Computational Modelling of the Role of Leadership Style for Its Context-Sensitive Control Over Multilevel Organisational Learning

Canbaloğlu, Gülay; Treur, Jan; Wiewiora, Anna

DOI
10.1007/978-981-19-1607-6_20

Publication date
2023

Document Version
Final published version

Published in
Proceedings of 7th International Congress on Information and Communication Technology, ICICT 2022

Computational Modelling of the Role of Leadership Style for Its Context-Sensitive Control Over Multilevel Organisational Learning

Gülay Canbaloğlu, Jan Treur, and Anna Wiewiora

Abstract This paper addresses formalisation and computational modelling of context-sensitive control over multilevel organisational learning and in particular the role of the leadership style in influencing feed forward learning flows. It addresses a realistic case study with focus on the role of managers for control of multilevel organisational learning. To this end a second-order adaptive self-modelling network model is introduced and an example simulation for the case study is discussed.

Keywords Organisational learning · Leadership style · Context-sensitive control · Computational modelling · Self-modelling networks

1 Introduction

Organisational learning is a shared knowledge development process involving individuals, groups and the organisation. Organisational learning occurs through formation of shared mental models and common believes developed by organisational members and institutionalised for future use. Intermediary agents such as projects or teams are also involved in the process of learning [7, 9, 23, 22]. The team level occurs through discussion and developing of shared understanding at the team level,

G. Canbaloğlu (✉)
Department of Computer Engineering, Koç University, Istanbul, Turkey
e-mail: gcanbaloglu17@ku.edu.tr

G. Canbaloğlu · J. Treur
Center for Safety in Healthcare, Delft University of Technology, Delft, The Netherlands
e-mail: j.treur@vu.nl

J. Treur
Social AI Group, Department of Computer Science, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

A. Wiewiora
QUT Business School, Queensland University of Technology, Brisbane, Australia
e-mail: a.wiewiora@qut.edu.au

X.-S. Yang et al. (eds.), *Proceedings of Seventh International Congress on Information and Communication Technology*, Lecture Notes in Networks and Systems 447,
https://doi.org/10.1007/978-981-19-1607-6_20

achieved through collective actions, dialogue, shared practices and mutual adjustment. Although organisational members are involved in the process of organisational learning, organisational level learning can be people-independent and captured in routines and practices, even if the organisation loses some of its members. The process of organisational learning is non-linear, dynamic and context specific. It can be influenced by contextual factors such as leadership style, organisational culture or structure [23].

The diversity of the involved individuals and contextual factors brings an abundance of possible learning scenarios. Even in a project run by a single team, there may be multiple learning scenarios and contextual factors affecting decisions related to the organisational learning process. The multilevel and context-dependent characteristic of organisational learning makes it hard to observe and analyse.

Computational modelling and in particular the self-modelling network modelling approach introduced in [19] and explained in Sect. 3 in this paper, offers a useful tool to comprehend and represent the complex process of organisational learning; e.g. [4–4]. A detailed real-world learning scenario, explained in the in Sect. 2, is used to observe and analyse the process of organisational learning, with a focus on a context specific control of a leadership style. Using self-modelling networks with different context factors allows to incorporate a variety of management contexts, which enriches the possible learning scenarios, and provide better understanding of the effects of these contexts on the learning outcomes. The designed computational model is described in more detail in Sect. 4. Simulation results of the model follow in Sect. 5 with added images for a simulation scenario and a discussion part is included in Sect. 6.

2 Multilevel Organisational Learning

In this section, it is briefly discussed how multilevel organisation learning works and by an example scenario it is illustrated how leadership style can play an important role in it.

2.1 Multilevel Organisational Learning

Organisations operate as a system or organism of interconnected parts. Similarly, organisational learning is considered a multilevel phenomenon involving dynamic connections between individuals, teams and organisation [7, 9]. Due to the complex and changing environment within which organisations operate, the learning constantly evolves and some learning may become obsolete. Organisational learning is a vital means of achieving strategic renewal and continuous improvement, as it allows an organisation to explore new possibilities as well as exploit what they have already learned [15]. Organisational learning is a dynamic process that occurs in

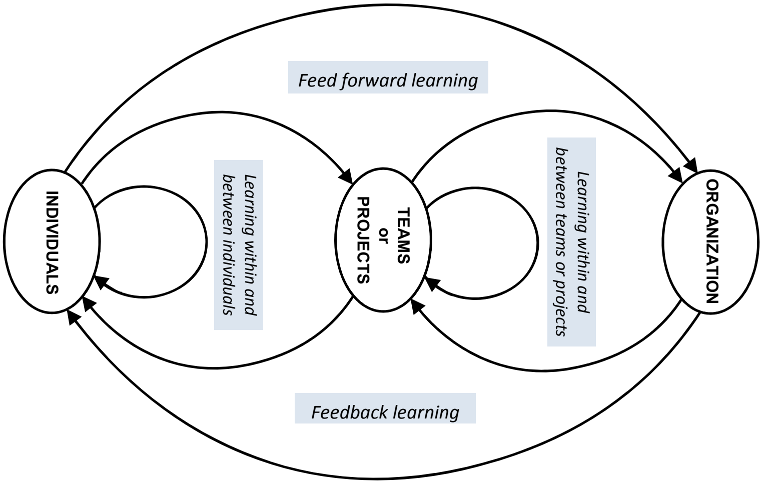

Fig. 1 Multilevel organisational learning: multiple levels and nested cycles (with depth 3)

