

An Adaptive Network Model for Procrastination Behaviour Including Self-Regulation and Emotion Regulation

Hildebert Moulie¹, Robin van den Berg¹, Jan Treur²

¹Computational Science, University of Amsterdam, Netherlands

²Social AI Group, Vrije Universiteit Amsterdam

h.moulie@gmail.com rvdb7345@gmail.com j.treur@vu.nl

Abstract In this paper, the goal is to model both the self-control and the emotion regulation dynamics involved in the process of procrastination. This is done by means of a temporal-causal network, incorporating learning and control of the learning. Additionally, the effect of stress regulation-therapy on the process of procrastination was investigated. The model's base level implementation was verified by making sure the aggregated impact matches the node values for certain stationary points and the model's Hebbian learning behaviour was also mathematically shown to be correctly implemented. The results proved this model's ability to model different types of individuals, all with different stress sensitivities. Therapy was also shown to be greatly beneficial.

Keywords procrastination, adaptive, emotion regulation, self-regulation

1 Introduction

Procrastination is defined as the act of delaying or postponing something. The problem has been increasing in size over the years [21]. It was estimated by Steel that approximately 80-95% of college students procrastinate [21]. Furthermore, Harriott and Ferrari [7] found that an estimated 20% of adults are self-proclaimed chronic procrastinators. Apart from the self-destructive consequences of procrastination, [19] also has shown that persistent procrastination can lead to mental and physical health problems such as depression, anxiety and even cardiovascular diseases.

For a long time, procrastination was regarded as a problem of self-control and time management. However, in current academia, there has been a growing amount of research that has focused on the emotional backdrop of procrastination [5]. It is often found that emotional thresholds, such as stress or fear of the result of an action, are what stimulate procrastination.

In this paper, an attempt was made at modelling both the self-control and the emotion-regulation dynamics involved in the process of procrastination. This is done by means of a temporal-causal network, incorporating first- and second-order adaptation for controlled learning. We set out to unveil the dynamics of the system. Additionally, the effect of stress regulation-therapy on the process of procrastination was investigated. As a starting point, research articles within psychology were analysed and used as a basis for the implementation. Subsequently, in the Methodology, we elaborate on the implementation of the model and translate the psychological connections to a computational model. Here, the experiments carried out are also presented. Thereafter, the results from the example scenarios are discussed and the report is finalised with a conclusion and recommendations for further research.

2 Background Knowledge

In order to create a model representing the process of procrastination, it is important to first look at existing literature in order to create a model compliant with past studies. Our findings include the following statements based on published papers and articles.

According to an article by Onwuegbuzie [13], using a regression method, it was found that 25% of academic procrastination was a direct result of self-regulation while 14% were linked to anxiety, depression and self-esteem. Additionally, the importance of self-regulation amongst other self-variables was found to be the highest for predicting procrastination tendencies in another paper [8]. Correlation results indicated that students with intrinsic reasons for pursuing academic tasks procrastinated less than those with less autonomous reasons, this once more confirms the importance of self-regulation [15]. Failure of self-control is often the result of conflicting goals. In this instance, the conflicting actions of instant gratification and pursuit of long-term goals [17, 22]. Additionally, procrastination was found to stem from the anxiety linked to possible failure as was reported by students [14]. Moreover, it was found by Steel that there exist significant relations between procrastination and task aversiveness, task delay, self-efficacy and impulsiveness [21].

However, it is important to note that there is a difference between active and passive procrastination [2-3]. The former is where people postpone doing a task but are able to meet a deadline and are satisfied with the outcome in the end while the latter is where people are unable to perform the task on time. The passive procrastinators are often troubled by their ability to achieve, subsequently provoking feelings of guilt and depression leading to more procrastination and thus to failure of the task [3]. Therefore, passive procrastination can be linked primarily to the emotional regulation.

Procrastination can lead to small boosts in enjoyment, this is why students often check social media when procrastinating [11]. Furthermore, Tice et al. [22] describe that the desire for evasion of emotional distress increases the inclination towards choices that render immediate pleasure. In this paper, we assume that the activities with which one procrastinates induce direct enjoyment. Therefore, we state a two-way relation between procrastination and anxiety/stress [9, 22]. Next to anxiety and stress, guilt and shame can also result from procrastination, both contributing to adverse mental health issues [4].

Furthermore, another method that was found to be very efficient against procrastination is therapy [24]. Therapy is not only great to deal with procrastination, it is also a great method used to fight against stress. Indeed, in this study by Gammon and Morgan-Samuel, it was shown that helping students with a tutorial support made these students end up with significantly less stress than students from a control group that did not benefit from therapy [6, 20]. Next to stress-control therapy, therapy can also be focused on self-compassion since low self-compassion has been found to be one of the linking factors between procrastination and stress [16].

