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published in
Fourth International Congress on Information and Communication Technology
2020

DOI (link to publisher)
10.1007/978-981-32-9343-4_18

document version
Publisher's PDF, also known as Version of record

A Temporal-Causal Modelling Approach to Analyse the Dynamics of Burnout and the Effects of Sleep

Hendrik von Kentzinsky, Stefan Wijtsma and Jan Treur

Abstract In this paper, a temporal-causal network model is introduced for a burnout in relation to sleep. The network model approach shows the impact of different lifestyle, personal and job factors on the development of a burnout. This model, for instance, can be used to schedule night shifts in order to preserve the needed recovery of exhaustive, irregular sleeping patterns or to investigate the effects of certain in lifestyles induced triggers on burnout.

Keywords Network model · Burnout · Sleep

1 Introduction

Most workers experience stress sometimes, and when this continues over longer periods of time, people can experience physical consequences of this. Examples include sickness and the feeling of being burn out or emotional exhaustion. In 2017, 15.9% of the Dutch population older than 15 reported burnout-related symptoms [4]. In light of social change and transformations in work situations, interest in this topic has grown. A lot can and is being done to prevent or alleviate burnout syndrome, especially by changing lifestyle or habits. We build on top of existing research by Dujmić et al. [6] by extending their model through adding sleep-related factors. This paper focuses on the optimization of sleep habits as this was found as a protector from burnouts [15].

In contrast to the traditional paradigm for assessing psychological diseases, where these were seen as a latent construct that could be measured by their symptoms, this paper uses a newer paradigm. This newer paradigm defines psychological diseases

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X.-S. Yang et al. (eds.), *Fourth International Congress on Information and Communication Technology*, Advances in Intelligent Systems and Computing 1027, https://doi.org/10.1007/978-981-32-9343-4_18

as the relation or dynamic interplay between symptoms [3]. This fits well to the Network-Oriented Modelling approach described in [23, 24], which is based on temporal-causal network modelling in which networks with dynamic and cyclic causal relations are addressed. This approach can be considered as a branch in the causal modelling area which has a long tradition in AI, e.g. see [11, 12, 18]. This paper aims to help understand the causes, elements, consequences, risk factors and protective factors of burnout syndrome gathered from the literature through network-oriented modelling. The dynamic interaction of these states forms (cyclic) patterns resembling real patterns.

In this study, a non-burnout scenario will be simulated, as well as a burnout scenario and a recovery from burnout scenario. Furthermore, we will show a cyclic pattern with a periodical sleeping pattern. Here, we will make use of a trigger as well (having kids after some point in time) that could potentially disrupt this cyclic pattern.

First, some background literature will be discussed, based on which the network model is constructed, which happens in Sect. 3. Simulations for some example scenarios are shown in Sect. 4, followed by verification of the model by mathematical analysis (Sect. 5) and validation by parameter tuning in Sect. 6. In Sect. 7, the results will be discussed.

2 Background Literature

The classical definition of a burnout, as given by Maslach and Jackson [13], is nowadays still relevant: emotional exhaustion, depersonalization and personal accomplishment are since then still described as the core elements of the burnout syndrome [10]. Maslach created the first measurement instrument for burnouts called the Maslach Burnout Inventory (MBI). She describes various job characteristics that form risk factors for developing a burnout. The most important risk factor is *experienced overload*, a term describing subjective stress. Long exposure to job-related stress can lead to cynicism and emotional exhaustion, in their turn increasing the chance of a burnout. Other risk factors include *job sacrifice*, describing how much someone is willing to sacrifice for achieving his or her ideals, and *role ambiguity*, pointing to the unclarity of what and how much is expected from a worker.