feedback and feed forward directions. Feedback learning helps in exploiting existing and institutionalised knowledge, making it available for teams and individuals to utilise. Feed forward learning assists in exploring new knowledge by individuals and teams and institutionalising this knowledge at the organisational level [7]. As such, organisations may learn from individuals and teams via feed forward learning. Institutionalised on the organisational level can subsequently be accessed and used by the teams and individuals via feedback learning. This dynamic and adaptive process is depicted in Fig. 1. There are number of ways by which individuals, teams and organisations learn. For example, individuals can learn by reflecting on their past experiences and observing others. Teams can learn via joint problem solving or sharing their mental models. Organisations can learn from individuals and teams by capturing learning and practices into organisational manuals, policies or templates, which are then made available for teams and individuals to utilise. Recent research has pointed to the role of leaders in influencing learning flows between individuals, teams and organisations, which is discussed in the following section.

2.2 The Influential Role of Leaders in Facilitating Multilevel Learning

Management research found that leaders influence organisational learning [8, 11]. Leaders have been described as social architects of organisational learning [6, 11] who can either inhibit or facilitate learning flows [22]. For example, findings from [16] suggest that leaders facilitate feed forward learning by creating an environment for open and transparent communication. Edmondson [8] demonstrated that those leaders who purposefully obliterate power differences and encourage input and debate promote an environment conducive to learning, whereas leaders who choose to retain their status and power tend to tighten control at the expense of learning. Such leaders provide environment in which individuals are discouraged to share ideas or be open to others.

More recently, research identified the role of leaders in facilitating learning linkages between individuals, teams and organisation. A case study on multilevel learning in the context of a global project-based organisation revealed that senior leaders facilitate individual to individual and team to team (same level), as well as individual to team and individual to organisation (feed forward) learning flows [22]. This is because senior leaders have access to different parts of the organisation, well developed networks and a position of power to influence the transfer of learning between the levels. As such, senior leaders can facilitate an environment in which individuals can exchange knowledge, bounce ideas off each other, discuss ideas and engage in joint problem solving. Furthermore, [22] research demonstrated that by using a position of influence, leaders can either restrict or promote individual ideas for organisational improvement, hence affect institutionalisation of learning. Overall, existing research found evidence that leaders and their leadership styles impact the flow of learning within organisations. Systematic literature review of mechanisms facilitating multilevel organisational learning revealed that although research begins to identify the role of leaders in facilitating learning flows, more studies are required to better understand this phenomena and uncover the specific contextual factors and connections that leaders can influence to enable multilevel learning flows [23].

2.3 The Example Scenario Used as Illustration

In this section, we illustrate a real learning scenario that occurred in a project-based setting. An experienced project manager—Tom (pseudo name) was recently employed in an established large, and highly hierarchical organisation—Alpha (pseudo name). For the scenario description, see the left hand column of Table 1. Variables identified in this example are: learning from past experiences, role of leaders to effectively transfer learning and institutionalise learning, and a resistance to learn from a novice. This example also demonstrates that leaders have a powerful role in the organisation to promote ideas and institutionalise them. In Table 1 further analysis of the scenario can be found in terms of the conceptual mechanisms involved and how they can be related to computational mechanisms.

3 The Self-modelling Network Modelling Approach Used

In this section, the network-oriented modelling approach used is briefly introduced. A temporal-causal network model is characterised by; here X and Y denote nodes of

Table 1 Further analysis of the example scenario

Scenario	Conceptual mechanisms	Computational mechanisms
(1) Tom brought with him to the organisation learnings and insights that he acquired in his previous roles as a project manager. One of the insight he acquired was about the use of tollgates in projects	**Individual learning** His individual mental models based on individual learning from past experiences	**Learning by observation within project teams** World states with mirroring links to mental states and hebbian learning for the mental model • Team 1 without tollgates → weaker world states • Team 2 with tollgates → stronger world states • Tom decides to learn the mental model of Team 2
(2) During a team meeting, he shared one of his past learnings with other project managers. It was an idea to implement tollgates (approval points before proceeding to the next stage of the project that allows to review reediness and progress of the project). The organisation did not use tollgates or other processes to monitor progress of the project	**Feed forward learning from individual Tom to Team 3** Individual to team learning / sharing mental models based on past experiences	**Controlled individual and feed forward learning from individual mental model of Tom to mental models of the other individuals in the team and to team mental model formation** • Controlled decision of Tom to communicate his individual mental model to the other individuals in Team 3 • Shared mental model formation within Team 3
(3) The idea was well received by the team, but no call for action to implement the idea was requested by Tom's immediate boss	**No feed forward learning from Team 3 to the organisation** Lack of approval for a novice. Organisational learning stops, due to lack of interest from the immediate leader/or reluctance to take on board insights suggested by a novice. Illustrating the influential role of leaders	**Controlled feed forward learning from team to organisation** • Controlled by a control state for the immediate manager's approval • Due to the lack of this approval no feed forward learning to the organisation level takes place • This depends on the context factor that Tom is a novice in the new organisation • This also depends on the leadership style of Tom's immediate boss. That leader choose to retain their power to tighten control in expense of learning

