

# An Agent Based Model of Effects of Sleep Deprivation on Suicidality

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**Abstract.** The use of computational models to understand psychological phenomena, including suicidal behavior and outcomes, has become more common. Here we extend a formal computational model of suicide with social and state-dependent dynamics enabled by ABM architecture to evaluate their effects on suicidal thought and aversive internal state. The proposed model implements the General Escape Theory of Suicide [34], combined with aspects of the Interpersonal Theory of Suicide [33], particularly burdensomeness and connectedness. It is based on a system of differential equations proposed by Wang et al. [34] and extended by Engels [11]. The prevalence of suicidal thoughts and aversive internal states was compared in three conditions: a baseline model, a model that included sleep deprivation, and a model that included both state-dependent and social dynamics. We found that sleep deprivation significantly increased both outcomes, while the addition of social dynamics reduced them and increased resistance to suicidal thought. These dynamics qualitatively align with contemporary suicide research showing the protective effects of sleep and socializing. The results demonstrate the utility of ABMs in representing the interactions of internal, social, and state-dependent processes. The model may support simulation of group-level interventions, although future work is needed for quantitative validation and refinement.

**Keywords:** Agent Based Model · Suicide · General Escape Theory · Sleep

## 1 Introduction

Suicide is a major cause of death worldwide. Although global deaths from suicide have decreased over the past several decades, the rate remains high [30,26]. However, the rate of suicide attempts is much higher, ranging from 30 [31] to more than 900 [28] per death by suicide in the United States, with many attempts

not recorded. Despite decades of research, there was no significant improvement in suicide prediction as assessed in 2014 [12]. Since then, smart-technology and wearables have allowed progress in the implementation of interventions and early identification of factors associated with suicidality [1]. However, due to the complex nature of suicidal ideation and suicide attempts, it remains difficult to determine exactly which factors are indicative of them. There are many potential paths to suicide and they vary between individuals.

Studies of complex systems increasingly involve computational modeling. The strength of the approach is that it allows for analysis of nonlinear relationships and their outcomes. There is an increasing body of work that shows that suicidal ideation and attempts can fluctuate greatly during small time frames [9,20], and be dependent on many factors [4,3], both of which are identifiers of parameters in a complex system. The field of computational psychology has begun to utilize computational models to analyze suicide as a complex system. Agent Based Models (ABMs) are known to be useful in modeling dynamic social environments with autonomous agents that have their own state-dependent interactions and exhibit varying behaviors. Despite that, the use of ABMs in suicide research remains limited. This paper attempts to answer the following research questions. 1) How does a combination of state-dependent and social effects within an ABM alter the dynamics of suicidality compared to a baseline mathematical model? 2) How do the effects of sleep alter the dynamics of suicidality within an ABM compared to a baseline mathematical model?

### 1.1 Related Work

The model proposed in this study is largely based on a formal theory of suicide proposed by Wang et al. [34], and extended by Engels [11]. Wang et al. proposed a mathematical model based on the General Escape Theory proposed by Millner et al., which is still in preparation. This theory, in turn, is based on Baumeister's Escape Theory [2], which frames suicidal outcomes as the result of wanting to escape an aversive internal state formed by stress, discomfort, and failure, among others. The mathematical model [34] is made up of 7 differential equations that represent the evolution of stress, aversive internal state, urge to escape, suicidal thought, escape behavior, and external and internal strategies to reduce harm. The model serves as a good foundation for simulation based on the General Escape Theory.

Engels [11] extended the model [34] with social interactions. Many other theories of suicide, such as the Interpersonal Theory of suicide (IPT) by Van Orden et al. [33] and the Integrated Motivational-Volitional model (IMV) by O'Connor and Kirtley [25], consider social effects such as burdensomeness and thwarted belongingness to be significant. Engels' key additions were a social burden parameter, a connectedness parameter, and a clustering coefficient. The relationships between parameters are maintained largely. With the model proposed in this article, we advance the extended model [34,11] by adding key features of suicidality such as memory [5,18] and time-dependent interactions.