3 The Modeling Approach Used

In this section, the network-oriented modeling approach to causal modeling adopted from [23] is briefly introduced. Following these, a *temporal-causal network model* is characterised by; here X and Y denote nodes (also called states) of the network with network connections for how they causally affect each other:

- *Connectivity characteristics*
Connections from a state X to a state Y and their weights $\omega_{X,Y}$
- *Aggregation characteristics*
For any state Y , some combination function $\mathbf{c}_Y(\cdot)$ defines the aggregation that is applied to the causal impacts $\omega_{X,Y}X(t)$ on Y from its incoming connections from states X
- *Timing characteristics*
Each state Y has a speed factor η_Y defining how fast it changes for given impact. The following difference (or differential) equations that are used for simulation purposes and also for analysis of temporal-causal networks incorporate these network characteristics $\omega_{X,Y}$, $\mathbf{c}_Y(\cdot)$, η_Y in a standard numerical format:

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

for any state Y and where X_1 to X_k are the states from which Y gets its incoming connections. The generic equation (1) is hidden in the dedicated software environment; see [23], Ch 9. Within the software environment described there, around 40 useful basic combination functions are included in a combination function library; see Table 1 for the ones used in this paper. The selected ones for a model are assigned to states Y by specifying combination function weights $\gamma_{i,Y}$ and their parameters used by $\pi_{i,j,Y}$.

Table 1 Basic combination functions from the library used in the presented model

	Notation	Formula	Parameters
Identity	$\mathbf{id}(V)$	V	-
Advanced logistic sum	$\mathbf{alogistic}_{\sigma,\tau}(V_1, \dots, V_k)$	$\left[\frac{1}{1+e^{-\sigma(V_1+\dots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}} \right] (1+e^{-\sigma\tau})$	Steepness $\sigma > 0$ Threshold τ
Hebbian learning	$\mathbf{hebb}_{\mu}(V_1, V_2, W)$	$V_1 V_2 (1 - W) + \mu W$	Persistence factor $\mu > 0$
Scaled sum	$\mathbf{ssum}_{\lambda}(V_1, \dots, V_k)$	$\frac{V_1 + \dots + V_k}{\lambda}$	Scaling factor λ

The above concepts allow for the design of network models and their dynamics in a declarative manner, based on mathematically defined functions and relations. The idea is that the network characteristics that define the design of the network model, are used as input for the dedicated software environment. Within this environment the generic difference equation (1) is executed for all states, thus generating simulation graphs as output. Note that ‘network characteristics’ and ‘network states’ are two distinct concepts for a network. Self-modeling is a way to relate these distinct concepts to each other in an interesting and useful way:

- A *self-model* is making the implicit network characteristics (such as connection weights ω or excitability thresholds τ) explicit by adding states for these characteristics; thus the network gets a self-model of part of the network structure; as self-models can change over time, this can easily be used to obtain an *adaptive network*.
- In this way, multiple self-modeling levels can be created where network characteristics from one level relate to states at a next level. This can cover *second-order* or *higher-order adaptive networks*; see [23], Ch 4.

Adding a self-model for a temporal-causal network is done in the way that additional network states $\mathbf{W}_{X,Y}$, $\mathbf{C}_{i,Y}$, $\mathbf{P}_{i,j,Y}$, \mathbf{H}_Y (*self-model states*) are added as nodes to the network for some of the states Y of the base network and some of their related network structure characteristics for connectivity, aggregation and timing (in particular, some from $\omega_{X,Y}$, $\gamma_{i,Y}$, $\pi_{i,j,Y}$, η_Y):

(a) Connectivity self-model

- Self-model states $\mathbf{W}_{X,Y}$ are added to the network representing connectivity characteristics, in particular connection weights $\omega_{X,Y}$

(b) Aggregation self-model

- Self-model states $\mathbf{C}_{j,Y}$ are added to the network representing aggregation characteristics, in particular combination function weights $\gamma_{i,Y}$
- Self-model states $\mathbf{P}_{i,j,Y}$ are added representing aggregation characteristics, in particular combination function parameters $\pi_{i,j,Y}$

(c) Timing self-model

- Self-model states \mathbf{H}_Y are added to the network representing timing characteristics, in particular speed factors η_Y

The notations $\mathbf{W}_{X,Y}$, $\mathbf{C}_{i,Y}$, $\mathbf{P}_{i,j,Y}$, \mathbf{H}_Y for the self-model states indicate the referencing relation with respect to the characteristics $\omega_{X,Y}$, $\gamma_{i,Y}$, $\pi_{i,j,Y}$, η_Y : here \mathbf{W} refers to ω , \mathbf{C} refers to γ , \mathbf{P} refers to π , and \mathbf{H} refers to η , respectively. For the processing, these self-model states define the dynamics of state Y in a canonical manner according to equations (1) whereby $\omega_{X,Y}$, $\gamma_{i,Y}$, $\pi_{i,j,Y}$, η_Y are replaced by the state values of $\mathbf{W}_{X,Y}$, $\mathbf{C}_{i,Y}$, $\mathbf{P}_{i,j,Y}$, \mathbf{H}_Y at time t , respectively. The dynamics of the self-model states themselves are defined in the standard manner based on the generic difference equation (1) by their incoming connections and other network characteristics (such as combination functions and speed factors) used to fully embed them in the created *self-modeling network*. As the self-modeling network that is the outcome of the addition of a self-model is also a temporal-causal network model itself, as has been shown in detail in [23], Ch 10, this construction can easily be applied iteratively to obtain multiple levels of self-models.

