# Too Overloaded to Use: An Adaptive Network Model of Information Overload During Smartphone App Usage

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**Abstract.** In this paper, a first-order adaptive self-modeling network model is introduced to model information overload in the context of cyclical usage of smartphone apps. The model consists of interacting attention resources and emotional responses to both attention taxation and the app engagements. The model makes use of first-order reification to simulate the agent's learning of the connections between app engagement and emotional responses, and strategic use of attention resources. Furthermore, external factors, such as context and influence of the environment to use the apps, are included to model the usage decision of the agent. Simulations in two scenarios illustrate that the model captures expected dynamics of the phenomenon.

**Keywords:** Adaptive Network Model · Information Overload · App Usage

## 1 Introduction

Information overload is often referred to as a major source of distress in contemporary world by both public media and in the academic literature (Arnold et al. 2023; Rutkowski and Saunders 2018; Stephens 2018). However, the models of the phenomenon tend to be either descriptive or statistical (e.g., Graf and Antoni 2023; Rutkowski and Saunders 2018) with a lack of computational formalism. Meanwhile, smartphone apps are used to facilitate travel, education, entertainment, and more. A study found that a normal person has around 40 apps installed on their phone, while average person only uses 18 of those apps for 89% of the time (Kataria 2021). Information overload caused by excessive information supply through apps can lead to users experiencing stress and ultimately for them to stop using the apps (Pang and Ruan 2023; Ye et al. 2023). Since smartphone apps are a major channel of receiving information in everyday life, it is important to understand its psychological effect on the average person, that is, the information overload they cause.


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In this paper, a computational model of information overload while interacting with multiple smartphone apps is proposed. An adaptive network model was designed that makes use of first-order learning, which is linked to emotional responses and attention capacity in relation to the app usage. The usage of the apps reflects how much they capture users' attention resources and arouses their emotional valence. Meanwhile, the emotional responses and the available attentional resources determines the user's decision to continue using the app. Model also incorporates effects of the environmental influences to use the apps, such as notifications, and the contextual factor which levels the attention and emotions.

By simulating different scenarios, the model illustrated expected dynamics of attention, emotions, and behavior as described in the literature on information overload (Graf and Antoni 2023; Rutkowski and Saunders, 2018). In the scenarios, user engagement with the apps initially arouses positive emotions in the user, but once the overuse of multiple attention taxes the attention capacities, the emotional responses turn negative. Furthermore, the cognitive and emotional dynamics result in user disengagement with the apps, as is expected.

## 2 Background

In this section, we present background of the phenomenon and propose a research question. Information overload refers to "a state of being overwhelmed by information, where one perceives that information demands exceed one's information processing capacity" (Graf and Antoni 2023, 2). Outcomes of information overload include stress, fatigue, poor task performance, and information avoidance (Graf and Antoni 2023). Information overload has been studied extensively, and causes, such as work environment and communication channel richness, and interventions, such as emotional coping training, have been proposed (Arnold et al. 2023). Information overload is often theorized in terms of limitations in human cognitive processing capacities, that is, the limitations of working memory or attention. However, many qualitative attempts to theorize information overload include descriptions of both cognitive and emotional processes and outcomes (Belabbes et al. 2023; Graf and Antoni 2023; Pang and Ruan 2023; Rutkowski and Saunders 2018).

Emotional-Cognitive Overload Model (Rutkowski and Saunders 2018) presents the building blocks of the model for information overload. ECOM includes information and the request to use information technology as the inputs of the model, cognitive processing – which consists of short-term memory chunking and long-term memories of past emotional-cognitive overload experiences – as the mental process, and cognitive overload (e.g., leaving part of the task undone, poorer decisions, shedding tasks) and emotional overload (e.g., stress, frustration) as the outcomes. Prior computational model of information overload (Gunaratne et al. 2020) considers only the attention limitations as the process of the information overload. The approach presented in this paper seeks to integrate the cognitive and emotional aspects to model information overload.

## 3 Network-Oriented Modeling

The network model presented in this paper adopts the network-oriented modeling approach. In this section, a brief introduction to network-oriented modeling approach is given. Generally, in this approach, network model is represented with a graph where nodes represent states of the modeled phenomenon, and the dynamics of the state changes are modeled by designating directed links between nodes with assistance of link weights, functions that map the values from sending nodes to receiving node, and speed factors, which determine how fast the sending nodes influence the state of the receiving node. More formally, temporal-causal network architecture is defined by the following characteristics (Treur 2020):

- ***Connectivity of the network***

 A connection weight $\boldsymbol{\omega}_{X,Y}$ for each connection from state (or node) $X$ to state $Y$.