## 2 Model

The agents' update rules are largely based on the formal theory of suicide [34] and Engels' extension [11], which was modified and extended based on expert opinion and literature. The ABM was developed in Python using the Mesa library [16], a standard choice for the development of ABMs. The Python libraries NumPy [15], Matplotlib [17] and Pandas [32] were used for efficient computation, plotting, and data handling, respectively. The code for the model is available at [the author's github repository](#). The following subsections will motivate the design of the model.

### 2.1 Agent States

The model includes a daily routine for all agents. A high-level overview of the routine is shown in figure 1.

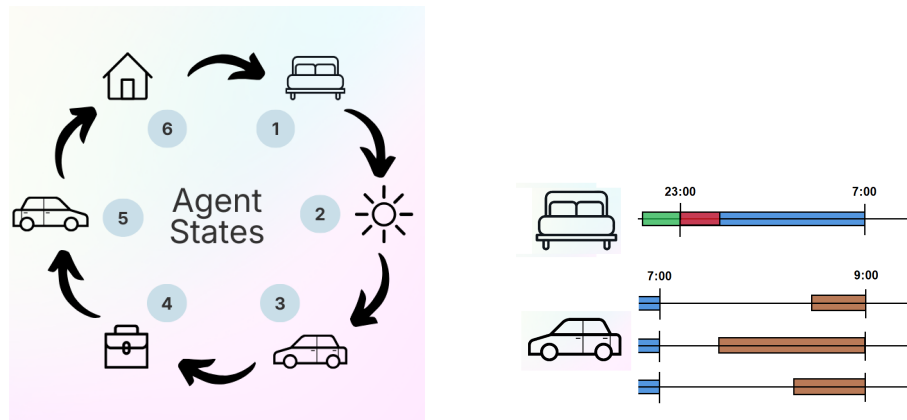


Fig. 1: Graphical representations of states and state-dependent effects in the ABM. Left: The daily schedule of an agent in the ABM. The agent sleeps (1), wakes up (2), commutes (3), works (4), commutes back (5), and is at home (6), before going to sleep again. Right: A sleep duration of less than 8 hours negatively affects stress and suicidal thought. Commutes are distributed so that short commutes are more likely, but long commutes are possible.

**1) Sleep:** Disrupted or inconsistent sleep is believed to be detrimental to a variety of physiological processes, including mental health. Correlations have specifically been found between disrupted sleep and suicidal ideation [27]. Later sleep timing and greater variability in sleep duration are generally associated with worse health outcomes [7]. The assumption is made that sleep always ends at 7:00 in the morning and that a healthy sleep duration is 8 hours. A sleep

deficit is defined as the number of hours slept less than 8. Sleep longer than 8 hours has no explicit negative effect.

**2) Morning:** After sleeping, the effects of potentially poor sleep are applied to the update equations of stress and suicidal thought during the "morning" state. The duration of this state depends on the length of the agent's commute; it ends such that it is 9:00, the start of work, after commuting.

**3) Commute:** Commuting is known to be a stressful event, and stress during commutes depends on various factors, including duration of commute [29]. The duration of the commute is drawn from a lognormal distribution with a mean and standard deviation specific to each agent type.

**4) Work:** In the "work" state, the effect of the urge to escape on other parameters increases. The workday starts at 9:00 in the morning and its duration is standardized to 8 hours for all agents.

**5) Home:** According to expert opinion, suicidal ideation is more likely to originate and sustain at home [35,21]. Escape behavior becomes easier to engage in when the daily work schedule is completed. The duration of the home state equals the amount of time between the commute back from work and the start of the sleep state.

