Improving Risk Management Through Cyberspace: Optimizing Neonatal Respiratory Support Through Network-Oriented Modeling

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Abstract This chapter presents an approach to enhancing neonatal care through the application of artificial intelligence (AI). Utilizing network-oriented modeling methodologies, the study aims to develop a network model to improve outcomes in neonatal respiratory support. The introduction sets the stage by outlining the significance of neonatal respiratory support and the challenges faced in this domain. The literature review delves into the existing body of work, highlighting the gaps and the need for a network modeling approach. The network-oriented modeling approach provides a robust framework that captures various states, such as world states, doctors' mental states, and AI coach states, facilitating a comprehensive understanding of the complex interactions in neonatal respiratory support. Through Matlab simulations, the study investigates multiple scenarios, from optimal conditions to deviations from standard protocol. The main contribution focuses on the introduction of an AI coach, which serves as a real-time intervention mechanism to fill in the doctor's knowledge gaps. The research serves as a seminal work in the intersection of

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artificial intelligence and healthcare, demonstrating the potential of network-oriented modeling in improving patient outcomes and streamlining healthcare protocols.

Keywords Adaptive network model · Infant care · AI coach

1 Introduction

In the Netherlands, 166,891 babies were born in 2022. That is 457.24 per day (Cijfers over geboorte | Nederlands Jeugdinstituut 2023). Approximately 7% experience respiratory distress at birth, necessitating immediate and specialized medical intervention (Edwards and Kotecha 2013). This translates to a staggering number of infants requiring critical respiratory support each day, highlighting the urgency for effective and optimized neonatal care. Neonatal respiratory support is a critical aspect of infant care, as timely interventions can have significant impacts on survival and long-term health outcomes (Kaltsogianni et al. 2023). With advancements in technology, Artificial Intelligence (AI) has emerged as a tool with potential applications across various healthcare domains, including neonatal care (Malak et al. 2018).

This chapter explores the question, 'How can the development and analysis of a network model, representing world, AI coach, and doctors' mental states, provide insights into neonatal respiratory support through the simulation of the process of respiratory support of a newborn baby?' The research builds on principles of network-oriented modeling by adaptive self-modeling networks (Treur 2020a, b), encompassing three key states and modeling three scenarios:

1. A Successful Scenario: Reflecting optimal processes as described in neonatal care guidelines.
2. An Error Scenario: Some deviation takes place: an often occurring error or omission.
3. An AI-Coached Error Detection and Knowledge Improvement Scenario: The AI coach detects an error and improves the knowledge of the doctor if needed.

By analyzing these scenarios, this chapter aims to contribute to the understanding of the AI Coach's role in optimizing neonatal respiratory support.

2 Background Literature

Neonatal respiratory support is a vital aspect of care for newborns, particularly in the moments immediately following birth. Roehr and Bohlin (2011) state that a protective respiratory support strategy from birth is essential as it may not only reduce breathing difficulties in the immediate neonatal period, but may also influence some known triggers for the development of BPD, such as inflammation, oxidative stress and lung growth. The importance of this intervention has been highlighted in various clinical guidelines, emphasizing the need for immediate assessment and support of breathing in newborns (Anne and Murki 2021). Advances in neonatal respiratory care have led to improved survival rates and outcomes for preterm infants and those with specific respiratory conditions.

Even with recent progress, there are still some hurdles in giving the best breathing support to newborns (Kaltsogianni et al. 2023). These hurdles include identifying which babies need help, choosing the right treatments, deciding when to offer support, and avoiding mistakes. There's also inconsistency in how treatments are given, making things even more complicated. However, technology like Artificial Intelligence (AI) could help overcome some of these issues (Kaltsogianni et al. 2023). By using network models that show different situations related to breathing support, healthcare providers could get a clearer idea of how to best handle this crucial part of caring for newborns.

