**ORIGINAL ARTICLE**

# Knowing When to Support: A Human-Aware Agent Model in a Psychological Domain

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## ABSTRACT

*The human mind is undoubtedly one of the most complicated entities in this world. The collection of processes that are performed by the human mind is indicated by cognition. Much progress has been made to allow scientists to understand this fundamental concept of mind. Formal analysis is one of the methods to unravel the mechanisms of mind. This is in line with the aim of cognitive modellers in their quest to explain the structures and the processes of the mind by building them. In this article, the foundations to develop a cognitive computational model will be discussed and a case study (model in anxiety state and traits) is presented as a basis to visualize those concepts (foundations). A number of well-known relations between events and the course of anxiety are summarized from the literature and it is shown that the model exhibits those patterns. In addition, the formal model has been mathematically analysed to find out which stable situations exist. Finally, it is pointed out how this model can be used in virtual simulation environment, supported by a software agent.*

***Keywords:*** *computational psychology, cognitive modeling, human functioning model, human-agent model*

## INTRODUCTION

As intelligent support technologies take on an increasing role in health care (especially in mental care fields), they must be able to understand a human's functioning process (e.g., psychological state), and provide actions appropriate to the estimated condition of the person. The emerging fields of ambient agents, computational modelling, and cognitive theories have recently reached the point where such models can be designed and studied to see the effects of support for individuals with cognitive disorders by the means of computational models. This raises an important question of how to design such technologies that are able to support cognitive related disorders[1].

The aim of this article is to present the basis of a computational cognitive modeling approach that complements the existing techniques to understand cognitive behaviours and its interplay between related concepts. This computational model is expected to have capabilities to understand its environment and the individual, providing a better monitoring and assessment of the situation. This article is structured as follows. After an introduction of the area of cognitive modeling, first the methodology and follow by modeling approaches are described in some detail. Next, the evaluation process is described. A case study in anxiety states model is used to describe the implementation of the cognitive modeling development process. Finally, a discussion concludes this article.

## COGNITIVE MODELING

### *Concepts and Techniques*

Research in psychology and cognitive science seeks to understand and explain the theoretical frameworks and processes of thought, emotion and behaviour. Most of these processes are very difficult to understand solely based on behavioural observations, especially when the underlying grounding theory of the observed conditions is not fully comprehended[1]. In addition, given the complexity of the human mind, and its effect in behavioural flexibility, it leaves a restricted option that only computational modelling can illustrate the process and its interactions. Moreover, computational modelling can go deeper in terms of level of process details and granularity of input-outputs interactions, which are essentially useful to explain the level of cognitive functions[2,3]. Basically, cognitive modeling refers to computational processes implemented into cognitive functions, and thereby it produces executable computational models. Detailed simulations are then conducted based on the computational models.

### *Why Bother to Model?*

Often, computational model provides a means of risk-free exploration in complex, critical, costly, time-consuming, or rare situations. A constructed computational model is capable of simulating certain key behaviours in the selected domain of interest. For example, in a neuroscience domain, theoretical neuroscientists use computational modelling to help explain and understand the mechanisms of cognition. This means developing explicit mathematical models of the processes that go on in the brain when humans perceive, act, learn, think or remember certain tasks. Despite the development of powerful brain imaging machines and software that allow scientists to investigate into greater details of our brain activities, these technologies still fall short to explain the detailed interaction between all of those activities involved. Thus, such use of computational models is regarded as a tool for internal and external investigation of cognition within brain activities.

Another important point is “Hawthorne Effect” may affect the experimental results. It is common that when people feel they are being observed, they will modify their behaviours[4]. Therefore, it may be very difficult to preserve the same condition for each different setting of the experiment. Scientific understanding also drives the use of computational models. For instance, if a computational model embodies a hypothesis about an observed system then it will allow scientists to simulate several conditions to see the possibilities of considering the pre-defined hypothesis[5,6]. In other words, if a hypothesis fails a test, it can be rejected without taking trouble to do more of the unnecessary experiments. The size of experiments and curse of dimensionality also play central roles why scientists choose to develop computational models. When the experiments of an observed system are infeasible, computational models can be designed using the processes studied by smaller sized experiments and then used to derive the large-sized effects[8,9]. From a number of perspectives explained above, it can be suggested that computational models are a good alternative when real world experiments are not practically feasible to be conducted

## METHODOLOGY

The methodology that has been used to explore human cognitive and physiological processes in cognitive related domains and to apply of such models within intelligent support systems (agents, robotics) encompasses a set of central elements. These central elements include:

1. **Identification of local dynamic properties**. It is essential to capture the underlying mechanisms of the process under study (normally in informal representations) based on expert discussions, literature review or empirical evidence.
2. **Formalization of these local properties**. In this phase, formal models are formulated on the basis of the underlying mechanisms obtained during the first phase. These formal models are intended to be in terms of executable dynamics properties to create executable models of the dynamic of the process.
3. **Simulation**.
   The formal models are then simulated in order to generate simulation traces. In addition, it provides an insight in the sequence of events over time in specific instances of the process. During this phase, the model was simulated using selected programming languages (*C++, Python, Java, Matlab*) and tools (*Leadsto, Repast, NetLogo, Temporal Trace Language*).
4. **Identification of relevant non-local dynamic properties**.
   This phase aims to describe the process from an external observable perspective instead of its cognitive states. These non-local dynamic properties are expected to hold (or not to hold) for the process under investigation.
5. **Formalization of these non-local dynamic properties**.
   These non-local properties are formalized in terms of global dynamic properties.
6. **Evaluation.**
   A set of local and global dynamic properties is verified against the generated simulation traces in step 3. A verified model is an output from this phase.