(continued)

Table 1 (continued)

Scenario	Conceptual mechanisms	Computational mechanisms
(4) After several months, Tom raised the idea again with a higher level manager, who liked the idea and discussed it with others in the organisation who supported the idea and requested that tollgates are implemented as a new process to manage projects	**Feed forward learning from Team 3 to the organisation** By approval from higher level manager: institutionalisation of learning takes place illustrating the influential role of leaders	**Controlled feed forward learning from team to organisation based on communication with others** Controlled by a control state for the higher maneger's approval • This control state does not depend on being a novice • Instead it depends on feedback of some others in the organisation • This is obtained by communication channels back and forth to them • This depends on the leadership style of the higher level manager who displayed openness and welcomed the new idea from the employee

the network that have activation levels that can change over time, also called states [19]:

- *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 single causal impacts $\boldsymbol{\omega}_{X,Y}X(t)$ on Y from 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 purposes; 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 and where X_1 to X_k are the states from which Y gets its incoming connections. The above concepts enable to design network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. The available dedicated software environment described in [19, Chap.9], includes a combination function library with currently around 50 useful basic combination functions. Some examples of combination functions that are applied here can be found in Table 2.

Table 2 Examples of combination functions for aggregation available in the library

	Notation	Formula	Parameters
Advanced logistic sum	$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\cdots+V_k-\tau)}} - \frac{1}{(1+e^{\sigma\tau})}\right]$ $(1 + e^{-\sigma\tau})$	Steepness $\sigma > 0$ Excitability threshold τ
Steponce	$\mathbf{steponce}_{\alpha,\beta}(..)$	1 if time t is between α and β, else 0	Start time α; end time β
Complement identity	$\mathbf{comp\text{-}id}(V_1, \ldots, V_k)$	$1 - V_1$	
Hebbian learning	$\mathbf{hebb}_{\mu}(V_1, V_2, V_3)$	$V_1 * V_2(1 - V_3) + \mu V_3$	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 μ

Combination functions as shown in Table 2 are called *basic combination functions*. For any network model some number m of them can be selected; they are represented in a standard format as $\mathrm{bcf}_1(..)$, $\mathrm{bcf}_2(..)$, …, $\mathrm{bcf}_m(..)$. In principle, they use parameters $\pi_{1,i,Y}$, $\pi_{2,i,Y}$ such as the λ, σ and τ in Table 2. Including these parameters, the standard format used for basic combination functions is (with V_1, …, V_k the single causal impacts): bcf_i ($\pi_{1,i,Y}$, $\pi_{2,i,Y}$, $V_1 \cdots, V_k$. For each state Y just one basic combination function can be selected, but also a number of them can be selected; this will be interpreted as a weighted average of them with *combination function weights* $\gamma_{i,Y}$ as follows:

$$\begin{aligned} &\mathbf{c}_Y(\pi_{1,1,Y}, \pi_{2,1,Y}, \ldots, \pi_{1,m,Y}, \pi_{2,m,Y}, \ldots, V_1, \ldots, V_k \\ &= \left(\frac{\gamma_{1,Y}\, \mathrm{bcf}_1(\pi_{1,1,Y}, \pi_{2,1,Y}, V_1, \ldots, V_k) + \cdots + \gamma_{m,Y}\, \mathrm{bcf}_m(\pi_{1,m,Y}, \pi_{2,m,Y}, V_1, \ldots, V_k)}{\gamma_{1,Y} + \cdots + \gamma_{m,Y}}\right) \end{aligned} \tag{2}$$

Selecting only one of them for state Y, for example, $\mathrm{bcf}_i(..)$, is done by putting weight $\gamma_{i,Y} = 1$ and the other weights 0. This is a convenient way to indicate combination functions for a specific network model. The function $\mathbf{c}_Y(..)$ can then just be indicated by the weight factors $\gamma_{i,Y}$ and the parameters $\pi_{i,j,Y}$, according to (2).

Realistic network models are usually adaptive: often not only their states but also some of their network characteristics change over time. By using a *self-modelling network* (also called a *reified* network), a similar network-oriented conceptualization can also be applied to *adaptive* networks to obtain a declarative description using mathematically defined functions and relations for them as well; see [19]. This works through the addition of new states to the network (called *self-model states*) which represent (adaptive) network characteristics. In the graphical 3-D format as shown in Sect. 4, such additional states are depicted at a next level (called *self-model level* or *reification level*), where the original network is at the *base level*. As an example, the weight $\omega_{X,Y}$ of a connection from state X to state Y can be represented (at a next self-model level) by a self-model state named $\mathbf{W}_{X,Y}$. Similarly, all other network characteristics from $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{i,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$ can be made adaptive by including self-model states for them. For example, an adaptive speed factor $\boldsymbol{\eta}_Y$ can be represented by a self-model state named $\mathbf{H}_Y$, an adaptive combination function weight $\boldsymbol{\gamma}_{i,Y}$ can be represented by a self-model state $\mathbf{C}_{i,Y}$.