## 2.2 Social network

Engels [11] modeled the social connections between agents according to a Newman-Watts-Strogatz small world graph [24]. In such a graph, the edges between nodes are initialized in a circle formation, after which the nodes are connected according to the mean degree of connectivity, with a probability of reassignment of edges. This effectively models a closed social network. For small numbers of nodes, such networks may be sufficiently realistic. According to Dunbar et al. [10], the average size of an individual's social network is 150 people, among which there are delimitations in closeness to the individual. One such delimitation is classified as "best friends", which consist of roughly 15 people who are either best friends or closer to the individual. A best friends network will form the basis of the analysis performed in the current project. All agents are connected to all other agents, with weights ranging between 0.99 and 1.

## 2.3 Parameters

A high-level overview of all parameters, coefficients, and agent states is shown in figure 2. In this figure, self-feedback relationships are omitted. All model parameters described in this section are functions of time. For all main parameters denoted with capital letters, the time dependency is omitted in writing for clarity, e.g.  $S(t) \rightarrow S$ . For visualization of a parameter's trajectory, refer to figure 3.

**Stress.** Within the field of psychology, stressors are understood to be systemic or chronic, as well as acute, with the existing literature advocating the consideration

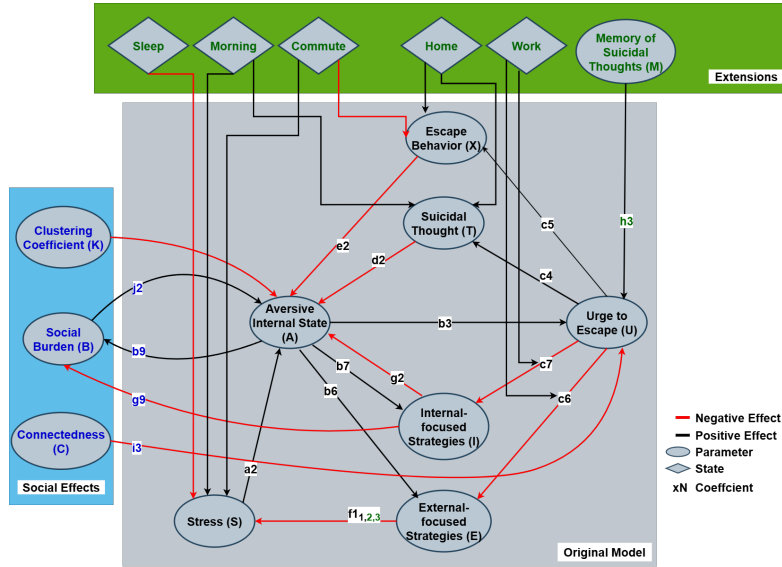


Fig. 2: Model schematic showing the relationships between parameters and states. The original model [34] is shown on the gray background. Engels’ contributions [11] are shown on the blue background. New model extensions made by this paper are shown on the green background.

of both types in psychological research [14,22]. Empirical data show a high spike in cortisol levels at wake-up and a series of work-related cortisol spikes. The wake-up spike is believed to occur in preparation for stressful events later in the day [13,6].

Informed by these observations, stress is modeled as a series of spikes of uniform size, the occurrence of which is dictated by a Poisson process. A noise term is added to model minor short-term fluctuations. This allows for a baseline stress level, *i.e.*, chronic stress, with spikes that decay to the baseline at a specified rate, *i.e.*, acute stress. Stress is affected by the external strategy parameter, as was the case in model [34]. This yields the stress equation

$$S(t + dt) = L_S + e^{-\lambda_S dt}(S - L_S) + \sum P \cdot (1 - f_{1,1}E) + dW\sigma \quad (1)$$

$$L_S = L_S(0) - f_{1,2}E \quad (2)$$

$$\lambda_S = \lambda_S(0) + f_{1,3}E,$$

where  $L_S$  is the baseline stress value,  $\lambda_S$  is the decay rate of the cortisol spikes,  $P$  is an impulse that occurs at time  $t$ , and  $dW$  is a stochastic noise term  $\sim \mathcal{N}(0, \sqrt{dt})$ , which is multiplied by  $\sigma$  to control the strength of the stochastic fluctuations.  $E$  is the external strategy parameter at time  $t$ ,  $f_{1,1}$  the strength of its effect on the size of impulses,  $f_{1,2}$  the strength of its effect on the baseline stress and  $f_{1,3}$  the strength of its effect on the decay rate.

