Fight or Flight: A temporal-causal analysis of the behavior of a bully-victim

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Fight or Flight: A temporal-causal analysis of the behavior of a bully-victim

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Abstract. This paper presents a temporal-causal network model of a (cyber) bullying victim. Temporal-causal modeling is a tool for examining complex processes by modeling internal states of an agent to examine internal processes. Bullying is a social-cognitive process, that involves mental processes which may put victims at risk for short or long-term physical and psychosocial problems. The temporal causal model for bully-victim is simulated in accordance to react the bully by fight or fly strategy. Subsequently, parameter tuning and mathematical analysis techniques were applied to the simulations to verify and optimize them with respect to patterns derived from empirical literature.

Keywords: temporal-causal modeling, bullying, cyberbullying, peer victimization.

1 Introduction

Bullying is recognized by an unwanted behavior among school adolescents or as a form of peer victimization that involves the targeted intimidation and humiliation of peers [1]. Bullying usually occurs in situations with an observed or perceived power imbalance and may occur repeatedly and in different settings [2]. Incidences of peer victimization can take the form of verbal attacks, or indirect or relational harassment [3]. Cyberbullying shares main characteristics of traditional bullying, but perceived anonymity of online interactions make it more hazardous for mental health, as the obvious consequences are unseen . This gives a feeling of increased tendency for power imbalance, and helplessness on the part of the victim.

Bullying may affect victims across a variety of domains. Bullying has been associated with poor physical and mental health [4]. Negative outcomes may last short-term or swipe in an adulthood, displaying a multitude of adjustment problems. These may include depressed mood and anxiety [5], psychosomatic problems [6]. This is also termed as social pain, which is more painful than physical one, emphasizing the long-term harm. Reported reactions to bullying include depression, fear, sadness, anxiety, suicidal ideation, remorse, worry, stress, embarrassment, and loneliness [7]. Experiences of peer victimization become embedded in the physiology of the developing person, placing him or her at risk for life-long mental and physical health problems [6].

Research has emphasized the prevalence and consequences of bullying [1]. Research concerning bullying has primarily been conducted through questionnaires in medium- to large-sized cohorts, although the usefulness of computer science applications has been explored previously [8]. However, the impact of a bully over a person is not studied with the perspective of network oriented modeling. In this paper we aim to address two things: It explains a) how brain of bully victim works if bullied. Moreover, it entails b) possible reactions of a victim with the help of various factors and internal processes, which drive decision-making and responses to bullying behavior.

The following paper is divided into the following sections. Section 2, describes the related work with respect to neuroscience and computational modeling. Section 3 shows a temporal-causal model developed for a victims perspective. Section 4 presents the simulation scenarios, while Section 5 shows mathematical analysis, and paper is concluded by Section 6.

2 Related Work

Various estimates have been made of the prevalence of bullying. A meta-analysis of 80 studies carried out in 2014 estimated that around 36% are involved in traditional bullying, while around 15% report being victimized in cyberbullying [9]. Much of neuroscience (fMRI) research focused on the victims of bullying and social exclusion [10].
Research concerning victims of peer aggression is often carried out through endocrinology tests with salivary hormone samples [11]. The hypothalamic-pituitary-adrenal axis (HPA axis) describes a set of interactions among the hypothalamus, pituitary gland and adrenal glands. Among many other functions, the HPA axis controls cortisol levels, a hormone which plays an important role in stress regulation within organisms. Cortisol levels follow a circadian rhythm, with elevated levels in the morning and declining over the course of the day [12]. These levels are elevated in stressful situations, and abnormally high cortisol levels may alter cortisol receptor sensitivity. Such alterations may cause a state of hyperarousal, or, alternatively, result in hypo secretion [4]. Abnormal cortisol patterns are consistent with those found in post-traumatic stress disorder (PTSD) patients [13]. Bullying victims tend to produce below-average cortisol levels. Notably, this effect has been recorded with respect to stress response elevation [11], as well as across the daily cortisol cycle [4], which could be linked to the aforementioned mixed bag of short- and long-term repercussions bully victims endure.

In situations of increased stress, coping responses serve as a type of self-regulation. Such self-regulation strategies may involve the steering of cognition, behaviour, physiology or the environment. These strategies are explored in the model presented in this paper. A framework that is often applied to stress coping is the Approach-Avoidance response framework [5]. In an approach coping response, the victim targets the stressor, while an avoidance coping response attempts to regulate feeling. In peer victimization settings, avoidance responses were associated with wanting to prevent an escalation of the event and approach responses were associated with wanting to defend oneself.