- ***Aggregation of the multiple connections in the network***

 A combination function $\mathbf{c}_Y(..)$ for each state $Y$ determining the aggregation of incoming impacts from other connected states.

- ***Timing in the network***

 A speed factor $\boldsymbol{\eta}_Y$ for each state $Y$ determining the speed of change from incoming impacts.

The model dynamics can be simulated with execution of following difference equation to each state $Y$ on each timestep $\Delta t$:

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

This generic difference equation based on the above characteristics has been implemented in MATLAB software (see Treur 2020, Ch. 9). Based on this, simulations are run by declaring the network characteristics of the model in the software and the software procedurally executes the difference equation for all states in parallel. The model is defined using role matrices which designate each specification of the network characteristics $\boldsymbol{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, and $\boldsymbol{\eta}_Y$ for each of the states in the network in a standard table format. The role matrices specified for the model presented in this paper can be found from the Appendix A (available as Linked Data at https://www.researchgate.net/publication/373490260).

The combination functions used in network-oriented modeling and implemented in the software are called basic combination functions. For any model, any number $m$ of them can be selected for the model design. The standard notation for them is $\mathrm{bcf}_1(..)$, $\mathrm{bcf}_2(..)$, …, $\mathrm{bcf}_m(..)$. The basic combination functions use parameters $\boldsymbol{\pi}_{1,i,Y}$, $\boldsymbol{\pi}_{2,i,Y}$, such as $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$, $\boldsymbol{\tau}$ in the basic combination functions, which further define the combination function characteristics. The basic combination functions used in the current model and their parameters are presented in Table 1. Using this notation, the combination function can be written as follows:

$$\mathbf{c}_Y\left(t, \boldsymbol{\pi}_{1,1}(t), \boldsymbol{\pi}_{2,1}(t), \ldots, \boldsymbol{\pi}_{1,m}(t), \boldsymbol{\pi}_{2,m}(t), V_1, \ldots, V_k\right) = \frac{\boldsymbol{\gamma}_{1,Y}(t)\mathrm{bcf}_1\left(\boldsymbol{\pi}_{1,1,Y}(t), \boldsymbol{\pi}_{2,1,Y}(t), V_1, \ldots, V_k\right) + \ldots + \boldsymbol{\gamma}_{m,Y}(t)\mathrm{bcf}_m\left(\boldsymbol{\pi}_{1,m,Y}(t), \boldsymbol{\pi}_{2,m,Y}(t), V_1, \ldots, V_k\right)}{\boldsymbol{\gamma}_{1,Y}(t) + \ldots + \boldsymbol{\gamma}_{m,Y}(t)} \tag{2}$$

Substituting the combination function into the above defined Eq. (1) gives the formula:

$$Y(t+\Delta t) = Y(t) + \mathbf{\eta}_Y(t)\left[\frac{\mathbf{\gamma}_{1,Y}(t)\mathrm{bcf}_1(\mathbf{\pi}_{1,1,Y}(t), \mathbf{\pi}_{2,1,Y}(t), V_1, \ldots, V_k) + \cdots + \mathbf{\gamma}_{m,Y}(t)\mathrm{bcf}_m(\mathbf{\pi}_{1,m,Y}(t), \mathbf{\pi}_{2,m,Y}(t), V_1, \ldots, V_k)}{\mathbf{\gamma}_{1,Y}(t) + \cdots + \mathbf{\gamma}_{m,Y}(t)} - Y(t)\right]\Delta t \tag{3}$$