## MODELING APPROACH

*Theoretical vs. Practical Models*

Although computational models are used for many possible reasons, this usage can be classified them under two main objectives; *theoretical understanding* and *practical applications*. From a theoretical model standpoint, one can understand how the real system operates. On the other hand, a practical model enables the prediction of the real system by which it will play a role in deciding feasible sets of action[6,7]. In an extreme case, theoretical models are usually expressed in dynamic equations yet they are often simple enough for scientists to comprehend the underlying process. It is useless to replace an observed system with a complex model that difficult to comprehend when it has not increased our deeper understanding of the observed domain[7,8,9].

In contrast, practical models normally sacrifice simplicity in order to offer more detailed and precise predictions for an observed system. Thus, practical models are often too complicated and only dedicated for computer simulations[9,10]. In this connection, it should also be mentioned that practical models entail detailed numerical accuracy, whereas this is not the case in theoretical models. Therefore, the details of the processes can be ignored only if it has less implication in achieving a better numerical

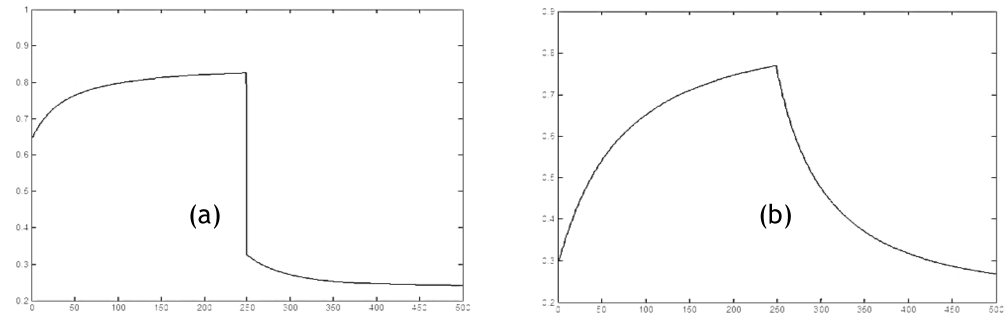


***Figure -1 Samples of Traces (a) Instantaneous (b) Temporal Relations***

accuracy. However, in theoretical models, the details of the processes can be left out if they are conceptually irrelevant to address important theoretical issues[11,12].

*Bonini's Paradox*

There are a number of important theoretical constructs need to be addressed in modeling cognitive phenomena. One of these constructs is the element of structural complexity. In general, when one talks about the structural complexity, it will involve this simple idea as "models that you can describe compactly are simpler than models that require a longer description"[13]. This concept is related to the Bonini's Paradox where the less information a model carries about its subject, the less useful it's going to be in helping someone understand that subject[14]. However, the more information a model carries about its subject, the less useful it's going to be in helping someone understand any single point of that subject.

Put it in the context of cognitive science, any sufficiently detailed model of brain functionality and constructs is going to be a brain itself. In other words, the risk in developing intricate and elaborate models is that they are no more understandable than the phenomena they are intended to explain. This means that, in choosing between a model providing a specific explanation for results obtained with a constrained research paradigm and one deriving from a theoretical view addressing a broad range of phenomena, one should take a definite choice to choose the latter[15].

*Abstraction*

Technically, abstraction is about providing a simplified overview of the complex cognitive process as cognitive models do not include all attributes and mechanisms of the original they represent, and not related to the respective original in a unique sense but only to fulfil certain goals and intended requirements[3,15]. This simplified view focusses on the important elements of a process so that scientists be able predict its behaviour under a variety of conditions. This allows them to understand that process better, or to explore ways of making the process behave differently under controlled environment. Moreover, abstraction provides us with a perspective of the building blocks than can be used to develop a set of design solutions, such as possible solution paths from a higher level of conceptual understanding [16,17].

Abstraction can be viewed into two concepts, 1) the simplifications of ideas where missing information can be inserted automatically, and 2) the simplifications of the process which is deliberately excluded in order to keep the model simple[17]. This abstraction process tends to be domain-specific with an ultimate goal to find general mechanism and interplay between related factors or processes. The first step in abstraction is to break the problem into as many functional parts, sub-problems, or meaningful units as possible[18,19]. Next, one should try to classify these functional aspects of the problems into more general categories in accordance with their distinctive characteristics.

*Temporal / Differential Equation*

Differential equation relates some function with its derivatives. In applications, the functions usually represent physical quantities, the derivatives represent their rates of change, and the equation defines an interaction or relationship between the two or more states[3,15]. There are two main relationships to represent the observed phenomena, namely; *instantaneous* and *temporal* relationship. Instantaneous relationship explains direct impact towards states and its connections. For example, given $f$,

$$f(t) = \alpha . z(t) + (1-\alpha) . h(t)$$

From this equation, parameter $\alpha$ is used to regulate possible contribution rate between $z$ and $h$. In this case, if $\alpha$ = 0.7, it means the function $z$ will contribute up to 70 percent towards the overall value (with 30 percent contribution from function $h$).