Furthermore, there are job-related factors that either suppress the effects of these risk factors or decrease the core elements of burnout syndrome that are called protective factors. An example of a protective factor is *social contact with co-workers*, which is found to decrease depersonalization and cynicism [5]. Also, *work experience* is an important protective factor, since the more experience someone has, the more sense of personal accomplishment one experiences [13]. Experience also lowers the experience of role ambiguity [5]. This study builds on earlier work [6], where similar job-related factors were used, and also some personal characteristics including *Neuroticism, Openness* and *Hardiness.* This study aims to extend this research by adding sleep-related factors that can either suppress or enforce burnout causes. Neuroticism is a risk factor associated with higher amounts of stress and experienced overload [9]. Openness, on the other hand, is shown to be negatively correlated with depersonalization and emotional exhaustion [7], and positively correlated with physical exercise [22], and therefore, more of a protective factor. The last personal characteristic we included is hardiness, which is found to protect from the effects of stress, but also is linked to the core elements of burnout [2, 8].

By analysing a questionnaire concerning stress at work, health, sleep and lifestyle factors of 676 employees, [21] identifies four factors as significant burnout predictors: work demands, thoughts of work during leisure time, sleep quality and getting too little sleep (less than six hours). The latter was identified as the main risk factor for clinical burnout. Söderström et al. [21] concludes that getting insufficient sleep and having difficulties detaching from thoughts of work during leisure time are stronger predictors of burnout syndrome than stressful work demands, highlighting the importance of recovery from stress—and not that much stress itself—in the process of developing a burnout. As described by Miró et al. [15], sleep quality, next to job-related factors, is a significant predictor of a burnout. Their research showed a higher impact on emotional exhaustion than job demands in our study described as ‘feeling of charged work’. Also, sleep quality interacts with other job-related factors. Furthermore, Rosen et al. [20] showed that not only sleep quality but also sleep quantity has a serious impact on the development of burnout. Analogically, whether a person has uniform working hours plays an important role in merely sleep quantity. Akerstedt and Wright [1] confirmed this and more importantly showed the impact of habitual sleep efficiency, a term to describe the percentage of time in bed that a person is asleep. Pagnin et al. [17] showed that daytime dysfunction is an important predictor for emotional exhaustion and cynicism. A meta-analysis by Pilcher and Huffcutt [19] showed that lack of sleep significantly impairs human functioning during daytime activities. Obviously, earlier named sleep factors have an influence on daytime dysfunction. To complete the sleep-related factors, sleeping pill intake and caffeine intake were added to the model. Sleeping pill intake has a positive effect on daytime dysfunction [25] and may vary depending on the sleep quality and sleep quantity. McGeary et al. [14] also showed a relation between caffeine intake and burnout, while caffeine intake can also reduce daytime dysfunction. These factors can result in a cyclic pattern when affecting other factors.

3 The Designed Network Model

Based on the literature discussed in the previous section, in this section, we describe the temporal-causal network model we used. This model is based on the Network-Oriented Modelling approach described in [23, 24] and was implemented using the software environment described in [16]. Table 1 provides a concise overview of a temporal-causal network model in general. The differential equations in the last row in Table 2 can be used for simulation and mathematical analysis.

Table 1 Representations of a temporal-causal network; adopted from [24]

Concepts	Notation	Explanation
States and connections	$X, Y, X \rightarrow Y$	Describes the nodes and links of a network structure (e.g. in graphical or matrix format)
Connection weight	$\omega_{X,Y}$	*Connection weight* $\boldsymbol{\omega}_{X,Y} \in [-1, 1]$ represents the strength of the impact of state X on state Y through connection $X \rightarrow Y$
Aggregating multiple impacts	$\mathbf{c}_Y(..)$	For each state Y, a *combination function* $\mathbf{c}_Y(..)$ is chosen to combine the causal impacts of other states on state Y
Timing of the causal effect	η_Y	For each state Y, a *speed factor* $\eta_Y \geq 0$ is used to represent how fast a state is changing upon causal impact