4 The Designed Adaptive Network Model

In order to describe the behaviour and emotional dynamics involved in procrastination, a computational model was developed in the form of a temporal-causal network. To this extent, we utilised a dedicated modeling environment implemented in MATLAB [23], Ch. 9. A graphical representation of the model can be found in Fig. 1 and an overview of the states in Table 2. The model is a multilevel self-modeling network model consisting of three levels. The base level addresses the interactions between the different emotional and behavioural states. Level 1 addresses the first-order adaptivity by a first-order self-model of base level connections, which allows for evolving connection weights within the base level. In addition, level 2 influences the speed by which the states on the first level change (adaptive learning rate). A more detailed description of the different levels can be found in Table 2. The role matrices for the network characteristics defining the model can be found in the Appendix at <https://www.researchgate.net/publication/350108642>.

Table 2 States in the model

Number	State name	Description	Level
X ₁	Task importance	The importance of the task at hand	Base level
X ₂	Stimulus	The stimulus to do work coming from a certain task	
X ₃	Procrastination	The act of procrastinating a task	
X ₄	Self-control	The ability to force oneself to tackle the task at hand	
X ₅	Shame	A task that was supposed to be done	
X ₆	Anxiety/stress	Emotion induced by fear of the result of one's actions	
X ₇	Joy	Procrastination-induced relief	
X ₈	General Happiness	The happiness about life in general	
X ₉	Doing Work	The rate of progress on work	
X ₁₀	Work Done	The amount of work done	
X ₁₁	Stress control state	Control state for the stress/anxiety	
X ₁₂	Therapy	Therapy to increase control over the stress/anxiety	
X ₁₃	$\mathbf{W}_{X_6, X_{11}}$	Self-model state for stress-induced learning representing connection weight $\omega_{X_6, X_{11}}$	First-order self-model
X ₁₄	\mathbf{W}_{X_4, X_9}	Self-model state for learning based on past experiences representing connection weight ω_{X_4, X_9}	
X ₁₅	$\mathbf{HW}_{X_6, X_{11}}$	Self-model state for speed factor (adaptive learning rate) $\eta_{\mathbf{W}_{X_6, X_{11}}}$ of self-model state $\mathbf{W}_{X_6, X_{11}}$	Second-order self-model
X ₁₆	\mathbf{HW}_{X_4, X_9}	Self-model state for speed factor (adaptive learning rate) $\eta_{\mathbf{W}_{X_4, X_9}}$ of self-model state \mathbf{W}_{X_4, X_9}	

The base level was designed using the psychological research described in Section 2. State X₁ represents the importance of the task at hand and X₂ is the stimulus to make progress on that same task. This pressure is associated with the importance of the task and portion of the task that remains. State X₃ is the central node of this network and constitutes procrastination. The activation value of the state denotes the amount of procrastination. Connected to this node, three main feedback loops can be distinguished, i.e., {X₂; X₃; X₆}, {X₃; X₅; X₆; X₇; X₈} and {X₃; X₄; X₁₀}, henceforth named L₁, L₂ and L₃ respectively. Loop L₁ embodies the effects of the stimulus X₂, this stimulus increasing the amount of experienced stress X₆, while also decreasing the amount of procrastination X₃. On its turn, procrastination increases stress and vice versa. Loop L₂

delineates a part of the balance between instant gratification and long term satisfaction. Here, we see a mutual exclusion of anxiety/stress X_6 with general happiness X_8 . Furthermore, procrastination X_3 induces shame X_5 , which subsequently reduces the procrastination-induced joy X_7 . Lastly, loop L_3 contains part of the behavioural system involved in limiting procrastination. It features self-control X_4 limiting the amount of procrastination X_3 as well as the total work done X_{10} , which positively influences the amount of self-control X_4 . The strength of the connection between the latter is determined by past experience X_{14} . Furthermore, we see that procrastination X_3 logically decreases the amount of work done X_{10} .

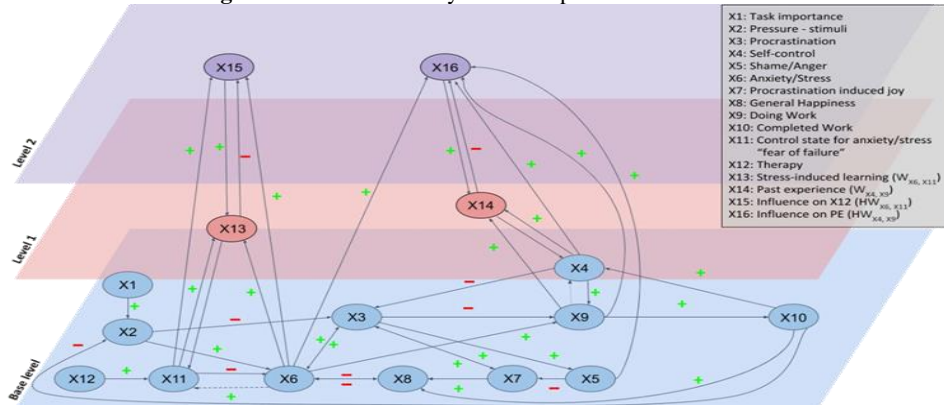
Outside of these three loops, two individual states influence the overall dynamics. Firstly, completed work state X_{10} increases the amount of self-control X_4 based on the perspective that one is often more inclined to continue working on a task after starting it. It also positively feeds back into general happiness X_8 through pride or an obtained reward. Furthermore, a higher completed work X_{10} means that less of the task remains, therefore lowering the stimulus X_2 . Secondly, we have the anxiety/stress control state X_{11} and the therapy state X_{12} . The therapy state X_{12} increases the amount of control one has over anxiety/stress X_6 , while the anxiety/stress control state X_{11} itself allows for lowering the anxiety/stress X_6 (van Eerde & Klingsieck, 2018).

