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An adaptive network model for AI-assisted monitoring and management of neonatal respiratory distress

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A R T I C L E I N F O

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Organizational learning
Hospital teams

A B S T R A C T

This article presents the use of second-order adaptive network models of hospital teams consisting of doctors and nurses, interacting together. A variety of scenarios are modelled and simulated, in relation with respiratory distress of a neonate, along with the integration of an AI-Coach for monitoring and support of such teams and of organizational learning. The research highlights the benefits of introducing a virtual AI-Coach in a hospital setting. The practical application setting revolves around a medical team responsible for managing neonates with respiratory distress. In this setting an AI-Coach act as an additional team member, to ensure correct execution of medical procedure. Through simulation experiments, the adaptive network models demonstrate that the AI-Coach not only aids in maintaining correct medical procedure execution but also facilitates organizational learning, leading to significant improvements in procedure adherence and error reduction during neonatal care.

1. Introduction

Organizations face the ongoing challenge of continual development and learning not only at personal but also at the team level. They encompass strategic management objectives which aim at creating better working conditions and structures that enhance employees' willingness and ability to learn, thereby improving organizational processes of adjustment and adaptation. Safety culture in healthcare needs perception, competency, and attitude of an individual and whole organization to take responsibility of their actions. However, actions without adequate training or the implementation of new processes may introduce the possibility of malfunction or errors and necessitate adjustments and modifications (Keith & Frese, 2011).

One approach that holds promise in this regard is 'organizational learning'. Organizational learning encompasses the process by which an organization acquires, interprets, and applies knowledge to improve its performance and adapt to changing circumstances. It involves capturing lessons learned, sharing information, fostering a learning culture, and implementing effective feedback mechanisms within the organization (Saadat & Saadat, 2016). By leveraging the principles of organizational learning, teams can promote their performance by enhancing their shared mental models. Through continuous learning, teams can identify and rectify deficiencies in their mental models, fostering a shared understanding of the tasks, roles, and interdependencies (Jonker et al., 2011).

This paper showcases the application of the adaptive network-oriented modelling approach from (Treur, 2020), coupled with the cognitive architecture for usage, adaptation and control of mental models described in (Van Ments & Treur, 2021; Treur & Van Ments, 2022). This study primarily aims to develop and analyze adaptive network models, honing in on the decision-making and mental processes of medical staff in neonatal respiratory distress scenarios. This is accomplished by modeling the mental processes of the medical staff on the floor, which are second-order adaptive and incorporating an AI-Coach to monitor and support these processes.

The integration of an AI-Coach in healthcare is a crucial advancement with significant implications, contributing to the wider context of AI support in the health area, e.g., (Abdi, Bagherzadeh, Gholami, & Tajbakhsh, 2021; 8. Catania, 2021; Jayachitra, Prasanth, Hariprasath, Benazir Begam, & Madiajagan, 2023; Kavitha, Roobini, Prasanth, & Sujaritha, 2023; Sitterding, Raab, Saupe, & Israel, 2019). It marks a critical step in improving patient care quality and safety, especially in critical environments like neonatal intensive care units. By enhancing medical team decision-making and reducing errors, an AI-Coach not

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only betters patient outcomes but also aids healthcare professionals in their vital roles. This research offers valuable insights into integrating technology in healthcare, emphasizing patient safety and staff efficiency.

Specifically, it illustrates how an AI-Coach can enhance the knowledge within the mental processes of medical team members. Uniquely, this study applies an adaptive network-oriented model to the intricate context of neonatal respiratory distress. It allows for a comprehensive analysis of how an AI-coach can effectively drive organizational learning in such specialized scenarios. Through simulation experiments, the models illustrate the dual role of the AI-Coach in both ensuring accurate medical procedure execution and fostering organizational learning. This facilitation by the AI-Coach leads to notable enhancements in adherence to procedures and a reduction of errors within neonatal care, underpinning the importance of technological support in critical healthcare settings. In Section 2, a comprehensive introduction and background are provided, encompassing topics such as respiratory distress, mental models, and organizational learning. Section 3 outlines the general approach used in designing the adaptive network models. The subsequent section, Section 4, presents the various scenarios to be examined in the study. Section 5 details the second-order models for each scenario, elucidating their design principles. Thereafter, Section 6 presents the simulations conducted, and the paper concludes with a conclusion and discussion in Section 7.

2. Background literature

The following section provides a comprehensive overview of the background literature. It begins by elucidating the concept of respiratory distress in neonates, including its clinical manifestations and observable signs. Additionally, we delve into the significance of mental models, shared mental models, and organizational learning in this context.

2.1. Respiratory distress in neonates

Section 2.1 presents the critical aspects of neonatal respiratory distress, including its prevalence, causes, clinical signs, and diagnostic approaches. This overview establishes a context for the advanced interventions explored in the following sections.

2.1.1. Introduction to respiratory distress in neonates

Respiratory distress in neonates refers to a condition where newborn experience difficulty in breathing or inadequate oxygenation. It is a significant concern in clinical practice as it can be a marker of underlying respiratory disorders or other medical conditions. Prompt recognition and appropriate management are crucial to prevent complications and ensure optimal outcomes for neonates. Common respiratory disorders observed include Respiratory Distress Syndrome (RDS), Transient Tachypnea of the Newborn (TTN), and Meconium Aspiration Syndrome (MAS) (Swarnkar & Swarnkar, 2015).

2.1.2. Understanding the varied prevalence and factors influencing respiratory distress in neonates

The prevalence of respiratory distress among neonates can vary depending on various factors such as gestational age, birth weight, and underlying medical conditions such as sepsis and congenital malformations. Premature infants, in particular, are more susceptible to respiratory distress due to prematurity. Studies have shown that respiratory distress syndrome affects approximately 50–60 % of infants born before 28 weeks of gestation, while the prevalence decreases with increasing gestational age (Sweet et al., 2017). As mentioned before, specific respiratory disorders commonly observed in neonates include RDS, TTN, and MAS. RDS is one of the most prevalent respiratory disorders among premature infants, especially those born before 32 weeks of gestation (Saboute et al., 2015). TTN typically affects near-term and full-term infants, with an incidence of around 1–2 % of all deliveries. MAS, although less common, can occur when the baby inhaled meconium-stained amniotic fluid during or before birth.

2.1.3. Recognizing and assessing clinical manifestations of respiratory distress in Neonates: Diagnostic approaches and indicators

Clinical manifestations of respiratory distress in neonates can vary depending on the underlying cause and severity of the condition. Common signs include tachypnea, which is characterized by rapid breathing with an increased respiratory rate above the normal range for the infant's gestational age. Retractions, observed as inward movement of the chest wall during inspiration, indicate increased work of breathing. Nasal flaring, where the nostrils dilate during inspiration, is another common manifestation. Grunting, a sound produced by the infant during expiration, signifies an attempt to maintain lung volume and improve oxygenation. Cyanosis, a bluish discoloration of the skin, lips, or mucous membranes, may also occur due to inadequate oxygenation (Machogu & Gaston, 2021).

To assess and confirm respiratory distress in neonates, healthcare professionals employ diagnostic approaches such as physical examination, pulse oximetry, chest X-rays, blood gas analysis, and other investigations (Bass et al., 2015). Bed-side lung ultrasound is another diagnostic technique that is now increasingly used. Physical examination involves a thorough assessment of the infant's respiratory effort, chest movement, breath sounds, and signs of distress. Pulse oximetry, a non-invasive method, measures the oxygen saturation level in the infant's blood, providing information about oxygenation adequacy. Chest X-rays are used to identify abnormalities like lung consolidations, fluid accumulation, or signs of RDS (Copetti et al., 2008). Blood gas analysis helps evaluate the acid-base status, oxygenation, and ventilation in neonates with respiratory distress. Additionally, SpO2 (oxygen saturation) and FiO2 (fraction of inspired oxygen) are evaluated to examine the oxygenation. Depending on the clinical presentation and suspected underlying cause, additional tests such as blood tests, respiratory viral panels, or echocardiography may be conducted.

2.2. Mental models and associated mental processes

Understanding the complexity of the brain poses a significant challenge due to the presence of cyclic patterns, recursion, and the absence of linear causality. As aptly stated by Scherer (2009), the conventional notion of linear causality cannot be applied to these mechanisms, primarily due to their constant recursion. This feature aligns with the characteristics typically found in self-organizing systems, where a simple and unidirectional sense of causality is absent. Also Nigg (2017, 2023) emphasizes that often several kinds of self-regulation play an important role in mental processes, which are typically cyclic processes without linear causality.

These phenomena observed within the brain share similarities with network structures, further supporting the idea that networks can serve as a suitable framework for describing such complex mental processes. Within their complex mental processes, humans often make use of mental models (Craik, 1943). According to Kim (1997), mental models serve as representations of an individual's perspective on the world. They provide the necessary context for understanding and interpreting new information. In essence, mental models act as cognitive frameworks through which individuals make sense of their experiences. Similarly, Jonker et al. (2011) describe mental models as internal representations that enable humans to interact with the world. These representations, known as mental models, consist of knowledge about physical systems and their behaviors. Mental models encompass an understanding of the system's structure, overall behavior, and the impact of disturbances on the system. By possessing these mental models, individuals can effectively engage with and navigate the systems they encounter. For more information and reviews about mental models, see (Van Ments, Treur, Klein, & Roelofsma, 2021; Van Ments & Treur, 2021; Treur & van Ments, 2022).

By combining these perspectives, it becomes clear that mental models play a crucial role in shaping our understanding of the world. They serve as internal constructs that enable individuals to navigate their surroundings and make sense of new information based on pre-existing knowledge and cognitive frameworks. To get the idea, mental models are like maps in our minds, connecting ideas like streets on a city map. They guide us in understanding new information, much like using a map to navigate a new place and to make informed decisions based on this information.

Mental models have proven valuable not only in elucidating human interactions with complex physical systems that require comprehension and control but also in the realm of teamwork. In the study conducted by Cannon-Bowers et al. (1993), the concept of a shared mental model is defined as knowledge structures collectively held by team members, see also further work in (Stout, Cannon-Bowers, & Salas, 2017). These structures enable accurate explanations and expectations regarding the task, facilitating coordinated actions and adaptive behavior in response to task demands and the presence of other team members. By this, a shared mental model adds valuable insights to the understanding of the tasks described by it and the impact on expert team decision making.

2.3. Organizational learning

Importance of seeking consultation and developing effective procedures through adaption is highly emphasized to effectively respond to the organizational challenges in order to optimize their performance (Wilden et al., 2018).

Organizational learning encompasses a multidisciplinary approach, drawing upon various fields such as information processing, organizational culture, and strategy implementation, resulting in a diverse range of conceptualizations (Crossan et al., 1999; Wiewiora, Smidt, & Chang, 2019; Wiewiora, Chang, & Smidt, 2020). According to García-Morales et al. (2012), organizational learning refers to an organization's capacity to preserve and enhance its performance through the utilization of previous experiences. This involves transitioning from tacit and explicit knowledge to the sharing and application of knowledge within the organization. For example, in a healthcare setting, when a hospital faces a surge in patient admissions during flu season, it learns from past experiences to adjust staffing and resources efficiently. In a similar vein, Saadat et al. defines organizational learning as an ongoing process of identifying errors and mistakes and subsequently resolving and rectifying them. This continuous process is facilitated by acquiring knowledge and improving performance over time (Hosseini, Kucharska, & Treur, 2023; Kucharska and Bedford, 2020; Kucharska and Rebelo, 2022; Saadat & Saadat, 2016). Consider an example case where a healthcare facility identifies a recurring issue in patient data entry errors, leading to billing discrepancies. Through organizational learning, the facility not only addresses the immediate errors but also implements training programs and improved data entry protocols to prevent future mistakes. Altman and Iles (1998) identified four significant theoretical advancements that contribute to the formation of the concept of organizational learning:

1. Strategic Management: This theoretical progression focuses on the internal processes and procedures within an organization. It recognizes the importance of aligning organizational goals and strategies with the external environment. Strategic management plays a vital role in shaping the understanding and implementation of organizational learning.
2. Systems Theory: This framework has played a crucial role in the development of the concept of organizational learning. Systems theory provides a holistic perspective that examines the interconnections and interdependencies within an organization. It helps to conceptualize how learning progress over the time, and how it influences the overall functioning and effectiveness of the organization.
3. Social Learning: Social learning theory encompasses a set of concepts that delve into learning at various levels within the organization. It emphasizes the role of interactions, social networks, and knowledge sharing in the learning process. Social learning theory recognizes that learning is not limited to individuals but also flourish through social interactions and collective experiences among a team.
4. Theoretical Approaches: This theoretical progression pays attention to organizational backgrounds, considering factors such as organizational culture and structure. It provides a fourth theoretical foundation for understanding organizational learning. By examining the organizational context, this approach sheds light on how factors like culture, structure, and processes influence the learning capabilities of the organization.

For the integration of these different perspectives on organizational learning mental models can be used as a crucial factor. Individual learning of mental models serves as the foundation for the formation of shared mental models within the organization, thereby facilitating organizational learning (Canbaloğlu et al., 2023a; Canbaloğlu et al., 2023b). By embracing and actively cultivating these mental models, organizations can develop a mechanism for continuous learning and improvement at all levels.

3. The Network-Oriented modeling approach

3.1. Network-Oriented Modelling: Capturing dynamics and interconnected causal processes in complex systems

In the field of modelling complex systems, a technique has emerged known as network-oriented modelling. This approach captures the intricate interplay of interconnected causal processes with temporal nature. Building upon the fundamental understanding of the direct relationship between dynamics and causal relations, network-oriented modelling integrates the dynamic aspects into the network structure which leads to a more comprehensive and accurate representation of the underlying phenomena (Treur, 2016). Thus, one key aspect of network-oriented modelling is its ability to model dynamic, temporal-causal networks. These networks operate on a continuous time dimension, enabling the modelling of cyclic causal networks and timing of causal effects. Consequently, this approach opens up possibilities for modelling a wide range of networks. In this modelling framework, the nodes within the networks represent state variables, while the connections between them represent causal relations that exert influence. This interconnectedness allows for a holistic depiction of the system's behavior, capturing the intricate cause-and-effect relationships between different components (Treur, 2020).

3.2. Modelling mental processes and adaptive networks

A temporal-causal network model includes various characteristics represented by causal states connected to each other. For example, states X and Y, are interconnected through weighted connections $\boldsymbol{\omega}_{X,Y}$ in a model. These connections enable the transmission of impacts $\boldsymbol{\omega}_{X,Y}X(t)$ from state X to Y. To aggregate the impact of all states connected to Y, a combination function $\mathbf{c}_Y(\cdots)$ is applied to state Y, determining how the impacts from incoming connections from states X to Y are aggregated. Table 1 provides an overview of the specific combination functions utilized in this article. Furthermore, each state Y possesses a speed factor $\boldsymbol{\eta}_Y$, which governs the rate at which it undergoes change in response to a causal impact. Together, these characteristics—connectivity, aggregation, and timing—form the foundation of the temporal-causal network model. The difference equation used to compute the change of all states from time t to a later time $t+\Delta t$ is:

Table 1
Combination functions used in the network models.