A wide variety of feelings were associated with peer victimization across various studies. Notably, four categories of feeling were derived from various entries in the literature [5]: fear, anger, sadness and rejection. These feelings were found to be associated with approach and avoidance responses [14]. Adolescents associated feelings of sadness and fear with avoidance responses in open questionnaires. Different individuals coped differently with rejection experiences - both aggressive and repressive responses were recorded [14]. Children with poor emotion regulation skills characteristically display reactive aggression, which resulted with increase in anger and correlated negatively with a feeling of sadness [5]. Children who respond to social exclusion by externalizing blame and seeking revenge report a greater frequency of depressive and anxious symptoms, while those who respond with avoidance responses (cognitive restructuring, minimization, ignoring) achieve more positive outcomes [14].

Looking into the temporal causal networks, quite research can be found on PTSD [15], this research indicate that how an event can cause this kind of disorder. There is a research which identifies how bully behaves in a temporal causal domain [16]. However, no research has focused on the factors which can help in order to react over bullying behavior [14].

3 The Temporal-Causal Network Model

This section describes conceptual and numerical representations of the temporal-causal network model designed to study the behavior of a bully-victim. The conceptual representation displays the states of the model along with its connections, which define a causal relationships between the states (Fig. 1). An arrow between two states represents a causal relationship between them [17]. For a given state, the change in its value at time-point *t* will be propagated through the connections due to its causal effect, affecting another state at time-point t + Δt. Arrowheads are labeled by '+' or '-' indicate positive progression or suppression for the following state. Bidirectional arrows indicate the causal impact of state on each other. Equation (1) shows the relationship between a future state $Y(t + \Delta t)$, which is computed by taking a previous state value $Y(t)$ and adding to it the influence of the states affecting it [17]:

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

where $X_1, \ldots X_k$ are the states with outgoing connections to Y.
$\boldsymbol{\eta}_Y$ = speed factor that modulates the rate of change of state Y's value.
$\mathbf{c}_Y$ = combination function used to aggregate impact of states X_i to Y.
$\boldsymbol{\omega}_{X_i,Y}$ = connection weights affecting the impact of states X_i to Y.
Δt = step size of time for each interaction from states X_i to Y.

The model basically take input from the bully from es_a state, which indicates a bullying event, and a sensor state to sense an approach response of the victim (this could be the 'rise' the bully is looking for) [16]. The state ws_s here indicates the bully-victim getting stimulus by using the social media. Together with world state ws_s, the bully's execution state activates the sensory apparatus ($ss_{s,b}$ and $srs_{s,b}$) of the victim. $srs_{s,b}$ activates all feeling states. The victim may experience feeling of fear (fs_f), sadness (fs_{sd}), rejection from society (fs_r), and feeling of anger (fs_a). A victim can choose between two possibilities, either he can avoid or he can confront for the bullying behavior. If the person feels rejected, sad and fear from bully, the respective states will ps_{avd} and es_{avd} will be activated, he can modify the situation. An example of situation modification can be starting reading a book. Similarly, if a person feels angry, rejected, and sad,

ps_{app} and es_{app} will be triggered. An executive action unit has been linked to the approach response network in order to model the ownership of the decision to undertake an approach action [17], indicated by pos, ros and srs_{pe}. The control state cs_n regulates feelings which arise in the person.

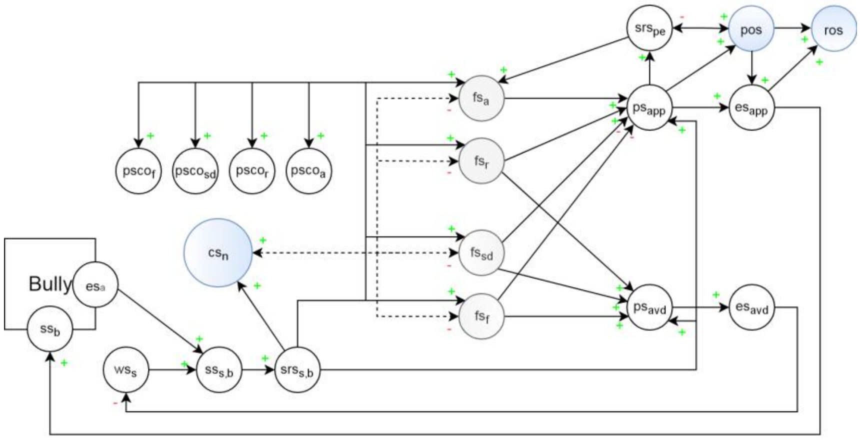

Fig. 1. Conceptual representation of Bully-Victim.