As the outcome of such a process of network reification is also a temporal-causal network model itself, as has been shown in ([19], Chap. 10), this self-modelling network construction can easily be applied iteratively to obtain multiple orders of self-models at multiple (first-order, second-order, …) self-model levels. For example, a second-order self-model may include a second-order self-model state $\mathbf{H}_{\mathbf{W}_{X,Y}}$ representing the speed factor $\eta_{\mathbf{W}_{X,Y}}$ for the dynamics of first-order self-model state $\mathbf{W}_{X,Y}$ which in turn represents the adaptation of connection weight $\boldsymbol{\omega}_{X,Y}$. Similarly, the weight $\omega_{Z,\mathbf{W}_{X,Y}}$ of an incoming connection from some state Z to a first-order self-model state $\mathbf{W}_{X,Y}$ can be represented by a second-order self-model state $\mathbf{W}_{Z,\mathbf{W}_{X,Y}}$.

This self-modeling network modeling approach has successfully been used to obtain computational models for dynamics, adaptation and control of mental models (e.g., [20, 17, 21]). The approach to multilevel organisational learning described in the current paper builds further on that previous work.

4 The Adaptive Computational Network Model Designed

In this section the designed computational network model will be explained. Based on the analysis of the learning scenario presented in Sect. 2 and Table 1 in particular the following computational mechanisms were considered for the different phases in the example scenario. Note that teams T1 and T2 are from Tom's previous organisation and team T3 is in his current organisation.

(1) **Team learning by observation for teams T1 and T2 and feedback learning from team T2 to individual A**

Team mental model learning for teams T1 and T2 is assumed to be based on observation of world states and mirroring them in the mental model combined with Hebbian learning. Here team T1 without tollgates shows weaker world states (lower activation levels), whereas team T2 with tollgates shows stronger world states. Based on this difference in success, A (which is Tom) makes a controlled decision to individually learn the shared team mental model from team T2 (feedback learning). The control is based on the good performance of team T2.

(2) **Individual and team learning from the individual mental model of A to mental models of the other individuals B and C in team T3 and to (feed forward) mental model formation by team T3**

Tom makes a controlled decision to communicate his individual mental model (learnt in the past from team T2) to the other individuals B and C in team T3 (individual learning from other individuals); control is based on providing space and time for team T3 to exchange knowledge. Within this team, this is followed by shared mental model formation which makes the mental model of Tom the shared team mental model of team T3 (feed forward learning).

(3) **Feed forward learning from team T3 to organisation controlled by A's immediate manager D**

Control is modelled by a control state related to the immediate manager D's approval. Due to the lack of this approval no feed forward learning to the organisation level takes place. D's non-approval depends on the context factor that Tom is a novice in the new organisation, and D's leadership style which is based on retaining power at the expense of learning.

(4) **Feed forward learning from team T3 to organisation controlled by a higher manager E**

Control is modelled by a control state related to the higher manager E's approval. This control state does not depend on being a novice; instead it depends on feedback of some other individuals F and G in the organisation. This feedback is obtained by communication from E (after having received the proposal) to F and G and from F and G back to E's state for approval. The leadership style of E also played a role. E displayed openness to ideas from others, hence he was more receptive welcomed the tollgate idea as a way to improve organisational processes.

In previous work [3, 4], a number of the involved computational mechanisms already have been described and used. In other work [5] some other mechanisms have been pointed out but not used yet. For example, learning by observation is only briefly described for individuals in [4], but in the current paper it is actually applied in (1) at the level of teams T1 and T2. Furthermore, the mechanisms for the control decisions for Tom (a) to decide to adopt the mental model of team T2 in (1), and (b) to decide to share this mental model with the members of team T3 in (2), are new too. Moreover, an important focus of the current paper is the control of the feed forward learning by managers in (3) and (4) above; this also is new here as that was not addressed in previous work such as Canbaloğlu et al. [3, 4].

4.1 Team Learning by Observation for Teams T1 and T2 and Feedback Learning from T2 to Individual A

In Fig. 2a adopted from Canbaloğlu et al. [5] it is shown how internal simulation of a mental model by any individual 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 connection weights. Here for the Hebbian learning [12], the self-model state $\mathbf{W}_{X,Y}$ for the weight of the connection from X to Y, uses the combination function $\mathbf{hebb}_{\mu}(V_1, V_2, W)$ shown in Table 2, last row. More specifically, this function $\mathbf{hebb}_{\mu}(V_1, V_2, W)$ is applied to the activation values V_1, V_2 of X and Y and the current value W of $\mathbf{W}_{X,Y}$. To this end upward (blue)

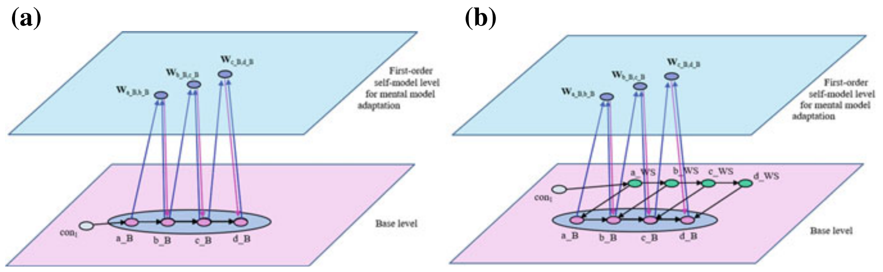

Fig. 2 **a** Left. Learning by internal simulation: Hebbian learning during internal simulation **b** Right. Learning by observation: Hebbian learning after mirroring of the world states

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 by individual B. 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.