The temporal relationship often related to the accumulated effect from previous contribution of the same function. This form of contribution can be considered as a "delay condition" (regardless accumulating or decaying contributions). Figure 1 depicts a visual representation of instantaneous and temporal relationships. A description of temporal representation of *y* function can be presented as:

$$y(t+\delta t) = Y(t) + \tau .\text{<change\_ expression>}.\delta t$$

and assuming $\tau \neq 0$, this is equivalent to <*change_expression*> = *0* for all variables *y*. Moreover, as;

$$\text{<change\_expression>} = (1-y(t)).\text{Pos}(\text{<basic\_change>}) - y(t).\text{Pos}(-\text{<basic\_change>})$$

the criterion for an equilibrium is:

$$(1-y(t)).\text{Pos}(\text{<basic\_change>}) - Y(t).\text{Pos}(-\text{<basic\_change>}) = 0$$

Note that always

$$Pos(x) = 0 \text{ or } Pos(-x) = 0.$$

Moreover, it is equally important to mention that the change process is measured in a time interval between $t$ and $t + \delta t$. In addition to all this, the rate of change for all temporal specifications are determined by a flexibility rate $\tau$.

Both relationships (instantaneous and temporal) are related to these three main causal relations, namely[20] :

- Strength of a causal relation
- Combining causal impacts on a state
- Speed of change of a state

These three are essential to represent the conceptual constructs in the real world as not all relationships are equally important (e.g. equal weightage) in representing the notion of states and connection among them.

*Formal Logic*

Another method to develop a model is using a collection of logical statements. It uses quantified variables (predicates and quantifiers) and relationships between these predicates can be stated using logical connectives (to form an expression)[21]. The meaning of an expression resides in its 'truth conditions', determining under which circumstances it is true. For example, the precise notion that talks about "an agent *q* knows that $\varphi$" can be represented as

$$\boldsymbol{K_q \varphi}.$$

Thus the extension representation for "agent *q* knows whether $\varphi$" can be viewed as in;

$$\boldsymbol{K_q \varphi} \vee \boldsymbol{K_q \neg \varphi}$$

Extending this concept from a basic-question answer episode "*Q*: $\varphi$? A:Yes" thus by asking the question, *Q* conveys he does not know if $\varphi$:

$$\neg \boldsymbol{K_Q \varphi} \vee \neg \boldsymbol{K_Q \neg \varphi}$$

and also that he expects *A* to know: that is at least:

$$\langle \boldsymbol{Q} \rangle \boldsymbol{K_A \varphi} \vee \boldsymbol{K_A \neg \varphi}$$

Therefore by answering affirmatively, A conveys he knows that $\varphi$ but also makes *Q* know this fact $(\boldsymbol{K_Q K_A} \varphi)$ leading to common knowledge, written as follows;

$$\boldsymbol{C_{\{Q,A\}} \varphi}$$

In logic, temporal logic is any system of rules reasoning and propositions qualified in terms of flows of time. Flows of time are known from mathematics as strict partial orders, such as $s > t$ for "$s$ is later than $t$" or $s \leq t$ for "either $s$=$t$ or $s < t$"[22]. For a point $t$, the set of $\{\boldsymbol{s} \in \boldsymbol{T} | \boldsymbol{t} < \boldsymbol{s}\}$ will be called the "future of $t$"; the past of $t$ is defined likewise. Another example could be used to show the implementation of temporal logic in cognitive modeling is as follow [23];

> "In any trace, if at any point in time t1 the virtual agent *A* observes that it is windy, then there exists a point in time t2 after t1 such that at t2 in the trace the virtual agent *A* believes that it is windy."

$$\forall \gamma\ \forall t1\ [\text{holds}(\text{state}(\gamma,t1),\text{observation\_ result}(\text{windy})) \Rightarrow \exists t2 > t1\ \text{holds}(\text{state}(\gamma,t2),\text{belief}(\text{windy}))]$$

## EVALUATION

Evaluation is one of the essential tasks of a modelling process. It aims to determine whether a given formal representation describes specified observed phenomena accurately. As for the local properties, these concepts are evaluated whether these properties reflect the main aspects in the theory by analyzing interaction among defined concepts using causal relationships that have been found in empirically founded literature.

Often, over a longer period, a process specified by temporally local properties in computational models generates patterns that can be considered as emergent phenomena or temporally global properties. These types of properties are[24]:

- *Achievement properties.*

These properties express that; given some conditions (initial and/or intermediate) eventually a certain state is reached.

- *Equilibrium properties.*
  There properties concern resulting in a stable, balanced, or unchanging state in the process.
- *Representation properties.*
  These properties explain how internal states relate to external states in past and /or future. They can be categorized into two specific types, namely: 1) backward representation relations (relations to the pre-cursor conditions) and 2) forward representation relations (relations to the future conditions).
- *Comparison properties.*
  These properties concern the comparison of certain state properties at different time points (e.g., monotonically increasing or decreasing), or comparison between different generated traces.