Impulses come from 2 different sources: morning impulses  $P_m$ , and day impulses  $P_d(t)$ . From the morning commute to the next sleep state, impulses  $P_d$  are determined with a Poisson process, such that the time between spikes is distributed exponentially with a given event rate  $r$

$$P_d(t) = \alpha_P N, \quad (3)$$

with  $\alpha_P$  = strength of impulse,  $N(t) \sim \text{Poisson}(rdt)$ . When commuting, the baseline stress increases by 0.2.

The morning impulse  $P_m$  is a single impulse after awakening at 7:00, its size being dependent on the length of sleep. The assumption is made that the increase in cortisol in the morning in anticipation of stressful situations is correlated with poor sleep, as there is evidence that poor sleep correlates with high stress [19]. The equation for the size of the spike is

$$P_m = \alpha_P \left( 1 + \exp \left( \frac{\text{deficit}}{\text{healthy sleep}} \right) \right). \quad (4)$$

**Urge to Escape & Past Suicidal Thought.** As in model [34], urge to escape is modeled as a linear combination of itself and the aversive internal state. However, this model does not account for past suicidal ideation as a factor in escape behavior, even though there is evidence that it has an effect [5,18]. To model the effect that past suicidal behavior has on escape behavior past suicidal thought is added as a factor. This is modeled in the form of a memory component that increases with suicidal thought, and can decay more slowly than suicidal thought itself:

$$M = \begin{cases} T, & \text{if } T \geq M \\ M + dt(-h_8 M), & \text{otherwise.} \end{cases} \quad (5)$$

Adding this to Engels' update equation for urge to escape with an added effect of social connectivity [11] yields

$$U(t + dt) = U + dt * (-c_3 U + b_3 A + h_3 M - i_3 C), \quad (6)$$

with Engels' additions to the model [11] highlighted in blue, and the new memory term highlighted in green.

**Suicidal Thought.** The update equation for suicidal thought follows [34]:

$$T(t + dt) = T + dt \left( -d_4 T + \frac{1}{1 + \exp(-c_{4,1}(U - c_{4,2}))} \right), \quad (7)$$

where  $c_{4,1}$  controls the steepness of the sigmoid and  $c_{4,2}$  controls the threshold. The equation includes a sigmoid function to allow for a steep increase in value when a certain threshold is reached.  $c_{4,2}$  is reduced proportional to the lack of sleep in the morning state to make agents more susceptible to suicidal thought after poor sleep:  $c_{4,2} = c_{4,2} - 0.1 \cdot \text{deficit}/\text{healthy sleep}$ .  $d_4$  is reduced by 0.1 in the home state, so suicidal thought decays less quickly. This reflects susceptibility to suicidal thoughts at home.

**Escape Behavior.** Escape behaviors other than suicidal thought, such as alcohol use and non-suicidal self-injury, are generalized as "escape behavior" in [34]. Escape behavior is modeled the same as suicidal thought, but with a lower threshold for the sigmoid function:

$$X(t + dt) = X + dt \left( -e_5 X + \frac{1}{1 + \exp(-c_{5,1}(U - c_{5,2}))} \right), \quad (8)$$

where the constants have the same meaning as in equation 7, but  $c_{5,2}$  has a lower value than  $c_{4,2}$ .