For learning by observation as used as an individual learning mechanism in the current paper, the above is applied in conjunction with mirroring links (e.g., [13, 14, 18, 10]) to model the observation; see Fig. 2b. Here mirror links are the (black) links from World States a_WS to d_WS to the corresponding mental model states a_B to d_B. When the world states are activated because things are happening in the world, through these mirror links they in turn activate B's related mental model states which in their turn activate Hebbian learning like in the case of pure internal simulation pointed out above. In the network model introduced in the current paper, the mechanism of learning by observation as described is applied at the team level to teams T1 and T2.

4.2 Abstracted Overall View on the Process

After the teams T1 and T2 have learned their (shared) mental models, individual A (Tom) decides to adopt the team mental model of team T2 as his own individual mental model: feedback learning. This is shown in Fig. 3 which gives an abstracted view of the overall process. This time, the ovals stand for groups of states: in the base plane groups of base states for one mental model and at the first-order self-model level (blue middle plane) for groups of self-model **W**-states for one mental model.

The arrow from the first-order self-model for the shared mental model for team T2 indicated by SMM-**W**-T2 to the first-order self-model for the individual A's mental model indicated by IMM-**W**-A-T2 depicts the adoption by A of the team mental model of team T2 as individual mental model (feedback learning).

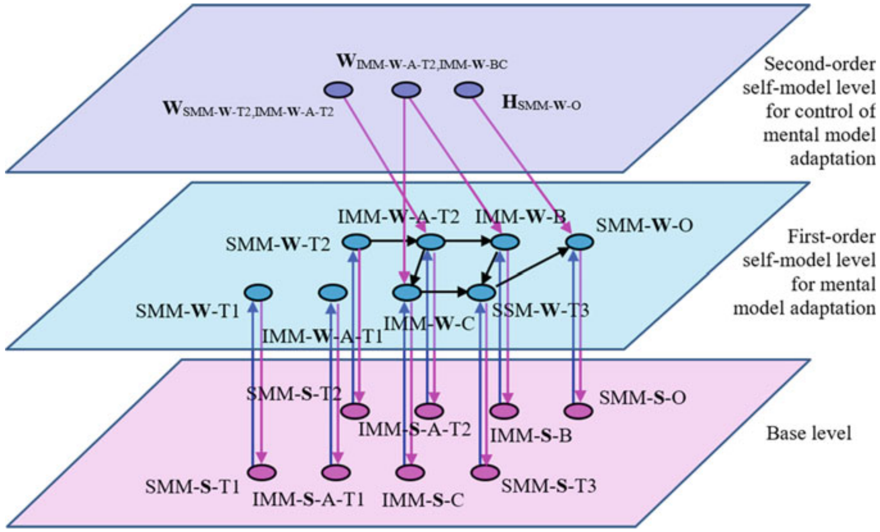

Fig. 3 Abstract view on the connectivity of the first- and second-order self-model of the mental models: SMM = Shared Mental Model, IMM = Individual Mental Model, **S** = States of mental model, **W** = Connection Weights of mental model, T1, T2 = teams from previous organisation, T3 = team in current organisation, A = Tom, B and C = team members in T3, O = organisation

This happens (via the pink downward link) under control of second-order self-model state $\mathbf{W}_{\text{SMM-}\mathbf{W}\text{-T2,IMM-}\mathbf{W}\text{-A-T2}}$ that gives the weight of this connection from SMM-**W**-T2 to IMM-**W**-A-T2 values 0 or 1. This second-order self-model state $\mathbf{W}_{\text{SMM-}\mathbf{W}\text{-T2,IMM-}\mathbf{W}\text{-A-T2}}$ depends on a sufficiently high activation value (>0.6) of team T2's world state d_WS_T2, which makes the control of the adoption decision for feedback learning context-sensitive.

In the new organisation, Tom decides to communicate this individual mental model to the team members (B and C) in team T3. This is depicted in Fig. 3 by the arrows from IMM-**W**-A-T2 to IMM-**W**-B and IMM-**W**–C. This is learning for one individual from another individual. Note that also here control is used for the decision to actually do this: the two pink downward arrows from the control state $\mathbf{W}_{\text{IMM-W-A-T2,IMM-}\mathbf{W}\text{-BC}}$ at the second-order self-model level to IMM-**W**-B and IMM-**W**-C. This control state $\mathbf{W}_{\text{IMM-W-A-T2,IMM-}\mathbf{W}\text{-BC}}$ is context-sensitive as it depends on a suitable time within team T3's meetings. After that, within team T3 this model is chosen as shared mental model, depicted in Fig. 3 by the arrows from IMM-**W**-B and IMM-**W**-C to SMM-**W**-T3 (feed forward learning).