The evaluation of cognitive models can be done by providing formal representations of a computational model of the system, and the correspondence between these computational models and their simulation traces, and actually observed conditions (obtained from the empirically founded literature)[25]. To do this, three aspects are expected to be present; (1) a formal specification of a model, (2) description of the environment that the model is supposed to operate in, and (3) properties that the model is intended to fulfil[26]. Given these requirements, the model can be evaluated using a mathematical and/or hybrid logical verification techniques to search for how input patterns that the environment or persons could generate follow (or violate) the properties[27]. Figure 2 summarizes the evaluation process to be used to verify the model.

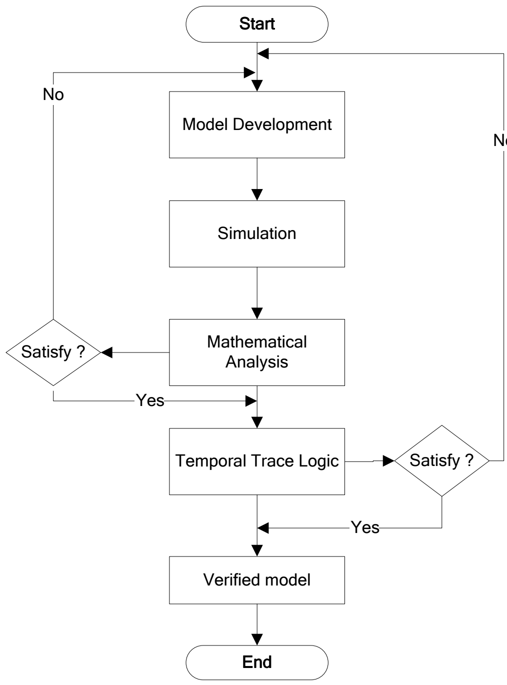


***Figure 2- Evaluation Process (Verification)***

The details of this process will be dealt in the next sub-section of this article.

*Mathematical Analysis*

For the mathematical verification, the equilibria analysis is used to describe situations in models where the values (continuous) approach a limit under certain conditions and stabilize[28]. It means, if the dynamics of a system is described by a differential equation, then equilibria can be estimated by setting a derivative (or all derivatives) to zero. One important note that an equillibria condition(s) is considered stable if the system always returns to it after small disturbances[20,29]. For example, using this autonomous equation,

$$f(t) = y(t+\delta t) = y(t) + \beta[q(t)-y(t)].\delta t$$

*therefore,* $dy(t)/dt = f'(t) = q-y$

the equilibria or constant solutions of this differential equation are the roots of the equation

$$f'(t) = 0$$

hence the equillibria point can be found when,

$$q = y$$

As such, the existence of reasonable equilibria is also an indication for the correctness of the model[30]. Moreover, it can be found when a certain state is increasing or decreasing when a state is not one of the equilibria points. For example[20];

- *y* has an equilibria point at *t* if *f(y)* = 0
- *y* is increasing if at *t* if *f(y)* > 0
- *y* is decreasing if at *t* if *f(y)* < 0

These equilibria conditions are interesting to be explored, as it is possible to explain them using the knowledge from the theory or problem that is modelled[28].

*Automated Logical Verification*

For the logical verification, the ability of the *Temporal Trace Language* (TTL) and its software environment as a specification language and verification tool can be utilized to evaluate the model. TTL is built on atoms referring to states of the world, time points, and traces[23]. This relationship can be presented as a *state* $(\gamma, t, output(R))|=p$, means that state property *p* is true at the output of role *R* in the state of trace $\gamma$ at time point *t*. TTL allows us to verify both qualitative and quantitative of process under analysis and has the ability to reason about time[31]. The interval of such checks varied from one second to a couple of months, related to the complexity of the models.

Using this technique, simulation models can verified whether they satisfy certain expected global properties. In general, TTL terms are constructed by induction in a standard way from variables, constants and function symbols typed with all before-mentioned TTL sorts. Transition relations between states are described by dynamic properties, which are expressed by TTL-formulae[31]. The set of well-formed TTL-formulae is defined inductively in a standard way using Boolean connectives (such as $\neg, \wedge, \vee, \Rightarrow, \exists, \forall$) , and quantifiers over variables of TTL sorts. For this purpose, special software has been developed for TTL, featuring both a property editor and a checking tool that enables formal verification of such properties against a set of simulated traces

**EXAMPLE: COGNITIVE MODEL OF THE TEMPORAL DYNAMICS IN ANXIETY STATES**

Anxiety can be defined as an unpleasant state of mental uneasiness or concern that causes physical and psychological discomfort. This unpleasant state may cause physical symptoms such as a racing heart and shakiness. There are various forms of anxiety disorders, including generalized anxiety disorder, phobic disorder, and panic disorder[32].

*Underlying Constructs of Anxiety States*

According to Well's model (Meta-cognitive Model), problematic worry develops over time. It begins when a person is initially faced an anxiety provoking event, positive beliefs about worry are compromised (known as *Type 1 Worry*). During the course of Type 1 worry, coping strategy and individual's sensitivity will regulate the formation of short-term worry. However, higher sensitivity increases the formation of beliefs about worry and reduces the ability to cope accordingly[33,34]. It also related to the engagement in ineffective coping strategies provides a chance about the belief that is uncontrollable that later leads to the maladaptation interpretation and short-term worry [34,35]. Individuals with anxiety traits and negative personality will later experience a negative reinforcement spiral experience of worry that further reinforces the worry (*Type 2 Worry*). An increased *Type 2 Worry* is posited to lead to a spiralling of the worry emotion in a long run[36,37]. This later increases the long-term worry that will influence individual's thought control over negative events (triggers).