The integration of Artificial Intelligence (AI) into healthcare has marked a transformative era, revolutionizing various medical domains, from diagnostics to personalized treatment (Khan et al. 2022). The convergence of AI technologies with medical practices has led to improved efficiencies, enhanced patient outcomes, and the opening of new avenues for research and innovation. In the context of neonatal care, AI has demonstrated promising applications, including the analysis of complex medical data, predictive modeling for patient outcomes, and assistance in decision-making (Bajwa et al. 2021). These applications extend to neonatal respiratory support, where timely and precise interventions are crucial.

One specific area where we can investigate if AI shows potential in the process of the respiratory support of neonatal is with the use of network modeling. This approach involves the construction of network models representing various states and relationships, enabling the simulation and analysis of different scenarios related to respiratory support (Treur 2020a, b). For instance, network models can represent the world states, AI coach states, and doctors' states, each with specific roles and interactions. The development of such network models allows for a systematic exploration of neonatal respiratory support processes, including the simulation of optimal processes, common deviations, and AI-coached interventions. By leveraging the computational capabilities of AI, these models can provide insights, guide clinical decisions, and potentially optimize respiratory support for newborns. Network modeling and analysis in neonatal respiratory support offers a novel approach to understanding and enhancing care, with potential implications for both immediate neonatal outcomes and the future of technology-driven medical care.

The development of network models that represent various states and interactions is an innovative approach in healthcare, providing a computational framework to understand and analyze complex processes. In the context of neonatal respiratory support, these models can include states such as:

- World States: capturing states of the baby and the broader context and environment, including hospital settings, equipment, and external factors that may influence care.

- AI Coach states: Representing an intelligent entity that guides, monitors, and supports the healthcare process, offering insights and interventions when needed.
- Doctors' mental and action states: Reflecting the healthcare provider's actions, decisions, knowledge, and interactions with both the world and AI coach states.

These states and their interactions are covered by the network model, allowing for the simulation and analysis of different scenarios. The scenarios can include:

1. Successful Processes: Simulating the ideal process of neonatal respiratory support, serving as a baseline for understanding best practices and optimal outcomes.
2. Common Deviations: Modeling frequent errors or omissions, highlighting potential risks, and areas for improvement in care delivery.
3. AI-Coached Error Detection and Knowledge Improvement: Integrating an AI coach to detect and rectify mistakes in real-time, enhancing accuracy and safety. And utilizing AI to support healthcare workers in enhancing their knowledge, skills, and adherence to guidelines, thus improving overall care quality.

The ability to model and simulate these scenarios offers valuable insights into neonatal respiratory support, allowing for a nuanced understanding of the interactions and dependencies within the process. It opens opportunities for targeted interventions, continuous learning, and optimization of care, aligning with the broader goals of precision medicine and technology-driven healthcare.

By leveraging network modeling, this approach fosters a data-driven, evidence-based practice that transcends traditional boundaries, offering a new perspective on neonatal care and beyond.

Computational causal modeling is a powerful tool in AI that can help us understand complex healthcare situations better (Sarker 2022). In the case of helping newborns breathe, this type of modeling can map out how different factors like doctors, AI coaches, and the baby's condition interact. This approach is unique because it shows not only what directly causes what but also how changes in one area can affect the whole system (Squires and Uhler 2022). By using this method, researchers can simulate different outcomes, such as what happens when things go right, when they go wrong, how AI can spot mistakes, and how AI can help improve our knowledge (Campos and Fleury 2022).

This kind of modeling can help identify why certain treatments work or fail and point out where critical decisions should be made to improve care. The research aims to add to the growing field of network modeling in healthcare. The findings could impact not just how doctors treat newborns, but also broader healthcare policies and future studies, laying the groundwork for improving the care of newborns overall.

In conclusion, the development and application of network modeling, coupled with computational causal modeling, represent a novel and promising avenue in neonatal respiratory support. By drawing on relevant literature and innovative methodologies, this research aims to shed new light on the complexities of neonatal care and pave the way for technology-driven improvements in this vital area of healthcare.