Note that in the model, for the sake of simplicity no explicit control over this shared mental model formation for T3 was included. As a next step it is shown in Fig. 3 how this shared mental model of T3 is institutionalised and becomes shared mental model for the organisation O. However, for this step control is needed by an authorised manager D or E (the pink downward connection from state $\mathbf{H}_{\text{SMM-}\mathbf{W}\text{–O}}$,

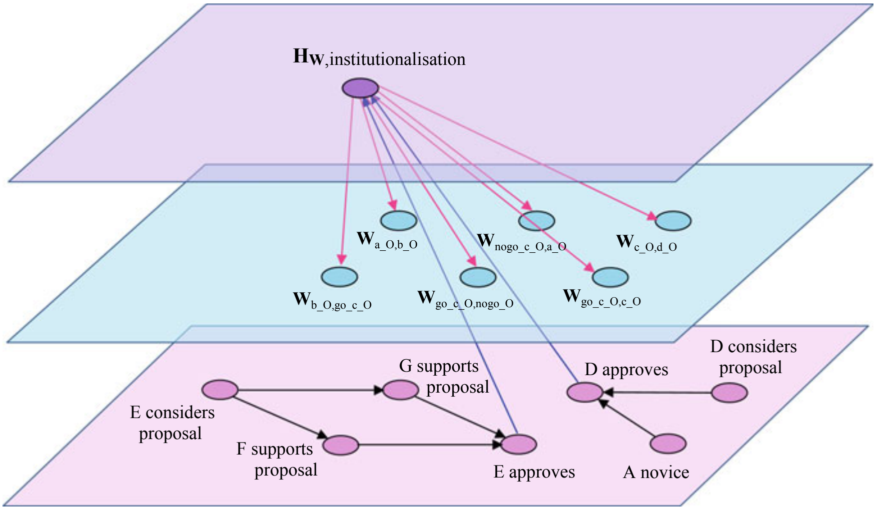

Fig. 4 Network for approval of institutionalisation and the context-sensitive control over it

which is also context-sensitive as it depends on approval by D or E. This form of context-sensitive control is described in more detail in Sect. 4.3 and Fig. 4.

4.3 *Context-Sensitive Control of Institutionalisation of the Shared Mental Model by Managers D and E*

For the control of the process of institutionalisation some context factors are crucial: approval from an authorised manager is required; see Fig. 4. In this scenario two of such managers act: D and E. As can be seen in the base plane, manager D makes approval dependent on the fact that Tom is a novice because of his leadership style focused on retaining control and power.

This makes that D does not approve. However, manager E whose leadership style was based on distributed power and opennes to ideas lets approval depend on whether some knowledgeable persons F and G from the organisation are in support of approval, and then follows their suggestion; see the four (two incoming and two outgoing) arrows in the base plane related to the states called F supports proposal and G supports proposal. The (blue) upward links from base plane to upper plane activate the control for effectuation of the decision for approval, by making the adaptation speed of the related **W**-states in the middle plane nonzero. It is by these mechanisms that the control of the institutionalisation is addressed in a context-sensitive manner. For more details of the model, see the Linked Data at https://www.researchgate.net/publication/355186556.

5 Simulation Results

In this section, the simulation results are discussed for the example scenario described in Sect. 2. In Fig. 5 the world states for team T1 (the team not using tollgates) and for team T2 (the team using tollgates) are shown. The monotonically increasing curves show the world states for team T1; here the value for the last task d stays under 0.4 (the thicker red curve). The curves for the world states for team T2 show increasing pattern with initially a slight fluctuation due to the nogo-feedback loop. Although a bit slower than for team T1, in the end the last task d for T2 reaches a value above 0.6 (the thicker green curve). This value satisfies the criterion of Tom for adopting the team mental model of T2 as his own individual mental model (feedback learning).

Figure 6 shows an overview of the adaptations of the different mental models learnt together with the context-sensitive control over these adaptations. In the different phases the following can be seen:

Time 0–150: Within the previous organisation, teams T1 and T2 learn their (shared) mental models (team learning by observation as discussed in Sect. 4.1).

Time 150–200: Within the previous organisation (because of good results in the world), at this point Tom decides to adopt the shared mental model of team T2 (time 150) and actually adopts it (around time 200). This control decision is based on the good results of the outcomes of team T2 (here state X_{10} is used as an indicator; see the green line in Figs. 5 and 6) together with an appropriate timing for, which is a context factor modelled by state X_{63} (pink curve occurring at time 150); these two together activate second-order self-model state $\mathbf{W}_{\mathbf{W},\mathrm{TomsChoice}}$ for control of the effectuation of this decision (the orange curve starting at time 150).

Time 300–400: In the new organisation, Tom decides to share (time 300) and actually shares (around time 350) his mental model of team T2 with team members B and C in team T3. This control decision is based on another context factor modelled

