A Second-Order Adaptive Cognitive Agent Model for Emotion Regulation in Addictive Social Media Behaviour

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ABSTRACT

Social media addiction has spread rapidly among young people in recent years. Individuals with social media addiction are more likely to avoid and suppress negative emotions instead of reappraising these emotions, which can cause psychological and even physical harm. This study presents a second-order adaptive cognitive agent model to simulate the process of emotion regulation in social media addicts and the impacts of stress and therapy in this process. This agent model can use three types of emotion regulation strategies: suppression, avoidance (by escaping to social media), and reappraisal. Using this cognitive agent model, two scenarios for a person with social media addiction are compared: with and without therapy. It is found that if therapy successfully improves the regulation by reappraisal, the use of suppression and avoidance can be reduced. Characteristics of this model were tuned by simulated annealing, using data points estimated from psychological literature, indicating that the model matches well with empirical information. The presented cognitive agent model may also be used for other types of addictions which involve avoidance of emotions, such as alcohol abuse and game addiction.

CCS CONCEPTS

• Computing methodologies • AI • Modeling and Simulation

KEYWORDS

Second-order adaptive, network model, social media addiction, emotion regulation

1 Introduction

The increasing prevalence of internet and social media addiction has resulted in psychological and physical problems among young people. This type of addiction is prevalent in multiple countries, with an increasing trend as shown in (Pan et al., 2020). For example, the prevalence of severe problematic internet use (PIU) or Internet addiction (IA) is up to 47.4% in Southeast Asia (Balhara et al., 2018). A study conducted in Europe shows that 14.1% of the adolescents show dysfunctional internet behaviour (Tsitsika et al., 2016). Internet addiction has been classified as a legitimate disorder and studied by psychological academia; addictive social media use is a form of internet addiction (Young, 2004). The addictive use of social media can bring multiple psychological and physical negative effects to individuals, such as insomnia, lower self-esteem, lower satisfaction in life, even depression (Kircaburun et al., 2016; Li et al., 2018; Balhara et al., 2018). Emotion regulation has been found to play a vital role in internet addiction. A study points out that PIU is associated with having greater difficulties in emotion regulation, and it seems to act as a dysfunctional regulator of emotional distress (Gámez-Guadix, 2014). According to Elhai et al. (2016), an inadequate ability in emotion regulation could be the reason why problematic internet use occurs.

Emotion regulation is a psychological term defined by Gross (2011), as *the activation of a goal to influence the emotion trajectory*. It includes both down-regulating negative emotions such as anxiety, anger, sadness, and up-regulating positive feelings such as happiness and interest (Gross, 2015). Emotion regulation abilities differ between individuals, and are impacted by cultural factors; one's adoption of emotion regulation strategies changes over time. John et al. (2004) show that people tend to use more reappraisal strategy, and less suppression strategy from 20s to 60s. Another study finds that the emotion regulation process is highly related to one's genetic traits from early in their life. (Canli & Duman, 2009). Men and women are found to have diverse emotion regulation approaches (Zimmermann et al., 2014). Haga et al., (2009) points out that the adoption of emotion regulation strategies is also influenced by contextual factors, such as cultures.

Emotion regulation can be learnt; this learning process can take place because a human's neural networks have plasticity; e.g., Hebb (1949). Plasticity in the human brain is a fundamental notion studied in neuroscience, it can be summarized as the ability to make adaptive changes related to the structure and function of the nervous system. Both internal and external stimuli can alter neuroplasticity. Stress can also bring neuroplastic changes. Relations between human neuroplasticity and emotion regulation have been found and studied by many researchers (Fuchs et al., 2014; Garcia, 2001).

A myriad of literature on the emotion regulation process among internet addicts has been published. Nevertheless, the internal mechanism underlying internet addiction and emotion regulation process is still intensively studied. Simulating human mental processes, such as emotion regulation processes among internet addicts, can help researchers make sense of human

behaviour (Waytz et al., 2015). Additionally, simulation can also predict and validate the internal mechanisms, and in return, provide insights on internet addiction prevention. This study proposes a second-order adaptive cognitive agent model to simulate the process of emotion regulation in internet addicts and the adaptive impacts of stress and therapy in this process. The model clearly depicts the adaptive changes in the process and impacts of different factors over time.

2 Background Literature

Drach et al. (2021) conclude that participants with problematic social media use have greater difficulties in impulse control, and more limited access to emotion regulation strategies. Gross (2015) states that stress coping has a longer temporal horizon than emotion regulation. A study shows that emotional distress changes people's choice on resisting temptations in favor of long-term benefits. This is because distress intensifies people's desire to feel better, and seeking immediate gratification can bring better mood to persons with emotional distress in the short-term (Tice et al., 2001).

In psychological theories, six often considered human emotion regulation strategies are acceptance, avoidance, problem-solving, reappraisal, rumination, and suppression. The emotion regulation strategy of reappraisal is argued as adaptive and protecting individuals against mental and physical illness, while suppression, and avoidance are theorized as maladaptive and risk factors of mental illness in psychopathology (Aldao et al., 2010). Parkinson, Totterdell (1999) and Larsen (2000) bring up a theory that distinguishes behavioural and cognitive strategies. Behavioural strategies are deeds in relation to physical actions, for instance, seeking for distraction when a person feels down; cognitive strategies are related to cognitive activities, for example, adopting a reappraisal strategy. A meta-analytic study indicates that reappraisal and avoidance are the most effective emotion regulation strategies among all strategies (Augustine & Hemenover, 2009). The time course of different regulation strategies might differ. Goldin et al., (2008) find in a study using an fMRI method that in comparison to behavioural suppression, cognitive reappraisal happens earlier. Two strategies happen in 0-4.5 seconds and later than 10 seconds, relatively after stimulus is given.