Function	Notation	Formula	Parameters
Alogistic – advanced logistic sum	$\mathbf{alogistic}_{\boldsymbol{\sigma},\boldsymbol{\tau}}(V_{1,..,}V_k)$	$[\frac{1}{1+\mathrm{e}^{-\boldsymbol{\sigma}(V_1+\cdots+V_k-\boldsymbol{\tau})}}-\frac{1}{1+\mathrm{e}^{\boldsymbol{\sigma\tau}}})](1+\mathrm{e}^{-\boldsymbol{\sigma\tau}})$	steepness $\boldsymbol{\sigma}$threshold $\boldsymbol{\tau}$
Steponce – one period of activation	$\mathbf{steponce}_{\boldsymbol{\alpha},\boldsymbol{\beta}}(V_{1,\cdots,}V_k)$	time$t$1if$\boldsymbol{\alpha} \leq t \leq \boldsymbol{\beta}$else0	start time $\boldsymbol{\alpha}$end time $\boldsymbol{\beta}$
Stepmod – step modulo	$\mathbf{stepmod}_{\boldsymbol{\delta},\boldsymbol{\tau}}(V_1,\cdots,V_k)$	time$t$0ifmod$(t,\boldsymbol{\rho}) < \boldsymbol{\delta}$else1	repeated time duration $\boldsymbol{\rho}$tipping point $\boldsymbol{\delta}$
Scalemap – mapping activation scale	$\mathbf{scalemap}_{\boldsymbol{\lambda},\boldsymbol{\upsilon}}(V)$	$\boldsymbol{\lambda}+(\boldsymbol{\upsilon}-\boldsymbol{\lambda})V$	lower bound $\boldsymbol{\lambda}$upper bound $\boldsymbol{\upsilon}$
Max with Hebbian Learning	$\mathbf{maxhebb}_{\boldsymbol{\mu}}(V_1,\cdots,V_k)$	max$(\mathbf{hebb}_{\boldsymbol{\mu}}(V_1,V_2,V_3),V_4,\cdots,V_k)$where$\mathbf{hebb}_{\boldsymbol{\mu}}(V_1,V_2,V_3) = V_1V_2(1-V_3)+\boldsymbol{\mu}V_3$	persistence factor $\boldsymbol{\mu}$

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

In Eq. (1), at the current time t, we have a state value $Y(t)$. This represents the current value of state Y. The equation determines how this state $Y(t)$ will change in the future, specifically at time $t+\Delta t$. To calculate this change, the concept of a speed factor is introduced, denoted as $\boldsymbol{\eta}_Y$, which characterizes how rapidly state Y responds to impacts from its environment. A higher $\boldsymbol{\eta}_Y$ implies quicker change. In addition to the speed factor, the influences from other states are considered, denoted as X_1 to X_k, which are interconnected toward state Y. These influences are modulated by weighted connections with weights $\boldsymbol{\omega}_{X_1,Y}$ to $\boldsymbol{\omega}_{X_k,Y}$. These weights modulate the strength of the impact that each state X has on Y by multiplying each state value $X_i(t)$ by $\boldsymbol{\omega}_{X_i,Y}$, thus obtaining impact $\boldsymbol{\omega}_{X_i,Y}X_i(t)$. Importantly, the current state values of these influencing states at time t, which are X_1(t) and X_k(t), need to be known at this point. These states represent where X_1 and X_k are at the present moment. The next step involves a combination function $\mathbf{c}_Y(\cdots)$, which takes into account all the incoming influences from states X_1 to X_k. This function aggregates the impacts $\boldsymbol{\omega}_{X_i,Y}X_i(t)$ and determines how they collectively affect the change in state Y. Finally, the aggregated impact is multiplied by a small time interval Δt and incorporates this to obtain the future state value $Y(t+\Delta t)$ following state $Y(t)$: this calculation results in the prediction of this future state value $Y(t+\Delta t)$. These calculations were computed by the network engine implemented within the dedicated software environment in MATLAB and described in detail in (Treur, 2020), Ch 9.

In summary, this difference equation serves as a valuable tool for both simulation and analysis within temporal-causal networks as it captures the dynamics and behaviors exhibited by the interconnected states within the network.

A self-modelling network, also known as a reified network, offers a powerful framework for conceptualizing adaptive networks using mathematically defined functions and relations. By introducing self-model states, it becomes possible to represent and capture the adaptive network characteristics of a network model. These self-model states are visualized at a higher level referred to as the self-model level or reification level, while the original network structure remains at the base level. For example, the weight $\boldsymbol{\omega}_{X,Y}$ of a connection between two states, X and Y, can be represented at the self-model level by introducing a self-model state named $\mathbf{W}_{X,Y}$. By changing the activation values of such self-model states over time, the related network characteristic becomes adaptive. Similarly, other network characteristics can also be made adaptive by incorporating corresponding self-model states. The process of network reification not only enhances the representation of adaptive networks but also generates a temporal-causal network model itself. This enables the iterative application of the self-modelling network construction, resulting in the creation of multiple orders of self-models at different self-model levels. Each subsequent level builds upon the previous one, further enriching the modelling capabilities and capturing the complex dynamics and adaptability within network systems (Treur, 2020). This allows modeling of higher-order adaptivity.

To illustrate self-modeling networks, consider their application in healthcare, specifically in neonatal care. In a neonatal intensive care unit, optimizing oxygen delivery to premature infants facing respiratory distress is critical. A self-modeling network can be used to achieve this. At the base level, the network represents components like sensors, oxygen sources, and monitors, with connection weights based on protocols. At the self-model level, we introduce self-model states for connection weights like.

$\mathbf{W}_{\text{Sensor, ControlUnit}}$

which adapt connection behaviors. By adjusting the values of these self-model states, the control system can autonomously optimize oxygen delivery in real-time based on individual patient needs. This adaptability enhances healthcare systems like the neonatal intensive care unit, ensuring optimal care for infants.

4. Description of the scenarios

In this paper, three distinct scenarios for simulation experiments will be presented. While each scenario presents a unique storyline, the central focus remains on the collaborative efforts of a doctor and a nurse in a hospital setting. Together, they form a cohesive team, utilizing their specialized knowledge, skills, and dedication to ensure the best possible care for neonates facing respiratory distress. The scenarios are designed to provide a narrative that illustrates the sequence of medical procedures in neonatal care, offering a storyline that brings the context to life. It is important to note that these scenarios are merely illustrative and serve as representations rather than being definitive.

4.1. The roles and responsibilities of the nurse and doctor in managing respiratory Distress: Scenario 1

Scenario 1 has two subvariants, namely 1a and 1b, which intricately illustrate the separate roles and responsibilities assumed by both the nurse and the doctor. This division is critical in delineating and emphasizing the distinct responsibilities involved in providing care for neonates experiencing respiratory distress in a hospital setting. In both scenarios 1a and 1b, the team members share a perfect team mental model. As a result, there are no differing individual instances of the team mental model, as all team members have the same understanding of their roles, responsibilities, and goals.

4.1.1. Nurse-led assessment and Intervention: Scenario 1a

A premature baby of 31 weeks of gestational age at birth is delivered with the assistance of a doctor. After birth there was a delay in the clearance of the fetal lung fluid. The nurse assumes responsibility for assessing the baby's respiratory vital signs. The nurse's duties include:

- monitor respiratory rate
- measuring oxygen saturation level
- observing for grunting
- observing for chest retractions
- observing for cyanosis

Upon completing the assessment and obtaining good results, the nurse permits the baby to bond with their mother by kangaroo care which involves skin-to-skin contact. However, if the assessment yields poor results, the nurse will contact the doctor for advice. In such cases, the nurse may provide:

- supplemental oxygen;
- respiratory support;
- transfers neonate to a NICU (a premature baby is always transferred to a NICU)

4.1.2. Nurse-led intervention with subsequent Doctor's Intervention: Scenario 1b

In the previous Scenario 1a, the nurse assesses the baby's respiratory vital signs and seeks the doctor's advice if respiratory distress is observed. In this case, the nurse administers supplemental oxygen without consulting the doctor. When the baby does not improve and enters a critical state a few hours later, the nurse contacts the doctor for immediate intervention. This makes the family of the baby emotionally distressed. The doctor's duties include:

- prepare medical procedure
- take X-ray and other evaluations
- providing treatment
- give advice

4.2. Collaborative adaptation and learning in nurse-led intervention and impact of a fatigued Doctor: Scenario 2

Scenario 2 is a variant of Scenario 1. This implies that Scenario 2 exhibits certain similarities with Scenario 1, while also introducing notable variations.

The nurse independently administers supplemental oxygen without consulting the doctor. The baby's condition does not improve and enters a critical state. Subsequently, the nurse seeks help, and the doctor's responsibilities encompass preparing medical procedures, conducting evaluations such as X-rays, providing suitable treatment, and offering guidance and advice to address the critical situation. However, in this scenario, the doctor experiences symptoms of fatigue, affecting his ability to perform optimally. Moreover, the team members do not possess a flawless team mental model. Consequently, individual instances of the team mental model differ, as team members hold varying understandings of their roles, responsibilities, and objectives. This situation fosters a learning environment for both the doctor and nurse. They observe real-world events, which impact their mental models, leading to an exchange of knowledge and an evolution of their understanding.

4.3. Collaborative adaptation and learning in nurse-led intervention with subsequent Doctor's intervention and the role of an AI-Coach: Scenario 3

Scenario 3 is a variant of Scenario 2, introducing additional factors such as workplace stress and the presence of an underlying congenital or genetic condition in the baby. Despite the doctor's illness and the critical state of the baby, the doctor's responsibilities remain unchanged.

A key difference is the introduction of a virtual AI-Coach in Scenario 3. This AI-Coach serves as a monitoring system during the medical procedure, signalling any deviations from the expected course. With its comprehensive mental model and vast knowledge, the AI-Coach provides guidance and support to both the doctor and the nurse. It continuously monitors the situation and activates its decision and communication features in the event of a mistake occurring in the real-world setting.

5. The adaptive network models

Every scenario is addressed its own network model, which invariably comprises a base level and for Scenarios 2 and 3 additional levels of reification. In the 3D format used to depict these models, the oval shapes represent the states, while the arrows signify the influences of one state on another. Each section will provide a comprehensive explanation of these 3D pictures. The detailed exploration of these models is critical to achieving the research objectives, as it allows for the simulation and analysis of the dynamic interactions within medical teams and the impact of an AI-Coach on decision-making and learning processes in a neonatal care context.

5.1. The roles and responsibilities of the nurse and doctor in managing respiratory Distress: The Computational models for Scenario 1

Scenario 1a and 1b solely comprise a base level as there is no requirement for additional levels of reification. This is due to the absence of any learning needs in both scenarios, as all team members possess flawless mental models, signifying perfect knowledge. Given the numerous similarities between the two models, it is justified to explain them together within a single section.

5.1.1. Base level Scenario 1a and 1b: Overview

Within the base planes, the world states indicating the actual steps in the world for the Scenarios 1a and 1b are depicted in Figs. 1 and 2 respectively by the green nodes with their connections in the middle area of the base plane. A few of these world states have a lighter green node because they are not directly influenced by the other world states. The actor is indicated within a world state name by D for doctor or N for nurse.

In both cases the base levels consist of two mental models, one of the nurse and one for the doctor. These mental models reflect the structure of the medical procedure explained in Sect. 4.1.1 and 4.1.2. The nodes of the mental model of the doctor are depicted by the orange ovals and the nodes of the nurse by pink ovals.

In order for the doctor and the nurse to determine their actions in the world, they rely on their individual mental models which in turn activate action ownership states. The doctor's action ownership states are visually depicted in a light orange colour, while the nurse's states are represented in light pink. These states incorporate input from the respective mental models and enable a form of mediation from the mental model to the real world by initiating the execution of the designated actions. Therefore, these states act as decision states to perform certain action by both of the actors in the real world, resulting from a shared mental model. By mutually observing each others' actions or by accompanying verbal comments about them, the nurse and doctor interact.

In Fig. 1, two contextual factors are depicted as nodes, with one in yellow and the other in dark orange. The yellow node signifies that the baby is born prematurely, while the dark orange node indicates that there was a delay in the clearance of fetal lung fluid. Within Fig. 2, the two contextual factors can be observed through a yellow node, symbolizing the critical state of the baby, and a grey shade, indicating emotional distress experienced by the family.

In the case of the model for Scenario 1a, Table 2 provides an overview encompassing the world states, the mental model states for both the doctor and nurse, their ownership states, and contextual factors, each accompanied by an explanation. A similar overview of the model of Scenario 1b can be found in Table 3.

Black arrows are used to denote the influence of one world state on another. Blue lines indicate the connection between ownership states and world states. The yellow lines represent observation arrows, indicating that the nurse and doctor observe events occurring in the world and activate the corresponding states in their mental models. Observation lines are selectively included from particular world states to the mental states only when those specific world states indicate observations, such as "Baby has a respiratory rate under 60 breaths per minute". Solid arrows originating from the context factors signify the strengthening of specific world states, while dotted arrows indicate the weakening of world states.

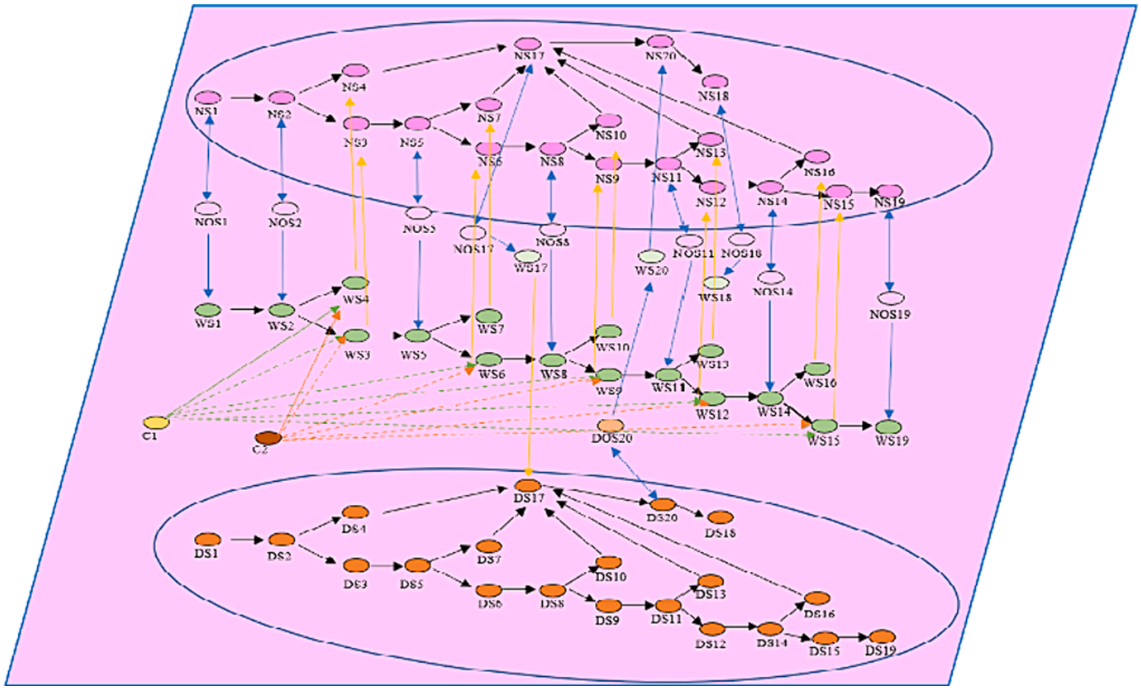

Fig. 1. Computational model for Scenario 1a.