Concepts	Numerical representation	Explanation
State values over time t	$Y(t)$	At each time point t, each state Y has a real number value in [0, 1]
Single causal impact	$\mathbf{impact}_{X,Y}(t) = \omega_{X,Y}\, X(t)$	At t, state X with connection to state Y has an impact on Y, using weight $\omega_{X,Y}$
Aggregating multiple impacts	$\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\mathbf{impact}_{X1,Y}(t),\ldots, \mathbf{impact}_{Xk,Y}(t)) = \mathbf{c}_Y(\omega_{X1,Y}X_1(t), \ldots, \omega_{Xk,Y}X_k(t))$	The aggregated impact of multiple states X_i on Y at t is determined using combination function $\mathbf{c}_Y(..)$
Timing of the causal effect	$Y(t + \Delta t) = Y(t) + \eta_Y\, [\mathbf{aggimpact}_Y(t) - Y(t)]\, \Delta t = Y(t) + \eta_Y\, [\mathbf{c}_Y(\omega_{X1,Y}X_1(t), \ldots, \omega_{Xk,Y}X_k(t)) - Y(t)]\, \Delta t$	The impact on Y is exerted over time gradually, using speed factor η_Y

They can also be written in differential equation format:

$$Y(t + \Delta t) = Y(t) + \eta_Y \\ [\mathbf{c}_Y(\omega_{X_1,Y} X_1(t), \ldots, \omega_{X_k,Y} X_k(t)) - Y(t)]\Delta t \tag{1}$$

$$\mathbf{d}Y(t)/\mathbf{d}t = \eta_Y[\mathbf{c}_Y(\omega_{X_1,Y} X_1(t), \ldots, \omega_{X_k,Y} X_k(t)) - Y(t)]$$

Based on the literature—and in particular on the work of [6]—we could identify 29 state variables relevant for a burnout, as shown in Table 2. The table includes the classification of the variables into the risk and protective factors, the elements of the syndrome and the consequent state and also shows the combination functions used and their parameters. Most of the combination functions were chosen as advanced logistic functions:

$$\mathbf{id}(V) = V \tag{2}$$

Table 2 States used in the model with their combination functions and their parameters

State	Abbr.	Description	Type	Function	σ	τ	Speed
X_1	FW	Feeling charged work	Risk factor	Identity			0.1
X_2	EX	Work experience	Protective factor	Advanced logistic			0.1
X_3	HA	Hardiness	Protective factor	Identity			0.1
X_4	JS	Job sacrifice	Consequent	Identity			0.1
X_5	RA	Role ambiguity	Risk factor	Advanced logistic	10	0.5	0.1
X_6	NE	Neuroticism	Risk factor	Identity			0.1
X_7	OP	Openness	Protective factor	Identity			0.1
X_8	EO	Experienced overload	Risk factor	Advanced logistic	10	0.5	0.1
X_9	EE	Emotional exhaustion	Burnout element	Advanced logistic	10	0.5	0.1
X_{10}	PH	Physical health problems	Consequent	Advanced logistic	10	0.5	0.1
X_{11}	JR	Job resignation	Consequent	Identity			0.1
X_{12}	CY	Cynicism/ depersonalization	Burnout element	Advanced logistic	10	0.5	0.1
X_{13}	SC	Social contact with co-workers	Protective factor	Identity			0.1
X_{14}	JD	Job detachment	Consequent	Advanced logistic	10	0.5	0.1
X_{15}	JP	Job performance	Consequent	Advanced logistic	10	0.5	0.1
X_{16}	JA	Job attendance	Consequent	Advanced logistic	10	0.5	0.1
X_{17}	DU	Drug and alcohol use	Protective factor	Advanced logistic	10	0.5	0.1
X_{18}	PA	Personal accomplishment	Burnout element	Advanced logistic	10	0.5	0.1
X_{19}	PE	Physical exercise	Protective factor	Advanced logistic	10	0.5	0.1
X_{20}	SQ	Sleep quality	Protective factor	Advanced logistic	10	0.5	0.1
X_{21}	FJ	Feeling risk of losing job	Risk factor	Advanced logistic	10	0.5	0.1
X_{22}	SY	Sleep quantity	Protective factor	Advanced logistic	10	0.5	0.1
X_{23}	HS	Habitual sleep efficiency	Protective factor	Identity			0.1