On top of the base level, there is the first-order self-model level for learning. This learning is materialised by therapy-induced learning through **W**-state $\mathbf{W}_{X_6, X_{11}}$, also named X_{13} , representing an adaptive connection weight from anxiety/stress X_6 to the anxiety/stress control state X_{11} . By therapy stimulating the stress-control, a quickened negative feedback loop is expected in the case of heightened stress. Moreover, **W**-state \mathbf{W}_{X_4, X_9} , also called X_{14} , models the learning from past experiences and represents the adaptive connection weight of the connection from work rate X_4 to self-control X_9 . Here, it is assumed that doing work increases self-control over time. Both connections are learned by the Hebbian learning adaptation principle, which describes an often used form of plasticity [23]. The combination function for this can be found in Table 1.

The second-order self-model level controls the learning by influencing the speed factors (learning rate) of the **W**-states in the first-order self-model level. To this end, **H**-state $\mathbf{HW}_{X_6, X_{11}}$, also called X_{15} , represents the speed factor of therapy-induced learning and, therefore, changes how fast the modelled individual can learn from therapy. Similarly, **H**-state \mathbf{HW}_{X_4, X_9} , also called X_{16} , represents the speed factor of X_{14} and thus changes how fast we learn from past experiences. Interesting dynamics are found when looking at X_{16} 's incoming connections. Since emotions change our perception of the work we are doing, connections were added from the negative emotions towards X_{16} . These negative emotions stimulate the rate at which one learns from past work,

resulting from the underlying idea that one would want to avoid such feeling in subsequent work.

Figure 1: The connectivity of the adaptive network model.



5 Experimental setup

The goal of this research is to computationally explore the dynamics of the procrastination by taking into account both the behavioural and the emotional aspects. To this extent, we modeled a variety of situations, three of which will be discussed here (for another one, Experiment 3, see the Appendix at <https://www.researchgate.net/publication/350108642>).

Experiment 1 Stress sensitivity In the primary experiment, three individuals are modeled exhibiting different susceptibilities to stress. Where, for instance, the case of high susceptibility could represent an individual close to a burn-out, while the individual with low susceptibility could model a person with differently placed priorities, therefore not so much influenced by the task at hand. To model this effect, we change the speed with which the stress/anxiety X_6 changes. The used speed factors for η_{x_6} are values from $\{0.05, 0.15, 0.25\}$.

Experiment 2 Stress-control therapy In a second experiment, we examine the effect of stress-control therapy. Here, it was chosen to keep the standard value for the stress speed factor $\eta_{x_6} = 0.15$. Since the value of the therapy state X_{12} remains constant throughout the simulation, the initial value was altered. The initial values for the different simulations of this experiment were chosen from $\{0, 0.1, 0.2\}$.

Experiment 4 The effect of a stress control therapy In Experiment 4, the individuals modelled in the previous experiment were taken as a basis. Using these same setups, therapy was added to varying levels in an attempt to combat stress. For therapy to be added, the initial value needs to be increased from its value of 0 of the baseline values as shown in Table 10 in the Appendix. Here the goal was to obtain a peak stress level as close as possible between the three individuals to examine the additional behaviour. To do so, the values 0.15 (anxious), 0.1 (average), and 0.02 (confident) were used.

6 Results of the Simulation Experiments

In this section the results of the main simulation experiments are discussed.

Base scenario To look into the results of the experiments, a baseline simulation first was established. To do so, the values specified in Tables 5, 6, 7, 8, 9 and 10 of the Appendix were used. The results of this simulation can be observed in Fig. 2 top row. Inspecting this, it is clear that there are positive correlations between the procrastination and the stress, a relation that was previously demonstrated by empirical research [19-20]. Furthermore, the model shows positive correlations between shame and procrastination as well as shame and stress, which reflects the results found in [16]. Moreover, these graph show a negative correlation between procrastination and general happiness as well as between stress and general happiness, which is also supported by literature [20]. Following the base situation, the effect of stress sensitivity was evaluated as well as the results from a stress control therapy. Subsequently, three different types of individuals were modeled on which the effect of therapy was tested.

Stress sensitivity experiment In order to test the stress sensitivity, the speed factor of the stress/anxiety state X_6 was altered. It was first lowered to 0.05 from 0.15 used in the base scenario, thus yielding the simulation shown in the middle row of Fig. 2. Here, lowering the sensitivity to stress results in a much slower stress increase than in the base scenario. For a stress speed factor of 0.15, the stress peak is reached at $t = 40.3$ with a stress value of 0.7944 while with a stress speed factor of 0.05, the stress peak is reached at $t = 61.61$ with a much lower value of 0.6701. This change is to be expected and it also affects other nodes as a result. Procrastination, and in turn also shame, since they are very closely related, sees its evolution being much slower. Indeed, the peak is reached at $t = 37.86$ with a value of 0.2826 when a stress speed factor of 0.15 is used while it is reached at $t = 54.27$ with a value of 0.2112 with a stress speed factor of 0.05. This more stable procrastination over time could be the result of the stress being less intense and therefore causing less abrupt psychological changes. Finally, the speed factor adaptation of therapy state X_{15} is strongly affected by stress which explains why in the middle row of Fig. 2 a much more sudden original increase can be observed in comparison to the base scenario. The peak is also higher and reached earlier with a higher stress speed factor. In the scenario shown in the bottom row of Fig 2, the stress speed factor was increased to a value of 0.25.