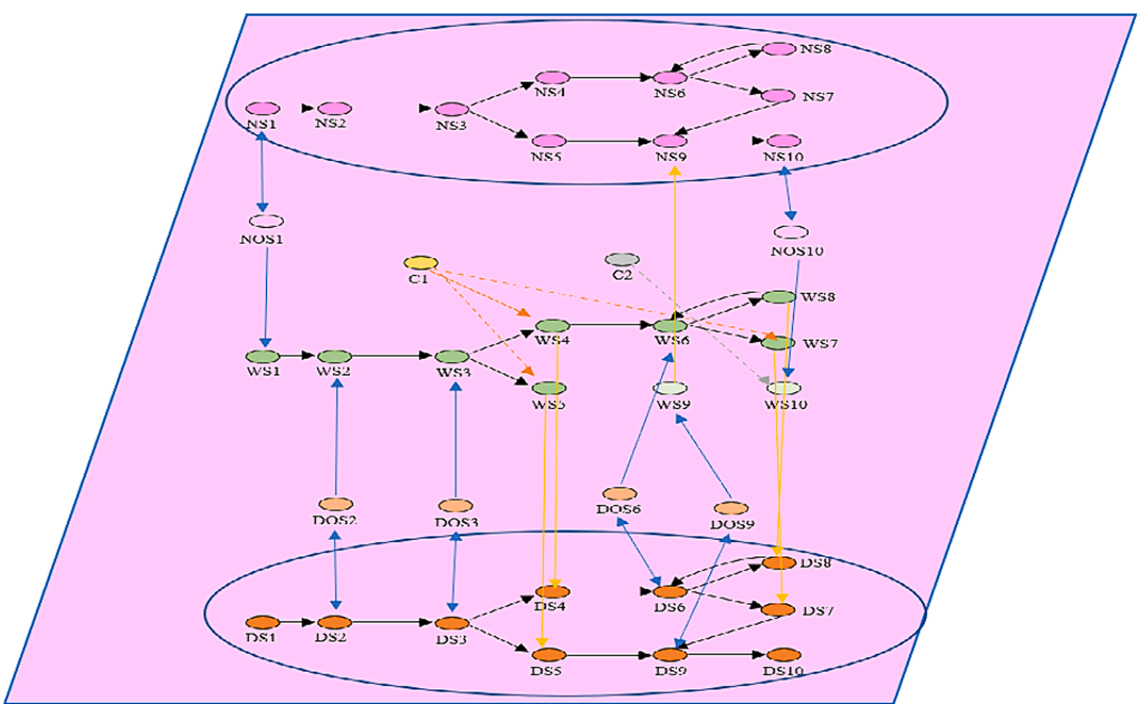

Fig. 2. Computational model for Scenario 1b.

The **alogistic** combination function stands for advanced logistic sum and includes a steepness and threshold parameter. The steepness parameter in the **alogistic** function determines how quickly the output changes in response to changes in the (weighted) sum of inputs. The threshold parameter in the **alogistic** function defines the input value at which the output starts to change significantly. Inputs below the threshold have minimal impact on the output, while inputs above the threshold cause the output to respond more significantly. The threshold essentially sets a boundary or activation point that triggers the transition in the output. On the other hand, the **steponce** combination function operates by encompassing a specific period of activation. It takes one period of activation from **α** to **β**, in which **α** stands for the start time and **β** for the end time. The combination functions utilized in the network model are the alogistic function for all the world states, mental model states, and ownership states. For the context factors, the stepmod function is used (see Table 1). This function is a **stepmod** function which takes as repeated time duration and a tipping point. The tipping point represents the critical point at which the output of the stepmod function changes its value based on the repeated time duration specified by its parameter.

Table 2
Overview of states for Scenario 1a: the world states, mental states, ownership states and context factors.

World, Doctor, Nurse, Context				Explanation
C1			Context	Baby is born prematurely
C2			Context	Delay in clearance of fetal lung fluid
WS1	NS1	DS1		Preparing to assess respiratory vital signs
WS2	NS2	DS2		Nurse monitors baby's respiratory rate
WS3	NS3	DS3		Baby has a respiratory rate under 60 breaths/minute
WS4	NS4	DS4		Baby has a respiratory rate above 60 breaths/minute (bad)
WS5	NS5	DS5		Nurse uses pulse oximeter to measure baby's oxygen saturation level
WS6	NS6	DS6		Baby has an oxygen saturation level above 89 %
WS7	NS7	DS7		Baby has an oxygen saturation level below 89 % (bad)
WS8	NS8	DS8		Nurse listens to baby's breathing and observes for grunting
WS9	NS9	DS9		Baby makes no grunting sounds
WS10	NS10	DS10		Baby makes grunting sounds (bad)
WS11	NS11	DS11		Nurse observes baby's chest for retractions
WS12	NS12	DS12		Baby shows no chest retractions
WS13	NS13	DS13		Baby shows chest retractions (bad)
WS14	NS14	DS14		Nurse observes baby's colour for signs of cyanosis
WS15	NS15	DS15		Baby has no discoloration of skin, lips, or mucous membranes
WS16	NS16	DS16		Baby has discoloration of skin, lips, or mucous membranes (bad)
WS17	NS17	DS17		Nurse calls for doctor's help
WS18	NS18	DS18		Nurse provides supplemental oxygen, respiratory support, or transfers the baby to a NICU
WS19	NS19	DS19		Nurse allows the baby to bond with the mother
WS20	NS20	DS20		Doctor gives advice
NOS1				Ownership state for the action of preparing to assess respiratory vital signs
NOS2				Ownership state for the action of nurse monitors baby's respiratory rate
NOS5				Ownership state for the action of nurse uses pulse oximeter to measure baby's oxygen saturation level
NOS8				Ownership state for the action of nurse listens to baby's breathing and observes for grunting
NOS11				Ownership state for the action of nurse observes baby's chest for retractions
NOS14				Ownership state for the action of nurse observes baby's colour for signs of cyanosis
NOS17				Ownership state for the action nurse calls for doctor's help
NOS18				Ownership state for the action of nurse provides supplemental oxygen, respiratory support, or transfers the baby to a NICU
NOS19				Ownership state for the action of nurse allows the baby to bond with the mother
DOS20				Ownership state for the action of doctor gives advice

Table 3
Overview of states for Scenario 1b: the world states, mental states, ownership states and context factors.

World, Doctor, Nurse, Context				Explanation
C1			Context	Baby is in critical state
C2			Context	Family is emotionally distressed
WS1	NS1	DS1		Nurse alarms doctor
WS2	NS2	DS2		Doctor preparing necessary equipment and supplies for a medical procedure
WS3	NS3	DS3		Doctor takes an X-ray and other medical evaluations
WS4	NS4	DS4		X-ray and other evaluations show lung expansion, airway obstruction, pneumothorax, infiltrates, or/and cardiomegaly
WS5	NS5	DS5		X-ray and other evaluations do not show anything abnormal
WS6	NS6	DS6		Doctor provides oxygen therapy, medications, re-expands lung, surgery or other treatments
WS7	NS7	DS7		Treatment works
WS8	NS8	DS8		Treatment does not work
WS9	NS9	DS9		Doctor advises to let neonate rest
WS10	NS10	DS10		Nurse informs family about doctor's advice
NOS1				Ownership state for the action of nurse alarms doctor
NOS10				Ownership state for the action of nurse informs family about doctor's advice
DOS2				Ownership state for the action of doctor preparing necessary equipment and supplies for a medical procedure
DOS3				Ownership state for the action of doctor takes an X-ray and other medical evaluations
DOS6				Ownership state for the action of doctor provides oxygen therapy, medications, re-expands lung, surgery or other treatments
DOS9				Ownership state for the action of doctor advises to let neonate rest

5.2. Collaborative adaptation and learning in nurse-led intervention and impact of a fatigued Doctor: The Computational model for Scenario 2

Scenario 2 diverges from the foundation established in Scenario 1, presenting itself as an extensive variant rather than a direct extension. The model for Scenario 2 introduces two adaptation levels (for first-order and second-order adaptation) on top of the base level. Each of these levels will be addressed in a separate section, providing a comprehensive explanation of their intricacies and details. In Scenario 2, the central concept revolves around different periods. The upcoming section will delve into the role of breaks and how they come into play. This is where the factors pertaining to periods and contextual states will be thoroughly explained to provide a more comprehensive understanding.

5.2.1. Base level for Scenario 2: Overview

Once more, the world states are depicted by green nodes with their connections in the middle area of the base plane (see Fig. 3). As usual, the lighter green nodes indicate that these nodes are not directly influenced by the other world states. In this case, there are again two mental models for the two actors, and these reflect the structure of the medical procedure explained in Sect. 4.1.3. The nodes of the mental model of the doctor are depicted by the orange nodes and the nodes of the nurse by pink nodes.

Also in this case, the doctor and nurse have certain actions that they have to do in the world. To determine at specific time points their actions, they again rely on their individual mental models and use action ownership states to initiate actions accordingly. The doctor's action ownership states are visually depicted in a light orange colour, while the nurse's states are represented in light pink.

In the model for Scenario 2, in total three contextual factors are at

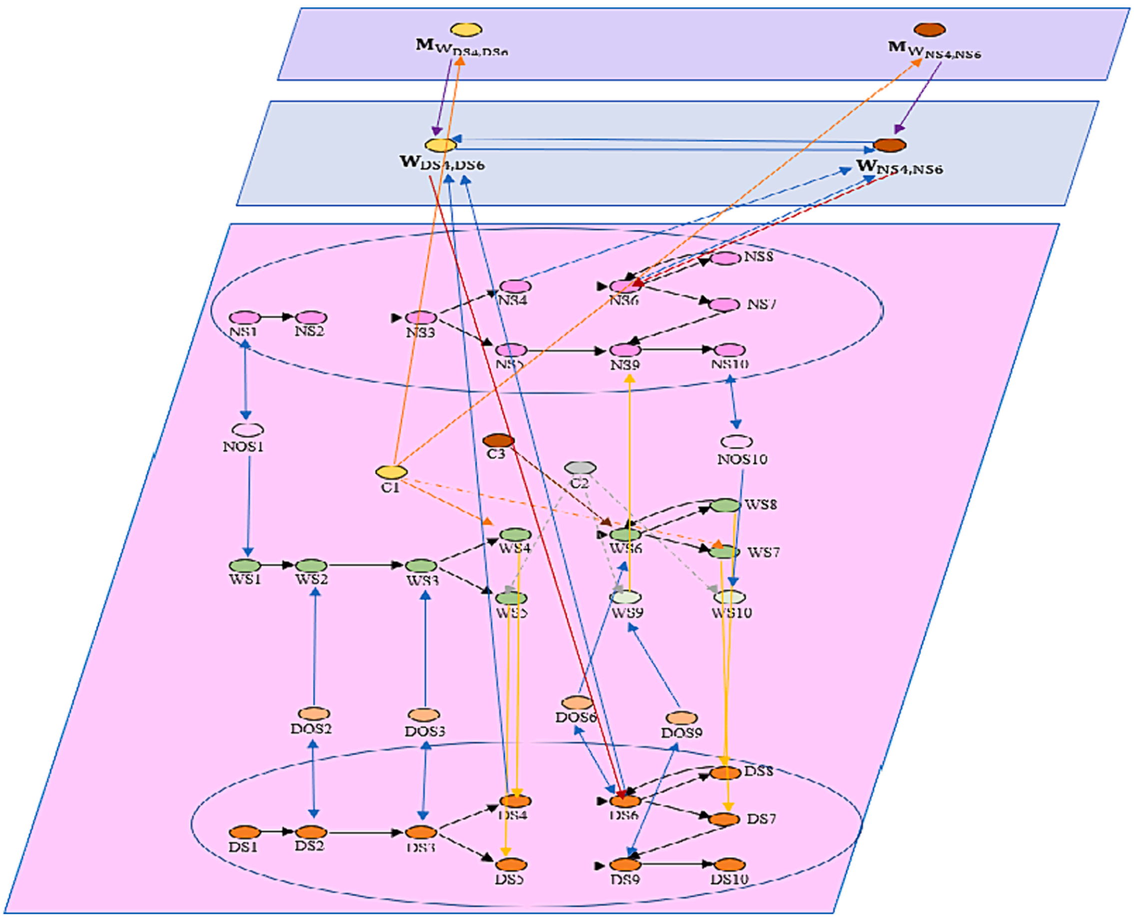

Fig. 3. Computational model for Scenario 2.

play. The first one, represented by the colour yellow, signifies that the baby is in a critical condition, causing both the nurse and doctor to experience stress. The second factor, depicted as a brown–red node, indicates that the doctor is personally unwell. As shown in Fig. 3, this particular context factor strengthens WS6. While it may initially seem illogical for it to strengthen the action of "Doctor gives treatment," there is a logical explanation behind it. Despite being sick, the doctor is making an effort to stay focused and provide the necessary treatment. Lastly, the third factor (represented by grey node) represents the premature birth of the baby, which diminishes the likelihood of favourable results in X-ray and other evaluations. Consequently, this also slightly weakens the doctor's ability to provide advice and the nurse's ability to communicate that advice to the family.

In addition to the three context factors mentioned earlier, there are three more states that are not included in the base level of the model. These states are part of the medical procedure and serve to represent different periods within the care process. They are intentionally designed to create pauses or breaks in the workflow. For instance, there is a state that weakens every world state during a specific time interval when there is no baby requiring immediate attention. Conversely, after a certain period, a new baby arrives, indicating a shift in the workload and responsibilities. These states are not considered contextual factors in the standard sense and therefore are not visually incorporated into the base level of the model. However, it is important to note that these states are included during the model's construction and used within the computer simulations. These states can be observed in Table 4, along with an explanation of their purpose and impact within the medical procedure. Moreover, Table 4 also provides an overview encompassing the world states, the mental model states for both the doctor and nurse, ownership states, and contextual factors, each accompanied by an explanation.