**External & Internal Strategies.** External strategies are aimed at reducing stressors, whereas internal strategies are directly aimed at reducing aversive internal state. The update equations for external and internal strategies are adapted directly from [34]:

$$E(t + dt) = E + dt(f_6 E(K_E - E) + b_6 A - c_6 U) \quad (9)$$

$$I(t + dt) = I + dt(g_7 I(K_I - I) + b_7 A - c_7 U). \quad (10)$$

The term  $\alpha_E E(K_E - E)$  models logistic growth: the strategies are naturally capped by  $K$  unless motivated by aversive internal state or discouraged by urge to escape. At work,  $c_6$  and  $c_7$  increase to reflect a stronger effect of existing urge to escape when spending a long time in a closed-off office space.

**Social Burden.** The social burden parameter is directly adapted from Engels, who describes its purpose as "captur[ing] anxiety contagion present in social networks" [11]. The parameter is governed by a weighted sum of the aversive internal states of an agent's connections, internal strategy to reduce social burden, and a feedback term:

$$B(t + dt) = \begin{cases} B + dt(-j_9 B_i - g_9 I + b_9 \sum_{n=1}^N w_n A_n), & \text{if } N_i > 0 \\ B + dt(P_{lonely}), & \text{if } N_i = 0. \end{cases} \quad (11)$$

**Aversive Internal State.** Wang et al. [34] conceptualized aversive internal state as a linear combination of suicidal thought, escape behavior, internal strategies, and stress, with an additional logistic growth term representing an individual's natural propensity towards an aversive internal state. Engels [11] added the social burden term and an effect of the agent's clustering coefficient within its social network. This yields the following update equation:

$$A(t + dt) = A + dt(b_2 A(K_A - A) + a_2 S - d_2 T - e_2 X - g_2 I + j_2 B - \kappa), \quad (12)$$

where  $K_A$  is the carrying capacity (maximum) of the logistic growth term, and  $\kappa$  the weighted clustering coefficient of the agent.

### 3 Methods and experimental design

For all simulations, the simulated time was 40 days in the model with no data collected for the first 20 days, which served as a warm-up period, unless specified. This warm-up period was chosen on the basis of visual inspection of the model dynamics to identify when they settled. The baseline coefficient values were chosen so that suicidal thought emerged as spikes a couple times in the defined time period, partially influenced by values suggested in section 8.1 of Engels [11]. Unless specified, these coefficient values were kept constant for all simulations, subject to potential modifications from state-dependent dynamics. The model was initially run with three different parameter settings: one with only the parameters as proposed in model [34], one where memory of suicide was introduced, and one in which all proposed extensions were included. The parameter values were tracked for each setting for high-level analysis of system dynamics.

An experiment was set up to evaluate whether the added effect of sleep deprivation on stress and suicidal thought has a significant impact on the emergence of aversive internal state and suicidal thought within the model. To compare the effect with a baseline, social effects and memory of suicidal thought were removed for this experiment, so that the only included modifications to the original model [34] were state-dependent effects.

Two types of agents were defined, the only difference being that one always sleeps 8 hours (good sleep agent), and the other always sleeps 6 hours (bad sleep agent). The commute duration was made the same for both types of agents. With that, the only differences in model output between agents would be due to the effects of sleep deprivation and stochasticity in the stress term. The stress term was kept heterogeneous due to the significant effect of sleep deprivation on stress [13].

The model was run 1000 times with one agent of each type, the output variable being the Area Under the Curve  $AUC(X) = \int_2^{20} X dt$  of the suicidal thought parameter  $T$  and of the aversive internal state  $A$ . Means tests were performed to assess the significance of difference. The means of both agent types were then compared to the means of a baseline agent with no state-dependent effects, *i.e.* one with update rules as described in [34]. The type of means test chosen depended on the distribution of the data: a two-sample t-test was performed if its assumption of normality was satisfied, and a Mann-Whitney test was performed if not.