Reappraisal involves attempts to focus on the positive side of a negative situation or to reformulate, re-interpret negative experiences in a positive manner (Augustine & Hemenover, 2009). According to a literature review done by Gross (2015), reappraisal is the best studied approach from the perspective of neuroscience. This strategy is well-identified as positive to ones' well-being in both social relationships and one's internal mood (Haga, 2009; John, 2004). Individuals can gain enhanced control over emotions by using reappraisal frequently (Gross & John, 2003).

Emotion *suppression* includes two mechanisms. A process where individuals effortfully allocate cognitive resources to distracting themselves from the undesired emotions; and a monitoring mechanism that seeks for stressful situations. When individuals suffer from stress, they have to use more cognitive resources in dealing with stress, thus less resources are allocated to distracting themselves, they thus focus more on the negative side of the situation (Beevers, Meyer, 2004; Wegner, 1994, Wenzlaff, 2000). A meta-analysis indicates that rebound effects exist after using emotion suppression strategy: emotions come back eventually to ones who use this strategy (Abramowitz et al., 2001). A study done by Wenzlaff & Bates (1998) indicates that individuals predisposed to depression are more likely to adopt a suppression strategy (Wenzlaff & Bates, 1998). The effectiveness of suppression is also dependent on stress levels, it is a protective mechanism when individuals face low levels of stress, while suppression makes people with high stress levels vulnerable to depression, and anxiety disorders (Beevers & Meyer, 2004; Gross et al., 2003).

Avoidance means attempting to remove oneself from the cause of a negative experience, both cognitively and physically (Feldner, 2003). Avoidance often takes place in the form of social withdrawal, which drives people away from social activities and relationships. This strategy is protective to individuals in a short time, while constantly adopting it leads to worsened mood and poorer well-being due to less social support (Gross, 2013). Avoidance is usually considered as an unhealthy strategy, and frequent adoption impairs one's well-being in a broader sense. A study shows that individuals with a strong tendency to use emotional avoidance are more likely to have greater anxiety when adopting suppression in comparison to emotional observation (noticing, observing the sensations, don't suppress them) (Felner et al., 2003). A longitude study finds that participants who adopt avoidance coping with life stressors are likely to suffer from more stressors after 4 years, avoidance coping also links to depressive symptoms in 10 years (Holahan et al., 2005). Ottenbreit et al., (2004) also elucidate that avoidance is associated with depression.

Depression therapy can take place in two forms, antidepressant and psychotherapy. Antidepressant treatments can increase brain-derived neurotrophic factor (BDNF) expression and glucocorticoid level, it could, in return, restore synaptic plasticity for certain cognitive functions (Garcia, 2002). In terms of psychotherapy, emotion regulation interventions often take place, they are meant to help individuals learn healthy emotion regulation approaches, and it mainly focuses on teaching individuals a reappraisal strategy (Gross, 2015).

Plasticity of the brain covers synaptic plasticity and intrinsic neuron plasticity. It is not a constant feature: the extent of plasticity changes over time, depending on circumstances. This involves a form of control of plasticity which is called *metaplasticity* (Abraham and Bear, 1996; Garcia, 2002). In particular in response to stress, cognitive functions get weakened, including plasticity that gets impaired, which is sometimes called negative metaplasticity (Garcia, 2002; Kim & Yoon, 1998). This phenomenon may be related to a study indicating that individuals with social anxiety adopt digital communication to avoid the anxiety, but this could eventually make them more vulnerable to anxiety (Erwin et al., 2004). The exact mechanisms underlying stress and plasticity may not be fully clear, but it can have a relation to the increased glucocorticoid level. Negative metaplasticity is also associated with depression because depression in humans is related to high levels

of glucocorticoids through multiple mechanisms, for instance, a reduction of BDNF expression in the hippocampus (Garcia, 2002).

3 The Adaptive Modeling Approach Used

The adopted modeling approach from Treur (2020) provides easy-to-use means to design and simulate cognitive agents that are adaptive of multiple orders; see also (Treur, 2021). The approach models mental and social agent processes by assuming causal relationships between dynamic agent states, while the causal relations themselves can change too, so that adaptive networks are obtained modeling adaptive cognitive agents. The nodes in such a temporal-causal network represent the state variables or states of a network. For example, if one state X affects another state Y, the connection $X \rightarrow Y$ between these states models this causal relation. The activation values of these states vary over time indicated by real numbers. A network model is described by the following network structure characteristics:

Connectivity characteristics These are defined by *connection weights* $\boldsymbol{\omega}_{X,Y}$ from state X to state Y; these weights can be positive or negative real numbers.

Aggregation characteristics These specify how the impacts on a given state are combined. The different impacts of the states that affect a state Y are aggregated using a combination function $\mathbf{c}_Y(..)$. Such functions can be selected from an available library provided by the dedicated software environment. For each state Y one or more basic combination functions $\mathbf{c}_j(..)$, $j = 1, .., m$ can be selected by indicating *weights* $\boldsymbol{\gamma}_{j,Y}$ (real numbers) which makes that within the software environment a weighted average of these functions $\mathbf{c}_j(..)$, $j = 1, .., m$, from the library is used as combination function $\mathbf{c}_Y(..)$ for state Y; these combination functions $\mathbf{c}_j(..)$ have combination function *parameters* $\boldsymbol{\pi}_{i,j,Y}$.

Timing characteristics Each state Y has a *speed factor* which is a real number $\boldsymbol{\eta}_Y \geq 0$. This makes that the states do not need to change in a synchronous manner, which makes applicability easier for real-world applications where states are often not synchronous.

These three concepts are used a standard numerical representation of the network model in difference equation format

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

where Y is any given state, which has incoming connections from states $X_1, \ldots, X_k$. This is automatically done within the software environment, based on the network characteristics $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{i,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$ as input. Note that this is a specific recurrent network model format. The combination functions used in the model in this paper are shown in Table 1.