As mentioned earlier in Section 5.1.1, black arrows are utilized to illustrate the influence of one world state on another. Blue lines, on the other hand, establish connections between ownership states and world states. The presence of yellow lines signifies observation arrows, indicating that the nurse and doctor actively observe events taking place in the world and integrate the obtained information into their mental models. Arrows originating from the context factors indicate strengthening effects of them on specific world states. Conversely, dotted arrows are used to represent negative connection weights which denote the weakening effect on certain world states. There are also red downward arrows incoming, but their explanation will be provided in next section. Furthermore, there are outgoing lines (blue and orange), which will be elaborated on in Section 5.2.3.

5.2.2. Middle level for Scenario 2: Adaptation and plasticity of the mental models

The blue plane focuses on the cognitive processes associated with learning and forgetting of mental models. Specifically, there are two distinct processes, one for the doctor and another one for the nurse. For the doctor, this represents the weights of the connections within their mental model, linking the state for "X-ray and other evaluations show something abnormal" to the state for "Doctor provides treatment", i.e., self-model state $\mathbf{W}_{DS4,DS6}$. From this **W**-state a downward adaptation effectuation link points to the state "Doctor provides treatment" within the doctor's mental model which is indicated by a red arrow. The nurse undergoes a similar process with their respective mental model and connections. Furthermore, the mental models of both the doctor and nurse mutually influence each other as a form of social learning: they learn from one another by communicating, modeled by an interplay of their respective **W**-states.

Table 4
Overview of the states for Scenario 2: the world states, mental states, ownership states, context factors, periods, and first- and second-order adaptation states (for the complete table, see the appendix).

World, Doctor, Nurse, and Context				Explanation	Level
C1			Context	Baby is in critical state	Base Level
C2			Context	Doctor is feeling sick himself	
C3			Context	Baby is born prematurely	
P1			Period	Period in which there is no critical ill baby to take care of	
P2			Period	Doctor takes a break	
P3			Period	Doctor is back doing their job	
WS1	NS1	DS1		Nurse alarms doctor	
……	……	……			
WS10	NS10	DS10		Nurse informs family about doctor's advice	
NOS1				Ownership state for the action of nurse alarms doctor	
……	……	……			
DOS9				Ownership state for the action of doctor advises to let neonate rest	
$\mathbf{W}_{DS4,DS6}$				First-order self-model state for the doctor's weight of the connection from DS4 to DS6	First-Order Adaptation Level
$\mathbf{W}_{NS4,NS6}$				First-order self-model state for the nurse's weight of the connection from NS4 to NS6	
$\mathbf{M}_{\mathbf{W}_{DS4,\ DS6}}$				Second-order self-model state for the persistence factor of the doctor's weight of the connection from DS4 to DS6	Second-Order Adaptation Level
$\mathbf{M}_{\mathbf{W}_{NS4,\ NS6}}$				Second-order self-model state for the persistence factor of the nurse's weight of the connection from NS4 to NS6	

The other type of learning covered is individual learning modeled by Hebbian Learning (see Table 1). The Hebbian learning combination function is commonly used to update on the fly the connection weights between neurons in neural networks when both neurons are often activated together. To integrate the social learning and the individual Hebbian learning processes, the $\mathbf{maxhebb}_{\mu}$ combination function is used which combines the regular Hebbian function with the max function. The $\mathbf{maxhebb}_{\mu}$ function selects the highest value of the incoming connections including the value by Hebbian learning. This approach ensures that the influence of the most significant connection is preserved while minimizing the impact of less relevant connections.

Like the standard Hebbian learning, the $\mathbf{maxhebb}_{\mu}$ function incorporates a persistence factor $\boldsymbol{\mu}$, which quantifies the fraction of the learned value that remains over each unit of time. By including this factor, Hebbian learning accounts for the phenomenon of extinction or forgetting. The persistence factor $\boldsymbol{\mu}$ determines the extent to which the learned value is retained or forgotten over time. A value of $\boldsymbol{\mu}$ between 0 and 1 represents the fraction of the learned value that persists per time unit. A higher value of $\boldsymbol{\mu}$ indicates a slower rate of forgetting, meaning that the learned associations will persist for a longer duration. On the other hand, a lower value of $\boldsymbol{\mu}$ accelerates the rate of forgetting, leading to a more rapid extinction of the learned associations.

5.2.3. Upper level for Scenario 2: Meta-Plasticity of the mental models

The adaptivity of the first-order self-model within the network is captured by incorporating a second-order self-model, represented by the $\mathbf{M_W}$-state, in the upper-level plane. The presence of the $\mathbf{M_W}$-state within the upper-level plane effectively captures the adaptive nature of the persistence factor $\boldsymbol{\mu}$. It enables dynamic adjustments and responses to changing conditions or contexts, ensuring that the network can adaptively modify the extent of persistence as needed. In the given scenario, it is assumed that when the baby is in a critical state, causing stress for both the doctor and nurse, the value of the $\mathbf{M_W}$-state decreases. This modelling approach captures the concept of forgetting under stressful circumstances. More precisely, the relationship described involves upward connections from the context state C1 in the base level to the $\mathbf{M_W}$-states, as well as downward connections from the $\mathbf{M_W}$-states to the $\mathbf{W}$-states. These $\mathbf{M_W}$-states are modelled with the help of the combination function **scalemap** (see Table 1) which maps activation scale [0,1] to scale $[\boldsymbol{\lambda}, \boldsymbol{\upsilon}]$ with $\boldsymbol{\lambda}$ as lower bound and $\boldsymbol{\upsilon}$ as upper bound. The scalemap function enables flexible manipulation and control of the $\mathbf{M_W}$-state activation levels, allowing them to effectively contribute to the model's behaviour and outcomes. By applying this function, the activation values of the $\mathbf{M_W}$-states can be effectively scaled to match the desired range of values which in this case is from 1.0 to 0.5.

5.3. Collaborative adaptation and learning in nurse-led intervention with subsequent Doctor's intervention and the role of an AI-Coach: The Computational model for Scenario 3

While Scenario 3 is a variant of Scenario 2, it introduces numerous significant changes that will be extensively examined in the following sections. In order to provide a clearer explanation of the models, each section focuses on different aspects of the overall model. As a result, multiple figures depicting the same model are presented throughout the various sections.

5.3.1. Base level for Scenario 3: Overview

In the base plane (see Fig. 4), the world states are once again represented by green nodes, with their corresponding connections situated in the middle region of the base plane. As usual, the lighter green nodes indicate that they are not directly influenced by other world states.

In this particular scenario, an additional mental model has been introduced at the base level. Alongside the mental models of the doctor and nurse, which reflect the structure of the medical procedure they follow, there is now a mental model of the virtual AI-Coach as well. The nodes of the AI-Coach's mental model are depicted as yellow nodes.

However, there are some distinctions in this case. While the doctor and nurse have specific actions to perform in the world, relying on their individual models mental and utilizing action ownership states to initiate their actions, the AI-Coach does not possess such action ownership states. This is because the AI-Coach does not directly interact with the physical world or execute real actions. Instead, its primary function revolves around observing each world state and initiating communication to the others. These observations by the AI-Coach are crucial for the monitoring and communication functions performed by it. Further elaboration on this function will be provided in the subsequent section, focusing on the middle level of the model.

Within this network model, four contextual factors come into play. The first factor, represented by the colour yellow, signifies the presence of stress experiences. The second factor, depicted as a grey node, indicates that the baby is in a critical state. The dark green colour represents the presence of an underlying congenital or genetic condition in the baby, while the brown factor denotes that the doctor is feeling ill themselves.

In the base level, the colours of the arrows remained the same. Black arrows depict the influence of one world state on another, while blue lines connect ownership states to world states. Yellow lines represent observation arrows, indicating active observation by the nurse, doctor,

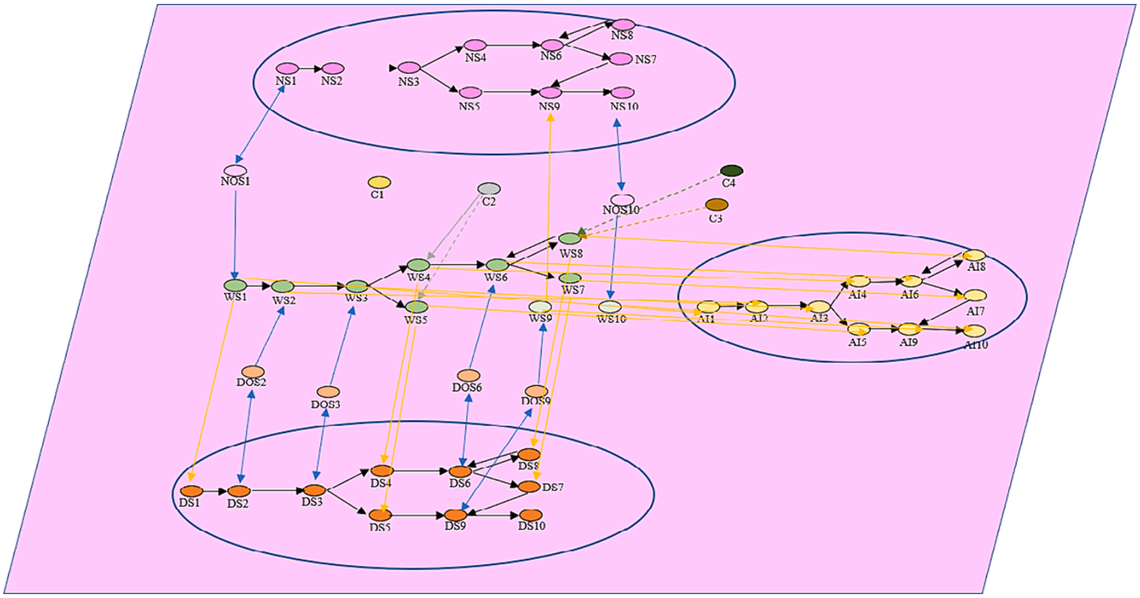

Fig. 4. Base Level for Scenario 3: World states, Mental model states, Ownership states, Context states.

and this time also by the AI-Coach. Solid arrows from context factors strengthen specific world states, while dotted arrows weaken certain world states.

The **alogistic** function is employed once more for the states at the base level, encompassing world states, mental model states, and ownership states. Context factors, on the other hand, make use of the **stepmod** function (see Tables 1 and 5).

Table 5
Overview the states for Scenario 3: the world states, mental states, ownership states, context factors, and first- and second-order states (for the complete table, see the appendix).

World, Doctor, Nurse, AI-Coach, Context					Explanation	Level
C1				Context	Experiences of stress	Base Level
C2				Context	Baby is in critical state	
C3				Context	Underlying congenital or genetic condition	
C4				Context	Doctor is feeling sick himself	
WS1	NS1	DS1	AI1		Nurse alarms doctor	
……	……	……	…..			
WS10	NS10	DS10	AI10		Nurse informs family about doctor's advice	
NOS1					Ownership state for the action of nurse alarms doctor	
……	……	……	……			
DOS9					Ownership state for the action of doctor advises to let neonate rest	
$\mathbf{W}_{DS1,DS2}$					First-order self-model state for the doctor's weight of the connection DS1,DS2	First-Order Adaptation Level
…..	…..	…..	…..			
$\mathbf{W}_{DS9,DS10}$					First-order self-model state for the doctor's weight of the connection DS9,DS10	
$\mathbf{W}_{NS1,NS2}$					First-order self-model state for the nurse's weight of the connection NS1,NS2	
…..	…..	…..	…..			
$\mathbf{W}_{NS9,NS10}$					First-order self-model state for the doctor's weight of the connection NS9,NS10	
$\mathbf{W}_{AI1,AI2}$					First-order self-model state for the nurse's weight of the connection AI1,AI2	
…..	…..	…..	…..			
$\mathbf{W}_{AI9,AI10}$					First-order self-model state for the doctor's weight of the connection between AI9,AI10	
Monitor WS2					Monitor feature of the AI-Coach to monitor doctor preparing necessary equipment and supplies for medical procedure	
…..	…..	…..	…..			
Monitor WS10					Monitor feature of the AI-Coach to monitor nurse informing family about doctor's advice	
Decision WS2					Decision feature of the AI-Coach to decide to signal about doctor preparing necessary equipment and supplies for medical procedure	
…..	…..	…..	…..			
Decision WS10					Decision feature of the AI-Coach to decide to signal about nurse informing family about doctor's advice	
CS2					Communication feature of the AI-Coach to signal/communicate about doctor preparing necessary equipment and supplies for medical procedure	Second-Order Adaptation Level
…..	…..	…..	…..			
CS10					Communication feature of the AI-Coach to signal/communicate about nurse informing family about doctor's advice	
$\mathbf{W}_{\mathbf{W}_{AI1,AI2},\mathbf{W}_{DS1,DS2}}$					Second-order self-model state representing connection weight for $\mathbf{W}_{DS1,DS2}$	
…..	…..	…..	…..			
$\mathbf{W}_{\mathbf{W}_{AI7,AI9},\mathbf{W}_{DS7,DS9}}$					Second-order self-model state representing connection weight $\mathbf{W}_{DS7,DS9}$	
$\mathbf{W}_{\mathbf{W}_{AI9,AI10},\mathbf{W}_{NS9,NS10}}$					Second-order self-model state representing connection weight for $\mathbf{W}_{NS9,NS10}$	

5.3.2. Middle level for Scenario 3: Adaptation and plasticity of the mental models

The middle level, denoted by the colour blue, exhibits significant differences compared to Scenario 2. At this level, numerous crucial processes of the AI-Coach take place. As previously mentioned, the AI-Coach possesses comprehensive knowledge and by observing the actions and states in the world is at each point in time is already aware of all relevant information. More specifically, it can observe each step of the medical procedure in the world, and this information is conveyed to the monitor states, represented by dark red nodes. Subsequently, this information is fed into the AI-Coach's decision-making states for performing signalling actions through communication, indicated by lighter red nodes. However, these decision states are suppressed by the world states if the medical procedure is progressing as intended, thereby eliminating the need for the AI-Coach to perform any signalling actions (see Fig. 5).

Nevertheless, if the AI-Coach's decision-making state becomes partly activated, it initiates its communication action, which resides in the upper level of the model (see Section 5.3.3). The communication states serve the purpose of signalling the correct **W**-state of either the doctor or nurse, depending on which step deviates from the expected course and who is responsible for that particular step. For instance, if the AI-Coach detects that WS6 has not occurred, it will decide to communicate this discrepancy to the doctor, as the doctor is responsible for administering the treatment. This signalling mechanism assists the team members in the process by helping to prevent mistakes.