The connections between feelings and the execution states were modeled after the research presented in Section 2; fear (fs_f) and sadness (fs_{sd}) increase the likelihood of avoidance (ps_{avd}), while fs_a increases the approach response (ps_{app}) and rejection (fs_r) boosts both. An executive action unit is linked to the approach response network to model the ownership of the decision to undertake an approach action [17]. Lastly, the approach execution state (es_{app}) activates the sensor state of the bully (ss_b), while the avoidance execution state (es_{avd}) modifies situation to resolve the bullying event (ws_s).

Table 1. Nomenclature of the model.

State	Definition
ws_s	World state for stimulus *s*
ss_x	Sensor state of X; X = bully *b* and X =*s,b* presence of stimuli *s* and *b*
es_a	Execution state of the bully *b*
srs_X	Representation state; X = *s,b* presence *s* and *b* or *pe* = predicted effect
cs_n	Control state for negative feelings
fs_i	Feeling state for i ; i = *f* (fear), *a* (anger), *r* (rejection), *sd* (sadness)
$psco_i$	Preparation state for communication of feeling i = *f*, *a*, *r*, *sd*
ps_k	Preparation state for the k. k = approach or avoidance response
es_k	Execution state for the k. k = approach or avoidance response
pos	Prior ownership state of action
ros	Retrospective ownership state of action

For simulation connection weights, speed factors were assumed to be in range [0,1]. The value of ws_s is 1. Different combination functions were used to determine the aggregated causal impact of the states. For the states ss_b, es_b, ws_s, $srs_{s,b}$, cs_n, es_{avd}, srs_{pe} and es_{app}, the identity function **id(V)** = V was used. The advanced logistic sum function was used for the preparation states for action (ps_{app} and ps_{avd}):

$$\textbf{alogistic}_{\sigma,\tau}(V_1,\ldots,V_k) = [(\frac{1}{1+e^{-\sigma(V_1+\cdots+V_k-\tau)}}) - 1/(1+e^{\sigma\tau})](1+e^{-\sigma\tau})$$

where σ = 18 (steepness of the curve), and
τ = 0.8 (threshold)

$V_1,\ldots, V_k$ are variables for single impacts $\boldsymbol{\omega}_{X,Y}X(t)$ and $\boldsymbol{\omega}_{Xk,Y}X_k(t)$, preceding states that affect the state value currently being computed.

For rest of the states ($ss_{s,b}$, $psco_f$, fs_f, $psco_{sd}$, fs_{sd}, $psco_r$, fs_r, $psco_a$, fs_a, pos, ros), the scaled sum function $\textbf{ssum}_\lambda(V_1, \ldots, V_k) = (V_1+ \ldots + V_k)/\lambda$ was used. Here, λ represents the scaling factor, which is equal to the sum of incoming positive weights for a state. A conceptual representation of a temporal-causal model can be transformed into a numerical representation as follows [17]:

1. Impact of state X on state Y is computed at t as $\textbf{impact}_{X,Y}(t) = \boldsymbol{\omega}_{X,Y}X(t)$ where $\boldsymbol{\omega}_{X,Y}$ is weight of the connection from X to Y, and $X(t)$ is activation value of the previous state (between 0 and 1)
2. Aggregated impact on Y is computed by combination function of Y from the (multiple) states X_1 to X_k with inward connections to Y.

$$\begin{aligned}\textbf{aggimpact}_Y(t) &= \mathbf{c}_Y(\textbf{impact}_{X1,Y}(\boldsymbol{t}),\ldots,\textbf{impact}_{X_k,Y}(\boldsymbol{t}))\\ &= \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(\boldsymbol{t}),\ldots,\boldsymbol{\omega}_{X_k,Y}X_k(\boldsymbol{t}))\end{aligned}$$

where $X_1, \ldots, X_k$ represents the states which have inward connections to Y. $\boldsymbol{\omega}_{x,y}$ represents connection weight between X and Y, and $\mathbf{c}_Y$ represent combination function that is used for state Y.