Table 1 Combination functions used in the model

Name	Formula and Parameters
Identity **id**(V)	V
Advanced logistic sum **alogistic**$_{\sigma,\tau}$($V_1, \ldots, V_k$)	$[\frac{1}{1+e^{-\sigma(V_1+\cdots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}}](1+e^{-\sigma\tau})$ Steepness σ>0, excitability threshold τ
Hebbian learning **hebb**$_\mu$(V_1, V_2, W)	$V_1V_2(1-W) + \mu W$ Persistence factor μ in the [0, 1] interval

In addition, for independent external environmental input for the network model, a (time-dependent) **stepmod**$_{\rho,\delta}$(t) combination function is used which over time t starts at 0, and at time δ jumps to 1, after which it drops back to 0 at time ρ, after which it repeats. This function is applied to represent therapy, which has value 1 during therapy for $t \in [\delta, \rho]$.

Note that 'network characteristics' and 'network states' are two distinct concepts for a network. Self-modeling is a way to relate these concepts to each other in an interesting and useful way. A *self-model* is making the implicit network characteristics (such as connection weights or excitability thresholds) explicit by adding states for these characteristics; thus, the network gets an internal self-model of part of the network structure; this can 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, for example, (Treur, 2020). Adding a self-model for a temporal-causal network is done in the way that for some of the states Y of the base network and some of its related network structure characteristics for connectivity, aggregation and timing (in particular, some from $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{i,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$), additional network states $\mathbf{W}_{X,Y}$, $\mathbf{C}_{i,Y}$, $\mathbf{P}_{i,j,Y}$, $\mathbf{H}_Y$ (self-model states) are introduced:

Connectivity self-model Self-model states $\mathbf{W}_{X,Y}$ are added representing connection weights $\boldsymbol{\omega}_{X,Y}$

Aggregation self-model Self-model states $\mathbf{C}_{j,Y}$ are added representing combination function weights $\boldsymbol{\gamma}_{i,Y}$ and/or self-model states $\mathbf{P}_{i,j,Y}$ representing combination function parameters $\boldsymbol{\pi}_{i,j,Y}$

Timing self-model Self-model states $\mathbf{H}_Y$ are added representing speed factors $\boldsymbol{\eta}_Y$

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 $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{i,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$: here **W** refers to $\boldsymbol{\omega}$, **C** refers to $\boldsymbol{\gamma}$, **P** refers to $\boldsymbol{\pi}$, and **H** refers to $\boldsymbol{\eta}$, respectively. For the processing, these self-model states define the dynamics of state Y in a canonical manner according to equations (1) whereby $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\gamma}_{i,Y}$, $\boldsymbol{\pi}_{i,j,Y}$, $\boldsymbol{\eta}_Y$ 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.

Networks equipped with a connectivity self-model state $\mathbf{W}_{X,Y}$ can apply a hebbian learning (Hebb, 1949) adaptation method by using combination function **hebb**$_\mu$**(..)** (see Table 1) to adapt the connection weight over time. This function is especially useful to model a form of natural (human-like or animal-like) plasticity as described within Neuroscience. This principle is often formulated in a simplified manner as 'what fires together, wires together'. This has been applied here.

In addition to adaptive connection weights another adaptation principle can be applied to make the excitability threshold of states adaptive. Such a form of adaptation has been found relatively recently for different parts of the brain, e.g., (Aizenman and Linden, 2000; Daoudal and Debanne, 2003; Debanne, Inglebert, and Russier, 2019; Titley, Brunel, and Hansel, 2017). This form of adaptivity was applied by making the

excitability threshold $\boldsymbol{\tau}_Y$ of the logistic function of one of the states Y adaptive.

As the outcome of the addition of a self-model is also a temporal-causal network model itself, as has been shown in (Treur, 2020), Ch 10, this construction can easily be applied iteratively to obtain multiple levels of self-models. Therefore second-order adaptation as, for example, plays an important role in metaplasticity to control plasticity (Abraham and Bear, 1996; Garcia, 2002), can easily be modelled as well. This also has been applied here.

4 The Second-Order Adaptive Cognitive Agent Model for Social Media Addiction

The information from the background literature (Section 2) and the modeling concepts from Section 3 are combined into an adaptive cognitive agent model of a person who suffers from social media addiction. The base level and the 3D multi-leveled model are visualized in Figure 1, and its nomenclature is given in Table 2. This model addresses a human's negative emotion and emotion regulation for it, and plasticity and metaplasticity of these processes. The base level in Figure 1 presents the process from the outside world's stimulus, and the emotion regulation processes to action execution. Stimuli emerge from two sources, namely events that could stimulate negative emotions (e.g., stressful situations) (ws_s) and the involvement in social media (ws_a). A person senses stimulus s (ss_s) and then makes a representation of it (srs_s). This representation can result in a positive belief state bs_+ of the person, or a negative belief state bs_- in the person, which both can be gradual too. This affects the emotional state of the person, where a positive belief causes a less negative emotion (less preparation ps_b for negative emotional response) and a negative belief causes a more negative emotion (more preparation ps_b for negative emotional response). The person either executes (by bodily expression) this emotion (by es_b), which is sensed (by ss_b), and then represented (by srs_b) according to a body loop, or directly represents this emotion by an as-if body loop (srs_b); e.g., Damasio (2000). Based on this srs_b, the feeling state fs_b occurs (representing among others parts of the Amygdala).