(continued)

Table 2 (continued)

State	Abbr.	Description	Type	Function	σ	τ	Speed
X_{24}	DD	Daytime dysfunction	Risk factor	Advanced logistic	10	0.5	0.1
X_{25}	CI	Caffeine intake	Risk factor	Advanced logistic	10	0.5	0.1
X_{26}	PI	Sleeping pill intake	Risk factor	Advanced logistic	20	0.75	0.1
X_{29}	HK	Having kids	Risk factor	Identity			0
X_{30}	SD	Sleep disturbance	Risk factor	Advanced logistic	18	0.2	0.04
X_{31}	UW	Uniform working hours	Protective factor	Advanced logistic	50	0.8	1

$$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k) = \left[\frac{1}{1 + e^{-\sigma}(V_1 + \cdots + V_{k-\tau})} - \frac{1}{(1 + e^{\sigma\tau})}\right](1 + e^{-\sigma\tau})$$

The literature suggests many causal relations between the various states in our model, either positive or negative. We captured these relations in the graphical conceptual representation of the model shown in Fig. 1. The strength of these causal relations is represented by assigned connection weight values, see Table 3.

The green lines represent a high positive effect and the yellow line a slight positive effect. The red, orange and cyan lines show a negative effect, ranging from a high effect (red) to a slight effect (cyan). Note that X_{27} and X_{28} are external factors which will be explained below.

Examples of the difference and differential equations in the model are following:

Examples of a states using the identity (3) and the logistic (4) combination function

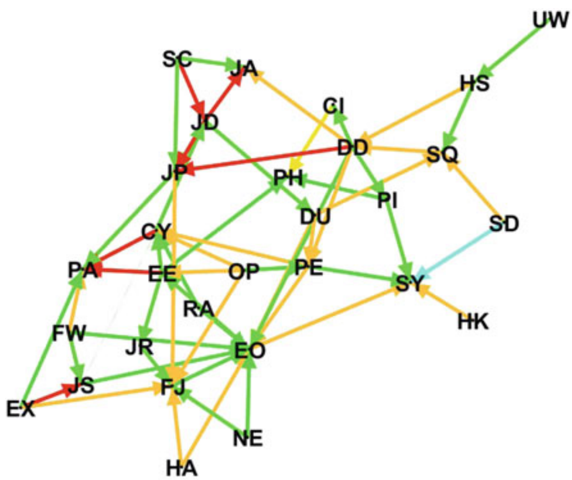

Fig. 1 Graphical conceptual representation of the temporal-causal network model

Table 3 Connection weights

		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X25	X26	X27	X28	X29	X30	X31
		FW	EX	HA	JS	RA	NE	OP	EO	EE	PH	JR	CY	SC	JD	JP	JA	DU	PA	PE	SQ	FJ	SY	HS	DD	CI	PI	ONE	EXT	HK	SD	UW
X1	FW	1			1				0.5										-0.5													
X2	EX		1			-1													0.5			-0.5										
X3	HA			1					-0.5													-0.5										
X4	JS								0.5				0.5																			
X5	RA								0.5				0.5																			
X6	NE						1		0.5													1										
X7	OP							1		-0.5			-0.5							0.5		-0.5										
X8	EO									1													-0.5									
X9	EE										0.5	1	1						-1													
X10	PH																															
X11	JR																					1										
X12	CY														1				-1													
X13	SC													1	-1	1	1															
X14	JD															-1	-1	1														
X15	JP																		1			-0.5										
X16	JA																															
X17	DU								-0.5											-0.5	-0.5											
X18	PA																															
X19	PE								-0.5				-0.5							1			0.5									
X20	SQ																								-0.5							
X21	FJ								0.5																							
X22	SY																				1				-0.5							
X23	HS																				0.5		0.5									
X24	DD								1							-1	-0.5			-0.5						1	1					
X25	CI										0.2																					
X26	PI										0.5												1									
X27	ONE					1																			1			1				
X28	EXT																												1	1		
X29	HK																						-0.5									
X30	SD																				-0.5		-0.2								1	
X31	UW																							1								1