3. The magnitude of the aggregated impact on Y is controlled by speed factor η_Y to observe the causal effect:

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y[\textbf{aggimpact}_Y(t) - Y(t)]\Delta t \textit{ and}$$
$$\frac{\mathbf{d}Y(t)}{\boldsymbol{dt}} = \boldsymbol{\eta}_Y[\textbf{aggimpact}_Y(t) - Y(t)]$$

Substituting $\textbf{aggimpact}_Y\textbf{(t)}$ yields the following difference and differential equations:

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y\big[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(\boldsymbol{t}),\ldots,\boldsymbol{\omega}_{X_k,Y}X_k(\boldsymbol{t})) - Y(t)\big]\Delta t \text{ and}$$
$$\frac{\mathbf{d}Y(t)}{\boldsymbol{dt}} = \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(\boldsymbol{t}),\ldots,\boldsymbol{\omega}_{X_k,Y}X_k(\boldsymbol{t})) - Y(t)]$$

Using Excel and Matlab software environments, the above steps were automated in order to be able to efficiently test simulations [17]. The numerical representation of the model was also used for mathematical verification of equilibrium state values, which is described in Section 6.

4 Simulation Experiments

Simulation experiments based on this model may offer insight into how its states change over time. To evaluate if the model and simulations are valid, the simulation experiments should be optimized by empirical data. Despite that there is extensive literature to be found about bullying and its implications for the victim, direct numerical empirical data related to victim behavior in the context of this paper is not available, therefore we deduced patterns from cited literature to deduce patterns. Table 2 enlist the patterns derived from literature.

Table 2. Patterns derived from empirical literature

Empirical Literature	Deduced simulation pattern
Stimulus triggers emotion [18]	Stimulus is present from the start: $ws_s \geq 0{,}1$. This activates $ss_{s,b}$ and $srs_{s,b}$
Varying intensity of bullying leads to less emotional reaction [19]	ws_s ranges from 0,1 to 1, and influences feeling states accordingly.
Emotions and feelings that occur consistently and frequently in (cyber)bully victims, correlations from multiple studies to get a more representative list of feelings [5]	From strongest correlation to weakest: (1) Fear (fs_f) (2) Angry (fs_a)) (3) Sad (fs_{sd})) (4) Rejected (fs_r)). The simulations with the feelings with the strongest correlations and prevalence will have higher values for these feelings in comparison with the other feelings.[1]
Emotions expression through different means [20].	The feeling states gradually become active and lead to different outcomes, based on the scenario
Feelings fear, sad, angry, rejected are perceived as negative feelings that are suppressed [5]	Control state cs_n increases as a result of higher feeling values. This suppresses the feeling states and prevents them from rising further.
Different emotions lead to different responses [14]	Preparation states for avoid and approach ps_{avd} and ps_{app} are activated after the feeling state values begin to increase.
Behaviour of a cyberbullying victim: suppressing negative feelings (emotion regulation) [20]	Feeling states either stagnate or decline after action. This depends on the action. Avoid leads to feeling states declining eventually while confronting the bully will let them stagnate due to suppression from the control state even though the bully stimulus remains active.
Predictive and inferential processes [17]	The prior-ownership state is involved in prediction of execution of 'approach' concerning aggressive behavior (feeling of angry in this case). The retrospective ownership state and sensory representation for predicted effect srs_{pe} will increase along with pos.

[1] Note that different studies use different terminologies to describe feelings. For this study, generic categories were used based on Gimènez et al. [16]; empirical data were interpreted to fit in these categories.

Studies that relied on self-reported data from victims and as such were mostly an indicative of subjective perceptions was taken to deduce qualitative expected patterns. These patterns were used as requirements for the model, in accordance with the fundamentals of requirements engineering in order to emulate different real world scenarios [21]. Following are two scenarios addressed along with the parameter tuning. a) First scenario simulates an event where a bullying victim avoids bully, while in the second scenario b) a victim chooses an approach response to the bullying behavior.