This cognitive agent model uses three emotion regulation strategies and control states (relating to areas in the prefrontal cortex): reappraisal with cs_{reapp}, suppression with cs_{supp} and avoidance with cs_a. Reappraisal reduces the strength of the negative belief when sensory representation srs_s is high. This process of reappraisal is also described as reinterpretation; it increases the intensity of positive emotions at the same time. On the other hand, suppression decreases the preparation and expression of emotions by reducing the preparation state of emotion expression. The more one uses one strategy, the less the person adopts another strategy. Emotion avoidance is another strategy, which is executed when individuals feel negative emotions; increase of negative emotions intensifies the execution of avoidance behaviours. In this case study, the emotion avoidance approach considered is occupy oneself with social media. The model also includes a therapy state tp, which uses the combination function $\mathbf{stepmod}_{\rho,\delta}(..)$; it activates at time $\boldsymbol{\delta}$ of the simulation and stops at time $\boldsymbol{\rho}$. During this time, therapy is provided, in the form of antidepressant and psychotherapy. With this therapy reappraisal cs_{reapp} can be strengthened, which stimulates re-interpretation. The resulting lower level of negative feelings also increases plasticity so that reappraisal is strengthened more by hebbian learning. This can get a person with mental problems out of a vicious circle.

The first- and second-order self-model levels (the blue and yellow planes in Fig. 1) elucidate plasticity and metaplasticity of the agent's emotion regulation systems. First-order adaptation for plasticity is shown in the first-order self-model level (blue plane). This self-model level applies Hebbian learning throughout psychotherapy, where the initially depressed person learns and unlearns emotion regulation strategies, and rebuilds mental health.

Table 2 Overview of the states in the adaptive network model

nr	state	explanation
X_1	ws_s	World state for stimulus s
X_2	ws_a	World state for avoidance a
X_3	ss_s	Sensor state for stimulus s
X_4	ss_b	Sensor state for emotion b
X_5	srs_s	Sensory representation state for stimulus s
X_6	srs_b	Sensory representation state for emotion b
X_7	bs_+	Belief state for positive interpretation
X_8	bs_-	Belief state for negative interpretation
X_9	ps_b	Preparation state for emotion b
X_{10}	ps_a	Preparation state for avoidance a
X_{11}	cs_{reapp}	Control state for regulating reappraisal
X_{12}	cs_{supp}	Control state to regulate suppression
X_{13}	cs_a	Control strate for avoidance a
X_{14}	fs_b	Feeling state for emotion b
X_{15}	tp	Therapy state
X_{16}	es_a	Execution state for avoidance a
X_{17}	es_b	Execution state for emotion b
X_{18}	$\mathbf{W}_{fs_b,cs_a}$	Adaptive weight for avoidance
X_{19}	$\mathbf{W}_{fs_b,cs_{supp}}$	Adaptive weight for suppression
X_{20}	$\mathbf{W}_{fs_b,cs_{reapp}}$	Adaptive weight for reappraisal
X_{21}	$\mathbf{T}_{ps_a}$	Adaptive threshold for avoidance
X_{22}	$\mathbf{HW}_{fs_b,cs_a}$	Adaptive learning speed for avoidance
X_{23}	$\mathbf{HW}_{fs_b,cs_{supp}}$	Adaptive learning speed for suppression
X_{24}	$\mathbf{HW}_{fs_b,cs_{reapp}}$	Adaptive learning speed for reappraisal

The **W**-states from this self-model represent connection weights $\boldsymbol{\omega}$ in the base level. In addition, the **T**-state represents the internet-resistance threshold of a person, as the more frequently the person goes to social media, the more this person is addicted to social media by adaptively reducing this threshold. The second-order adaptation is modeled in the second-order self-model level (yellow plane), where learning speeds adapts to circumstances to model metaplasticity. The **H**-states represent adaptation of the speed factors from the **W**-states in the first-order self-model level, thus modeling adaptive learning rates. The role matrices shown in the Appendix specify this multi-level model.

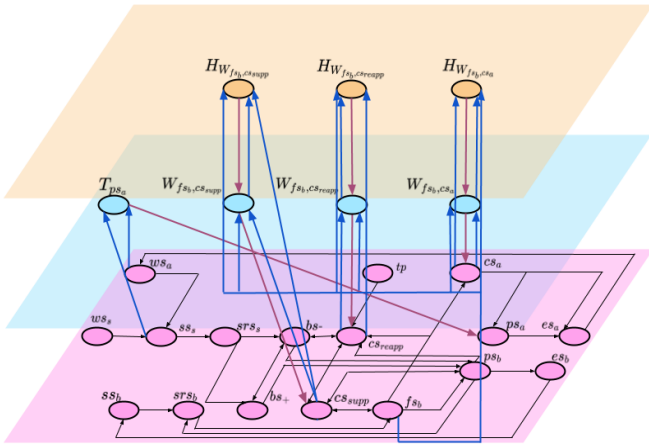

Fig. 1 Connectivity of the adaptive cognitive agent model

5 Simulation Results for Different Scenarios

This section compares two scenarios using the cognitive agent model described in Section 4. Two emotion regulation strategies are adopted of a client which is prone to depression and social media addiction. The initial values of this person are given in Table 9. Initially, the client has a more negative belief state bs- (value 0.7) than positive belief state bs+ (value 0.2). Further, this person is more likely to suppress negative emotions using cs_{supp} (0.6) or seek out for avoidance using cs_a (0.6) than reappraise these using cs_{reapp} (0.2). In the first scenario the client does not receive any therapy, while in the second scenario this client receives therapy.

Scenario 1: without therapy

In the first scenario the given person does not receive any therapy. In this situation there is no connection from the therapy state tp to the control state of reappraisal cs_{reapp} (i.e. $\boldsymbol{\omega}_{tp,csreapp} = 0$). The upper graph in Figure 2 visualizes the avoidance states. From this graph, it can be observed that avoidance a is opposite to the natural way of perceiving emotions ss_s and srs_s. This is common for addictive behaviour, where a person responds to negative emotions with avoidance as natural emotion regulation. This is in line with the research by Macklem (2008), which emphasized that addictions are associated with inability to regulate emotions. Note that the graph has ups and downs. If the person feels negative, he or she avoids this emotion by going to social media, which gives a short-term positive feeling (Hormes & Timko, 2014). During these moments, less avoidance is required, and the threshold to avoidance $\mathbf{T}_{ps_a}$ increases. However, this increase is not enough to prevent the person from seeking avoidance again as the sensing of the stressful stimulus comes back as soon as there is no avoidance applied anymore. The next time the person feels negative, he or she seeks for avoidance (ws_a) again, and the avoidance threshold $\mathbf{T}_{ps_a}$ is pushed back down to 0. This way, the avoidance strategy of regulation used makes that this person stays in a cycle of addiction.