### 4 Results

Figure 3 shows the dynamics of a randomly chosen agent in a best friends social network subject to social burden and state-dependent effects, *i.e.* the dynamics of the extended model, as well as the dynamics of a baseline agent with no social influences and no state-dependent effects, *i.e.* an agent with dynamics approximately as described in [34]. Figure 4 provides a comparison between the

dynamics of the baseline agent and the dynamics of an agent with an added parameter that represents memory of suicidal thought.

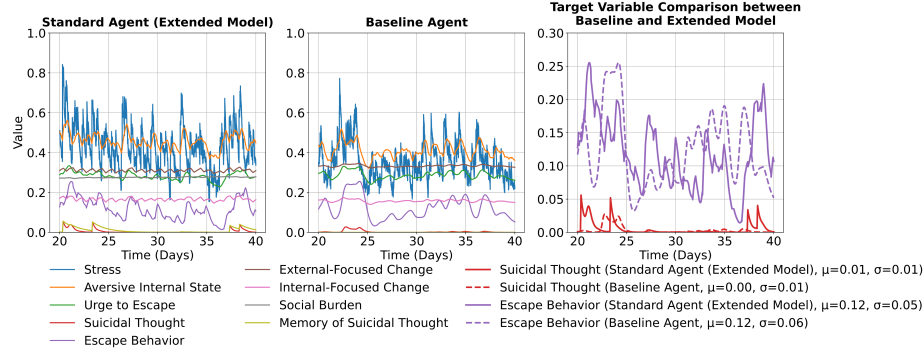


Fig. 3: Comparison of system dynamics for a random agent from the extended model (left) and an agent from the baseline model (middle). The rightmost plot shows a comparison between the suicidal thought and escape behavior parameters of each agent over time.

Figure 5 shows the dynamics of a random simulation of both the good sleep agent and the bad sleep agent, as described in section 3.

Figure 6 shows the distributions of the AUC of suicidal thought and aversive internal state for each agent type over 1000 simulations. The mean AUC of the aversive internal state of the good sleep agent  $\mu_A^{\text{good}}$  is 8.55.  $\mu_T^{\text{good}}$  is 0.16.  $\mu_A^{\text{bad}}$  is 8.98 and  $\mu_T^{\text{bad}}$  is 1.05.  $\mu_A^{\text{base}}$  is 8.22 and  $\mu_T^{\text{base}}$  is 0.09.

Two-sample t-tests and Mann-Whitney tests were performed to compare  $\mu_A$  and  $\mu_T$  between the good sleep, bad sleep, and baseline groups. All tests yielded p-values much lower than  $\alpha = 0.05$  (in the order of  $10^{-100}$ ), demonstrating highly significant differences between the means of the three groups.

## 5 Discussion

**System Dynamics.** In figure 3, the most notable differences between baseline dynamics and extended system dynamics seem to be related to escape behavior and suicidal thought. In the plot representing the baseline agent, the trajectory of escape behavior is smoother and never reaches 0. Despite that, there are only a couple of minor increases in suicidal thought. One could argue that never-ending escape behavior is unlikely, even in people with suicidal tendencies. In the extended model’s dynamics, escape behavior fluctuates at a smaller amplitude but a higher frequency. Increases in suicidal thought are also higher. These dynamics most likely arise from the daily schedule the agent experiences, which causes fluctuations in parameter values by design. The short-term fluctuation of