3 Modeling Approach for Neonatal Respiratory Support

The research conducted for this chapter employs a network-oriented modeling approach to understand and analyze the complex interactions and processes in neonatal respiratory support (Weigl et al. 2023), see also Weigl et al. (2025), this volume. This methodology encompasses various states, such as the world, AI coach, and doctor states, capturing the interactions and causal impacts within the system. Key features characterize the structure of the network (Weigl et al. 2023). State are often indicated by X and Y; they have activation values (real numbers, usually in the interval [0, 1]) *X(t)* and *Y(t)* that vary over time *t*. *Connectivity Characteristics* specify connections from a state X to a state Y as defined by their weights $\boldsymbol{\omega}_{X,Y}$, symbolizing the strength of the causal impact from X to Y. *Aggregation Characteristics* are specified for any state Y by a combination function $\mathbf{c}_Y(\ldots)$ outlines the aggregation applied to the single causal impacts $\boldsymbol{\omega}_{X,Y}X(t)$ on Y from its incoming connections from states X. *Timing Characteristics* specify for each state Y a speed factor $\boldsymbol{\eta}_Y$, indicating how quickly it changes for a given causal impact.

Based on these network characteristics a standard numerical format described by the difference equation defines the dynamics of the network model:

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

Various combination functions are available to handle the aggregation of multiple impacts, with the specific functions used here detailed in Table 1.

The modeling approach also includes the concept of network reification or self-modeling network, extending the base model by additional states, referred to as reification states or self-model states (Treur 2020a, b). Examples are self-model states $\mathbf{W}_{X,Y}$, $\mathbf{C}_Y$, $\mathbf{H}_Y$ (reification states) to represent the adaptive network structure characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y$, $\boldsymbol{\eta}_Y$ for a state Y of the base network. Such self-model states are called **W**-states, **C**-states and **H**-states, respectively. This can be iterated to get higher-order self-model states. For example, the self-model state $\mathbf{W}_{\mathbf{W}_{X_1,Y_1}}, \mathbf{W}_{X_2,Y_2}$ is a second-order self-model state that indicates the weight of a communication channel from $\mathbf{W}_{X_1,Y_1}$ to $\mathbf{W}_{X_2,Y_2}$. This will be used in the introduced model for communication from AI Coach to Doctor.

In Treur (2021), Hendrikse et al. (2023), it is shown that any smooth dynamical system has a canonical representation as a temporal-causal network and any smooth (multi-order) adaptive dynamical system has a canonical representation as a

Table 1 Combination functions used

Function	Notation	Formula	Parameters
Advanced logistic sum	$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\ldots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right](1 + e^{-\sigma\tau})$	Steepness $\boldsymbol{\sigma}$ Threshold $\boldsymbol{\tau}$
Identity	$\mathbf{id}(V_1, \ldots, V_k)$	V_1	–

(multi-order) self-modeling temporal-causal network. Therefore, compared to adaptive dynamical systems in general, the network-oriented modeling approach used here does not introduce any fundamental limitations concerning what it can model. This has also been confirmed by applications to case studies in practice, e.g., for mental models in Treur et al. (2022) and for organizational learning in Canbaloğlu et al. (2023).

This network-oriented methodology provides a robust framework to explore and analyze scenarios related to neonatal respiratory support. The modeling and simulations are conducted using Matlab, providing a comprehensive approach to simulating and analyzing the scenarios related to neonatal care. In the development of an network model for optimizing neonatal respiratory support, two essential mathematical functions as shown in Table 1 have been employed within the MATLAB environment.

The advanced logistic sum function represents a nonlinear transformation that takes the weighted sum of the input variables $V_1,\ldots,V_k$ for incoming single causal impacts and applies a logistic function. This function is characterized by two parameters: the steepness $\boldsymbol{\sigma}$ and the threshold $\boldsymbol{\tau}$. The steepness parameter $\boldsymbol{\sigma}$ controls the slope of the logistic curve, whereas the threshold parameter $\boldsymbol{\tau}$ determines the point at which the function transitions from one state to another. In the context of neonatal respiratory support, this function can be utilized to model complex relationships and transitions within the respiratory system, such as the response to different ventilatory support parameters. The identity function is a straightforward mathematical transformation that just returns the input value itself. In terms of the respiratory support model, the identity function can represent parameters or variables that are directly observed or controlled without the need for transformation or scaling. Together, these two functions serve critical roles within the network model. The advanced logistic sum provides the capability to capture nonlinear dynamics and complex relationships within the respiratory system, while the identity function ensures that certain aspects of the system can be modeled in a direct and unaltered manner. They enable the creation of sophisticated graphs that can be analyzed to better understand the underlying mechanisms of neonatal respiratory support. The ultimate goal is to leverage these insights to develop more effective and personalized interventions for post-birth infant care.