The lower graph in Figure 2 visualizes the emotional states of negative emotion b. Similar to the avoidance states, peaks and valleys can be observed. The positive and negative belief states swing, but over time the positive belief (bs+) stays low and the negative belief (bs-) stays high. This gives an indication that without therapy, the client has emotion regulation by avoidance, but in the long term, he or she will stay in a negative vicious cycle. When focused on the feeling states, high variability can be noted. Positive periods (fs_b value ≈ 0.05) alternate with moments of depression (fs_b value ≈ 0.89). These peak moments are alternating with negative emotions b.

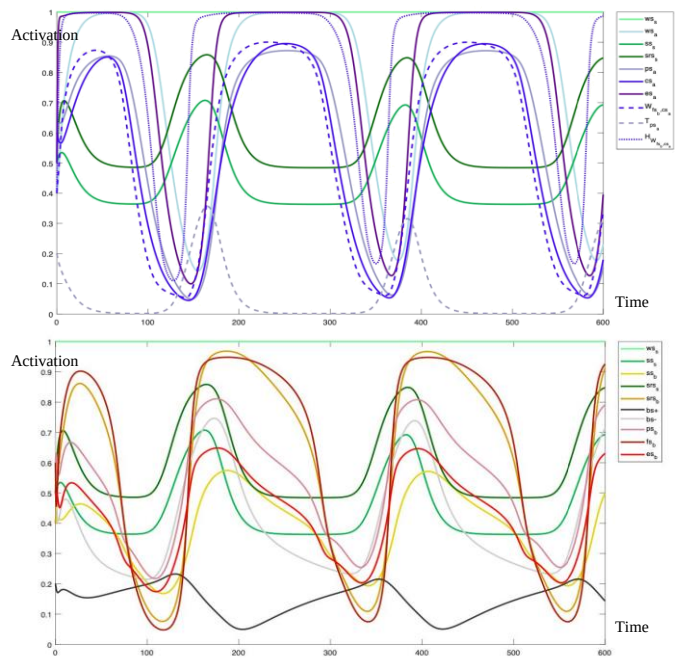

Figure 2: Emotion regulation by avoidance, without therapy.

Figure 3 visualizes the control and feeling states of the client without therapy. High values of fs_b indicate a strong negative feeling b. During these peak moments, the person typically suppresses the negative emotions: cs_{supp} gets values ≈ 1. According to Yilfiz (2017), addicts attempt to control their desires by suppression. While the suppression is high, the reappraisal regulation stays low (cs_{reapp} has value ≈ 0.12 and $\mathbf{W}_{fs_b,cs_{reapp}}$ has value ≈ 0.03), indicating that without therapy the person does not reappraise, but is more likely to suppress or avoid negative stimuli.

Scenario 2: with therapy

In the second scenario the impact of therapy on the same client is investigated. This therapy is incorporated in the model by adjusting the weight value from the therapy state to the control state of reappraisal from 0 to 0.9 (i.e., this time $\boldsymbol{\omega}_{tp,cs_{reapp}}$ has value 0.9). Figure 4 visualizes the avoidance strategy in the situation with therapy, which has been administered to the client between time 200 and 400.

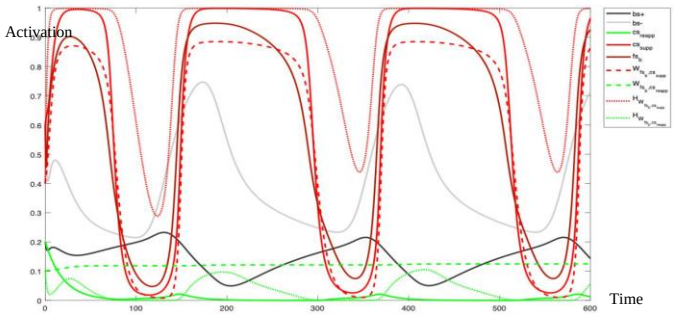

Figure 3: Suppression and reappraisal states, applying plasticity and meta-plasticity, without therapy.

Before therapy has started, the avoidance strategy is identical to the strategy in Figure 2. But after time 200 the avoidance states have increased significantly. These are the states ws_a, ps_a, cs_a, es_a, the plasticity $\mathbf{W}_{fs_b,cs_a}$, modelled by the first-order self-model, and metaplasticity $\mathbf{Hw}_{fs_b,cs_a}$, modelled by the second-order self-model. At the same time, the threshold $\mathbf{T}_{ps_a}$ for avoiding has increased. In other words, after therapy, the person is less sensitive to going to social media than before therapy, despite possible external stimuli which may trigger negative emotions. The natural emotional stimulus input ss_s and srs_s is higher after therapy, as (almost) no avoidance is applied anymore. This implies that the therapy has been useful in eliminating addiction to avoidance.

