a basis for modeling dynamics, adaptation and control of mental models in [21]. The obtained computational mechanisms provide mathematical formalizations that form a basis for simulation experiments for the area of organizational learning, as has been shown in [4, 5], Canbaloğlu et al. (2021a, b). For example, in [4, 5], it is shown how specific forms of context-sensitivity of feedforward aggregation to obtain shared mental models can be modeled by second-order adaptive self-modeling networks according to the self-modeling network modeling approach applied to mental models from [20, 21].

The different types of mechanisms addressed cover almost all of the overall picture of multilevel organizational learning shown in Fig. 1, but by no means cover all relevant mechanisms. For example, for the sake of shortness factors that affect all levels, such as leaders, organization structure and culture, have been left out of consideration here. However, the modeling approach described here provides a promising basis to address in the future also the ones that were not addressed yet.

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