In Appendix (2023) tables with explanations for all states and for the role matrices that are used for the simulation of the scenarios can be found. Here we explain the base world states. The pathway shown in Fig. 1 is followed. The red cross represents what happens from Scenario 3, where the doctor has no knowledge that you have to follow certain instructions after gasping, or he forgets to do this.

The concept of a world state encompasses the environment in which neonatal respiratory support takes place. Understanding the world state is pivotal for the realistic simulation of scenarios that aim to optimize neonatal respiratory support. Within the network model, various states coexist to collectively influence the outcome of respiratory support for a neonate. These states can be categorized as follows see Table 2.

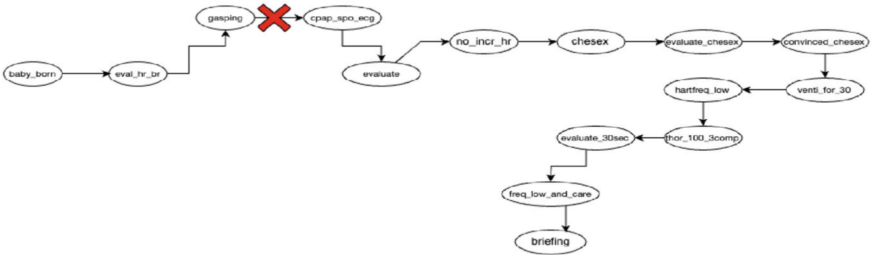

Fig. 1 The base level world states in the network model

- Context States: These states provide information on specific conditions that could influence respiratory support. For example, Context State G Indicates that the baby is gasping in this scenario.
- Evaluation States: These states, like eval_hr_br and evaluate_30sec, are pivotal for ongoing assessment of the baby's physiological parameters.
- Intervention States: These states dictate the medical interventions that should be considered, such as cpap_spo_ecg and infl_spo_ecg.
- Outcome States: These states represent the outcomes of previous actions and evaluations, like true_incr_hr and hartfreq_high.
- eval_hr_br (Evaluate heart rate, breathing, color, and muscle tone): This state is crucial for the initial evaluation post-birth. It encapsulates the assessment of multiple physiological parameters to decide the subsequent course of action.
- infl_spo_ecg (Open airway, give 5 inflation breaths (30 cm H_2O), SpO_2 and ECG monitoring): This state outlines the protocol for cases where initial assessment indicates respiratory distress, thereby requiring inflation breaths and continuous monitoring.
- evaluate_30sec (Evaluate heart rate every 30 s): This state underscores the necessity for frequent re-evaluation to adapt the treatment strategy effectively.

The states are not static but interact dynamically within the network model. For example, if the state hartfreq_low is activated, the network transition to thor_100_3comp for immediate intervention. This dynamic interplay is essential for simulating the real-world complexity of neonatal respiratory care. The granularity and complexity of these states make them ideal candidates for network modeling. By applying advanced functions like $\mathbf{alogistic}_{\sigma,\tau}$ for nonlinear relationships and **id** for direct variables, the model can simulate intricate scenarios that mimic real-life conditions. These simulations, therefore, hold the potential to significantly improve neonatal respiratory support protocols.