*Formal Model of Anxiety States*

The implemented relations between different concepts are based on related findings in literature on anxiety states, traits, and disorder. The general structure of the formal model for anxiety state is shown in Fig. 3. In this figure, it can be seen that the model consists of several interrelated nodes. Once the structural relationships in the model have been determined, the model can be formalized. In the formalization, all nodes are designed in a way to have values ranging from 0 (low) to 1 (high).

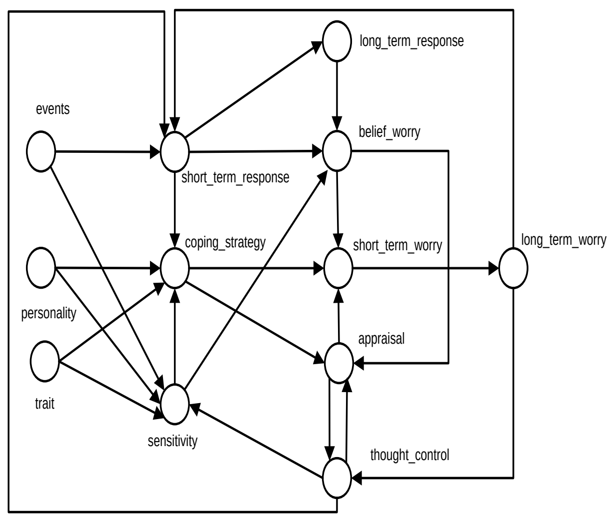


***Figure -3 Global Relationships of Variables Involved in the Formation of Worry***

These conceptual factors will be formalized to develop a set of formal specifications (refers to Table 1)

***Table -1 Nomenclature of Factors in Anxiety States***

| | Concept | Formalization |
|---|---|---|
| **1.** | Physical event | *Pe* |
| **2.** | Threatening event | *Te* |

| | | |
|---|---|---|
| **3.** | Coping skills / strategy | *Cs* |
| **4.** | Sensitivity | *Sy* |
| **5.** | Personality | *Ps* |
| **6.** | Short-term response | *Sr* |
| **7.** | Personal traits | *Tr* |
| **8.** | Long-term worry | *Lw* |
| **9.** | Appraisal | *Ap* |
| **10.** | Thought control | *Tc* |
| **11.** | Norm (sensitivity) | $Sy_{norm}$ |
| **12.** | Long-term response | *Lr* |

This model involves a number of instantaneous and temporal relations (local and global properties), as the following:

Instantaneous relationships:

$$Bw(t) = \alpha_b.[\beta_b.Sr(t) + (1-\beta_b).Lr(t)] + (1-\alpha_b).Sy(t)$$

$$Sw(t) = [1 - \left((\theta_s.Cs(t) + (1-\theta_s).Ap(t))\right).(1 - Bw(t))]$$

$$Tc(t) = (1 - Ap(t)).Lw(t))$$

$$Sy(t) = \Psi_s.Sy_{nom}(t).[1 - Ps(t)] + (1-\Psi_s).[\lambda s_1.Sy_{nom}(t) + \lambda s_2.Pe(t)].(1 - Tc(t))$$

$$Pe(t) = \sigma_p.Te(t)$$

$$Cs(t) = [\gamma_c.(1 - Sy(t)) + (1-\gamma_c).Ps(t)].(1 - Sr(t))$$

$$Sr(t) = [\alpha_s.Pe(t) + (1-\alpha_s).Lw(t)].(1 - Tr(t))$$

Temporal relationships:

$$Lr(t+\delta t) = Lr(t) + \beta\_L.[Pos(Sr(t) - Lr(t)).(1 - Lr(t)) - Pos(-(Sr(t) - Lr(t)).Lr(t)].\delta t$$

$$Lw(t+\delta t) = Lw(t) + \phi_L.[Pos(Sw(t) - Lw(t)).(1 - Lw(t)) - Pos(-(Sw(t) - Lw(t)).Lw(t)].\delta t$$

$$Ap(t+\delta t) = Ap(t) + \rho_a.[Pos(Sg(t) - Ap(t)).(1 - Ap(t)) - Pos(-(Sg(t) - Ap(t)).Ap(t)].\delta t$$

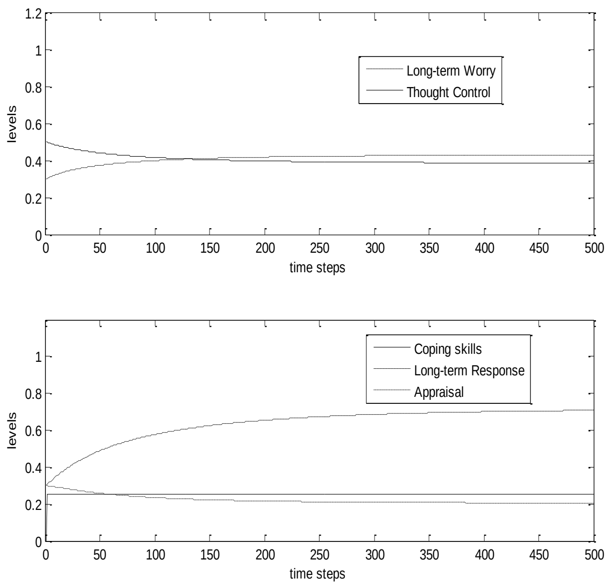


***Figure-4 Simulation Results of Moderate Risk Conditions***

where $Sg(t) = [Ws_1.Cs(t) + Ws_2.Tc(t)].(1 - Bw(t))$

Next, a number of simulations have been carried out in which the effect of different variants of conditions on a fictional person with related personality and trait are compared. For example, Figure 4 visualizes the results of individuals with moderate risk of anxiety.