Additionally, team members can enhance their accuracy by leveraging organizational learning. The AI-Coach, assumed to have

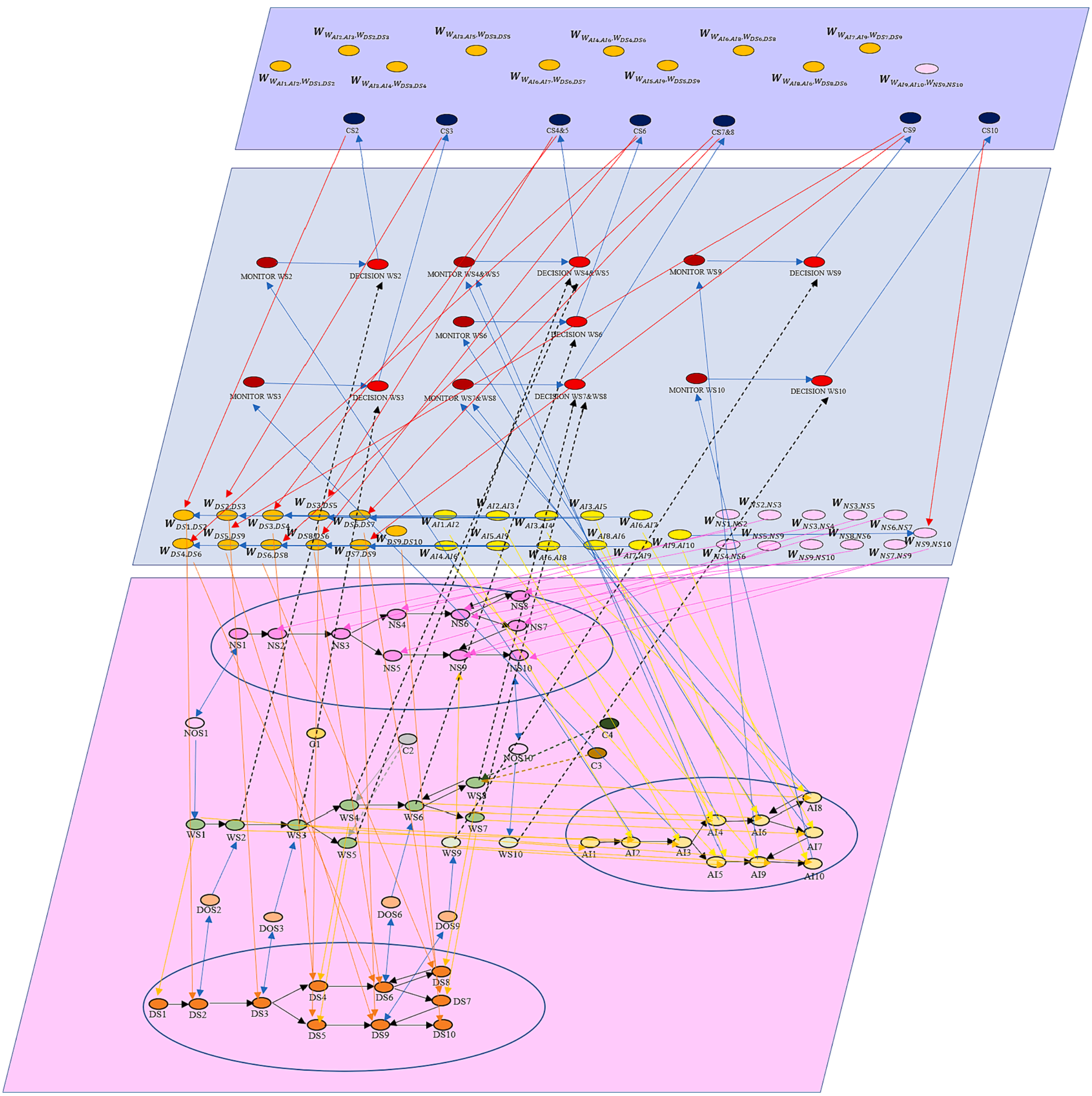

Fig. 5. Middle Level for Scenario 3: **W**-states, Monitor states, and Decision states.

perfect knowledge, establishes connections between the **W**-states of itself and the corresponding **W**-states of the doctor and nurse. This enables the transfer of knowledge, aiding the team members in their decision-making processes and reducing the likelihood of errors.

In this specific scenario, Hebbian Learning is not employed. Instead, the **alogistic** function is utilized for each **W**-state. The **alogistic** function's characteristic of being suitable for modelling states that require a smooth transition between different values makes it an appropriate choice. Therefore, the **alogistic** function is chosen to ensure the appropriate handling of the **W**-states, as well as the monitor, decision, and communication states, maintaining consistency throughout the system.

5.3.3. Upper level Scenario 3: Meta-Plasticity of the mental models

The upper level, represented by the colour purple, contains second-order self-model states that determine the weight of connections from the AI Coach's **W**-states to individual mental model connection weight self-model states in the middle level (see Fig. 6). These higher order **W**-states are distinct from the $\mathbf{M_W}$-states utilized in the model of scenario 2. The $\mathbf{W_{WW}}$-states, in particular, specify the weights of connections from the AI Coach's **W**-states to the individual **W**-states of doctor or nurse and vice versa, enabling the initiation and control of shared organizational mental model learning by individuals. As previously mentioned, the communication states are situated in the upper level. This arrangement is necessary because the influence of the communication states needs to be adaptation of the **W**-states in the middle level. The communication states employ the **alogistic** function as their combination function, while the $\mathbf{W_{WW}}$-states are modelled using the **scalemap** function (see Table 1).

6. Simulation experiments

Each scenario has its own set of simulation results. Scenario 1a and 1b will be discussed together in one section, while the remaining scenarios will each have their dedicated sections. In Scenario 1 and 2, the analysis primarily focuses on the world states. However, for Scenario 3, additional aspects such as mental states, ownership states, and W-states are analyzed. These elements are of particular interest as they contribute to the complexity of the processes under examination. Notably, the simulations in the third scenario hold significant importance as the ultimate goal is to create a scenario featuring an AI-Coach. Hence, thorough analysis of these simulations is crucial as it represents the culmination of the scenario-building efforts. The purpose of the graphs is to provide a visual representation of the sequential order or progression of the processes rather than to provide specific temporal details. The horizontal axis of the graphs represents an abstracted dimensionless time scale, denoting the sequence of events without a specific unit of time such as seconds or minutes, while the vertical axis quantifies the occurrence of a state, by an activation level ranging from 0 (absent) to 1 (fully present).

6.1. *The roles and responsibilities of the nurse and doctor in managing respiratory Distress: Results of Scenario 1*

6.1.1. Nurse-led assessment and Intervention: Results of Scenario 1a

Fig. 7 displays the simulation output representing the world states,

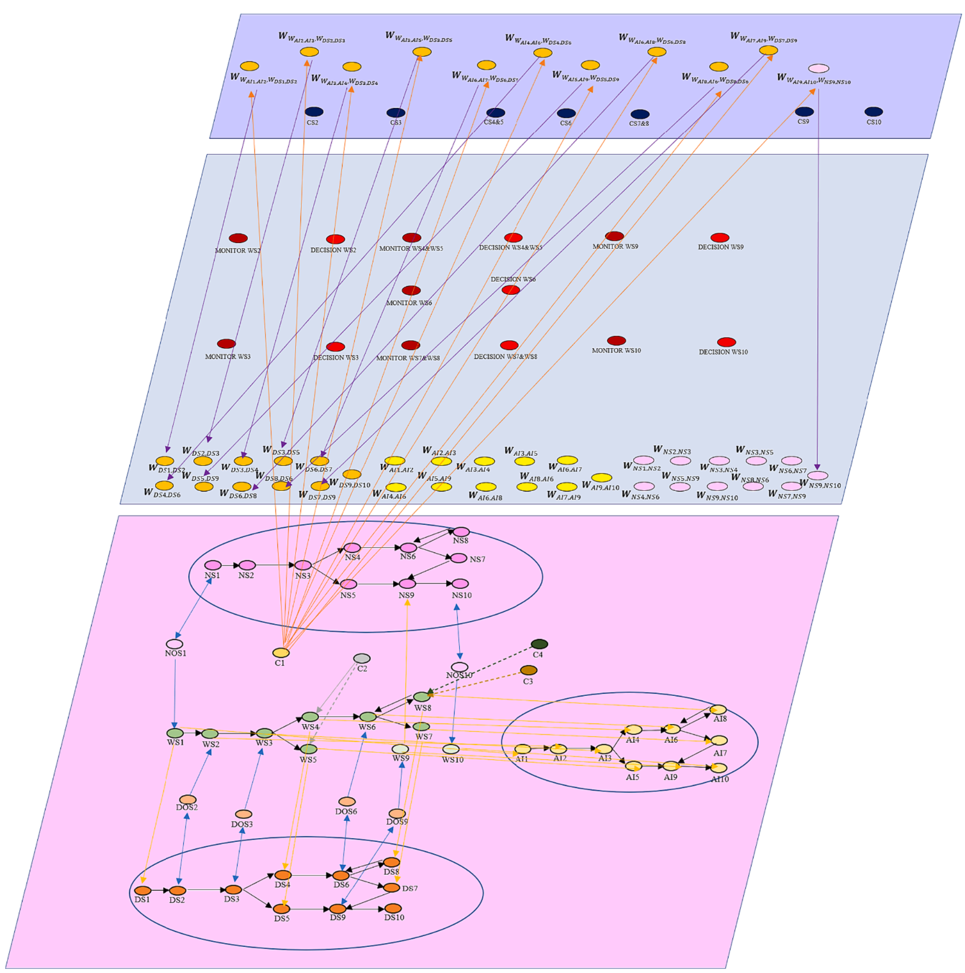

Fig. 6. Upper-Level for Scenario 3: $\mathbf{W_{WW}}$-states and Communication states.

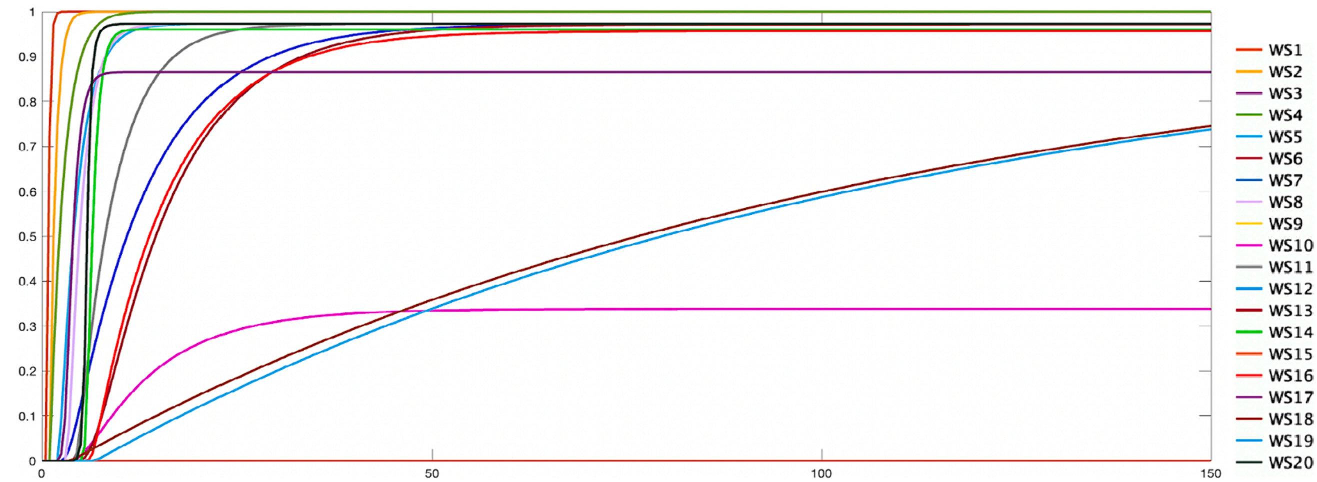

Fig. 7. Results Scenario 1a: the World States.

providing an overview of the actual progression of events in the simulated scenario. The figure illustrates the medical procedure, starting with the nurse preparing to assess the baby's respiratory vital signs, as indicated by the orange line (WS1). Subsequently, the yellow line represents the nurse's monitoring of the baby's respiratory rate (WS2). The green line (WS4) reaching a value of 1 and remaining constant signifies that the baby has a respiratory rate above 60 breaths per minute, while the purple line remains at zero, indicating the absence of a healthy respiratory rate (WS3). Following this, the purple line (WS17) shows that the nurse requests assistance from the doctor, triggered by the state where the baby has a respiratory rate that is too high. The nurse promptly notified the doctor as a high respiratory rate in the baby is undesirable and requires attention. The doctor promptly provides advice, represented by the dark green line (WS20). Additionally, the light blue line (WS5) depicts the nurse using a pulse oximeter to measure the baby's oxygen saturation level. The dark blue line at 0 indicates that the oxygen saturation level is below 89 % (WS7), while the absence of a red line above 89 % suggests a healthy saturation level (WS6). Continuing further, the light cyan line (WS8) represents the nurse's assessment of the baby's breathing, particularly for grunting sounds. The yellow line (WS9) at 0 indicates the absence of grunting sounds, while a non-zero value on the yellow line would indicate the presence of grunting. This is corroborated by the pink line (WS10) reaching a level of 0.35, indicating minimal grunting sounds. However, considering the earlier observations of poor oxygen levels and respiratory distress, the presence of even minimal grunting supports the notion that the baby is experiencing respiratory distress. The medical procedure proceeds with the nurse monitoring for chest retractions, as depicted by the light grey line (WS11). The bordeaux red line (WS13) suggests that the baby is indeed experiencing chest retractions, while the light blue line (WS12) at 0 indicates the absence of chest retractions. Next, the nurse observes the baby's colour for signs of cyanosis, represented by the neon green line (WS14) in the graph. The red line (WS16) indicates the presence of skin, lip, or mucous membrane discoloration, suggesting the baby is experiencing cyanosis. Finally, based on the observations made, the nurse may provide supplemental oxygen, respiratory support, or transfer the baby to a Neonatal Care Intensive Unit, as shown by the brown line (WS18). The last light blue line signifies that the baby is allowed to bond with the mother (WS19).