In this part, we'll look at the roles of doctors and AI coaches in helping newborns breathe, see Fig. 2. These roles are complex and include everything from the decisions healthcare providers make to the medical guidelines they follow. The idea is to understand how doctors think and act in these situations. For example, if a doctor knows that a baby is having trouble breathing, they would follow a specific treatment plan, known as the CPAP_SPO_ECG procedure. This decision is based on the

Table 2 World states and their explanations

State name	Description
Context State N.	Whether or not there is: no_incr_hr
Context State L.	Whether or not there is: hartfreq_low
Context State G.	Whether or not there is: gasping
Context State I.	Whether or not there is: inadequate
Context State T.	Whether or not there is: true_incr_hr
Context State H.	Whether or not there is: hartfreq_high
baby_born	Birth
eval_hr_br	Evaluate heart rate, breathing (color and muscle tone)
inadequate	Inadequate breathing
gasping	Gasps or apnea
cpap_spo_ecg	Open airway, consider CPAP SpO2 and ECG monitoring
infl_spo_ecg	Open airway, give 5 inflation breaths (30 cm H_2O) SpO2 and ECG Monitoring
evaluate	Evaluate heart rate
no_incr_hr	No increase in heart rate
true_incr_hr	Increase in heart rate
chesex	Check head and mask position. Consider alternate airway strategies. Repeat 5 inflation breaths
evaluate_chesex	Evaluate whether chest excursions had an effect on heart rate
convinced_chesex	Convinced of chest excursions
venti_for_30	Ventilation for 30 s
hartfreq_high	Heart rate is higher than 60/min
hartfreq_low	Heart rate is less than 60/min
thor_100_3comp	Start chest compressions. Increase oxygen percentage to 100%. 3 compressions on 1 breath

(continued)

Table 2 (continued)

State name	Description
evaluate_ 30sec	Evaluate heart rate every 30 s
freq_low_ and_care	If heart rate <60/min: Provide i.v. access and give adrenaline Consider other causes (such as pneumothorax, hypovolemia, congenital abnormalities)
briefing	Inform parents, debrief with team and register

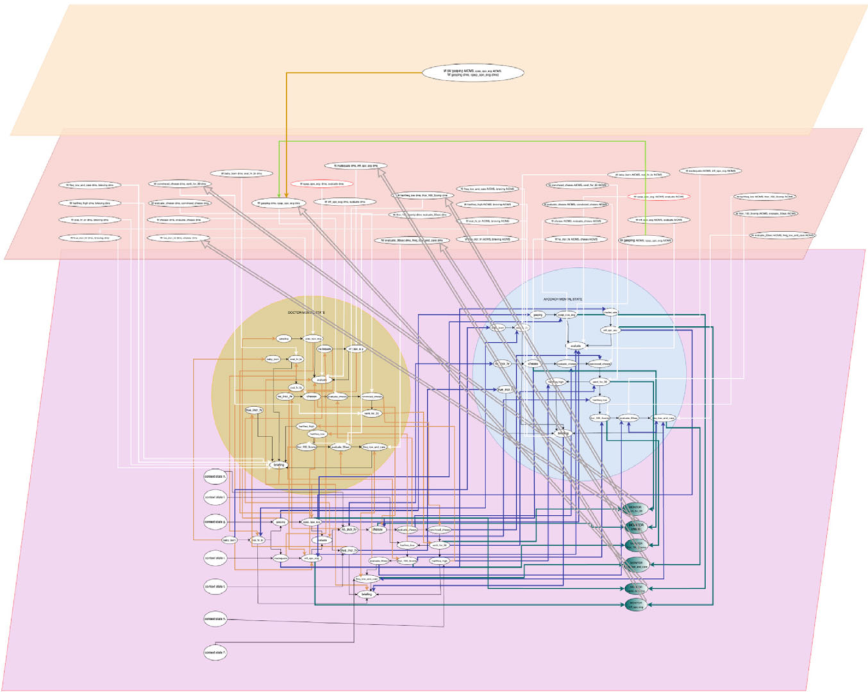

Fig. 2 The introduced overal network model

doctor's existing knowledge and experience. By breaking down the thought processes and actions of healthcare providers in this way, we can get a clearer picture of how decisions are made and treatments are administered in neonatal respiratory care.

So, if the **W**-state of this relation has no value, the doctor would not know that it needs to do CPAP_SPO_ECG after he diagnoses that the baby has gasping. The doctor states encapsulate various functionalities:

- Intervention States: Such as cpap_spo_ecg (doctor MS) and infl_spo_ecg (doctor MS), dictating specific medical actions.