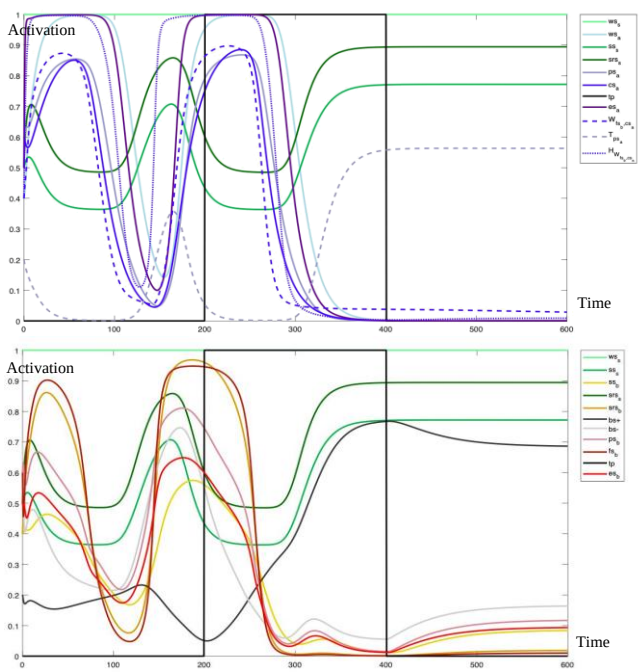

Figure 4: Adaptation from regulation by avoidance to regulation by reappraisal, using therapy

Figure 4, lower graph visualizes the effect of therapy on the emotional state of the given client. The states which represent negative emotions (ss_b, srs_b, bs-, ps_b, fs_b, and es_b) decrease steeply during therapy and stay low and constant post-therapy, compared to pre-therapy. The natural emotion regulation (ss_s, srs_s) and the positive belief state (bs_+) are higher and more constant during post-therapy compared to pre-therapy. This indicates that therapy has helped to deal with negative emotions and in the long run made room for positive and more natural emotion regulation.

Figure 5 visualizes the control states of the situation with therapy. Before the therapy has started, the control state for reappraisal is almost zero, in spite of high stress levels every now and then. During therapy, this has increased to approximately 0.44, and it drops down after therapy. As a result of the increase in the control state of reappraisal, the plasticity $\mathbf{W}_{fs_b,cs_{reapp}}$, and metaplasticity $\mathbf{Hw}_{fs_b,cs_{reapp}}$ of reappraisal have increased strongly with values ≈ 0.83 for $\mathbf{W}_{fs_b,cs_{reapp}}$ and ≈ 0.98 for $\mathbf{Hw}_{fs_b,cs_{reapp}}$. The control state for emotion suppression cs_{supp} has decreased, as it is not needed anymore now reappraisel is applied. This means that the learnability for reappraisal is well-functioning. The next time this client has a negative feeling, he or she is more likely to reappraise instead of suppressing an emotion and applying avoidance.

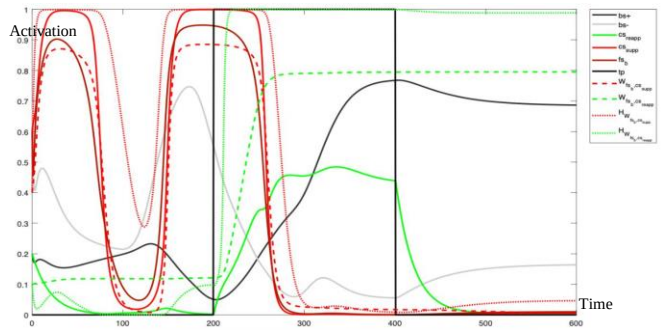

Figure 5: Control and feeling states, plasticity and meta plasticity, with therapy

6 Validation of the Model by Parameter Tuning

In order to investigate the validity of the cognitive agent model, parameters have been tuned using data points for time points $t \in \{100, 200, 300, 400, 500, 600\}$, estimated from the empirical literature (Section 2) and the conclusions from a questionnaire by Hawi and Samaha (2017) about social media addiction and life satisfaction of university students; see Table 3. Since the wellbeing of a person and social media addiction have a negative connection, the pre-therapy values are estimated as a low positive belief state bs_+ value, no reappraisal strategy and low plasticity $\mathbf{W}_{fs_b,cs_{reapp}}$ for reappraisal. The incoming weights of these states have been tuned using the simulated annealing approach.

The lowest obtained RMSE value is around 0.02. This indicates that after parameter tuning, the final model coincides well with the considered data points. Fig. 6 visualizes the model values versus the data points. It can be noted that these values are reasonably close to each other, indicating a good model quality.

Table 3 Chosen data points for Parameter Tuning

time t	100	200	300	400	500	600
bs+	0.21	0.05	0.4	0.75	0.70	0.69
cs_{reapp}	0	0	0.5	0.4	0	0
$\mathbf{W}_{fs_b,cs_{reapp}}$	0.1	0.1	0.8	0.8	0.8	0.8

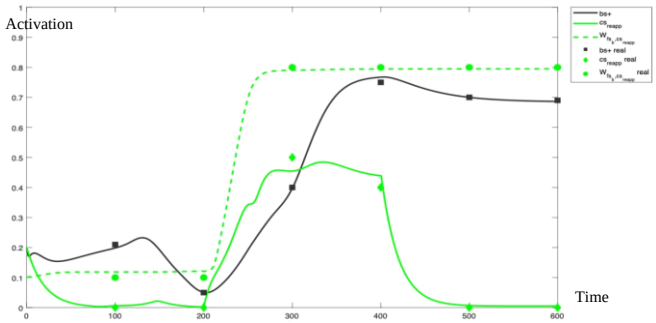

Figure 6: Comparison between the data points and model values after parameter tuning.

7 Verification by Equilibrium Analysis

To investigate whether the implemented agent model verifies the mathematical design specification, this section discusses mathematical equilibrium analysis. Given standard equation (1), a *stationary point* (i.e., where d*Y(t)*/d*t* = 0) is defined by $\boldsymbol{\eta}_Y = 0$ or the following criterion in terms of the other network characteristics:

$$\mathbf{aggimpact}_Y(t) = Y(t) \qquad (2)$$

where $\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y} X_1(t), \cdots, \boldsymbol{\omega}_{X_k,Y} X_k(t))$ (3)

and the incoming connections of Y are from states X_1 , …, X_k. The model is in *equilibrium* if all of its states Y are stationary, so if the equations (2) holds for all Y, which are called *equilibrium equations* then. Table 4 presents the verification results obtained by checking for an equilibrium observed in a simulation whether these equilibrium equations hold.