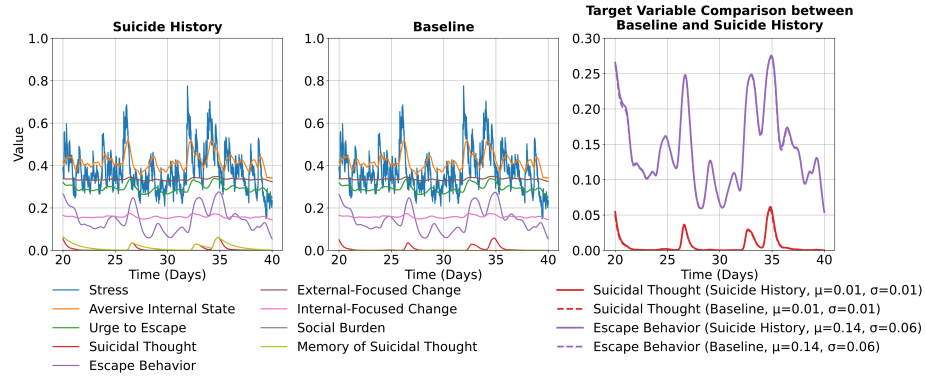


Fig. 4: Comparison of system dynamics for an agent with the memory of suicidal thought parameter added (left) and an agent from the baseline model (middle). The rightmost plot shows a comparison between the suicidal thought and escape behavior parameters of each agent.

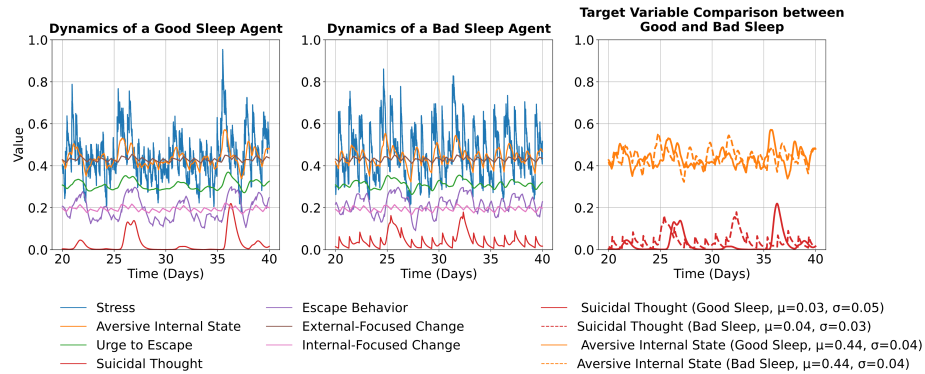
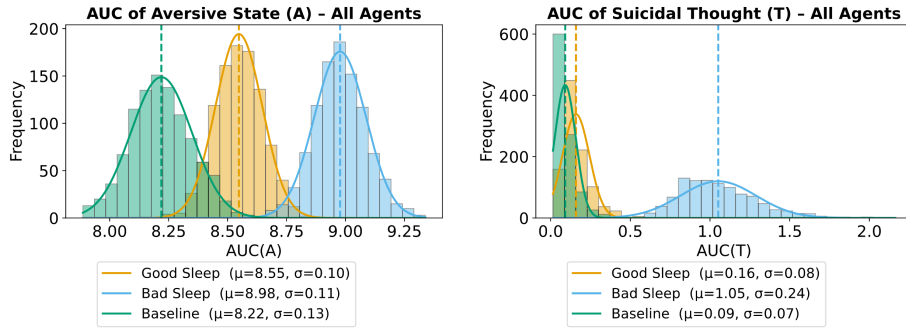


Fig. 5: Comparison of system dynamics for a good sleep agent (left) and a bad sleep agent (middle). The rightmost plot shows a comparison between the suicidal thought and aversive internal state variables of each agent.



(a) All agents'  $AUC(A)$  value distributions (b) All agents'  $AUC(T)$  value distributions

Fig. 6: Distribution of AUC values for aversive internal state A and suicidal thought T over 1000 simulations across three agent types: sufficient sleep, sleep deprived, and a baseline agent with dynamics as described in [34]. The mean is shown as a dashed line, and a fitted normal distribution is shown as a solid line.

escape behavior and the sudden onset of suicidal thought resemble the dynamics of suicidal thought in real life more closely [9,20].

Social burden is consistent throughout the simulation of the extension agent. The agent is connected in a best friends network, meaning social connections are strong, and agents are well-connected. This may explain a lack of suicidal thought despite social burden: connectivity reduces aversive internal state and urge to escape.