While the difference between this simulation and the baseline one is not as significant as the one between the simulations shown in the middle row in Fig. 2 and the baseline, the impact of a higher stress remains very clear. Indeed, this simulation shows a faster rate of increase for stress at first with a peak at 0.8174 reached at $t = 31.27$ but also a higher procrastination, and shame, with a peak of 0.2972 reached at $t = 30.3$. The speed factor adaptation of therapy state X_{15} is also impacted in the same way but to a lesser extent with a peak of 0.88 at $t = 35$. Overall, these impacts make a lot of sense as a person more sensitive to stress is expected to have their stress peak faster and higher when given an important task. The impacts on procrastination, while not as large, remain present. These can be asserted to what was described in Tice et al. [22]'s paper, which is that, as explained in Section 2, procrastination is often used to combat emotional distress. Furthermore, it can be concluded that the correlations noted in the base

simulation also apply across variations in different individuals, therefore confirming the agreement between the model results and empirical psychological research.

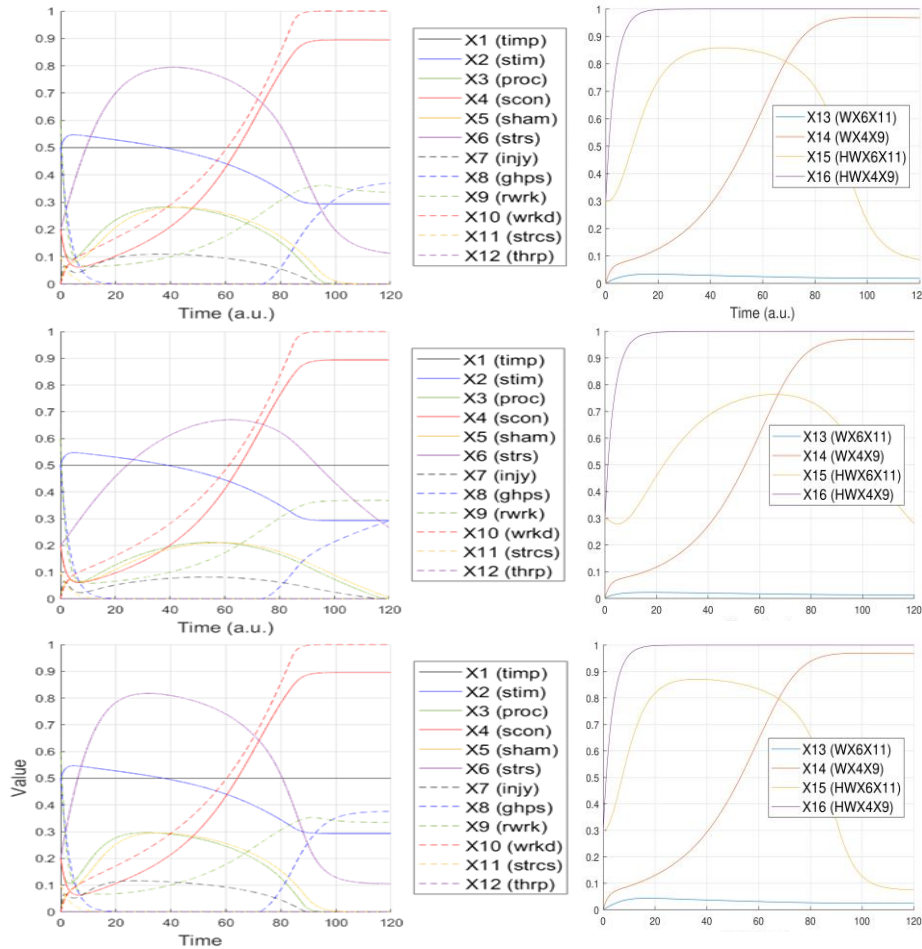


Fig. 2: The state values of the base level (left) and adaptation levels (right) with varying speed factors of the stress/anxiety state: 0.15 (top row) 0.05 (middle row), and 0.25 (bottom row)

Stress-control therapy experiment Now that different values for stress speed factors were analysed, the effects of therapy regarding stress are taken into consideration, the level of procrastination and the time to fully finish the task at hand. In order to analyse those results, the same baseline as for the previous analysis was used. The top row in Fig. 2 shows the results using an initial value for therapy of 0, this means that therapy was absent from the model. For the current experiment, first the therapy initial value was set to 0.1, the results of which can be observed in the top row of Fig. 3. Note that a speed factor of 0.15 was used for the stress state (X_6) as this was the baseline value.