- Assessment States: Focused on continuous evaluations, e.g., evaluate (doctor MS) and evaluate_30sec (doctor MS).
- Outcome States: Representing the results of interventions, like hartfreq_high (doctor MS) and hartfreq_low (doctor MS).

In our model, **W**-states serve as quantitative indicators of the doctor's level of knowledge, confidence, or belief regarding the relationship between other states. For example:

- $\mathbf{W}_{\text{baby\_born dms,eval\_hr\_br dms}}$ represents the doctor's confidence in the necessity of immediate evaluations like heart rate and breathing following birth.
- $\mathbf{W}_{\text{gasping dms, cpap\_spo\_ecg dms}}$ reflects the level of belief the doctor has in initiating CPAP and monitoring when gasping or apnea is detected in a newborn.

These **W**-states are crucial for capturing the cognitive landscape of the medical practitioner, incorporating both objective knowledge and subjective beliefs into the decision-making model. Understanding the Doctor States, especially the cognitive aspects captured by **W**-states, is pivotal for our model aiming to interface effectively with healthcare providers. By modeling these intricate cognitive processes, the AI system can be trained to offer real-time, knowledge-aligned recommendations that can improve neonatal respiratory care outcomes.

The AI coach functions by monitoring various states and **W-**states in real-time, identifying gaps in the practitioner's actions or knowledge, and providing timely interventions to enhance learning and improve patient care. Learning states are specialized **W-**states for the AI Coach that interact with the corresponding **W**-states in the doctor model. They serve as the mechanism through which the AI Coach improves the practitioner's knowledge and decision-making. When the AI Coach detects a gap or a deviation in the doctor's actions, it uses these learning states to adjust the doctor's weight states, thus facilitating learning and improvement.

This goes as follows. The AI coach continuously monitors the doctor's actions. When it identifies a lapse, such as the doctor forgetting to initiate cpap_spo_ecg upon detecting gasping, it triggers the learning **W**-state

$$\mathbf{W}_{\mathbf{W}_{\text{gasping AICMS,cpap\_spo\_ecg AICMS}},\,\mathbf{W}_{\text{gasping dms,cpap\_spo\_ecg dms}}}$$

This second-order self-model state models a communication channel from AI Coach to Doctor that adjusts the corresponding doctor's **W-**state, $\mathbf{W}_{\text{gasping dms,cpap\_spo\_ecg dms}}$, to fill in the knowledge gap. This adjustment informs the doctor of the necessary action, thereby enhancing the doctor's knowledge and improving patient outcomes. In a scenario where a newborn is detected to be gasping, and the doctor fails to initiate cpap_spo_ecg, the AI coach monitors this and intervenes. Through this learning state, the AI coach updates the doctor's corresponding **W-**state, in turn making them aware of the need to initiate CPAP, thereby facilitating immediate and appropriate medical intervention.

The incorporation of an AI coach equipped with learning states into the network model offers several advantages:

- Real-Time Intervention: The AI coach provides immediate feedback, allowing for real-time adjustments in the doctor’s actions.
- Knowledge Enhancement: The learning states serve as a conduit for knowledge transfer from the AI coach to the medical practitioner, ensuring that the doctor is always updated on the best course of action.
- Adaptive Learning: The model can adapt and evolve over time, capturing the nuances of each practitioner’s learning curve and adjusting its coaching strategy accordingly.

By effectively utilizing learning states, the model becomes an invaluable tool for continuous professional development, ensuring that healthcare providers are always at the forefront of medical knowledge and practice, ultimately leading to improved patient outcomes.