4.1 Scenario 1: Choosing the avoidance response

As ws_s and bullying event is there, the sensory state and sensory representation state values ($ss_{s,b}$ and $srs_{s,b}$) increase. Subsequently, feeling states increase, thus fs_f has the highest value, followed by fs_{sd} and then fs_r. The corresponding preparation states for communication of these feelings $psco_f$, $psco_{sd}$ and $psco_r$ increase accordingly. The value of control state cs_n rises alongside the feeling state values, gradually suppressing them. $fs_a = 0$, because it has no association with the avoid action, meaning it is not triggered. As a result, the approach response-related states of pos, ros, srs_{pe} remain at 0. Figure 2 shows the results of the simulation of the avoidance response scenario.

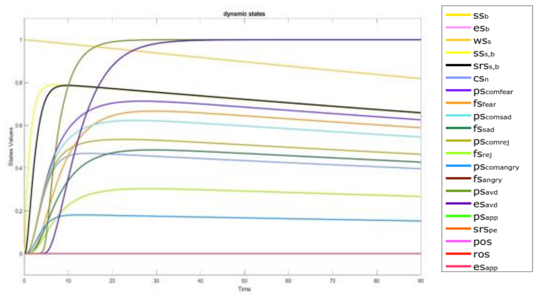

Fig. 2. Victim chooses to avoid the bully, based on Table 1, time point = 0 - 90

Initially, the state values describing the bullying behaviour (ss_b, es_b), visibly decline again when the victim begins to execute the avoid response. This pattern is expected, since avoiding the bully ceases the interaction and stops exposure to the bullying for the moment by decreasing the value of world state ws_s. This can be observed that all states eventually go towards 0 as a result of the avoid action directly decreasing the stimulus, as described in the model. This can be observed in Figure 3.

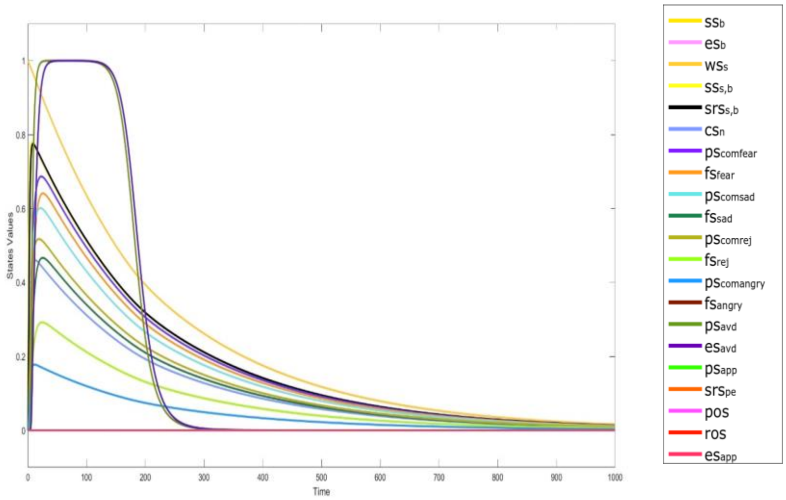

Fig. 3. Victim avoiding bully time point 0 - 1000

4.2 Parameter Tuning

Parameter tuning is a technique used to optimize various model parameters as to make the simulated model correspond as closely as possible with an empirical pattern-driven model. This optimization is performed by minimizing the error function (usually RMSE) by modulating different parameters. In this case, parameter tuning was applied to the speed factor (η) values used in simulations before. To do this, first we provided patterns presented in Table 2 to a subject matter expert as requirements [22], who helped to extract expected patterns for the model. So, the pattern for states in the approaching scenario were used with the states: $ss_{s,b}$, $srs_{s,b}$, fs_r, fs_a, ps_{app} and es_{app}. For each of these states, 10 discrete data points were taken and interpolated through cubic interpolation technique (Fig. 4).

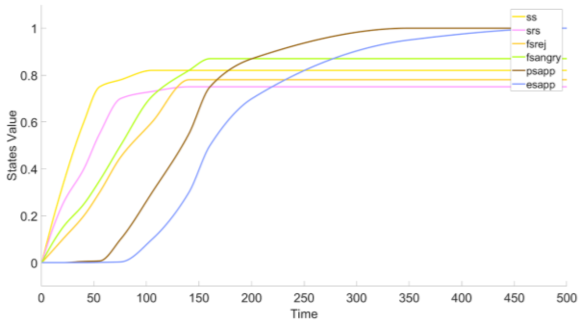

Fig. 4. Patterns for $ss_{s,b}$, $srs_{s,b}$, fs_r, fs_a, ps_{app} and es_{app} after applying cubic interpolation

Secondly, we used Simulated Annealing (SA) optimization for tuning method. Simulated annealing is a technique that attempts to minimize the error function by navigating the model space and finding a minimum on the loss surface (i.e., a set of parameters that minimizes the error between the model and the empirical data). There are many algorithms which are used for optimization of the model [23]. However, Simulated Annealing is considered to be a good choice. A major advantage of SA is that it has increased likelihood of finding a global minima. Figure 5, shows the difference between the initial results of approaching scenario, and the empirical curves.