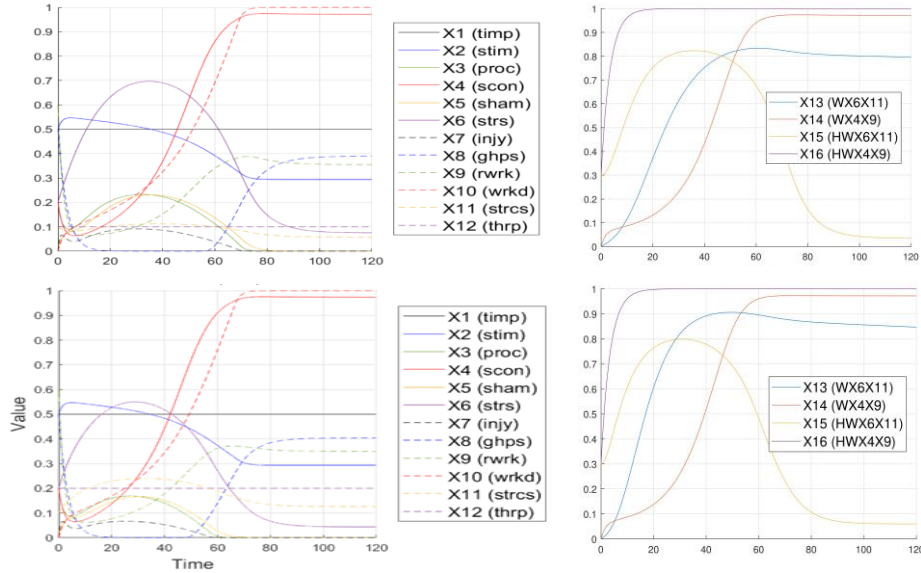


Fig. 3: The state values of the base level (left) and adaptation levels (right) with varying initial values for therapy: 0.1 (top row) and 0.2 (bottom row)

Here, a few things can be observed. First, the level of stress was decreased a lot from a peak of 0.7944 in the base scenario simulation compared to a peak of 0.6969 here. Secondly, the procrastination level and therefore also the shame/anger are much lower throughout with a peak of around 0.2329 compared to the 0.2826 of the baseline simulation. This makes sense, given that the subject is helped to deal with his procrastination through therapy. Overall and most importantly, this simulation makes the individual complete his task much quicker than he did in the previous one finishing it at $t = 83.22$ compared to the original $t = 97.95$. Furthermore, the general happiness at the end of the simulation is increased in comparison to the simulation without the influence of therapy. In order to further test the effects of therapy, the initial value of therapy was changed to 0.2. This change yielded the results shown in the middle row of Fig. 3. In this second variation of the initial value for therapy, the same positive impacts can be observed but to a greater extent when compared to the baseline simulation. While therapy helps even more than it did, doubling the therapy's initial value isn't causing as great of an impact as introducing therapy into the model. Here the stress peaks slightly earlier at $t = 28.78$ with a value of 0.55 while procrastination, closely followed by shame, peaking at $t = 26.54$ with a value of 0.1685. The speed at which the task is completed is also further improved with a completion time of $t = 80.67$. Overall, this shows that while therapy helps get work done quicker while also lowering stress and procrastination, it does not scale linearly. Therapy being an efficient method to circumvent procrastination was also shown in Section 2 [24]. It was also shown in Section 2 that therapy greatly helps in dealing with stress [6], thus also matching our simulations of this experiment.

The effect of a stress-control therapy Continuing from the previous experiment, the three modeled persons were used to test the effect of stress-control therapy. First, we modeled P_1 with an initial value for therapy changed to 0.15. The results can be seen in the graph of the upper row in Fig 4. Then, we look at the averagely-stressed individual P_2 ; see Fig. 4 bottom row left.

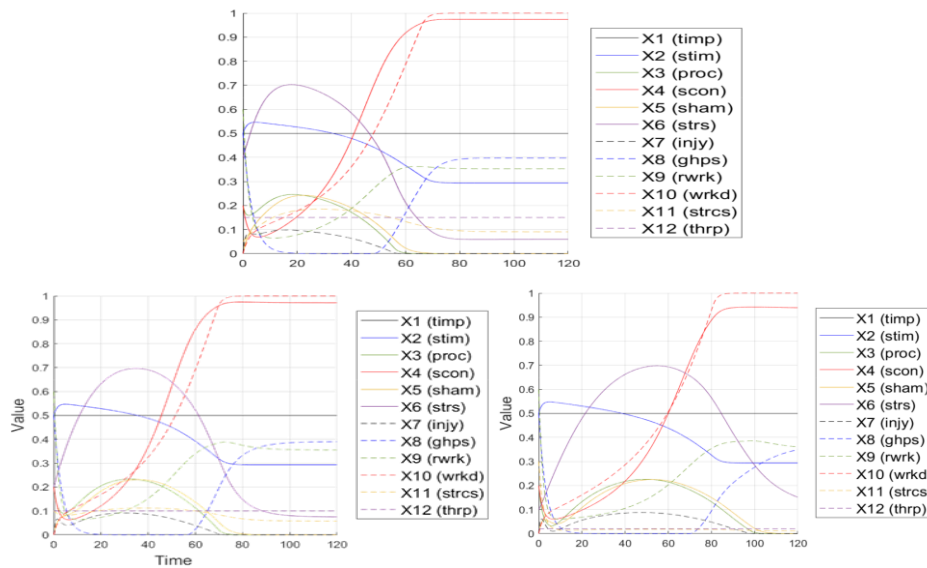


Fig. 4 Modeling different types of persons: anxious (top row left), average (top row right) and confident (middle row left). Modeling the effect of therapy: (middle row right) (bottom row left) (bottom row right)

Here the initial value for therapy (X_{12}) was changed to 0.1. Finally, we simulate the confident person P_3 using an initial value for X_{12} of 0.02; see Fig. 4 bottom row right. Here, the inclusion of therapy changed the results in several ways. Since the level of therapy was adjusted to obtain a similar peak value for stress across the three individuals, analysing the behaviour of X_6 is a good place to start. P_1 's stress peaks at $t = 17.39$ with a value of 0.7027 while P_2 peaks with a value of 0.6969 at $t = 34.40$ and P_3 with 0.6979 at $t = 54.66$. While these peak times are very different in the same way they were in the previous experiment, we can say that the values are very close with a maximum deviation across them which can be rounded to 0.05%. The experimental setup here had as a first goal to get the modeled individuals with a very close stress peak value to compare what the other dynamics would show. This experimental setup attempt can therefore be considered successful.