From Figure 4, it shows that the individual experiences a gradual decreasing level of potential onset long-term worry, but possibly will experience anxiety in the future if that individual is having constant exposure towards stressors[35].

*Mathematical Analysis*

As first step to obtain possible equilibrium values for the other variables, first the temporal equations are described in a differential equation form,

$$\frac{dLr}{dr} = \beta_L.[Pos(Sr(t) - Lr(t)).(1 - Lr(t)) - Pos(-(Sr(t) - Lr(t)).Lr(t)]$$

$$\frac{dLw}{dt} = \phi_L.[Pos(Sw(t) - Lw(t)).(1 - Lw(t)) - Pos(-(Sw(t) - Lw(t)).Lw(t)]$$

$$\frac{dAp}{dt} = \rho_a.[Pos(Sg(t) - Ap(t)).(1 - Ap(t)) - Pos(-(Sg(t) - Ap(t)).Ap(t)]$$

Next, the equations are identified that describe:

$$\frac{dLr}{dt} = \frac{dLw}{dt} = \frac{dAp}{dt} = 0$$

Assuming all parameters are non-zero, this provides the following equilibrium equations;

$$Pos(Sr(t) - Lr(t)).(1 - Lr(t)) = 0$$
$$-Pos(-(Sr(t) - Lr(t)).Lr(t) = 0$$

Notice that *Pos*(x) > 0, so this equilibrium equation is equivalence to;

$$Pos(Sr - Lr).(1 - Lr) - Pos(-(Sr - Lr).Lr) = 0$$

Therefore,

$$(Sr \le Lr \wedge Sr \ge Lr) \vee (Sr \le Lr \wedge Lr = 0) \vee (Lr = 1 \wedge Sr \ge Lr) \vee (Lr = 1 \wedge Lr = 0)$$

The latter case cannot exist, and as $0 \le Lr \le 1$ the other three cases are equivalent to *Sr=Lr*. Similar cases for equations (13) and (14), the equillibria state occurs when *Sw* = *Lw* and *Sg* = *Ap* respectively. Note that for each of the distinguished cases, further information can be found about the equilibrium values of other variables using the other non-dynamic-equations

***Case #1: Sr = Lr***

$$Cs = [\gamma_c.(1 - Sy) + (1 - \gamma_c).Ps].(1 - Lr)$$
$$Bw = \alpha_b.[\beta_b.Lr + (1 - \beta_b).Sr] + (1 - \alpha_b).Sy$$

***Case #2: Sw = Lw***

$$Sr = [\alpha_s.Pe + (1 - \alpha_s).Sw].(1 - Tr)$$
$$Tc = (1 - Ap).Lw$$

**Case #3: *Sg = Ap***

$$Sw = [1 - \left(\left(\theta_s.Cs + (1 - \theta_s).[ws_1.Cs + \right.\right.$$
$$ws2.Tc.1{-}Bw.1{-}Bw]$$
$$Tc = (1 - [ws_1.Cs + ws_2.Tc].(1 - Bw)).Lw)$$

**Case #4: *Lr* =1 ^ *Sr = Lr***

$$Cs = 0$$
$$Bw = \alpha_b.[\beta_b + (1 - \beta_b)] + (1 - \alpha_b).Sy$$

Assuming the proportional contribution of $\beta_b = \alpha_b = 0.5$, therefore, $Bw = 0.5 + 0.5Sy$
*Automated Logical Verification*

For each of the global properties, first an informal description is given, and next the formal description that has been used for the automated checking software.

**VP1: Low Trait and Positive Personality will Reduce Anxiety State**
Individuals with less negative personality and low anxiety trait develop lesser chance of having a long-term worry condition[36].

VP1≡ ∀γ:TRACE, t1, t2, t3 :TIME, v1,v2,w1,w1,h1, h2:REAL
[state(γ, t1)|=personality(v1) &
state(γ, t1)|=personal_trait(w1) &
state(γ, t1)|=long_term_worry(h1) &
state(γ, t2)|=personality(v2) &
state(γ, t2)|=personal_trait(w2) &
v2 < v1 & w2 < w1]
⇒ ∃t3:TIME > t2:TIME &
t2:TIME > t1:TIME
[ state(γ, t3)|= long_term_worry(h2) & h1 > h2]

**VP2: Higher Sensitivity Increases Worry**
Individual's sensitivity is related to the risk of long term worry[33].

VP2 ≡ ∀γ: TRACE, ∀t1, t2:TIME, ∀F1,F2,H1,H2, d:REAL
[state(γ,t1)|= sensitivity(F1) &
state(γ,t1)|= long_term_worry(H1) &
state(γ,t2)|= sensitivity(F2) &
state(γ,t2)|= long_term_worry(H2) &
t2 ≥t1 +d &
F1< F2] ⇒ H2 > H1

**VP3: Monotonic Decrease of Long-term Worry for Any Individual When Sensitivity and Belief about Worry, are Reduced**
When a person manages to control his or her perception (sensitivity) and belief about the negative consequences of the experienced events throughout time, then the person will reduce the level of long-term worry in future[33,35,37].