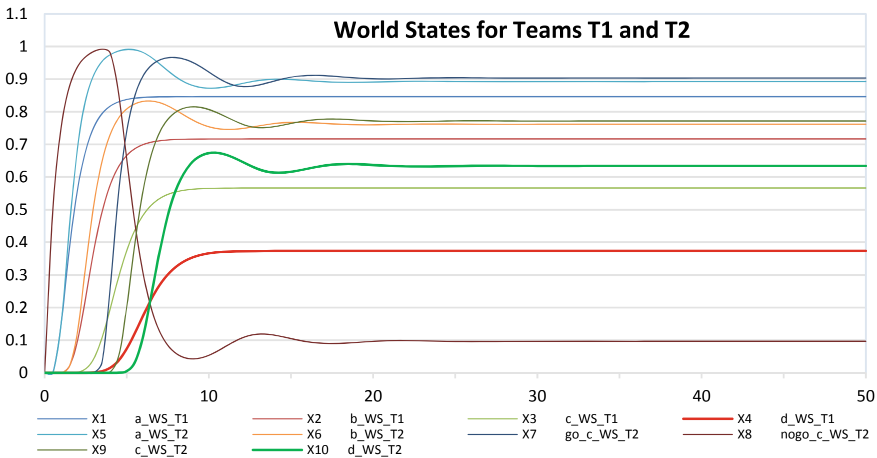

Fig. 5 Simulation outcomes for the world states for teams T1 and T2

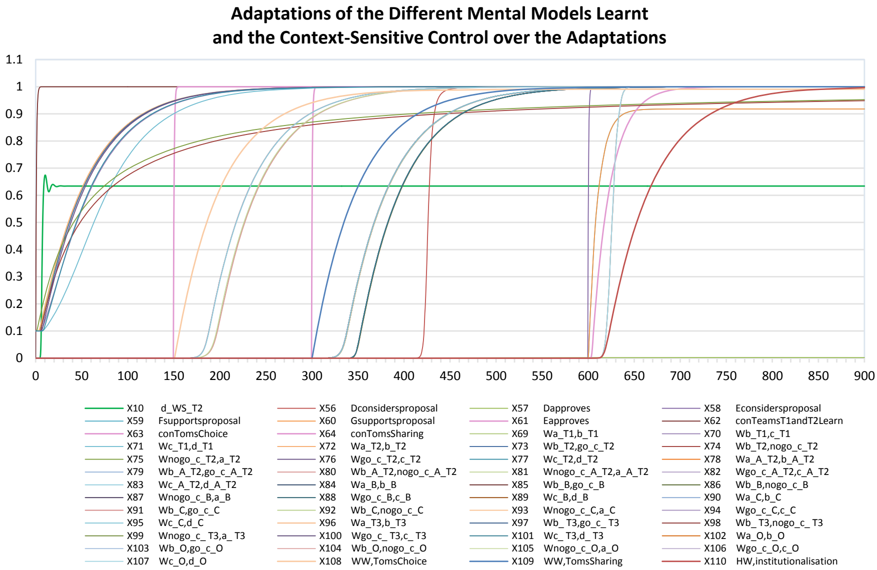

Fig. 6 Simulation outcomes for the first-order self-model states for adaptation of the various mental models learnt, the second-order self-model states for control over the adaptation, and the context factors making this control context-sensitive

by state X_{64} (pink curve occurring at time 300). This context factor activates second-order self-model state $\mathbf{W}_{\mathbf{W},\mathrm{TomsSharing}}$ for control of the effectuation of this sharing decision (the blue curve starting at time 300), so that the communication actually takes place. After having received it, B and C adopt the communicated individual mental model as shared mental model for team T3 (at time 350).

Time 400–450: The just formed shared mental model of team T3 is proposed for institutionalisation to manager D (between time 350 and 400); D does not approve it, due to Tom being a novice and due to D's leadership style of retaining power (yet another context factor, modelled by state X_{55}).

Time 600–650: Tom happens to meet manager E and uses the occasion to propose the institutionalisation (this is a last context factor, modelled by state X_{61}; see the curve occurring at time 600). Manager E communicates this proposal to F and G, and they give supportive feedback. Upon this E approves the proposal (state X_{61}, the pink curve occurring between times 600 and 625). This activates second-order self-model state $\mathbf{H}_{\mathbf{W},\mathrm{institutionalisation}}$ (the brown curve starting around time 615) which controls that the institutionalisation is actually realised (around time 650).

6 Discussion

As holds for many social processes, multilevel organisational learning suffers from the many context factors that often influence these processes and their outcomes in decisive manners. For example, an important decision for the organisation may depend on unplanned and occasionally meeting a higher manager like in the example case study addressed in this paper. Due to such context factors it may seem that sustainable generally valid laws or models will never be found, as any proposal often can easily be falsified by putting forward an appropriate context factor violating it. Given this perspective of highly context-sensitive processes, in particular when addressing a serious challenge like mathematical formalisation and computational modelling of multilevel organisational learning, it makes sense to explicitly address relevant context factors within such formalisations. This already has been done in particular for the specific process of aggregation of mental models in feed forward multilevel organisational learning in [1, 2]. In the current paper, this idea of context-sensitivity also has been addressed for other subprocesses in multilevel organisational learning.

Analysing a realistic case study, context factors have been identified that play a role in a number of steps within the example multilevel organisation learning process covered by the case study. These context factors have decisive effects on different parts of the process, such as adopting mental models for proven good practices and managers with their specific world view that need to give approval to institutionalisation. In the case study, the context factors had a proper setting so that in the end institutionalisation actually took place. However, if only one of the chain of these context factors would have had a different setting, that outcome would not have been achieved. The developed computational model explicitly addresses these decisive context factors and is able to explore for any setting of them what the outcome will be, thus covering both successful and less successful outcomes.

In previous work Canbaloğlu et al. [3, 4], a number of the computational mechanisms involved in the case study addressed here already have been introduced. However, there are a number of new ones too. For example, learning by observation is briefly pointed out for individuals in Canbaloğlu et al. [5] but here it is actually applied in (1) in Table 2 at the level of Team 1 and Team 2 for simulation. Furthermore, the mechanisms for the control decisions for Tom (a) to decide to adopt the mental model of Team 2 in (1) and (b) to decide to share this mental model with the members of Team 3 in (2) in Table 2, are new too. Moreover, an important focus of the current paper is the control of the feed forward learning by managers in (3) and (4) in Table 2; this indeed is new here as that was not addressed in previous work such as Canbaloğlu et al. [3, 4].