$$\mathrm{JS}(t + \Delta t) = \mathrm{JS}(t) + \eta_{\mathrm{JS}}[\omega_{\mathrm{FW,JS}}\mathrm{FW}(t) - \mathrm{JS}(t)]\Delta t \tag{3}$$

$$\frac{\mathrm{dJS}(t)}{\mathrm{d}t} = \eta_{\mathrm{JS}}[\omega_{\mathrm{FW,JS}}\mathrm{FW}(t) - \mathrm{JS}(t)]$$

$$\begin{aligned} \mathrm{JD}(t + \Delta t) &= \mathrm{JD}(t) \\ &\quad + \eta_{\mathrm{JD}}[\mathbf{alogistic}_{\sigma,\tau}(\omega_{\mathrm{CY,JD}}\mathrm{CY}(t), \omega_{\mathrm{SC,JD}}\mathrm{SC}(t)) - \mathrm{JD}(t)]\,\Delta t \\ \frac{\mathrm{dJD}(t)}{\mathrm{d}t} &= \eta_{\mathrm{JD}}[\mathbf{alogistic}_{\sigma,\tau}(\omega_{\mathrm{CY,JD}}\mathrm{CY}(t), \omega_{\mathrm{SC,JD}}\mathrm{SC}(t)) - \mathrm{JD}(t)] \end{aligned} \tag{4}$$

4 Simulations for Three Example Scenarios

To validate our model against typical burnout patterns described in the literature, we created three example scenarios and simulated them using the dedicated software environment described in [16]. First, Scenario 1 in which no burnout occurs, and next Scenario 2 in which burnout does occur. For Scenario 1, we expected a stable situation, where a person has high enough protective factors and low enough risk factors, such that the burnout elements diminish and all states will move into equilibrium. For the burnout Scenario 2, we expected that high-risk factors would overwhelm low protective factors, such that the burnout elements and its consequences would increase over time. Suitable initial values were assigned as shown in Table 4. For instance, a situation where a burnout occurs is probably accompanied with a low amount of sleep and a high daytime dysfunction in contrast to a no burnout scenario. In addition, we added Scenario 3 of 'recovery', namely where a person would experience some burnout elements, but then recovers and state values of burnout

Table 4 Initial values for the three different scenarios

State	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}	X_{20}	X_{21}
Abbr.	FW	EX	HA	JS	RA	NE	OP	EO	EE	PH	JR	CY	SC	JD	JP	JA	DU	PA	PE	SQ	FJ
Scen. 1	0.1	0.8	0.9	0.2	0.15	0.23	0.75	0.1	0.1	0.2	0	0.1	0.9	0.1	0.85	0.99	0.1	0.85	0.8	0.85	0.2
Scen. 2	0.85	0.2	0.2	0.9	0.7	1	0.2	0.3	0.3	0	0	0.2	0.2	0.1	0.75	0.95	0.3	0.8	0.7	0.2	0.8
Scen. 3	0.1	0.8	0.9	0.9	0.95	0.23	0.75	0.99	0.98	0.99	0.98	0.99	0.9	0.95	0	0	0.99	0	0.99	0	0.99

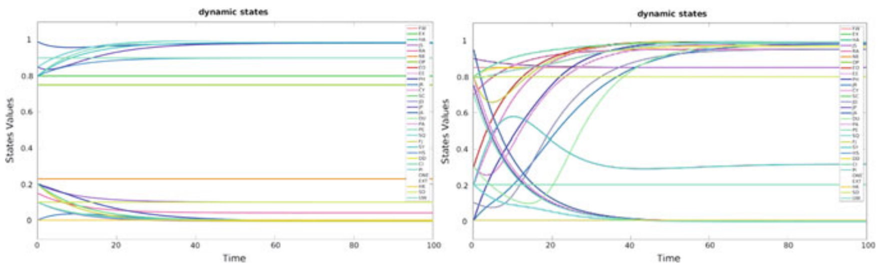

Fig. 2 Simulation of Scenario 1 (left, no burnout) and 2 (right, burnout)

elements would slowly fade away. To model this scenario, we created a mix of high- and low-risk factors—as also shown in Table 4.