Table 4 Results of Equilibrium Analysis

state *Y*	**ws_s**	**ws_a**	**ss_s**	**ss_b**	**srs_s**
value of *Y*	1	$7.188*10^{-5}$	0.77204	0.01919	0.89449
$aggimpact_Y$	1	$7.082*10^{-5}$	0.77204	0.01919	0.89449
deviation	0	$-1.06*10^{-6}$	$3.3*10^{-7}$	$1.1*10^{-8}$	$3.2*10^{-8}$
state *Y*	**srs_b**	**bs+**	**bs-**	**ps_b**	**ps_a**
value of *Y*	0.019190	0.68474	0.16542	0.11850	$2.470*10^{-5}$
$aggimpact_Y$	0.019190	0.68474	0.16542	0.11850	$2.467*10^{-5}$
deviation	$-1.1*10^{-6}$	$7.3*10^{-8}$	$1.7*10^{-8}$	$1.6*10^{-8}$	$-3.6*10^{-8}$
state *Y*	**cs_{reapp}**	**cs_{supp}**	**cs_a**	**fs_b**	**es_a**
value of *Y*	$5.246*10^{-3}$	$5.774*10^{-3}$	$5.282*10^{-5}$	0.010328	$7.083*10^{-5}$
$aggimpact_Y$	$5.246*10^{-3}$	5.7735410^{-3}	$5.127*10^{-5}$	0.010328	$7.072*10^{-5}$
deviation	$2.8*10^{-8}$	$3.0*10^{-9}$	$-1.6*10^{-6}$	$1.3*10^{-9}$	$-1.0*10^{-7}$
state *Y*	**es_b**	**W_{fs_b,cs_a}**	**$W_{fs_b,cs_{supp}}$**	**$W_{fs_b,cs_{reapp}}$**	**T_{ps_a}**
value of *Y*	0.094798	$3.0924*10^{-3}$	$1.908*10^{-4}$	0.79725	0.56366
$aggimpact_Y$	0.094798	$2.474*10^{-3}$	$1.908*10^{-4}$	0.79725	0.56366
deviation	$6.4*10^{-9}$	$-6.2*10^{-4}$	$-9.2*10^{-10}$	1.6*10-6	$9.6*10^{-7}$
state *Y*	**HW_{fs_b,cs_a}**	**$HW_{fs_b,cs_{supp}}$**	**$HW_{fs_b,cs_{reapp}}$**		
value of *Y*	$7.356*10^{-3}$	0.046352	0.98857		
$aggimpact_Y$	$7.356*10^{-3}$	0.046352	0.98857		
deviation	$-7.0*10^{-7}$	$-1.2*10^{-8}$	$2.0*10^{-7}$		

The considered time point chosen to allow all states to become stationary is t = 2000. For significance level 0.001, it can be noted from the table that for each state, the difference between the left-hand side values and right-hand side values is small enough for the states to be considered stationary. Hence, the simulation results match well with the design specification.

8 Discussion

This paper studies the impact of social media addiction on a human's emotion regulation processes using a multi-level adaptive cognitive agent model. This agent model contains three emotion regulation processes: regulation by suppression, regulation by reappraisal, and regulation by avoidance. Two scenarios are reported, which address the conditions of with and without anti-depression therapy. From these scenarios it can be obtained that if therapy supports the reappraisal of negative emotions, both emotion suppression and avoidance can be reduced. Hence, therapy can be effective in reducing both depression and addiction.

This study proposes a second-order adaptive cognitive agent model, partly inspired by a simple example model described in Treur (2021) and by models for age and gender differences described in (Ullah et al., 2020; Ullah & Treur, 2020). The aim here was to simulate the process of emotion regulation in internet addicts and the impacts of stress and therapy in this process. This model clearly depicts the adaptive changes of the processes and impacts of different factors over time obtained from the literature on internet addiction. As indicated in that literature, individuals adopt addictive behaviours to avoid negative emotions. These behaviours relate to different forms of emotion regulation. The presented model can also be elaborated further for other types of addictions, where the person seeks out for avoidance in a negative emotional situation. Examples can be game addiction, gambling addiction or alcohol and drug abuse.

The impacts of social media on emotion regulation are complex, the mechanism behind this is still under further discussion. This paper addresses part of the literature. This shows the usefulness of human mental simulation, because it can analyse the considered mechanism. This adaptive agent model can be useful for psychologists to pick up early signals on avoidance behaviour, and treat the patient on time.

Appendix: Model Specification by Role Matrices

The **mb** matrix presents the connectivity between states, the **mcw** matrix shows respective connection weights, the **mcfw**, **mcfp** and **ms** matrix show how for aggregation combination functions are used and for timing speed factors. The Hebbian learning process can be seen from these matrices, the adaptivity of the mental network is represented by self-model states X_i for i = 18-21 (first-order **W**-states and **T**-state) and i = 22- 24 (second-order **H**-states). The role matrix specification of the entire network model can be found in Figure 7.

mb	base connectivity	1	2	3	4	5
X_1	ws_s	X_1				
X_2	ws_a	X_{16}				
X_3	ss_s	X_1	X_2			
X_4	ss_b	X_{17}				
X_5	srs_s	X_3				
X_6	srs_b	X_4	X_9			
X_7	bs+	X_5	X_8			
X_8	bs-	X_5	X_7	X_{11}		
X_9	ps_b	X_7	X_8	X_{12}	X_{14}	
X_{10}	ps_a	X_{13}				
X_{11}	cs_{reapp}	X_8	X_9	X_{12}	X_{14}	X_{15}
X_{12}	cs_{supp}	X_9	X_{11}	X_{14}		
X_{13}	cs_a	X_{14}				
X_{14}	fs_b	X_{12}	X_6			
X_{15}	tp	X_{15}				
X_{16}	es_a	X_{10}	X_{13}			
X_{17}	es_b	X_9				
X_{18}	W_{fs_b,cs_a}	X_{13}	X_{14}	X_{18}		
X_{19}	$W_{fs_b,cs_{supp}}$	X_{12}	X_{14}	X_{19}		
X_{20}	$W_{fs_b,cs_{reapp}}$	X_{11}	X_{14}	X_{20}		
X_{21}	T_{ps_a}	X_2	X_5			
X_{22}	HW_{fs_b,cs_a}	X_{13}	X_{14}	X_{18}	X_{22}	
X_{23}	$HW_{fs_b,cs_{supp}}$	X_{12}	X_{14}	X_{19}	X_{23}	
X_{24}	$HW_{fs_b,cs_{reapp}}$	X_{11}	X_{14}	X_{20}	X_{24}	