VP3 ≡ ∀γ:TRACE,t1,t2:TIME,D1,D2,E1,E2, H1, H2:REAL
[state(γ, t1)|= sensitivity(D1) &
state(γ, t2)|= sensitivity(D2) &
state(γ, t1)|= belief_about_worry(X,E1) &
state(γ, t2)|= belief_about_worry(X,E2) &
state(γ, t1)|= long_term_worry(X,H1) &
state(γ, t2)|= long_term_worry(X,H2) &
t2 > t1 & D2 ≥ D1 & E1 ≥ E2]
⇒ H2 ≤ H1

**VP4: Good Coping Strategy Decreases Worry**
A good coping skill (e.g. problem-focused coping) is a better option to reduce worry[38].

VP4 ≡ ∀γ: TRACE, ∀t1, t2:TIME, ∀F1,F2,H1,H2, d:REAL
[state(γ,t1)|= coping_skills(F1) &
state(γ,t1)|= long_term_worry(H1) &
state(γ,t2)|= coping_skills(F2) &
state(γ,t2)|= long_term_worry(H2) &
t2 ≥t1 +d & F1 ≥ 0.6
F1≤ F2] ⇒ H2 < H1

**VP5: Monotonic Increase of Variable, v for Worry Amplifies Future Response over Negative Events**
For all time points t1 and t2 between tb and te in trace γ if at t1 the value of v is x1 and at t2 the value of v is x2 and t1 < t2, then x2 ≥ x1

VP5 ≡ ∀γ: TRACE, ∀t1, t2:TIME, ∀X1,X2:REAL
[state(γ,t1)|= has_value(v, X1) &
state(γ,t2)|= has_value(v, X2) &
tb ≤ t1 ≤ te &
tb ≤ t2 ≤ te &
⇒ x2 ≥ x1

## DISCUSSION

Within many cognitive science domains, among which behavioural analysis, psychology, neuroscience, and artificial intelligence, multiple interacting processes occur with dynamics that are difficult and complicated to handle. Current approaches such as brain imaging, human / biological experiments still fall short to explain the detailed interaction between all of cognitive activities involved. Thus, such use of computational cognitive models is regarded as a tool for internal and external investigation of cognition within brain activities.
Computational model provides a means of risk-free exploration in complex, critical, costly, time-consuming, or rare situations.

Moreover, a constructed computational model is capable of simulating certain key behaviours in the selected domain of interest. This model can be used to simulate different scenarios in which personal characteristics determine the effect of related observed cognitive perspectives of a person. A mathematical analysis illustrated the different equilibriums of the model for persons with different characteristics. By formally checking properties of the simulation traces, the adherence of the model to the most important ideas in the theories was internally validated. This work provides the first step in the development of an intelligent software agent or robot to support individuals with cognitive dysfunctionality in a personal manner. Thus it promotes a better way to fluidly embedded this into any monitoring and health informatics system.

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**COMPETING INTERESTS**

There is no conflict of interest.