The above characteristics form the base-level architecture for the network model. However, many phenomena in the world are adaptive. To incorporate the adaptive characteristics into the network model, the principle of reification of the network model (also called self-modeling) is introduced. The adaptive characteristics are added to the model in a form of *self-model states*. In the case of the first-order adaptive network, the self-model states include states that represent the network characteristics $\mathbf{\omega}_{X,Y}$, $\mathbf{c}_Y(..)$, and $\mathbf{\eta}_Y$ of the base-level network. For example, the model presented in this paper makes use of self-model states $\mathbf{W}_{X,Y}$, which represents adaptive weight $\mathbf{\omega}_{X,Y}$ of connection from state $X$ to state $Y$ aggregated by Hebbian learning function, and $\mathbf{T}_Y$, which represents the basic combination function excitability threshold $\mathbf{\tau}_Y$. The reification level is visualized in Fig. 1. Similarly, all of the network characteristics can be reified: $\mathbf{H}_Y$ (self-model state of speed factor $\mathbf{\eta}_Y$), $\mathbf{W}_{X,Y}$ (self-model state for the connection weight), $\mathbf{C}_{i,Y}$ (self-model state of the combination function weight), and $\mathbf{P}_{i,j,Y}$ (self-model state for basic

**Table 1.** The combination functions used in the network model.

| | Notation | Formula | Parameters |
|---|---|---|---|
| Advanced logistic sum | $\mathbf{alogistic}_{\sigma,\tau}(V_1,\ldots, V_k)$ | $[\frac{1}{1+e^{-\sigma(V_1+\ldots+V_k-\tau)}} - \frac{1}{1+e^{\sigma\tau}}](1 + e^{-\sigma\tau})$ | Steepness $\sigma > 0$, Excitability threshold $\tau$ |
| Hebbian Learning | $\mathbf{hebb}_{\mu}(V_1, V_2, V_3)$ | $V_1\, V_2\,(1 - V_3) + \mu V_3$ | $V_1$, $V_2$ activation levels of connected states; $V_3$ activation level of first-order self-model state representing the connection weight, Persistence factor $\mu$ |
| Identity function | $\mathbf{id}(V)$ | $V$ | Activation level of state $V$ |
| Random step function | $\mathbf{randstep\text{-}mod}_{\alpha,\beta}(..)$ | 0 if mod($t$, $\alpha$) < $\beta$, else $\frac{1}{2} + \frac{rand(1,1)}{2}$; rand() function returns a random draw from uniform distribution | Time $t$ Repeated time duration $\alpha$, Duration $\beta$ until value 1, |

combination function parameters) are the standard notations of the reification states for the adaptive characteristics of the network.

Replacing now the network characteristics in (3) with the corresponding self-model state values gives the following:

$$Y(t+\Delta t) = Y(t) + \mathbf{H}_Y(t)\left[\frac{\mathbf{C}_{1,Y}(t)\mathrm{bcf}_1(\mathbf{P}_{1,1,Y}(t), \mathbf{P}_{2,1,Y}(t), \mathbf{W}_{X_1,Y}(t)X_1(t), \ldots, \mathbf{W}_{X_k,Y}(t)X_k(t)) + \cdots + \mathbf{C}_{m,Y}(t)bcf_m(\mathbf{P}_{1,m,Y}(t), \mathbf{P}_{2,m,Y}(t), \mathbf{W}_{X_1,Y}(t)X_1(t), \ldots, \mathbf{W}_{X_k,Y}(t)X_k(t)))}{\mathbf{C}_{1,Y}(t) + \cdots + \mathbf{C}_{m,Y}(t)} - Y(t)\right]\Delta t \quad (4)$$

The self-model states change based on the three network cracteristics that were presented above, and by self-model state values changing they alter the behavior of the base-level network. The reification can be applied to implement reifications of multiple order (first-order, second-order, third-order, …) as has been shown in Treur (2020, Ch. 8). However, these are out of the scope for the current model.

## 4 Adaptive Network Model of Information Overload

In this section, the model design is presented. The goal of the model was to simulate how cognitive limitations and emotional responses together interact to generate effects of the information overload (Rutkowski and Sanders 2018), that is, stress, information avoidance, and disengagement from the apps (Graf and Antoni 2023; Pang and Ruan 2023). In the context of app usage, we interpreted this to be exemplified in continuous negative emotions and disengagement with the apps that otherwise would be enjoyable to the user. Next, the architecture of the network model is described. The nodes of the model are listed and explained in Table 2, and the full architecture is illustrated in Fig. 1. Unless specified differently, all the nodes described below use advanced logistic function as the combination function. Detailed specification of the role matrices is presented in the Appendix A.