mcfw	combination function weights	1 alogistic	2 hebb	3 id	4 stepmod
X_1	ws_s			1	
X_2	ws_a			1	
X_3	ss_s	1			
X_4	ss_b			1	
X_5	srs_s	1			
X_6	srs_b	1			
X_7	bs+	1			
X_8	bs-	1			
X_9	ps_b	1			
X_{10}	ps_a	1			
X_{11}	cs_{reapp}	1			
X_{12}	cs_{supp}	1			
X_{13}	cs_a	1			
X_{14}	fs_b	1			
X_{15}	tp				1
X_{16}	es_a			1	
X_{17}	es_b			1	
X_{18}	W_{fs_b,cs_a}		1		
X_{19}	$W_{fs_b,cs_{supp}}$		1		
X_{20}	$W_{fs_b,cs_{reapp}}$		1		
X_{21}	T_{ps_a}	1			
X_{22}	HW_{fs_b,cs_a}	1			
X_{23}	$HW_{fs_b,cs_{supp}}$	1			
X_{24}	$HW_{fs_b,cs_{reapp}}$	1			

mcw	connection weights	1	2	3	4	5
X_1	ws_s	1				
X_2	ws_a	1				
X_3	ss_s	1	-0.35			
X_4	ss_b	0.9				
X_5	srs_s	1				
X_6	srs_b	1	1			
X_7	bs+	1	-0.94			
X_8	bs-	1	-0.93	-0.15		
X_9	ps_b	-0.05	1	-0.2	0.7	
X_{10}	ps_a	1				
X_{11}	cs_{reapp}	0.410	0.375	-0.742	X_{20}	0.919
X_{12}	cs_{supp}	1	-0.04	X_{19}		
X_{13}	cs_a	X_{19}				
X_{14}	fs_b	-0.1	0.8			
X_{15}	tp	1				
X_{16}	es_a	1	1			
X_{17}	es_b	0.8				
X_{18}	W_{fs_b,cs_a}	1	0.8	0.8		
X_{19}	$W_{fs_b,cs_{supp}}$	0.8	0.8	0.8		
X_{20}	$W_{fs_b,cs_{reapp}}$	0.36	0.402	1		
X_{21}	T_{ps_a}	-0.45	1			
X_{22}	HW_{fs_b,cs_a}	0.5	1	0.1	0.6	
X_{23}	$HW_{fs_b,cs_{supp}}$	0.5	1	0.1	0.5	
X_{24}	$HW_{fs_b,cs_{reapp}}$	0.5	0.6	0.5	1	

mcfp	combination function parameters	1 alogistic σ	1 alogistic τ	2 hebb μ	3 id	4 stepmod ρ	4 stepmod δ
X_1	ws_s						
X_2	ws_a						
X_3	ss_s	5	0.75				
X_4	ss_b						
X_5	srs_s	5	0.3				
X_6	srs_b	6	0.8				
X_7	bs+	4	0.5				
X_8	bs-	5	0.5				
X_9	ps_b	2	0.15				
X_{10}	ps_a	3	X_{21}				
X_{11}	cs_{reapp}	5	1				
X_{12}	cs_{supp}	8	0.7				
X_{13}	cs_a	4	0.1				
X_{14}	fs_b	8	0.3				
X_{15}	tp					400	200
X_{16}	es_a	5	0.3				
X_{17}	es_b						
X_{18}	W_{fs_b,cs_a}			1			
X_{19}	$W_{fs_b,cs_{supp}}$			1			
X_{20}	$W_{fs_b,cs_{reapp}}$			1			
X_{21}	T_{ps_a}	6	0.85				
X_{22}	HW_{fs_b,cs_a}	4	0.5				
X_{23}	$HW_{fs_b,cs_{supp}}$	4	0.2				
X_{24}	$HW_{fs_b,cs_{reapp}}$	10	0.95				

	X_1 ws_s	X_2 ws_a	X_3 ss_s	X_4 ss_b	X_5 srs_s	X_6 srs_b	X_7 bs+	X_8 bs-	X_9 ps_b	X_{10} ps_a	X_{11} cs_{reapp}	X_{12} cs_{supp}	X_{13} cs_a	X_{14} fs_b	X_{15} tp	X_{16} es_a	X_{17} es_b	X_{18} W_{fs_b,cs_a}	X_{19} $W_{fs_b,cs_{supp}}$	X_{20} $W_{fs_b,cs_{reapp}}$	X_{21} T_{ps_a}	X_{22} HW_{fs_b,cs_a}	X_{23} $HW_{fs_b,cs_{supp}}$	X_{24} $HW_{fs_b,cs_{reapp}}$
ms	0	0.1	0.1	0.1	0.5	0.2	0.1	0.5	0.5	1	0.05	0.2	0.05	1	2	1	1	X_{22}	X_{23}	X_{24}	0.1	0.5	0.5	0.5
iv	1	0.4	0.5	0.4	0.5	0.4	0.2	0.7	0.6	0.5	0.2	0.6	0.6	0.6	0	0.5	0.5	0.4	0.4	0.1	0.2	0.2	0.4	0.1

Figure 7: Role matrix specification of the network model.

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