Monitor states serve as an integral part of the network model, capturing real-time or near-real-time observations or measurements from the system. In the context of neonatal respiratory support, these states are crucial for continuously assessing various conditions and parameters. They provide the data that informs the weight states, thus influencing the medical practitioner’s decision-making process. The primary role of monitor states is to provide timely and accurate data for various attributes or conditions that are crucial in neonatal care. This data is then used to adjust the **W**-states, which represent the level of confidence or belief a medical practitioner might have in certain protocols or interventions. For example, if the doctor forgets to do the proces that comes with the state cpap_spo_ecg, the monitoring of the AI coach will make sure that the doctors knowledge about this will be updated. Examples of monitoring states are:

- MONITOR cpap_spo_ecg: This monitor state observes the effectiveness of CPAP (Continuous Positive Airway Pressure) along with SpO2 and ECG monitoring. The data collected helps in dynamically adjusting the weight state W gasping dms, cpap_spo_ecg dms, which influences the decision to initiate or continue CPAP.
- MONITOR freq_low_and_care: This state keeps track of the frequency and quality of care provided when the heart rate is below 60/min. The information is then used to adjust the weight at W evaluate_30 sec dms, freq_low_and_care dms, affecting the urgency and type of interventions considered.

Incorporating monitor states allows the AI system to make real-time adjustments based on current observations, making the model more adaptive and robust. These states serve as a bridge between the realworld conditions and the weight states, providing a dynamic feedback loop that enhances the model’s predictive and decision-support capabilities. By understanding and effectively utilizing these monitor states, the model can offer more precise, timely, and context-sensitive recommendations, contributing to improved outcomes in neonatal respiratory care.

4 Findings from Network Model Simulations

This section presents the findings derived from simulations of the network model using Matlab. These simulation results are visualized as graphs, offering valuable insights into the model's effectiveness across various scenarios. The primary aim of this research is to address specific errors commonly made during the respiratory support of neonatal infants. In our Matlab simulations, we concentrated on rectifying a particular error: the omission of the cpap_spo_ecg action by doctors upon recognizing that the baby is gasping.

Importantly, all actions that a doctor can take are structured similarly within the network model. For the sake of simplicity and focus, we chose to zero in on the cpap_spo_ecg process. We posit that if our solution proves effective for this process, it should be generalizable to other processes as well. For all scenarios, see Appendix (2023). Here we focus on Scenario 3. This scenario involves an AI coach that not only detects the error or omission with the help of monitor states but also aids healthcare workers in improving their knowledge.

In this scenario, both the cpap_spo_ecg state and the corresponding **W**-state representing the doctor's knowledge remain deactivated. However, the introduced AI Coach is connected to the doctor's knowledge **W**-state. A specialized higher-order **W**-state denoted as $\mathbf{W}_{\mathbf{W}_{\text{gasping AICMS,cpap\_spo\_ecg AICMS}},\ \mathbf{W}_{\text{gasping dms,cpap\_spo\_ecg dms}}}$ is in place to facilitate the transfer of knowledge from the AI Coach to the doctor when needed. Essentially, if the state values are already optimal (e.g., knowledge value is 1), the AI coach will not intervene, and the monitor state will remain in observational mode without triggering any actions. The inclusion of the specialized higher-order **W**-state provides an opportunity for the doctor to gain knowledge from the AI Coach. As observed in Fig. 3, the doctor's knowledge initially starts at 0 but increases to 0.9 due to the input from the AI coach. The concept underlying the connection between the AI coach's knowledge and the doctor's knowledge is that a single intervention should suffice for knowledge improvement. In other words, if the doctor receives guidance from the AI coach once, that guidance should be sufficient for future situations, thus negating the need for repeated AI interventions for the same action. The monitor state value for cpap_spo_ecg is notably low in Fig. 3, where the doctor's knowledge stands at 0. Interestingly, the monitor state value escalates significantly when the AI coach imparts knowledge to the doctor. This monitor state serves as an error-detection mechanism, intervening only when necessary. As evidenced in Fig. 4, when the doctor's knowledge level is already at 1 and the cpap_spo_ecg procedure has been performed, the monitor state peaks at 0.24. In contrast, in the absence of the doctor's knowledge, the peak is 0.52. In this instance, the monitor state only checks for errors and does not take any further action, as the necessary conditions are already met.