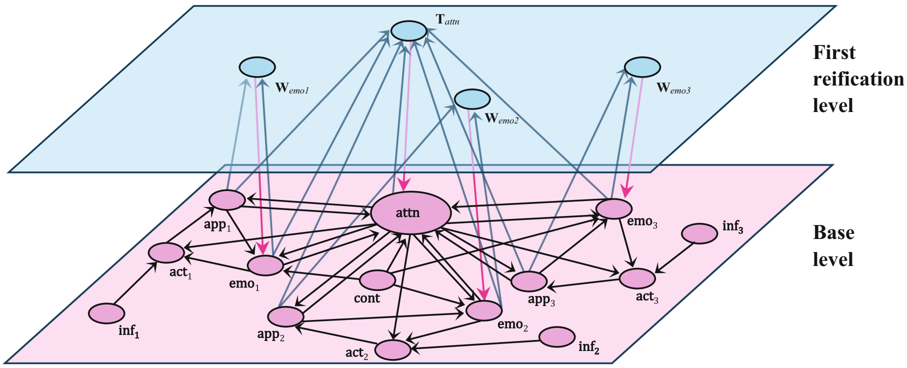


**Fig. 1.** Architecture of the adaptive network model

First, the user needs to have a source of information that they attend to. In the model, three apps were implemented to account for the effect of different numbers of information sources. In the model, *app nodes* represent the engagement with the app by the user, and ranges from 0 to 1 indicating none to full engagement. Although the current includes three app nodes, the model could be updated by implementing different number of app nodes.

Second, engaging with any object requires the user to attend to it. This requirement is facilitated by the *attention node*, whose values range from 0 to 1. A value of 0 indicates that the user has the most attention available to divert to their app usage, whilst 1 means that the user has no attention left to use the smartphone apps. The attention node is the crux of the entire model, for it dictates how invested the user can be. The attention node is connected to the app engagement negatively since they divide the attentional resources.

To simulate a natural form of replenishment and longevity of a user's attention, a *context node* was also added. The context node represents the specific situation in which the user is attending to the apps, and thus changing context restores the attention by attention re-allocation. The same applies to emotions since context also facilitates how the emotions change. Thus, the context node is connected to the attention node as well as the emotion nodes. The model treats context as a constant, and thus the identity function was used as its combination function.

**Table 2.** Explanations of the nodes of the network model

| | State | Explanation | Level |
|---|---|---|---|
| $X_1$ | $app_1$ | Agent's engagement with application 1 | Base level |
| $X_2$ | $app_2$ | Agent's engagement with application 2 | |
| $X_3$ | $app_3$ | Agent's engagement with application 3 | |
| $X_4$ | attn | Agent's attention capacity | |
| $X_5$ | $emo_1$ | Agent's emotional response to application 1 | |
| $X_6$ | $emo_2$ | Agent's emotional response to application 2 | |
| $X_7$ | $emo_3$ | Agent's emotional response to application 3 | |
| $X_8$ | $act_1$ | Agent's decision to use application 1 | |
| $X_9$ | $act_2$ | Agent's decision to use application 2 | |
| $X_{10}$ | $act_3$ | Agent's decision to use application 3 | |
| $X_{11}$ | cont | Context influence on the agent | |
| $X_{12}$ | $inf_1$ | Influence from the environment to use application 1 | |
| $X_{13}$ | $inf_2$ | Influence from the environment to use application 2 | |
| $X_{14}$ | $inf_3$ | Influence from the environment to use application 3 | |
| $X_{15}$ | $\mathbf{W}_{emo1}$ | Weight self-model state for connection from $app_1$ to $emo_1$ | First reification level |
| $X_{16}$ | $\mathbf{W}_{emo2}$ | Weight self-model state for connection from $app_2$ to $emo_2$ | |
| $X_{17}$ | $\mathbf{W}_{emo3}$ | Weight self-model state for connection from $app_3$ to $emo_3$ | |
| $X_{18}$ | $\mathbf{T}_{attn}$ | Excitability of attn threshold parameter | |

The *emotion nodes* represent the emotional valence that the app nodes cause on the user. The user's emotions drive their interest in their smartphone app usage. This can be seen as the user's (dis)enjoyment of the app. A value of 1 would indicate that the app evokes very positive emotions for the user, whilst a value of 0 would indicate that the app evokes very negative emotions for the user; 0.5 means neutral emotional response. Furthermore, since information overload is hypothesized to be caused by the over taxation of the cognitive resources, the attention node has a high impact on the emotion nodes, meaning that the more the attention is taxed, the more negative emotions the user will have.