**REFERENCES**

1. Scassellati, B. (2002). Theory of Mind for a Humanoid Robot. *Autonomous Robots*, 2002, vol. 12, pp. 13-24.
2. Treur, J. On Human Aspects in Ambient Intelligence. In: *Proceedings of the First International Workshop on Human Aspects in Ambient Intelligence*. In M. Mühlhäuser, A. Ferscha, and E. Aitenbichler (eds.), *Constructing Ambient Intelligence: AmI-Workshops Proceedings*. Communications in Computer and Information Science (CCIS), 2008, vol. 11, Springer Verlag, pp. 262-267.
3. Farrell, S., and Lewandowsky, S. Computational Models as Aids to Better Reasoning in Psychology. *Current Directions in Psychological Science*, vol. 19, 2010, pp. 329-335.
4. Rosenthal, R. *Experimenter Effects in Behavioural Research*. 1966, New York: Appleton.
5. Epstein, J. M. Why model? *Journal of Artificial Societies and Social Simulation* 11.4:12, 2008.
6. Bechtel, W. & Abrahamsen, A. Dynamic mechanistic explanation: Computational modeling of circadian rhythms as an exemplar for cognitive science. *Studies in History and Philosophy of Science Part A* 41.3 , 2010, pp. 321-333.
7. Lewandowsky, S. & Farrell, S. *Computational modeling in cognition: Principles and practice*. Sage, 2010.
8. Eldabi, T., and Young, T. Towards a Framework for Healthcare Simulation. In Henderson, S.G., Biller, B. Hsieh, M-H., Shortle, J., Tew, J.D., and Barton, R. R., (Eds.) *Proceedings of the Winter Simulation Conference*, 2007, pp. 1454-1560.
9. Ellner, S.P., & Guckheimer, J. *Dynamic Models in Biology*. Princeton University Press, 2006, pp. 1-28.
10. Gentner, D., Holyoak, K. J., & Kokinov, B. N. *The analogical mind: Perspectives from cognitive science*. 2001,MIT press.
11. Papadimitriou, C. H. *Computational complexity* (pp. 260-265). 2003, John Wiley and Sons Ltd..
12. Frank, M. J., Loughry, B., & O'Reilly, R. C. Interactions between frontal cortex and basal ganglia in working memory: a computational model. *Cognitive, Affective, & Behavioral Neuroscience*, *1*(2), 2001, 137-160.
13. Ervik, L. K., Flam, S. D., & Olsen, T. E. (1981). Comprehensive Modelling of Fisheries: Comments and a Case Study. In *Applied Operations Research in Fishing*, 1981, Springer,pp. 1-32.
14. Usó-Doménech, J. L., Nescolarde-Selva, J., & Lloret-Climent, M. Saint Mathew law and Bonini paradox in textual theory of complex models. *American Journal of Systems and Software*, *2*(4), 2014, pp. 89-93.
15. Sun, R., & Sun, R. Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation, 2008.
16. Borshchev, A., & Filippov, A. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. In *Proceedings of the 22nd international conference of the system dynamics society* (Vol. 22), 2004.
17. Miller, J. H., & Page, S. E. *Complex adaptive systems: An introduction to computational models of social life*. 2009, Princeton university press.
18. Kramer, J. Is abstraction the key to computing? *Communications of the ACM*, *50*(4), 2007, pp 36-42.
19. Chwif, L., Barretto, M. R. P., & Paul, R. J. On simulation model complexity. In *Proceedings of the 32nd conference on Winter simulation* , 2000. pp. 449-455.
20. Treur, J., Dynamic Modeling Based on a Temporal-Causal Network Modeling Approach. *Biologically Inspired Cognitive Architectures*, *16*, 2016, pp. 131-168.
21. Kamp, H., & Reyle, U. *From discourse to logic: Introduction to model theoretic semantics of natural language, formal logic and discourse representation theory* (Vol. 42). 2013, Springer Science & Business Media.
22. Gabbay, D. M., Hodkinson, I., & Reynolds, M. Temporal Logic Mathematical Foundations and Computational Aspects, 1994.
23. Sharpanskykh, A., & Treur, J. A temporal trace language for formal modelling and analysis of agent systems. In *Specification and verification of multi-agent systems*, 2010, Springer US, pp. 317-352.
24. Aziz, A. Exploring Computational Models for Intelligent Support of Persons with Depression, Ph.D Thesis, VU Amsterdam, 2011.
25. Clarke, E.M., Grumberg, O., and Peled, D.A. *Model Checking*. 2000, MIT Press.
26. Baier, C., Katoen, J. P., & Larsen, K. G. *Principles of model checking*. , 2008, MIT press.

27. Visser, W., Havelund, K., Brat, G., Park, S., & Lerda, F. Model checking programs. *Automated Software Engineering*, *10*(2), 2003, pp. 203-232.
28. Korn, G. A., &Korn, T. M. *Mathematical Handbook for Scientists and Engineers: Definitions, Theorems, and Formulas for Reference and Review*. Dover Publications, Mineola, 2000, New York.
29. Gazi, V. *Stability analysis of swarms* (Doctoral dissertation, 2002, The Ohio State University).
30. Ayasun, S., Fischl, R., Vallieu, S., Braun, J., & Cadırlı, D. Modeling and stability analysis of a simulation–stimulation interface for hardware-in-the-loop applications. *Simulation Modelling Practice and Theory*, *15*(6), 2007, pp. 734-746.
31. Bosse, T., Jonker, C. M., van der Meij, L., & Treur, J. A Temporal Trace Language for the Formal Analysis of Dynamic Properties, 2006.
32. Brosschot, J.F., Pieper, S. & Thayer, J.F Expanding Stress Theory: Prolonged Activation and Preservative Cognition, Psychoneuroendocrinology, vol. 30(10), 2005, pp. 1043-1049.
33. Gale, C.K. & Oakley-Browne, M. Generalized Anxiety Disorder, Am Fam Physician, vol. 67, 2003, pp. 135-138.
34. Gliatto, M.F. Generalized Anxiety Disorder, Am Fam Physician, vol. 62(7), 2000, pp. 1591-1600.
35. Brandes, M. & Beivenu, O.J. Personality and Anxiety Disorders, Current Psychiatry Reports, vol. 8(4), 2006, pp. 263-269.
36. Deacon, B & Abramowitz, J. Anxiety Sensitvity and Its Dimensions Across the Anxiety Disorders, Anxiety Disorders, vol. 20, 2008, pp. 837-857.
37. Kashdan, T.B., Zvolensky, M.J, & McLeish, A.C. Anxiety Sensitivity and Affect Regulatory Strategies: Invidual and Interactive Risk Factors for Anxiety-related Symptoms, Anxiety Disorders, 22, 2008, pp. 429-440.
38. Blalock, J.A, & Joiner-Jr, T.E. Interaction of Cognitive Avoidance Coping and Stress in Predicting Depression/Anxiety, Cognitive Therapy and Research, 24, 2000, pp. 47-65.