6.1.2. *Nurse-led intervention with subsequent Doctor's Intervention: Results of Scenario 1b*

Fig. 8 reveals the presence of two context factors: the baby being in a critical state from $t = 1$ to 50 and the family experiencing emotional distress from $t = 1$ to 80. The initial light blue line (WS1) indicates the nurse alarming the doctor. Subsequently, the bordeaux red line (WS2) represents the doctor preparing the necessary equipment and supplies for a medical procedure, followed by the dark blue line (WS3) indicating that the doctor performs an X-ray and other evaluations. The orange line (WS4) demonstrates that the X-ray and other evaluations indeed reveal

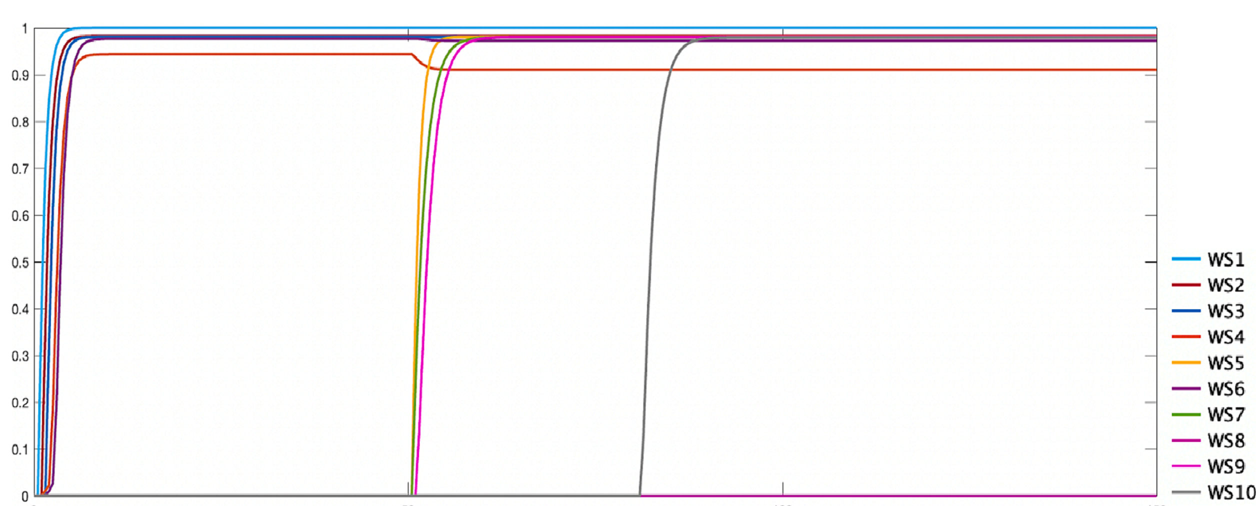

Fig. 8. Results Scenario 1b: the World States.

lung expansion, airway obstruction, pneumothorax, infiltrates, and/or cardiomegaly. It is worth noting a slight decrease at $t = 50$, as the period of the baby being in a critical state has ended, making it slightly less likely for the X-ray and other evaluations to indicate an abnormality. Afterward, the doctor provides oxygen therapy, medications, re-expands the lung, performs surgery, or administers other treatments (WS6). From $t = 50$ onward, the yellow line (WS5) illustrates a rapid increase in the state "X-ray and other evaluations do not show anything abnormal". This indicates that during the period when the baby was in a critical state, we observed abnormalities in the X-ray and other evaluations. However, after treatment was administered, the state "X-ray and other evaluations do not show anything abnormal" starts increasing because the treatment was effective, as evidenced by the green line (WS7). The light purple line (WS8) remains constant at 0, indicating that the treatment is not ineffective. The pink line (WS9) signifies the doctor providing advice, while the nurse only informs the family about this at $t = 80$, as indicated by the grey line (WS10). This timing is chosen because it aligns with the point when the family's emotional distress subsides, making it an appropriate moment for the nurse to communicate with them.

6.2. *Collaborative adaptation and learning in nurse-led intervention and impact of a fatigued Doctor: Results of Scenario 2*

This scenario incorporates multiple distinct periods occurring between $t = 0$ and $t = 1000$. It is important to note that the world steps progress rapidly, causing them to have slightly different time values but appearing on the same timeline in the graph (Fig. 9).

The first period takes place between $t = 0$ and $t = 150$. During this time, the nurse contacts the doctor for assistance, as depicted by the light blue line (WS1). The doctor promptly prepares the necessary equipment and supplies for a medical procedure, indicated by the bordeaux red line (WS2). Following this preparation, the doctor conducts an X-ray and other medical evaluations, as shown by the dark blue line (WS3). These evaluations reveal an abnormality (orange line, WS4), leading the doctor to proceed with treatment (purple line, WS6). However, due to the doctor being sick himself, errors occur during the administration of the treatment, resulting in even worse X-ray and evaluation results, as indicated by the increasing orange line. In an attempt to address the situation, the doctor switches to a different treatment (referred to as treatment 2). Unfortunately, this alternative treatment does not appear to be effective, and the doctor makes mistakes during the process, as evidenced by the green line (WS7). Consequently, the doctor reverts back to treatment 1 (purple line), which proves successful this time. The improved X-ray and evaluation results are depicted by the yellow line (WS5), while the decrease in the orange line signifies a positive outcome. Furthermore, the doctor advises the nurse to ensure that the neonate gets plenty of rest indicated by the red line (WS9). The nurse promptly conveys this information to the baby's family, depicted by the dark blue line (WS10).

Between $t = 150$ and $t = 300$, there are no critically ill babies requiring immediate attention. As a result, both the doctor and nurse get a break from their duties. However, between $t = 300$ and $t = 450$ the results show that the nurse reaches out to the doctor once more to help with a new baby. The doctor proceeds to prepare the required equipment and follow the usual steps, but unfortunately, he repeats the same mistakes as before. It's apparent that he is not feeling well, and this is reflected in his incorrect actions. The results show that he has already failed to administer the appropriate treatment to two babies due to his condition. Between $t = 450$ and $t = 900$, the doctor takes a significant break to recuperate and overcome his illness, with the aim of performing his duties more effectively once he returns to work.

After $t = 900$, the figure shows that once more, the nurse reaches out to the doctor for assistance with baby 3. The doctor follows the same steps as before, but this time, the results indicate that he has performed his duties accurately. He administers the treatment correctly on the first attempt, which proves to be effective, and he avoids any further errors. The break he took before did him good.

6.3. *Collaborative adaptation and learning in nurse-led intervention with subsequent Doctor's intervention and the role of an AI-Coach: Results of Scenario 3*

As mentioned earlier, Scenario 3 incorporates a virtual AI-Coach. This coach can monitor and signal when mistakes are made during the medical procedure. However, the coach can also provide the doctor and nurse with its perfect knowledge, facilitating organizational learning. Hence, there will be a differentiation between two cases: one in which organizational learning plays a big role and another in which the communication feature is important.

6.3.1. *Case 1: Organizational learning*

At the first-order adaptation level, specific **W**-states of the doctor and the nurse receive inputs from the **W**-states generated by the AI-Coach. This arrangement facilitates a comprehensive learning and recalling experience for the doctor and nurse, as the AI-Coach possesses a flawless mental model and imparts knowledge to them. In both cases, the $\mathbf{W}_{\mathbf{WW}}$-states won't be further explored in detail since these states remain

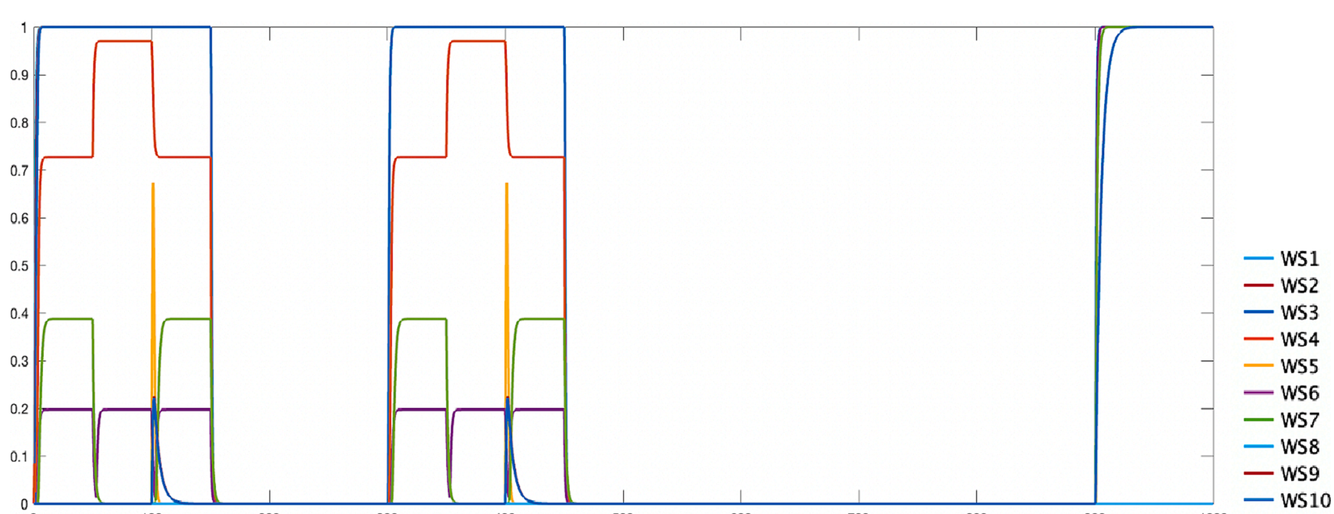

Fig. 9. Results Scenario 2: the World States.

constant at 1 with no speed and exhibit no variation.

6.3.1.1. The world states in case 1. As Fig. 10 depicts, the usual medical procedure happens by the nurse alarming the doctor (light blue line, WS1). This is followed by a bordeaux line (WS2) which means the doctor is preparing necessary equipment and supplies for the medical procedure. The dark blue line (WS3) shows that the doctor takes an X-ray and other evaluations, and the orange line (WS4) shows that the evaluations show that there indeed is something abnormal. While the yellow line (WS5) first started growing too because it seemed that there was nothing wrong, but eventually quickly went to zero because both states cannot happen at the same time; if the X-ray and other evaluations show there is something abnormal, it cannot show that there is nothing wrong. After this, the doctor already advises to let the neonate rest as much as possible because rest is needed for recovery (WS9). After this, the purple line (WS6) shows that the doctor is giving treatment with the green line (WS7) indicating that the treatment is working. In the end, the dark green line (WS10) shows that the nurse informs the family when the medical procedure is done.

6.3.1.2. Example WS2 in case 1: Learning state, mental state, ownership state, world state, and communication state. For instance, consider the graph (Fig. 11) below that illustrates the process behind WS2, which involves the doctor preparing necessary equipment and supplies for a medical procedure. The doctor's learning curve, represented by the blue line for adaptation state $\mathbf{W}_{\mathrm{DS1,DS2}}$, experiences an immediate rise as the knowledge provided by the AI-Coach is assimilated. The orange line represents DOS2, the ownership state triggered by the mental model state DS2 (bordeaux red line), followed by the neon green line (WS2), which signifies the actual occurrences in the real world. Furthermore, there is a temporary spike in learning as the AI-Coach briefly communicates (depicted by the light blue line, Communication WS2), but this interaction quickly diminishes because the need for continuous signalling from the AI-Coach diminishes as WS2 actively unfolds, resulting in a swift cessation of communication. The doctor's learning journey reaches a sustained level of approximately 0.7 instead of reaching a perfect score of 1. This is because even with the invaluable knowledge provided by the AI-Coach, it is impossible for the doctor to retain and recall every piece of information; in this case, the doctor retains around 70 % of what the AI-Coach imparts, resulting in the learning curve plateauing at this level. Therefore, in this particular scenario, the need for frequent communication by the AI-Coach is not significant, thanks to the presence of organizational learning that ensures the seamless advancement of medical procedures within the hospital.

This behaviour is applicable to all other states in this particular case. The learning states consistently increases, ensuring the correct progression of all subsequent states and rendering the communication function of the AI-Coach unnecessary.

6.3.1.3. Understanding the learning states of the doctor in case 1: A comprehensive exploration. Within the model, there are three key actors: the doctor, the nurse, and the AI-Coach. Each of these actors exhibits a distinct process in their learning states. Consideration should be given to the fact that the learning states of the doctor are here taken as an example, and a similar exploration of learning states could have been conducted for the nurse, for instance.

Fig. 12 illustrates the learning states of the doctor. At the beginning, all W-states demonstrate a comparable pattern of learning, characterized by a gradual increase, followed by a noticeable spike, and then a slight decline indicating some degree of forgetting. However, the learning process is consistently supported by the AI-Coach's impeccable knowledge, preventing the knowledge states from ever reaching zero. As a result, a stable level of knowledge is maintained, ensuring a continuous learning experience throughout the process. However, it is worth noting that WDS9,DS10 follows a different trajectory. This learning state decreases to 0 since it is not triggered by the communication state of the AI-Coach. This is due to the fact that the doctor is not involved in the final step of the medical procedure, which involves informing the family, a responsibility undertaken by the nurse.

6.3.2. Case 2: AI-Coach's monitoring and communication functions

In the previous case, at the initial reification level, the **W**-states of the doctor and nurse are influenced by the **W**-states generated by the AI-Coach. However, in cases where these links are not present, the AI-Coach can still contribute to the improvement of the nurse and doctor's knowledge in a different manner. This is achieved through the AI-Coach's monitoring and communication feature, which enables it to identify and address mistakes (Fig. 14).

6.3.2.1. The world states in case 2. In this case (Fig. 13), the process of the world states is significantly different from that of case 1. It is important to present these world states too to provide a comprehensive view of the entire story, ensuring that no crucial details are overlooked.

As usual, the nurse initially alarms the doctor (light blue line, WS1), prompting the doctor to prepare the necessary equipment and supplies (bordeaux line, WS2). Subsequently, the doctor performs X-ray and

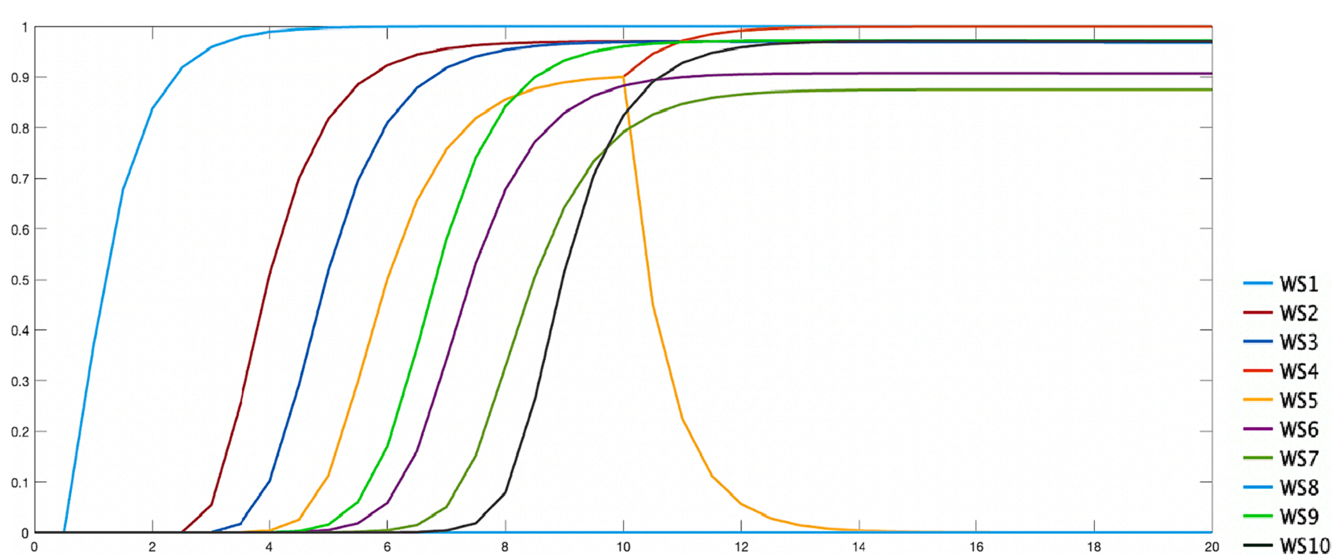

Fig. 10. Results Scenario 3: the World States during case 1.