The *action node* represents the user's decision to use the app. The purpose of the action node is to regulate the respective app node. Higher the decision to use the app, the more the user will engage with it. The action nodes are influenced by the attention nodes, the emotion nodes, and the influence nodes. Thus, the decision to use the app is a combination of the user's positive emotion toward the app, the availability of the attentional resources, and the strength of the environment's influence to use the apps.

The *influence node* dictates the environment's role in using the app. There are many types of influences that the environment can pose on individuals to use some apps. These include notifications, work context, social influence, and peer pressure, or context-dependent need. The influence node represents the total sum of environment-based influences to the user ranging from 0 to 1. For the influence nodes, random step mod function was used that simulates the effects of stochastic activation of the influence. Practically, it means that environment acts on the individual in periods of time while being inactive else and the activation level of the influence is stochastically determined.

The adaptive elements of the network are rooted in the $\mathbf{W}_{\text{em}}$ nodes and $\boldsymbol{\tau}_{\text{attention}}$. State $\mathbf{W}_{\text{em}}$ is a first-order adaptive weight self-model state which dictates the strength of the connection between the app and emotion nodes by applying Hebbian learning. The more that an app is used, the greater the connection between the app engagement and the emotion that is evoked from the app, thus there is a greater impetus for the user to use the app in the case where the emotion evoked is positive. The state $\boldsymbol{\tau}_{\text{attention}}$ is used to represent the attention node's ability to increase its capacity for using multiple apps. While the threshold of the attention function adapts through repeated usage, the attention is taxed less in relation to the app usage. As apps are being used more and more, the user can distribute their attention more easily between apps without becoming overloaded by app overuse.

## 5 Simulation Results

Two simulated scenarios are presented to illustrate how the model works. In scenario one, only one smartphone app is active and interacting with the user. In the second scenario, three parallel apps are active and interacting with the user in parallel illustrating a common situation where the user needs to allocate their attention between multiple apps. For more simulations that illustrate the model behavior in different scenarios, see Appendix B.

In both scenarios it is assumed that the apps the user engages with influence the positive emotions in the user, that is, the user likes the apps. It is also assumed that initially the user has neutral emotional relation to the apps ($\mathbf{Em}_{1\text{–}3} = 0.5$), and that each app is equally engaging, equally emotion provoking, and equally attention taxing, that is, the weight of the connections in the network are equal for the three apps. These parameters are defined in more detail in Appendix A.

***Scenario 1: One application active.***

The Figs. 2 and 3 present the simulation results of the scenario one with different time frames. Figure 2 shows how in the beginning (0–5 $t$) the user starts by using the app (**Act**$_1$; blue dash-dotted line). Next (5–10 *t*) the user engagement with the app (**App**$_1$; blue solid line) gives rise to the positive emotions (**Em**$_1$; blue dashed line), while engaging with the app taxes the user's attention (**Attention**; purple line). Furthermore, there is an outside influence to use the app (**Inf**$_{app1}$; dotted line) which strengthens the user's next decision to use the app. After a while (10–15 *t*) the user disengages with the app (**App**$_1$), which results in attention resources recovering slightly (**Attention**). What follows is a series of engaging and disengaging with the app each followed by taxing and recovering of the attention resources.