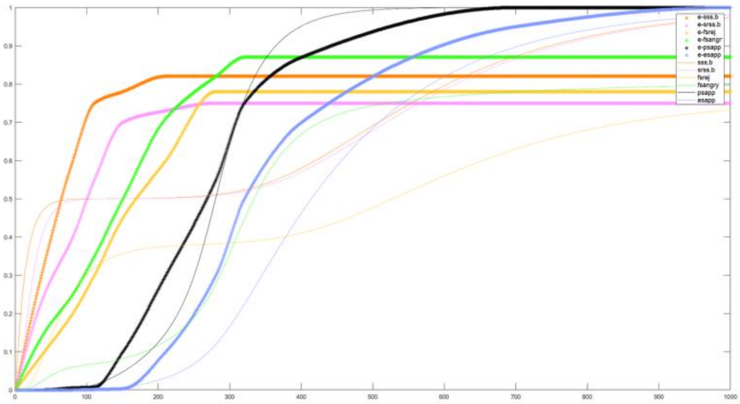

Fig. 5. Plot showing the deviation between empirical values (*) and initial results (-)

Optimization was completed at 2143 iterations, with a linear error root mean square error (RMSE) of 0,162, indicating well-tuned parameter values for the speed factors. This produced the results in Table 2. .

Table 2. Speed factor values obtained after parameter tuning.

State	ss_b	$srs_{s,b}$	fs_r	fs_a	ps_{app}	es_{app}
Speed factor (η)	0,708	0,936	0,981	0,925	0,517	0,056

4.3 Scenario 2: Choosing the approach response

In this scenario the approach action is selected, an example can be replying him in a text message. Therefore, when ws_s and es_a is high, the preparation state ps_{app} and execution state es_{app} are as expected to get high values (Fig. 6). Consequently, the preparation and execution states for the avoidance response are expected to be 0. The feeling states assume values that describe their correlation with the selected action, regulated by cs_n. In this scenario, all feelings including anger fs_a has high values, leading corresponding psco states to get high. The control state cs_n suppresses the negative feelings. fs_f and fs_{sd} are more suppressed, as these feelings may suppress the approach action. We used tuned speed factors(Table 2) to generate this simulation.

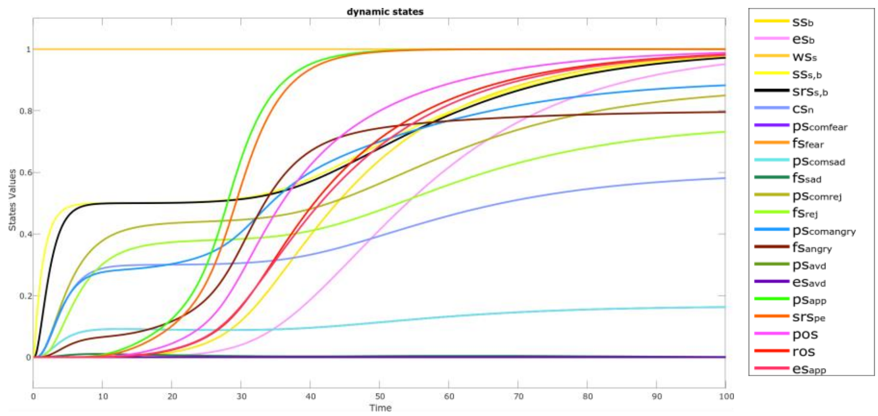

Fig. 6. Victim chooses to approach the bully, based on Table 1.

Unlike in the avoidance response scenario, the states regarding the bully behavior (ss_b, es_b) continue to increase towards their maximum value in this scenario. Since approach leads to more interaction with the bully. This means more exposure to bullying, these values do not decline afterwards, despite the fact that the feeling states are heavily suppressed by cs_n and do not increase.