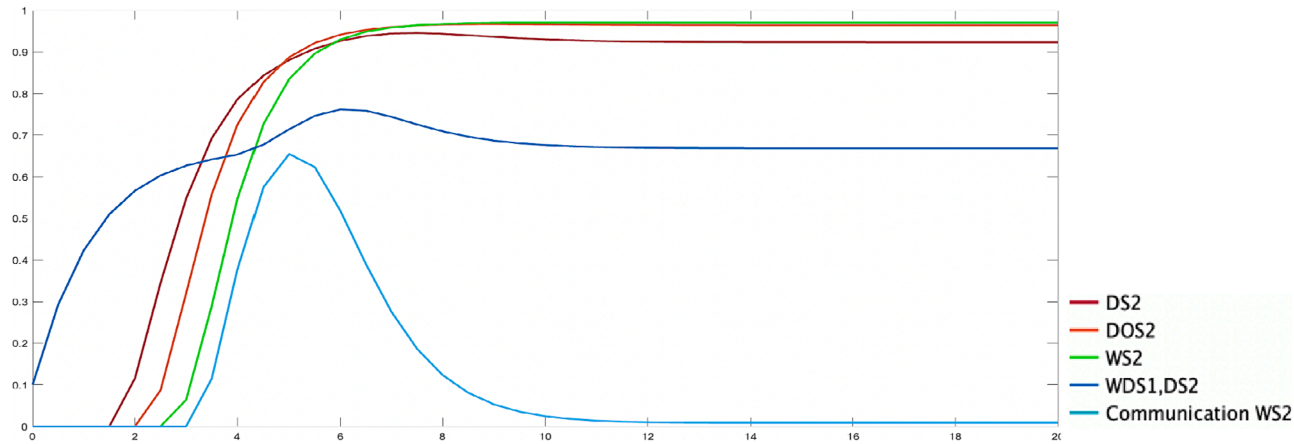

Fig. 11. Results Scenario 3: example WS2 during case 1.

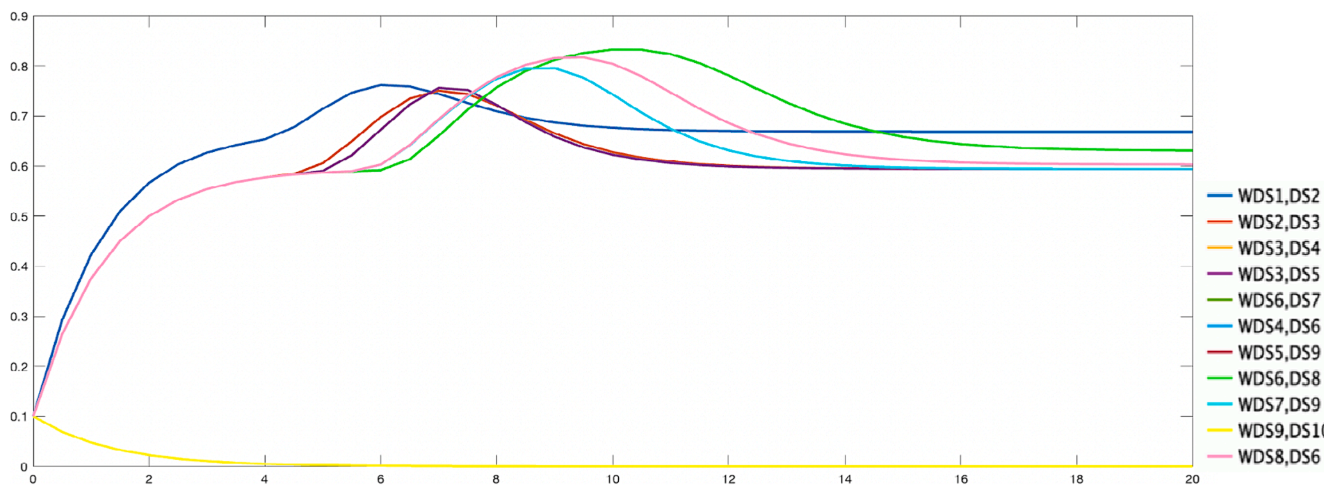

Fig. 12. Case 1 Results Scenario 3: learning done by doctor.

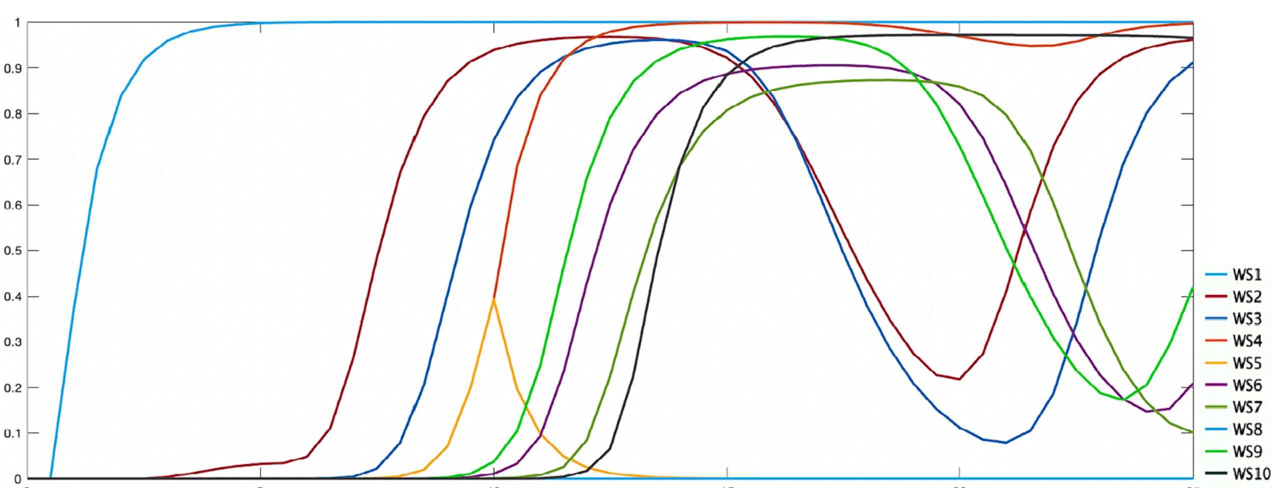

Fig. 13. Results Scenario 3: the World States during Case 2.

other evaluations (dark blue line, WS3), which confirm the presence of an abnormality (orange line, WS4). The yellow line (WS5) briefly suggests no issue, but it quickly returns to zero as the abnormal and normal X-ray and other evaluations results cannot coexist simultaneously. The doctor advises providing ample rest for the neonate's recovery (WS9). Treatment is then administered (purple line, WS6) and proves effective (green line, WS7). Finally, the nurse informs the family when the medical procedure is completed (dark green line, WS10).

However, when compared to case 1, it is evident that in this particular scenario the word states experience a decline instead of remaining

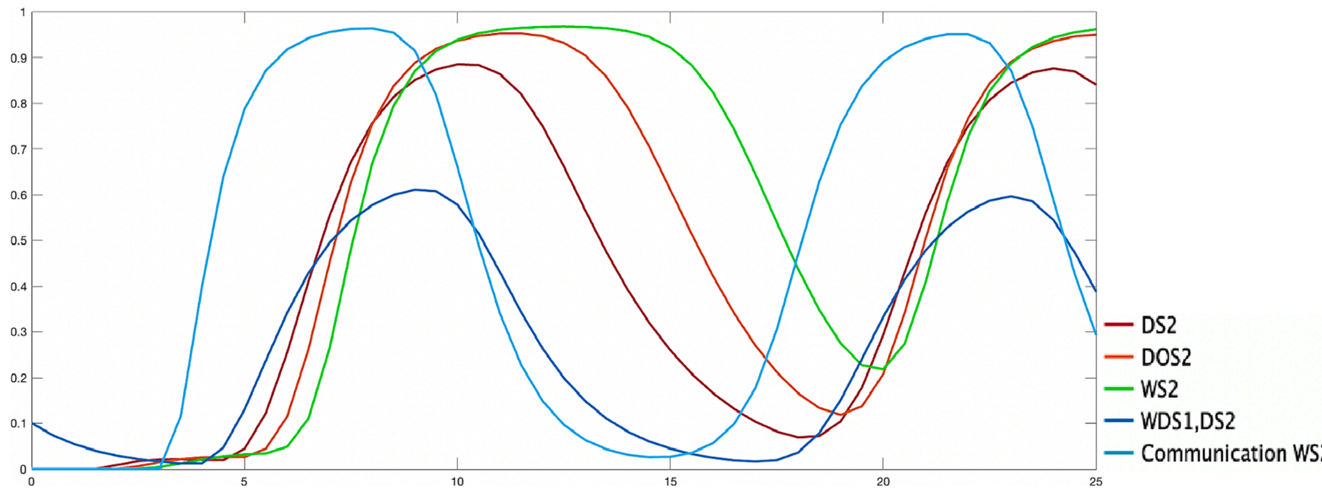

Fig. 14. Results Scenario 3: example WS2 during Case 2.

constant. This decline signifies the occurrence of mistakes during the medical procedure, which were uncommon in the case where organizational learning was present. However, it is important to note that these world states never fully reach zero, except for cases where it is necessary for them to be zero, such as when "X-ray and other evaluations show nothing abnormal." The world states never reach zero because the communication feature of the AI-Coach promptly signals the mistakes, causing the lines to increase again, indicating that the doctor/nurse is aware of their error.

6.3.2.2. Example WS2 in case 2: Learning state, mental state, ownership state, world state, and communication state. As previously mentioned, in the initial reification level, certain **W**-states of the doctor and nurse receive inputs from the **W**-states generated by the AI-Coach, resulting in optimal knowledge for both. However, if these inputs were hindered and the connections between the **W**-states of the AI-Coach and the nurse/doctor were disrupted, a different outcome would occur. In such a scenario, the 'communication' feature provided by the AI-Coach becomes valuable.

The following graph illustrates the same WS2 state but with a delay in the learning state receiving input from the AI-Coach's learning state. Consequently, the learning first decreases and when the AI-Coach detects forgetfulness, it signals accordingly. The graph depicts a dark blue line for adaptation state $\mathbf{W}_{DS1,DS2}$ representing the learning process. It is evident that the doctor initially begins to forget, prompting the AI-Coach to initiate communication to indicate that WS2 should be taking place (light blue line, Communication WS2). Subsequently, the orange line representing DOS2 gets triggered by the mental model state DS2 which is indicated by the bordeaux red line. Eventually, the occurrence of the neon line indicates the manifestation of WS2 in the real world. As a result, the need for the AI-Coach to communicate and signal the necessity of WS2 diminishes. Subsequently, there is a subsequent occurrence of forgetfulness, resulting in a decline in the mental model state, action state, and world state. This prompts the AI-Coach to signal once more, indicating the need for further learning. As a response, the doctor resumes the learning process, striving to enhance their understanding and proficiency. Thus, it becomes apparent that the communication feature is particularly useful when the doctor and nurse lack perfect knowledge and experience forgetfulness.

6.3.2.3. Understanding the learning states of the doctor in case 2: A comprehensive exploration. Fig. 15 illustrates the learning states of the doctor. Initially, all **W**-states exhibit a similar pattern of forgetting, followed by subsequent learning, and eventually a big decrease indicating forgetting again.

This learning process is facilitated by the AI-Coach's signalling when something goes wrong. Thus, when the big decrease in learning happens, the AI-Coach signals this and helps the doctor in increasing their knowledge again. However, it is worth noting that $\mathbf{W}_{DS9,\ DS10}$ follows a different trajectory. This learning state decreases to 0 since it is not triggered by the communication state of the AI-Coach. This is due to the fact that the doctor is not involved in the final step of the medical procedure, which involves informing the family, a responsibility undertaken by the nurse.

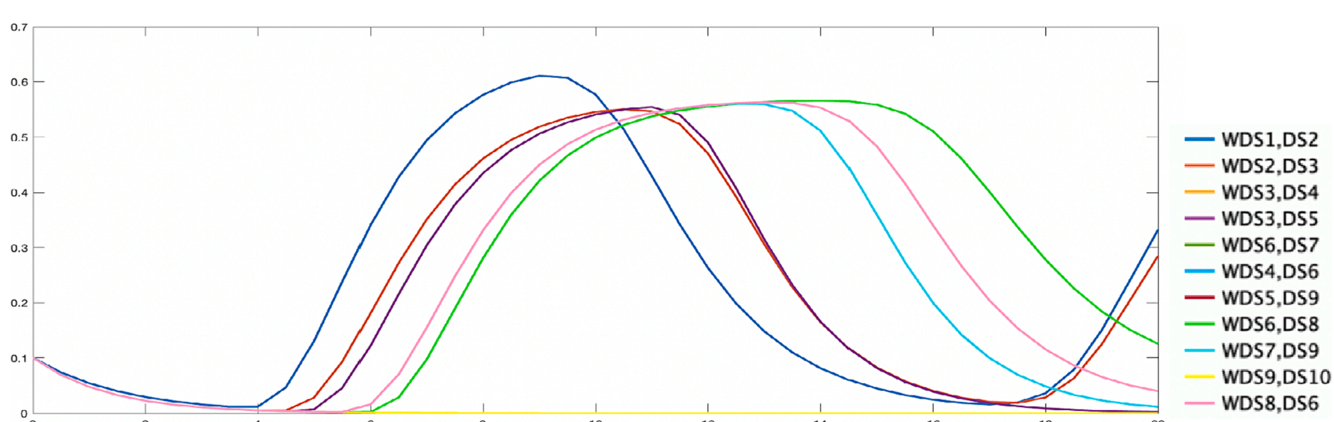

Fig. 15. Case 2 Results Scenario 3: learning by doctor.

In this particular case, the example focuses on the doctor; however, it is important to note that similar processes of learning and forgetting occur with the nurse as well. Both the doctor and the nurse experience the same patterns of learning and forgetting within their respective roles. Additionally, it is worth highlighting that the learning states of the AI-Coach consistently maintain a constant line at 1. This is due to the AI-Coach possessing perfect knowledge from the outset and not requiring any further learning itself.