Stress also keeps the same trend throughout the simulation as in the previous experiment, all, however, with lower amplitudes. The peaks are also reached quicker than they were. This can be attributed to the therapy helping to deal with the stress a lot quicker than would have otherwise been possible. Secondly, we look into procrastination. Here, X_3 peaks with 0.2458 at $t = 17.99$, 0.2329 at $t = 31.77$ and 0.2259 at $t =$

48.94 for P₁, P₂ and P₃, respectively. Just like for stress, therapy has a very positive effect on procrastination, not only are the peaks lower than the ones observed in the previous experiment, they also come significantly earlier. Finally, the times at which the work is completed are $t = 79.81$, $t = 83.22$ and $t = 94.58$ for P₁, P₂ and P₃, respectively, while they were all very close in the previous experiment. In comparison to the previous experiment, the work was completed 17.12%, 15.04% and 4.13% faster for P₁, P₂ and P₃, respectively. P₁ received more therapy than P₂ and P₂ more than P₃. Overall, these results demonstrate a very positive impact for therapy and while a more anxious individual could potentially benefit more from it, any individual subject to therapy seems to see significant improvement in their emotional states and task efficiency. Moreover, an increase in general happiness is observed for all individuals.

7 Verification by Analysis of Stationary Points

To verify the behaviour of the implemented network model against the conceptual specification, analysis of stationary points was performed. As a stationary point for a state Y is a point where $dY(t)/dt = 0$, from (1) the following general criterion for it can be derived:

$$\mathbf{\eta}_Y = 0 \quad \text{or} \quad \mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) = Y(t) \quad (2)$$

where X_1 to X_k are the states from which Y gets its incoming connections. We verify that the aggregated impact defined by the left hand side of (2) matches the state value for some stationary points observed in a simulation. This was done for base states X₃, X₅, X₇, X₈ and X₉, all using the scaled sum function as a combination function (see Table 3). As seen in that table, the maximum deviation is 0.000013, which provides evidence that the base level functions as intended.

Table 3 Verification of the model using temporary stationary points.

State X _i	X3	X5	X7	X9 ₁	X9 ₂
Time point t	27.26	30.70	25.44	10.09	65.37
$X_i(t)$	0.1657438	0.163772	0.0654626	0.061891	0.3715222
aggimpact _{X_i} (t)	0.1657392	0.163767	0.0654619	0.061904	0.3715170
deviation	-0.0000046	0.000005	0.0000007	-0.000013	0.0000052

To verify the Hebbian learning behaviour of the model, its behaviour was also analysed by checking X₁₃ and X₁₄. For this analysis, we used the simulation shown in Fig. 3 bottom row right, as the learning is most pronounced there. Locating the stationary point in the graph, we find that this occurs for X₁₃ at $t = 4.961$ with a value of $W = 0.90435484$. The incoming connections are from X₆ and X₁₁, which at the time of the stationary point have values of 0.43416206 and 0.21773694, respectively. Based on (2), the relation derived in [23], Ch 3, Section 3.6.1, is as follows:

$$W = \frac{V_1 V_2}{1 - \mu + V_1 V_2} \quad (3)$$

Filling in the above values in (3), right hand side, yields $W = 0.904336$ which is a deviation of 0.000018 from the observed value 0.9043548 for W . Similarly, for X_{14} , a stationary point at $t = 7.349$ was found with a value of $W = 0.972595236$. Based on the incoming states X_4 and X_9 for X_{14} , which have values of 0.974656883 and 0.364125516 at that time point, it was found $W = 0.972595039$. Again, the analysis result matches well with a deviation of 0.000000197. This provides evidence that also the learning behaves as expected.

8 Conclusion and Future Research

In this paper, it was endeavoured to create a model describing procrastination including both the behavioural and emotional components. To this extent, an adaptive network model was created featuring both first- and second-order adaptation by using self-models. The simulations created with the model show the dynamics and correlations found in psychology research. This leads us to believe the main dynamics of the model are valid. To test the model more extensively, it will be required to obtain empirical data that demonstrates the evolution over time; unfortunately, this is currently not available.

In the current state of the model, therapy is included as a constant level starting at the beginning of the simulation. For future research, this can be modeled in a more detailed manner. Furthermore, one may address adaptive variation of the threshold of the stress node, through which one could also regulate an individual's sensitivity to stress. Lastly, it is found in the literature that self-compassion has been shown to have a significant correlation with the level of stress experienced by the procrastinator [16]. It has also been observed that therapy can be of help in this aspect and as such it could also be included in the model in future research [1, 10]. The developed computational model may be used as a basis to advise therapists about timing and duration of certain therapies for their clients.