5 Mathematical Analysis

The model presented can also be verified by mathematical analysis. This can be done by studying the equilibrium property of model. A model is in equilibrium if at a given time-point *t* all states are stationary points (**dY(t)/dt = 0**), expressed as [17]:

$$\mathbf{aggimpact}_Y(t) - Y(t) = 0 \quad \Leftrightarrow \quad Y(t) = \mathbf{c}_Y(\omega_{X_1,Y}X_1(t),, \ldots, \omega_{X_k,Y}X_k(t))$$

Mathematical analysis was performed for the scenario when victim chooses to approach bully. For most states, it can be observed that the model starts to converge towards around time point t = 60. For instance, most values are converged between the time point of 200 and 250. The differences between simulation values and linear equation solutions were computed by WIMS[2] solver showed that deviations did not exceed 0.02. The results are presented in Table 4 and equations mentioned below.

Table 4. State equilibrium values and linear solver values.

State	ss_b	$srs_{s,b}$	cs_n	$psco_f$	fs_f	$psco_{sd}$	fs_{sd}	$psco_r$	fs_r
Time t	208	140	206	203	112	203	112	150	214
Y(t)	0.9999	0.997	0.6	0.1667	0	0.1667	0	0.8786	0.7600
aggimpact$_Y$(t)	1	1	0.6	0.1651	0.0021	0.1651	0.0015	0.8800	0.7600
Deviation	0.0001	0.0033	0	0.0016	0.0021	0.0016	0.0015	0.0014	0

[2] http://wims.unice.fr/wims/wims.cgi

State	$psco_a$	fs_a	ps_{avd}	es_{avd}	ps_{app}	srs_{pe}	pos	ros	es_{app}
Time t	204	121	126	138	74	76	103	136	206
Y(t)	0.8999	0.7987	0	0	1	1	0.9928	0.9976	1
aggimpact$_Y$**(t)**	0.9	0.8	0.00001	0.00001	1	1	1	1	1
Deviation	0.0001	0.0013	0.00001	0.00001	0	0	0.0072	0.0024	0

Eq1. $1{,}87ss_b = 0{,}87ss_b + es_{app}$
Eq2. $ws_s = 1$
Eq3. $es_b = ss_b$
Eq4. $2ss_{s,b} = ws_s + es_b$
Eq5. $srs_{s,b} = ss_{s,b}$
Eq6. $cs_n = 0{,}6srs_{s,b}$
Eq7. $1{,}2psco_f = 0{,}2srs_{s,b} + fs_f$
Eq8. $fs_f = -0{,}3cs_n + psco_f$
Eq9. $1{,}2psco_{sd} = 0{,}2srs_{s,b} + fs_{sd}$
Eq10. $fs_{sd} = -0{,}3cs_n + psco_{sd}$
Eq11. $2psco_r = srs_{s,b} + fs_r$
Eq12. $fs_r = -0{,}2cs_n + psco_r$
Eq13. $2psco_a = srs_{s,b} + fs_a$
Eq14. $2fs_a = -0{,}5cs_n + psco_a + srs_{pe}$
Eq15. $ps_{avd} = 0{,}00001$
Eq16. $es_{avd} = 0{,}3ps_{avd}$
Eq17. $ps_{app} = 1$
Eq18. $srs_{pe} = ps_{app}$
Eq19. $2pos = ps_{app} + es_{app}$
Eq20. $2ros = pos + es_{app}$
Eq21. $es_{app} = ps_{app}$

6 Conclusion and Future Work

In this paper a temporal-causal model for a bully victim was presented. Feelings of fear, anger, sadness and rejection along with their relationship to approach and avoidance of bully were explored.

Neurological literature was studied in order to get the expected patterns of the model. Two scenarios were simulated. The regulation involved the control state, which modulated the negative feelings and the corresponding actions were selected. At the end of simulation, parameter tuning was used to optimize the model, and mathematical verification was done, which showed that model behavior was as expected.

Future research could focus more on the role of the prior ownership state. Despite being implemented in the model and functioning as an inhibitor for the anger feeling state (fs_a) through effect prediction, its function was outside the focus of this research. Additionally, the use of empirical data collected in the real world would improve the validity of the methods used in this paper (simulation and parameter tuning), rather than processing expected patterns to subjectively determine parameter settings. Another direction could be to use this model to identify the victims and to provide support of victims.

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