7. Conclusion and discussion

This study introduces adaptive computational network models that examine the processes involved in the execution of a medical procedure related to respiratory distress in a hospital setting. The development of these models incorporates the adaptive network-oriented modelling approach (Treur, 2020) in combination with the specialized software written in MATLAB. The full specifications by role matrices of all models can be found as Linked Data at.

https://www.researchgate.net/publication/371986708

Initially, the study presents models that include the mental models of a doctor and a nurse. Subsequently, it explores the integration of a mental model and the utilization of a virtual AI-Coach. This AI-Coach possesses advanced capabilities, employing a monitoring system to assess whether it should provide alerts or not. The initial simulation results highlight the progression of the first two scenarios without the presence of the AI-Coach. However, subsequent simulations demonstrate that the AI-Coach can provide significant benefits in two distinct ways. Firstly, by leveraging organizational learning, the AI-Coach educates team members about each step of the medical procedure, effectively reducing the likelihood of errors in the workplace. This approach ensures that team members have a comprehensive understanding of the procedure, minimizing the occurrence of mistakes. Secondly, the monitoring feature of the AI-Coach plays a crucial role. It promptly alerts team members whenever it detects deviations or delays in the procedure. This vigilance helps mitigate forgetfulness among nurses and doctors, enabling them to relearn and operate without making mistakes. It is important to note that organizational learning, as observed in case 1, has a superior effect compared to the communication feature alone. In case 1, learning consistently increased and reached a constant state, indicating the correct execution of the medical procedure. On the other hand, in case 2, learning increased only when the AI-Coach signalled an issue. Furthermore, in case 2, the world states decreased, while in case 1, these word states remained constant, indicating a successful medical procedure. However, despite the effectiveness of organizational learning facilitated by the AI-Coach, the communication feature played a crucial role in averting critical mistakes. When something went wrong, the AI-Coach's communication feature promptly addressed the issue, ensuring timely resolution. In conclusion, while organizational learning via the AI-Coach resulted in better outcomes, the communication feature proved essential in preventing fatal mistakes by swiftly identifying and rectifying issues as they arose.

Xu et al. (2022) demonstrated a model of doctors and nurses assisting a distressed newborn with breathing. The case they addressed is whether the equipment is used effectively. Also, their findings demonstrated an AI-coach that prevents errors. This is consistent with the findings in this article, which show that an AI-coach enables organizations to identify and reduce errors, ultimately improving performance. An adaptive model for communication in labour and delivery rooms, including doctor-nurse communication, was developed by Doornkamp et al. (2023). This doctor-nurse communication was also done with observation arrows in this article. However, one significant difference is that their study encourages a doctor to speak up when problems arise, whereas this article focuses on how an AI-coach monitors and warns doctors and nurses about mistakes. Weigl et al. (2023) investigated computational network models depicting communication between fathers and healthcare providers during childbirth. They discovered that organizational learning promotes knowledge growth and communication. This is consistent with this article, which emphasizes how organizational learning improves the knowledge of the medical team and the overall procedure. However, in this article, a distinction was made between two scenarios: one involving organizational learning facilitated by the AI-Coach, and another involving only the AI-Coach's monitoring and warning function. This enabled a thorough examination of the differences in their impact.

The differences between their work and this article vary not only in scope but also in models. In the upper level of their work, Xu et al. used $\mathbf{M_W}$-states; Scenario 2 of this paper also used $\mathbf{M_W}$-states but Scenario 3 used $\mathbf{W_{WW}}$-states. This decision was made with the intention of facilitating individual learning of shared organizational mental models, as $\mathbf{W_{WW}}$-states define connections between AI-Coach's **W**-states and a doctor's or nurse's individual **W**-states. In order to maintain the strongest connection, this study used the maximum Hebbian function in Scenario 2 as opposed to Xu et al. who used the Hebbian combination function for **W**-states. In the papers of Doornkamp et al. and Weigh et al., no Hebbian learning was used, whereas here, two different versions of learning are used: Hebbian learning in Scenario 2 and the alogistic function for the **W**-states in Scenario 3. Furthermore, whereas Doornkamp et al.'s model focuses on fear of repercussions, this paper takes into account a variety of contextual factors. The AI-Coach process differs significantly between the three papers and this paper. In this study, the AI-Coach observes what happens in the world and this information is sent to the monitoring state, which then activates the decision states. If everything goes well, the decision states are suppressed, but if they activate, the upper-level communication states are activated. The papers by Xu et al., Doornkamp et al., and Weigh et al. do not address this specific process.

The primary limitation of the models is their narrow focus on neonates in respiratory distress, which limits their applicability to other medical conditions and patient populations. Future research should prioritize validating and adapting the model to encompass a wider range of healthcare scenarios, enhancing its versatility and effectiveness across diverse medical contexts. Moreover, expanding the communication capabilities of the AI-Coach beyond signalling the doctor and nurse to include other stakeholders, such as patients and their families, has the potential to enhance the overall functioning of the hospital work floor. By establishing communication channels with these additional stakeholders, the AI-Coach can improve coordination, collaboration, and overall efficiency within the healthcare environment. Additionally, it is essential to explore strategies that promote effective collaboration and trust between healthcare professionals and the AI-Coach. Developing methodologies that position the AI-Coach as a supportive tool, rather than a substitute for human expertise, is crucial. By fostering collaboration and trust, healthcare professionals can effectively leverage the capabilities of the AI-Coach while maintaining their essential roles in decision-making and patient care. Furthermore, future work will extend to validating these models against clinical outcomes from neonatal care, adjusting them based on empirical data to improve their predictive power and practical application. Engaging with healthcare professionals will be essential to this validation process to ensure the models' effectiveness in real-world settings.

CRediT authorship contribution statement

Nisrine Mokadem: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Fakhra Jabeen:** Data curation, Methodology, Project administration, Software, Supervision. **Jan Treur:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. **H. Rob Taal:** Conceptualization, Data curation, Investigation, Resources, Supervision. **Peter H.M.P. Roelofsma:**

Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Abdi, S., Bagherzadeh, J., Gholami, G., & Tajbakhsh, M. S. (2021). Using an auxiliary dataset to improve emotion estimation in users' opinions. *Journal of Intelligent Information Systems, 56*, 581–603.

Altman, Y., & Iles, P. (1998). Learning, leadership, teams: Corporate learning and organizational change. *The Journal of Management Development, 17*(1), 44–55.

Bass, C., Sajed, D., Adedipe, A., & West, E. (2015). Pulmonary ultrasound and pulse oximetry versus chest radiography and arterial blood gas analysis for the diagnosis of acute respiratory distress syndrome: A pilot study. *Critical Care, 19*, 282. https://doi.org/10.1186/s13054-015-0995-5

Cannon-Bowers, J. A., Salas, E., & Converse, S. A. (1993). Shared mental models in expert team decision-making. In N. J. Castellan, Jr. (Ed.), *Individual and group Decision Making* (pp. 221–246). Lawrence Erlbaum.

Copetti, R., Cattarossi, L., Macagno, F., Violino, M., & Furlan, R. (2008). Lung ultrasound in respiratory distress syndrome: A useful tool for early diagnosis. *Neonatology, 94* (1), 52–59. https://doi.org/10.1159/000113059

Canbaloğlu, G., Treur, J., & Wiewiora, A. (Eds.). (2023). *Computational modeling of multilevel organisational learning and its control using self-modeling network models*. Cham: Springer Nature.

Canbaloğlu, G., Treur, J., & Wiewiora, A. (2023). From conceptual to computational mechanisms for multilevel organisational learning. In G. Canbaloğlu, J. Treur, & A. Wiewiora (Eds.), *Computational modeling of multilevel organisational learning and its control using self-modeling network models* (p. 5). Cham: Springer Nature. https://doi.org/10.1007/978-3-031-28735-0_5.

Catania, L. J. (2021). AI applications in prevalent diseases and disorders. *Foundations of Artificial Intelligence in Healthcare and Bioscience*, Elsevier, 293-444.

Craik, K. J. (1943). *The nature of psychology*. Cambridge University Press.

Crossan, M. M., Lane, H. W., & White, R. E. (1999). An organizational learning framework: From intuition to institution. *The Academy of Management Review, 24*(3), 522–537. https://doi.org/10.2307/259140

Doornkamp, S., Jabeen, F., Treur, J., Taal, H. R., & Roelofsma, P. (2023). A controlled adaptive computational network model of a virtual coach supporting speaking up by healthcare professionals to optimize patient safety. *Cognitive Systems Research, 81*, 37–49. https://doi.org/10.1016/j.cogsys.2023.02.002

García-Morales, V., Jiménez-Barrionuevo, M., & Gutierrez, L. (2012, July 01). Transformational leadership influence on organizational performance through organizational learning and innovation. *Journal of Business Research*. doi:10.1016/j.jbusres.2011.03.005.

Hosseini, M., Kucharska, W., & Treur, J. (2023). An Adaptive Network Model for a Double Bias Perspective on Learning from Mistakes within Organizations. In *Proc. of the 12th International Conference on Complex Networks and their Applications, ComplexNetworks*' 23. Springer Nature Switzerland AG.

Jayachitra, S., Prasanth, A., Hariprasath, S., Benazir Begam, R., & Madiajagan, M. (2023). AI enabled internet of medical things in Smart Healthcare. In *AI Models for Blockchain-Based Intelligent Networks in IoT Systems: Concepts, Methodologies, Tools, and Applications* (pp. 141–161). Cham: Springer International Publishing.

Jonker, C. M., van Riemsdijk, M. B., & Vermeulen, B. (2011). Shared mental models. In S. Parsons, M. Wooldridge, & J. Müller (Eds.), *Coordination, Organizations, Institutions, and Norms in Agent Systems VI* (p. 132). Springer.

Kavitha, M., Roobini, S., Prasanth, A., & Sujaritha, M. (2023). Systematic view and impact of artificial intelligence in smart healthcare systems, principles, challenges and applications. *Machine Learning and Artificial Intelligence in Healthcare Systems*, 25–56.

Keith, N., & Frese, M. (2011). Enhancing firm performance and innovativeness through error management culture. In N. Anderson, & P. Herriot (Eds.), *Handbook of Research on Professional Misconduct in Management and Public Administration* (pp. 137–157). Edward Elgar Publishing. https://doi.org/10.4135/9781483307961.n9.

Kim, D. H. (1997). The link between individual and organizational learning. In D. A. Klein (Ed.), *The Strategic Management of Intellectual Capital*: Vol. 1st Edition. Routledge. Doi: 10.4324/9780080517926.

Kucharska, W., & Bedford, D. A. (2020). Love your mistakes!—they help you adapt to change. How do knowledge, collaboration and learning cultures foster organizational intelligence? *Journal of Organizational Change Management, 33*(7), 1329–1354.

Kucharska, W., & Rebelo, T. (2022). Knowledge sharing and knowledge hiding in light of the mistakes acceptance component of learning culture-knowledge culture and human capital implications. *The Learning Organization, 29*(6), 635–655.

Machogu, E., & Gaston, B. (2021 February 18). Respiratory distress in the newborn with primary ciliary dyskinesia. *Children (Basel), 8*(2), 153. https://doi.org/10.3390/children8020153

Nigg, J. T. (2017). Annual Research review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology. *Journal of child psychology and psychiatry, 58*(4), 361–383.

Nigg, J. T. (2023). Considerations toward an epigenetic and common pathways theory of mental disorder. *Journal of Psychopathology and Clinical Science, 132*(3), 297.

Saboute, M., Kashaki, M., Bordbar, A., Khalessi, N., & Farahani, Z. (2015 October 19). The incidence of respiratory distress syndrome among preterm infants admitted to neonatal intensive care unit: A retrospective study. *Open Journal of Pediatrics, 5*, 285–289. https://doi.org/10.4236/ojped.2015.54043

Saadat, V., & Saadat, Z. (2016 September 12). Organizational learning as a key role of organizational success. *Procedia - Social and Behavioral Sciences, 230*. https://doi.org/10.1016/j.sbspro.2016.09.028

Scherer, K. R. (2009). Emotions are emergent processes: They require a dynamic computational architecture. *Philosophical Transactions of the Royal Society B: Biological Sciences, 364*(1535), 3459–3474. https://doi.org/10.1098/rstb.2009.0141

Sitterding, M. C., Raab, D. L., Saupe, J. L., & Israel, K. J. (2019). Using artificial intelligence and gaming to improve new nurse transition. *Nurse Leader, 17*(2), 125–130.

Stout, R. J., Cannon-Bowers, J. A., & Salas, E. (2017). The role of shared mental models in developing team situational awareness: Implications for training. In *Situational awareness* (pp. 287–318). Routledge.

Sweet, L. R., Keech, C., Klein, N. P., Marshall, H. S., Tagbo, B. N., Quine, D., Kaur, P., Tikhonov, I., Nisar, M. I., Kochhar, S., & Muñoz, F. (2017). M., & Brighton collaboration respiratory distress in the neonate working group. In *Respiratory distress in the neonate: case definition & guidelines for data collection, analysis, and presentation of maternal immunization safety data*. https://doi.org/10.1016/j.vaccine.2017.01.046

Swarnkar, M., & Swarnkar, K. (2015). Neonatal respiratory distress in early neonatal period and its outcome. *International Journal of Biomedical and Advance Research, 6*, 643–647.

Treur, J. (2016). *Network-oriented modeling: Addressing complexity of cognitive, affective and social interactions*. Cham: Springer Nature.

Treur, J. (2020). *Network-oriented modeling for adaptive networks: Designing higher-order adaptive biological, mental and social network models*. Cham, Switzerland: Springer Nature.

Treur, J., Van Ments, L. (eds.) (2022). *Mental models and their dynamics, adaptation and control: a self-modeling network modeling approach.* Cham: Switzerland, Springer Nature (2022).

Van Ments, L., Treur, J. (2021). Reflections on dynamics, adaptation and control: a cognitive architecture for mental models. *Cognitive Systems Research, 70*, 1–9.

Van Ments, L., Treur, J., Klein, J., & Roelofsma, P. H. M. P. (2021). A second-order adaptive network model for Shared mental models in hospital teamwork. In N. T. Nguyen (Ed.), *Lecture Notes in AI* (vol. 12876, pp. 126–140). Springer Nature.

Weigl, L. M., Jabeen, F., Treur, J., Taal, H. R., & Roelofsma, P. H. M. P. (2023). Modeling learning for a better safety culture within an organisation using a virtual AI coach: Reducing the risk of postpartum depression by more communication with Parents. *Cognitive Systems Research, 80*, 1–36. https://doi.org/10.1016/j.cogsys.2023.06.001

Wiewiora, A., Chang, A., & Smidt, M. (2020). Individual, project and organizational learning flows within a global project-based organization: Exploring what, how and who. *International Journal of Project Management, 38*, 201–214.

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. *European Management Review, 16*, 93–115.

Wilden, R., Hohberger, J., Devinney, T. M., & Lavie, D. (2018). Revisiting James March (1991): whither exploration and exploitation? *Strategic Organization, 16*(4). doi: 10.1177/147612701876503.

Xu, Y., Jabeen, F., Treur, J., Taal, H. R., & Roelofsma, P. H. M. P. (2022). Adaptive agent network models with internal mental models supporting patient safety. In *Proc. of the 15th International Conference on Social Computing and Networking, SocialCom'22 IEEE Computer Society*. https://www.researchgate.net/publication/363832332.