References

1. Birnie, K., Speca, M., Carlson, L.E.: Exploring self-compassion and empathy in the context of mindfulness-based stress reduction (mbsr). *Stress and Health* **26(5)**, 359-371 (2010).
2. Choi, J.N., Moran, S.V.: Why not procrastinate? development and validation of a new active procrastination scale. *The Journal of Social Psychology* **149(2)**, 195-212 (2009).
3. Chu, A., Choi, J.: Rethinking procrastination: effects of active procrastination behavior on positive attitudes and performance. *Journal of Social psychology* **145**, 254-264 (2005).
4. Fee, R.L., Tangney, J.P.: Procrastination: A means of avoiding shame or guilt? *Journal of Social Behavior and Personality* **15(5)**, 167-184 (2000).
5. Flett, A.L., Haghbin, M., Pychyl, T.A.: Procrastination and depression from a cognitive perspective: An exploration of the associations among procrastinatory automatic thoughts, rumination, and mindfulness. *Journal of Rational-Emotive & Cognitive-Behavioral Therapy* **34(3)**, 169-186.
6. Gammon, J., Morgan-Samuel, H.: A study to ascertain the effect of structured student tutorial support on student stress, self-esteem and coping. *Nurse education in Practice* **5(3)**, 161-171 (2005).

7. Harriott, J., Ferrari, J.R.: Prevalence of procrastination among samples of adults. *Psychological Reports* **78**(2), 611-616. doi: 10.2466/pr0.1996.78.2.611 (1996).
8. Klassen, R.M., Krawchuk, L.L., Rajani, S.: Academic procrastination of undergraduates: Low self-efficacy to self-regulate predicts higher levels of procrastination. *Contemporary Educational Psychology* **33**(4), 915-931. doi: 10.1016/j.cedpsych.2007.07.001 (2008).
9. Lay, C.H.: Trait procrastination and affective experiences: Describing past study behavior and its relation to agitation and dejection. *Motivation and Emotion* **18**(3), 269-284 (1994).
10. Lee, W.K., Bang, H.J.: The effects of mindfulness-based group intervention on the mental health of middle-aged Korean women in community. *Stress and Health* **26**(4), 341-348 (2010).
11. Myrick, J.G.: Emotion regulation, procrastination, and watching cat videos online: Who watches internet cats, why, and to what effect? *Computers in Human Behavior* **52**, 168-176.
12. Nordal, K.C., Ballard, D.W., Diaz-Granados, J., Vaile Wright, C., Jackson, J.S., Salomon, M., Bossolo, L.: Stress in America: The impact of discrimination. Retrieved from <https://www.apa.org/news/press/releases/stress/2015/impact-of-discrimination.pdf> (2016).
13. Onwuegbuzie, A.J.: Academic procrastination and statistics anxiety. *Assessment & Evaluation in Higher Education* **29**(1), 3-19 (2004).
14. Schouwenburg, H.C.: Academic procrastination. In: *Procrastination and task avoidance* (pp. 71-96). Springer Boston (1995).
15. Senecal, C., Koestner, R., & Vallerand, R.J.: Self-regulation and academic procrastination. *The Journal of Social Psychology* **135**(5), 607-619 (1995).
16. Sirois, F.: Procrastination and stress: Exploring the role of self-compassion. *Self and Identity* **13**, 128-145. doi: 10.1080/15298868.2013.763404 (2014).
17. Sirois, F., Pychyl, T.: Procrastination and the priority of short-term mood regulation: Consequences for future self. *Soc. and Pers. Psychology Compass* **7**(2), 115-127 (2013).
18. Sirois, F.M.: Is procrastination a vulnerability factor for hypertension and cardiovascular disease? Testing an extension of the procrastination-health model. *Journal of Behavioral Medicine* **38**(3), 578-589 (2015).
19. Sirois, F.M., Melia-Gordon, M.L., Pychyl, T.A.: 'I'll look after my health, later': an investigation of procrastination and health. *Personality and Individual Differences* **35**(5), 1167 - 1184 (2003).
20. Stead, R., Shanahan, M.J., Neufeld, R.W.: 'I'll go to therapy, eventually': Procrastination, stress and mental health. *Personality and Individual Differences* **49**(3), 175-180 (2010).
21. Steel, P.: The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological bulletin* **133**(1), 65-94 (2007).
22. Tice, D., Bratslavsky, E., Baumeister, R.: Emotional distress regulation takes precedence over impulse control: If you feel bad, do it! *Journal of Personality and Social Psychology* **80**, 53-67. doi: 10.1037/0022-3514.80.1.53 (2001).
23. Treur, J.: *Network-oriented modeling for Adaptive Networks: Designing Higher-Order Adaptive Biological, Mental and Social Network Models*. Springer Nature (2020).
24. van Eerde, W., Klingsieck, K.B.: Overcoming procrastination? a meta-analysis of intervention studies. *Educational Research Review* **25**, 73 - 85 (2018).
25. Wypych, M., Matuszewski, J., Dragan, W.: Roles of impulsivity, motivation, and emotion regulation in procrastination - path analysis and comparison between students and non-students. *Frontiers in Psychology* **9**, e891. doi: 10.3389/fpsyg.2018.00891 (2018).