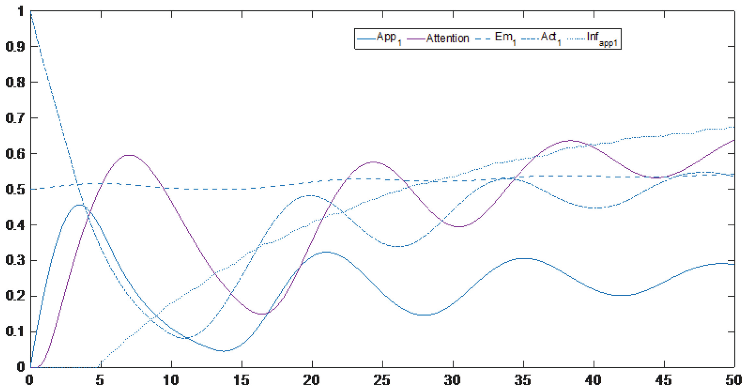


**Fig. 2.** Base level states of simulation of scenario one (50 time steps)

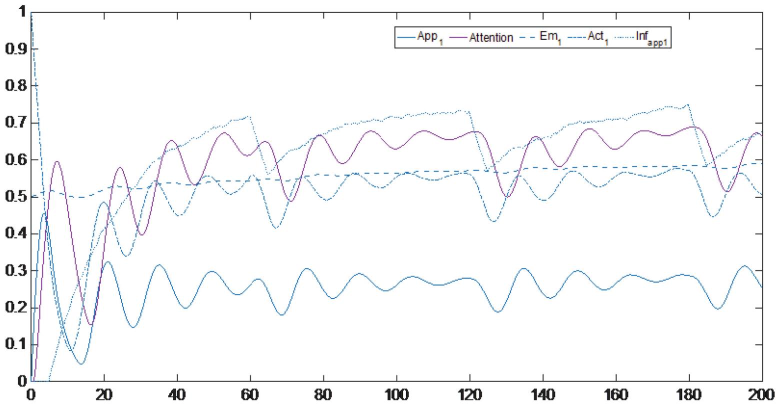


**Fig. 3.** Base level states of simulation of scenario one (200 time steps)

Figure 3 shows the results of the same simulation with a longer time frame. Figure 3 shows the same dynamical behavior as Fig. 2 but what is easier to perceive here is the influence from the environment (**Inf**$_{app1}$; dotted line). Within each 60 time step interval

(60 $t$, 120 $t$, 180 $t$, …), the influence gradually increases and then drops which results in users disengaging from the app (**App**$_1$) slightly more. What is also visible from the figure is the general trend of the emotional response (**Em**$_1$) losing the positive valence and converging to the neutral zone (**Em**$_1 \approx 0.5$).

***Scenario 2: Three applications active.***

Figures 4 and 5 present simulation results from scenario two with the similar time frames to the previous section. As Fig. 4 shows, in the beginning (0–5 $t$) user starts to use the apps (**Act**$_{1\text{–}3}$; blue, red, and yellow dash-dotted lines). After this (5–10 $t$), the user engages with the apps (**App**$_{1\text{–}3}$; blue, red, and yellow solid lines) which is followed by the combined positive emotional response (**Em**$_{1\text{–}3}$; blue, red, and yellow dashed lines). Furthermore, there are influences from the environment to use the three apps to which the user's decision to use the apps increases (**Inf**$_{\mathbf{app}1\text{–}3}$; blue, red, and yellow dotted lines). The app engagements (**App**$_{1\text{–}3}$) are followed by the proportional attention taxation (10–15 $t$; **Attention**, purple line). As there are more apps than in scenario one, the attention taxation (**Attention**) is significantly higher which leads to stronger disengagement (**App**$_{1\text{–}3}$) and negative emotional response (15–25 $t$; **Em**$_{1\text{–}3}$).

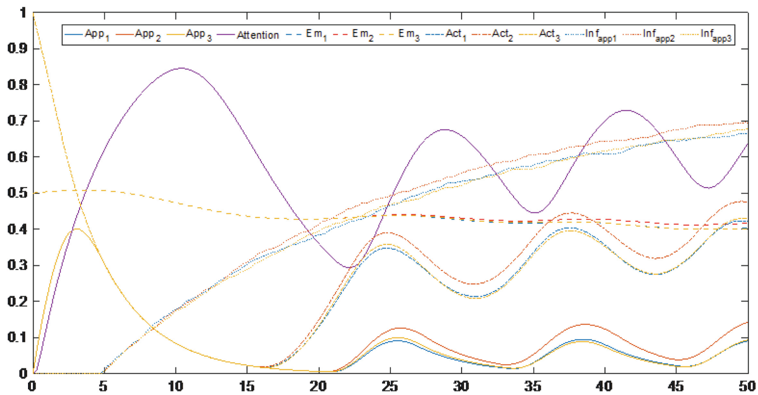


**Fig. 4.** Base level states of simulation of the scenario two (50 time steps)

What is shown in Fig. 5 is the results of the same simulation in a longer time frame. The figure shows that when the user engages with three apps (**App**$_{1\text{–}3}$), the constant attention taxation (**Attention**) is higher than in the single app case. The emotion lowering is also steeper, and the overall outcome is that the emotions converge towards negative emotions (**Em**$_{1\text{–}3} < 0.5$).