In Scenario 1, there is not one sudden change in state values to be observed, as the protective factors continue to increase (if not constant), while the opposite holds true for the risk factors. Thus, the burnout elements drop even further until an equilibrium situation is reached. Scenario 2 displays a situation where a person gradually develops a burnout. Low protective factors like work experience, openness and social contact with co-workers are not enough to diminish the high-risk factors like daytime dysfunction, neuroticism and with feeling charged work. Thus, experienced overload increases and consequently with it the burnout elements emotional exhaustion and cynicism, while the third burnout element personal accomplishment is decreasing to zero. Consequently, job resignation and physical health problems both increase. Sleep quantity increases first, as the high daytime dysfunction is leading to an increase in sleeping pill intake, until daytime dysfunction and high experienced overload peak, causing the sleep quantity to settle on a lower level.

Scenario 3 shows a person who is starting to experience a burnout, but then it fades away due to high enough protective factors. Burnout elements and its consequences, like job detachment, are all high in the beginning, while sleep quality is low. In addition, protective factors like working experience and hardiness are high, while some risk factors like sleep deprivation and with feeling charged work are low. The combination of low-risk factors and high protective factors is enough for the burnout symptoms to lower over time, until a stable no burnout scenario is reached (Figs. 2 and 3).

5 Verification of the Model by Mathematical Analysis

For verification, we analysed the stationary points and equilibria occurring in the model. A *stationary point* of a state Y at time t occurs when $\mathrm{d}Y(t)/\mathrm{d}t = 0$. The network model is in *equilibrium* at t when all states have a stationary point at t. As described in Sect. 3 Eq. (1) in a temporal-causal network model, the differential equation for all states is $\mathrm{d}Y(t)/\mathrm{d}t = \eta_Y\ [\mathbf{aggimpact}_Y(t) - Y(t)]$. As all speed factors η_Y in the model