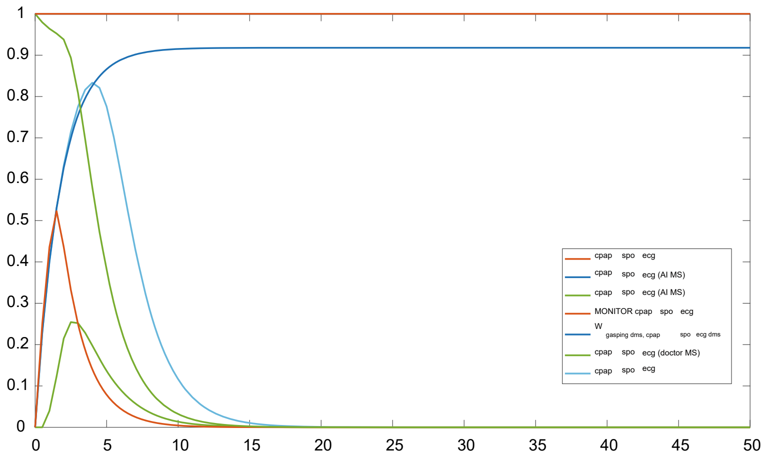

Fig. 3 Scenario 3 focused

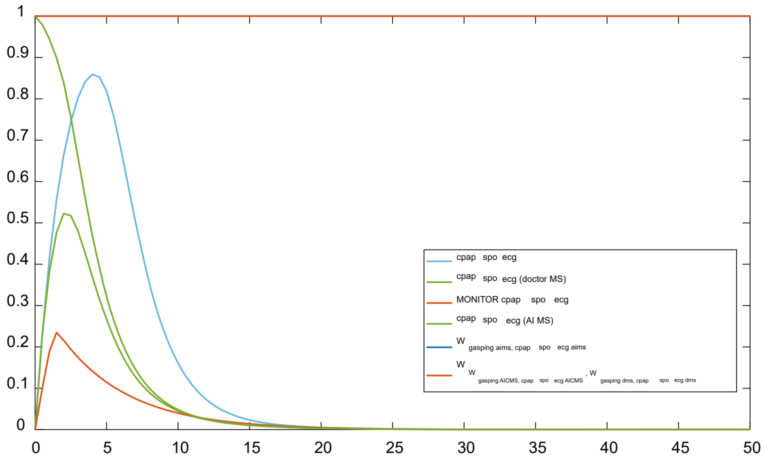

Fig. 4 cpap_spo_ecg knowledge is already adequate

5 Discussion

The primary objective of this chapter was to investigate how network modeling could optimize neonatal respiratory support protocols. The material comes from Sebahi et al. (2024). Utilizing a network-oriented modeling approach as outlined in Treur (2020a, b), various scenarios were created and analyzed within the Matlab environment. The findings from these scenarios contribute significantly to both the fields of neonatal respiratory support and network modeling. The second scenario emphasized the interconnectedness within the model. It revealed that missing links or incomplete knowledge could have far-reaching implications, affecting multiple aspects of neonatal respiratory support. This finding underscores the need for comprehensive and accurate data in models. The third scenario illustrated the potential of incorporating an AI coach into the model. The AI can not only act as a fail-safe tool but also as an educational tool. It provided real-time decision-making support and reinforced the doctor's knowledge base for future scenarios. The AI coach's intervention is a one-time requirement for each specific action or decision, equipping the doctor for future similar situations without additional AI assistance. Monitor states proved effective as safeguards, ensuring optimal performance and error minimization across different scenarios.

These findings provide evidence that an AI coach can be successfully applied to healthcare settings, particularly in the area of neonatal respiratory support. Some limitations concern that scaling up has not been addressed yet, the effectiveness has not yet been validated, and only some scenarios have been explored. Moreover, when dealing with healthcare data, you are primarily dealing with Personal Health Information (PHI), a category of data that is highly sensitive and heavily regulated to protect individuals' privacy. Health data can be a target for cyber attackers. Thus, robust security measures need to be in place to prevent unauthorized access and protect against data breaches. Future Research may address such limitations. For further details, see Appendix (2023).

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