***Excitability of the attention.***

Another feature of the model that is not visible in the sub-1000 time frame is the effect of the excitability of the attention node. Figures 6 to 8 shows how the excitability changes the behavior of the model in a long time frame in scenario two. The rise of the excitability factor ($\boldsymbol{\tau}_{\text{attention}}$; black dashed line) during the 1000 first time steps gradually increases the threshold of the advanced logistic function of the attention node (**Attention**; purple line) which can be seen in Fig. 6.

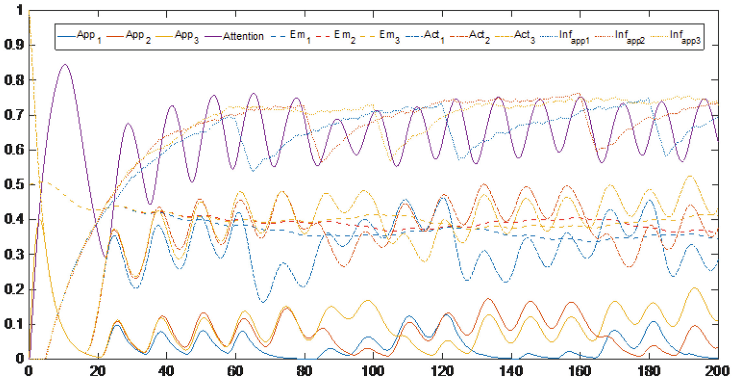


**Fig. 5.** Base level states of simulation of the scenario two (200 time steps)

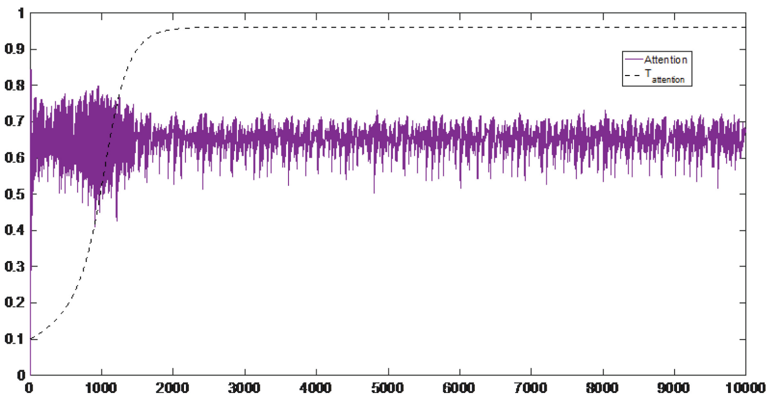


**Fig. 6.** Activation levels of the attention node in simulation of the scenario two (10 000 time steps).

Meanwhile, rise of excitability factor ($\boldsymbol{\tau}_{\text{attention}}$) results in major change in the emotional responses ($\mathbf{Em}_{1-3}$; blue, red, and yellow dashed lines) which is visible in Fig. 7.

Figure 8 shows that as the excitability factor and emotion connection weights are increased ($\mathbf{W}_{\text{app-em}}$; purple, pink, and green solid lines), the attention reacts less to the engagement with the apps and engaging with the apps evokes more positive emotions, which in turn leads to more engagement with the apps ($\mathbf{App}_{1-3}$; blue, red, and yellow solid lines). Increased threshold shows how learning attention results in increase of the available attention resources and less negative emotions due to attention limits not being constantly exceeded. In fact, after the 1000 time steps the model exhibits constant positive emotions again related to the app usage.

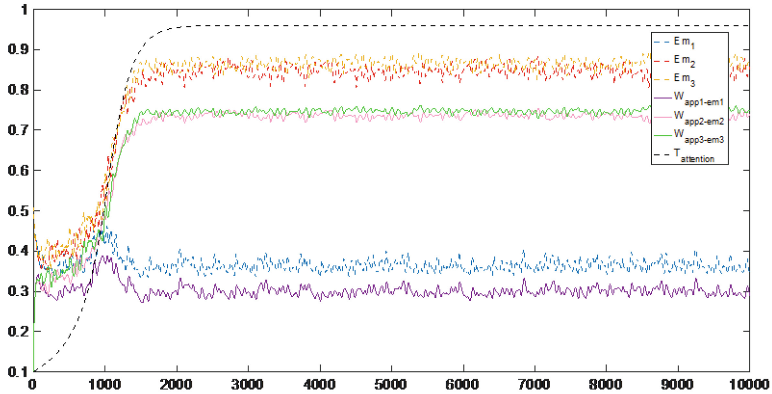


**Fig. 7.** Activation levels of the emotion nodes and the reification level nodes in simulation of the scenario two (10 000 time steps).