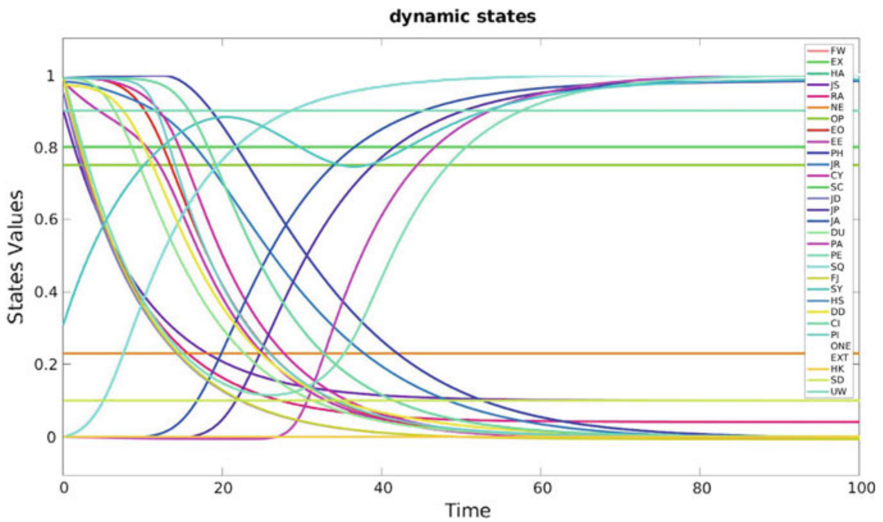

Fig. 3 Simulation of Scenario 3: recovery from burnout

are nonzero, all stationary points must follow the criterion $\mathbf{aggimpact}_Y(t) = Y(t)$, also formulated as: in a temporal-causal network model, there is a stationary point for state Y at t if and only if $\eta_Y = 0$ or $\mathbf{c}_Y(\omega_{X1,Y}X_1(t), \ldots, \omega_{Xk,Y}X_k(t)) = Y(t)$. Using this criterion, first we looked at the burnout Scenario 1 from above and identified a stationary point for emotional exhaustion at $t = 3.3$. The aggregated impact, other states have on emotional exhaustion, is modelled with an advanced logistic function with steepness $\sigma = 10$ and threshold $\tau = 0.5$. Openness and experienced overload are the two states affecting emotional exhaustion with connection weights of -0.5 and 1, respectively. The values for emotional exhaustion at time $t = 3.3$ for the stationary point and at time $t = 100$ for the equilibrium are 0.25301 and 0.98177, respectively. In addition, the values for experienced overload are 0.49759 resp. 0.99997, while openness has a constant value of 0.2. We used the values for openness and experienced overload to compute the aggregated impact they have on emotional exhaustion, as shown in Table 6. We did this also with the stationary points and equilibria occurring for sleep quantity and drug use. The state values and aggregated impacts show little differences, which add to confidence that the model does what is expected (Table 5).

Table 5 Outcomes of the verification

State	EE	EE	SY	SY	DU	DU
Time point t	3.3	100	10.2	100	14.1	100
$X(t)$	0.25301	0.98177	0.57697	0.31436	0.09493	0.98863
aggimpact(t)	0.25927	0.98189	0.57364	0.31491	0.0997	0.98915
aggimpact(t) – $X(t)$	0.00626	0.00012	– 0.00333	0.00055	0.00477	0.00052

6 Validation of the Model by Parameter Tuning

For further validation of the model, we used simulated annealing based on acquired data for parameter tuning. For this, we evaluated the prevailing literature regarding the relation of daytime dysfunction and quality and quantity of sleep (e.g. [1, 15, 17, 20, 21]), as well as the use of caffeine and sleeping pills to overcome daytime dysfunction (e.g. [14, 15]). Through these scientifically based relations, we were able to create expected patterns of how those factors would interact. Based on that, we could create data points meeting those expected patterns, as shown in Table 6.

Over time, we expected a sequential pattern, where high daytime dysfunction would increase sleeping pill intake, leading to a subsequent rise in sleeping quantity. A rise in sleeping quantity in turn starts to have an effect on sleep quality and daytime dysfunction. With a lowered daytime dysfunction, the sleeping pill intake decreases, until sleep quantity decreases again and the causal chain begins all over again. We started to create this pattern for a person with high daytime dysfunction. For a high daytime dysfunction (0.92), we could expect an equally low sleep quality (0.07). For a sleep-deprived person, we expected a higher resistance using sleeping pills in comparison with caffeine intake thus the higher value for caffeine than for sleeping pill intake. The combination of high daytime dysfunction (0.92) and relatively high sleeping pill intake (0.74) should result in a medium sleep quantity (0.44). With a decreasing daytime dysfunction and recovering sleep quality, we expected the sleeping pill intake to decrease faster than the caffeine intake (e.g. time 10–20). Likewise, as daytime dysfunction increases again, sleeping pills should show a higher increase used over time, as they are more addictive than caffeine (e.g. time 40–50). With the generated data obtained from interpolating our expected values, we could compare these to our model. Indeed, parameter tuning gave a higher steepness as well as a higher threshold for sleeping pill intake. The root mean square error (RMS) for the five selected factors is 0.028758, which is relatively low. Perhaps, this may be because our estimation of empirical values was partly biased by what we knew already about typical model patterns. With our tuned model, we validated our model against expected patterns based on personality and lifestyle factors. At first, our aim is to model a high demanding job situation, including a low value