The presented findings have important implications for management studies, suggesting that computational modelling is a promising tool to predict changes in learning over time and demonstrate, via modelling, how different leadership styles can facilitate or inhibit organisational learning, hence further expand on findings by Edmundson [8] and [22].

Using computational tools for modelling learning scenarios has many benefits for practice. Modelling learning is a cost-effective decision making tool that helps predict learning outcomes and select best mechanisms for learning without investing time and money on implementing untested solutions. Using computational modelling enables to forecast different scenarios, which then provide basis for more informed decisions about the best possible mechanisms for implementation in the real world. For example, as demonstrated in our study, computational modelling can help organisations make more informed decisions on the most suitable leadership styles that will promote organisational learning. In doing so, organisations can invest in leadership training to achieve greater learning outcomes.

References

1. Canbaloğlu G, Treur J (2021a) Context-sensitive mental model aggregation in a second-order adaptive network model for organisational learning. In: Proceedings of the 10th international conference on complex networks and their applications. studies in computational intelligence, Springer Nature
2. Canbaloğlu G, Treur J (2021b) Using boolean functions of context factors for adaptive mental model aggregation in organisational learning. In: Proceeding of the 12th international conference on Brain-Inspired Cognitive Architectures, BICA'21. Studies in computational intelligence, Springer Nature (2021b)
3. Canbaloğlu G, Treur J, Roelofsma PHMP (2021) Computational modeling of organisational learning by self-modeling networks. Cog Sys Res 73:51–64
4. Canbaloğlu G, Treur J, Roelofsma PHMP (2022) A self-modeling network model for the role of individual and team learning in organisational learning. In: Proceeding of the 7th International Congress on Information and Communication Technology, ICICT'22. Lecture notes in networks and systems, Springer Nature
5. Canbaloğlu G, Treur J, Wiewiora A (2022a) Computational modeling of multilevel organisational learning: from conceptual to computational mechanisms. In: Proceeding of computational intelligence: automate your world. The Second International Conference on Information Technology, InCITe'22. Lecture Notes in Electrical Engineering, Springer Nature
6. Chang A, Wiewiora A, Liu Y (2021) A socio-cognitive approach to leading a learning project team: a proposed model and scale development. Int J Project Manage 39(6):646–657
7. Crossan MM, Lane HW, White RE (1999) An organizational learning framework: from intuition to institution. Acad Manag Rev 24:522–537
8. Edmondson AC (2002) The local and variegated nature of learning in organizations: a group-level perspective. Organ Sci 13:128–146
9. Fiol CM, Lyles MA (1985) Organizational learning. Acad Manag Rev 10:803–813
10. Van Gog T, Paas F, Marcus N, Ayres P, Sweller J (2009) The mirror neuron system and observational learning: Implications for the effectiveness of dynamic visualizations. Educ Psychol Rev 21(1):21–30
11. Hannah ST, Lester PB (2009) A multilevel approach to building and leading learning organizations. Leadersh Q 20(1):34–48
12. Hebb DO (1949) The organization of behavior: a neuropsychological theory. John Wiley and Sons, New York
13. Iacoboni M (2008) Mirroring people: the new science of how we connect with others. Farrar, Straus & Giroux, New York
14. Keysers C, Gazzola V (2014) Hebbian learning and predictive mirror neurons for actions, sensations and emotions. Philos Trans R Soc Lond B Biol Sci 369:20130175

15. March JG (1991) Exploration and exploitation in organizational learning. Organ Sci 2(1):71–87
16. Mazutis D, Slawinski N (2008) Leading organizational learning through authentic dialogue. Manag Learn 39(4):437–456
17. Van Ments L, Treur J (2021) Reflections on dynamics, adaptation and control: a cognitive architecture for mental models. Cogn Syst Res 70:1–9
18. Rizzolatti G, Sinigaglia C (2008) Mirrors in the brain: how our minds share actions and emotions. Oxford University Press
19. Treur J (2020) Network-oriented modeling for adaptive networks: designing higher-order adaptive biological, mental and social network models. Springer Nature, Cham
20. Treur J, Van Ments L (eds) (2022) Mental models and their dynamics, adaptation, and control: a self-modeling network modeling approach. Springer Nature
21. Van Ments L, Treur J, Klein J, Roelofsma PHMP (2021) A second-order adaptive network model for shared mental models in hospital teamwork. In: Nguyen NT et al (eds) Proceeding of the 13th International Conference on Computational Collective Intelligence, ICCCI'21. Lecture Notes in AI, vol 12876. Springer Naturem, pp 126–140
22. Wiewiora A, Chang A, Smidt M (2020) Individual, project and organizational learning flows within a global project-based organization: exploring what, how and who. Int J Project Manage 38:201–214
23. Wiewiora A, Smidt M, Chang A (2019) The 'How' of multilevel learning dynamics: a systematic literature review exploring how mechanisms bridge learning between individuals, teams/projects and the organization. Eur Manag Rev 16:93–115