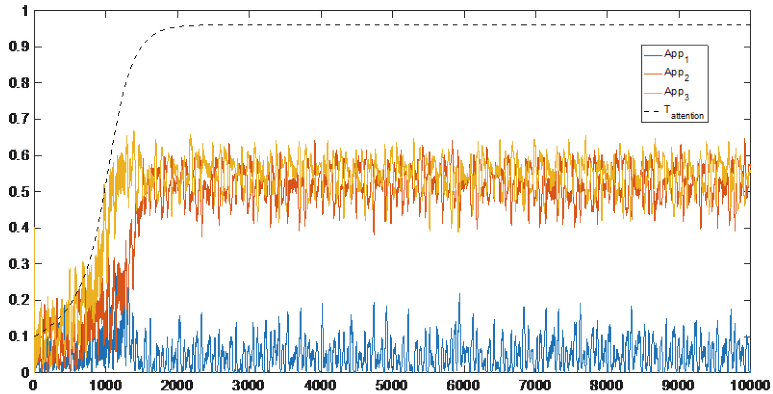


**Fig. 8.** App engagement and excitability factor dynamics in simulation of the scenario two (10 000 time steps).

## 6 Discussion

In the literature, information overload is often defined as a state in which an individual cannot process all the information available in the situation due to cognitive limits of information processing capacity, which leads to negative emotional reaction and poorer performance (Graf and Antoni 2023; Rutkowski and Saunders 2018). The proposed model formalizes the key components of the individual information overload as a process where attention limitations and emotional responses interact to produce engaging and disengaging behavior related to the information sources, for instance, smartphone apps. As smartphones are ubiquitous in modern society and one of the main sources of information for individuals, the presented model exhibits one realistic case of information overload.

The results of the simulation scenarios seem to demonstrate that the proposed model captures the key dynamics of the information overload in the case of using several smartphone apps. Both scenarios simulate similar behavior where the user seeks to disengage with the apps when the emotions start to become negative due to the taxation on attention resources. In the situations where the taxation of attention resources starts to reach the bearable limit (**Attention** $\approx 0.8$) in the model, the positive emotions elicited by the engagement with the apps are not enough to keep the user's emotional level positive but rather leads to negative emotions and stronger likelihood of disengagement.

The model also suggests that information overload can in this limited case be overcome with learning. As the simulation with 10 000 time steps shows, the first-order adaptive excitability of the attention node's function threshold affects how the attention-emotion dynamics can be altered. As the threshold increases, the maximum attention taxation is lowered to level of 0.7 and the fluctuation of the attention is dampened. The natural interpretation of this effect is that as the user adapts to use three apps in parallel, the attention resources are used more and more strategically leading to less over taxation. This effect is well-known in psychology as the role of expertise in attention allocation and better chunking abilities (Pulido 2021).

For the future work, the parameters of the model could be adjusted to simulate different types of scenarios. For example, if the apps would have different levels of engaging features (i.e., some engage users more than the others), this could be modeled by adjusting the connection weights, function parameters, and the speed factors related to the engagement nodes. As an example, one can think of engaging features of short-form video apps and contrast them with the ones of a calculator. By adjusting the connection weights between the app engagement and the attention capacity, one can model performance in situations where the apps have different levels of attention requirements (e.g., intense gaming apps vs. photo gallery). Furthermore, the model parameters can be fitted to account for individual differences and different environmental situations. By adding app nodes, the model can be simulated in the situation where the number of apps varies. By adjusting the first-order reification level components, one can simulate different individual characteristics such as emotional sensitivity (i.e., $\mathbf{W}_{\mathrm{em}}$ states) or expertise (i.e., $\boldsymbol{\tau}_{\mathrm{attention}}$ parameter). In the future, the model can be improved by including further details from the ever-growing body of literature on human cognition. Some further examples of specifications and simulation results are presented in the Appendix available as Linked Data at https://www.researchgate.net/publication/373490260.

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