In figure 4, no meaningful differences can be observed between the agent with the memory of suicide parameter added and the baseline agent, apart from the presence of that parameter. The reason for this lack of effect is most likely due to the relatively low amounts of suicidal thought exhibited in the performed simulations, as well as the parameter tuning; it only slightly extends the duration of suicidal thought's effect on urge to escape. Decreasing the parameter's decay so that it persists longer could allow it to exercise its influence on the system in a more pronounced way. More research will have to be performed to justify such changes.

**Sleep Deprivation.** By visually inspecting the baseline dynamics in figure 3 and the dynamics of both agents in figure 5, one can already deduce that both  $\mu_T$  and  $\mu_A$  differ between all agent types. The good sleep agent has slightly more suicidal thoughts than both the baseline agent and the agent with all extensions applied, as shown in figure 3. This is in line with the observation made in section 5 and in Engels [11] that a certain range of social burden is indicative of a healthy amount of social connections to other agents, which reduces suicidality.

The simulated values of  $AUC(A)$  are roughly normally distributed for all agents, as shown with the overlaid normal distributions in figure 6. The distri-

butions satisfy the assumption of normality of the t-test. The  $AUC(T)$  distributions of the good sleep agent and the baseline agent are skewed, which is a boundary effect due to the low occurrence of suicidal thought during the simulated period. As such, the non-parametric Mann-Whitney test was employed to means-test the  $AUC(T)$  distributions. The results of the means tests support the intuition obtained in figure 6: the AUC means are significantly different between all agent types. Thus, the conclusion can be drawn that consistently shorter sleep, *i.e.* chronic sleep deprivation, increases aversive internal state and suicidal thought prevalence in the model. The significant difference in both aversive internal state and suicidal thought between an agent who sleeps 8 hours a day and one who sleeps 6 hours a day qualitatively agrees with research findings on the relationship between poor sleep quality and mental health [7,27].

**Future Research** Due to the inherent complexity of suicidality, there are many avenues for future research and improvement of the model. The model has been validated qualitatively, but should still be validated quantitatively. Although many of the parameters are based on subjective metrics, such as social burden, the dynamics can be directly compared to data obtained from ecological momentary assessment studies.

The parameter update rules can be expanded to make the model more specific. Stress, for example, is known to be caused by a wide variety of events, with some having a greater impact than others [8]. Instead of the intensity of the stressors being dependent only on the local context, stressor impulses could be expanded with different types that lose intensity based on prior encounters.

Another area of improvement is agent interaction. Currently, agents have very minimal social interactions in the form of a constantly active social burden. Agents could be made to have social interactions at work dependent on their job or on cohesion within their team. The influence of social media is of great relevance as well, so any extension involving online social networks would be insightful.

Finally, the state-dependent effects could be refined and expanded. For example, social burden persists during sleep, which does not make much sense intuitively. Agents go to work every day, thus not accounting for weekends, the inclusion of which could change long-term dynamics and statistics. Work breaks could be introduced to mitigate the negative effects of being at work within the model. In future work, such additions can be introduced based on data obtained from smartphones [23] containing information about movement, location, and phone-based social interactions.

## 6 Conclusion

We demonstrate the utility of the ABM architecture to model interacting internal, social, and state-dependent processes in suicidality. The inclusion of social effects altered model dynamics by increasing resistance to suicidal thought through social connectivity, while sleep deprivation significantly increased both

aversive internal state and suicidality compared to baseline conditions. These findings are consistent with existing literature, supporting the conclusion that such dynamics can be represented in an abstract yet meaningful way within ABMs.

The proposed model produces dynamics that are closely aligned with contemporary suicide research, including short-term fluctuations in escape behavior and the onset of suicidal thought. Its contribution to computational psychology lies in integrating internal agent dynamics with social and state-dependent effects within a unified framework. With further validation and refinement, the model could support the simulation of group-level interventions and inform policy by identifying societal factors that mediate suicidality.

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