Table 6 Expected pattern of sleeping factors

Time	Sleep quality	Sleep quantity	Daytime dysfunction	Caffeine intake	Sleeping pill intake
0	0.07	0.44	0.92	0.88	0.74
10	0.41	0.75	0.73	0.93	0.79
20	0.55	0.5	0.43	0.67	0.31
30	0.24	0.19	0.67	0.63	0.14
40	0.09	0.13	0.86	0.83	0.48
50	0.09	0.49	0.92	0.93	0.78

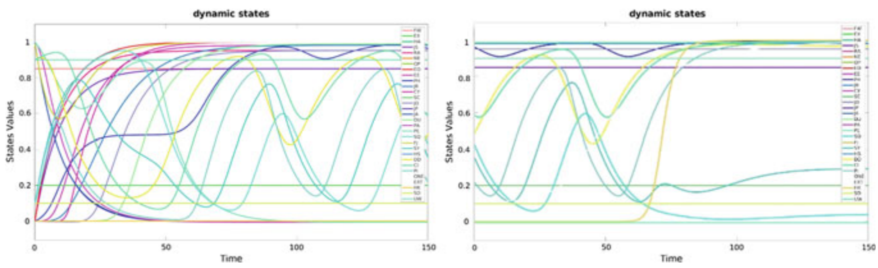

Fig. 4 Burnout Scenario 1 with periodic sleeping pattern (left) and having kids after some point in time lower the sleep quantity, thus breaking the cyclic pattern (right)

of personal accomplishment and high values of cynicism and emotional exhaustion. Low protective factors and high-risk factors lead to a scenario where a burnout occurs. In addition, through the high experienced overload and low physical exercise, the sleeping quantity decreases. This turns into a rise in daytime dysfunction, which is causing a higher intake of sleeping pills. In turn, the sleep quantity rises, until daytime dysfunction lowers and consequently the intake of sleeping pills. Thus, it causes daytime dysfunction to rise again and the pattern repeats itself. Simultaneously, personal health problems fluctuate with the sleeping pill intake (Fig. 4).

After the model settles down to its equilibria, we introduce an external state variable with impact on having kids at around $t = 210$ (150 + 60), which in turn can negatively affect the amount of sleep. We implemented this via introducing the external factor EXT, which has an impact on having kids HK. This external factor EXT was modelled using a connection to itself and with an advanced logistic sum combination function with $\sigma = 18$, $\tau = 0.2$ and speed 0.04; the state HK has $\sigma = 50$, $\tau = 0.8$ and speed 1. Thus, the external factor EXT builds up very slowly and has very little impact on having kids HK, until the threshold is reached (at birth) and the state value of having kids HK changes quite abruptly. In this scenario, it is enough that even an increased sleeping pill intake can no longer match the negative effects on sleeping quantity, which results in increase of daytime dysfunction. This in turn causes sleep quantity and quality to fall to low equilibrium values.

7 Discussion

In this study, we introduced a temporal-causal network model for a burnout in relation to sleep. The Network-Oriented Modelling approach described in [23, 24] was used, and for implementation the dedicated software environment is described in [16]. The modelling approach showed the impact of different lifestyle, personal and job factors on the development of a burnout. This model can be the basis for different types of simulations. For instance, an agent-based model can be used to schedule night shifts in order to preserve the needed recovery. Also, our model can be used to simulate the effects of certain changes in lifestyle on the development of burnout, especially when even more states are added to resemble the real-world complexity.

For validity, it was critical to implement both risk and protective factors. To analyse computationally their roles in development and recovery, we designed different scenarios, such as the one of a burnout and a non-burnout, and a scenario where a burnout occurs and a periodic pattern between sleep-related factors arises. It showed that a small increase in sleep disturbance in an already demanding situation can cause a non-recoverable downwards movement. Unfortunately, there was no numerical empirical data available to test these patterns in more detail. For example, it is unclear to extract from the literature how strong and fast certain variables relate. Consequently, this gives room for improvement on our model regarding how the relations of the variables vary in type, speed and weight.

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