Cybernetics and Systems: An International Journal

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/ucbs20

A MODEL OF SINGLE-AGENT ILLNESS SELF-REGULATION

Umberto Giani a & Carmine Garzillo a

a Department of Preventive Medical Sciences, Section of Medical Statistics and Informatics, Faculty of Medicine, University of Naples Federico II, Napoli, Italy

To cite this article: Umberto Giani & Carmine Garzillo (2013) A MODEL OF SINGLE-AGENT ILLNESS SELF-REGULATION, Cybernetics and Systems: An International Journal, 44:8, 627-640, DOI: 10.1080/01969722.2013.789647

To link to this article: http://dx.doi.org/10.1080/01969722.2013.789647

PLEASE SCROLL DOWN FOR ARTICLE

Taylor & Francis makes every effort to ensure the accuracy of all the information (the “Content”) contained in the publications on our platform. However, Taylor & Francis, our agents, and our licensors make no representations or warranties whatsoever as to the accuracy, completeness, or suitability for any purpose of the Content. Any opinions and views expressed in this publication are the opinions and views of the authors, and are not the views of or endorsed by Taylor & Francis. The accuracy of the Content should not be relied upon and should be independently verified with primary sources of information. Taylor and Francis shall not be liable for any losses, actions, claims, proceedings, demands, costs, expenses, damages, and other liabilities whatsoever or howsoever caused arising directly or indirectly in connection with, in relation to or arising out of the use of the Content.

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is expressly forbidden. Terms & Conditions of access and use can be found at http://www.tandfonline.com/page/terms-and-conditions
A Model of Single-Agent Illness Self-Regulation

UMBERTO GIANI and CARMINE GARZILLO
Department of Preventive Medical Sciences, Section of Medical Statistics and Informatics, Faculty of Medicine, University of Naples Federico II, Napoli, Italy

This article is an attempt to develop a formal model of single-actor illness self-regulation; that is, a goal-oriented, emotional and cognitive process based upon the creation of anticipated possible futures that trigger plans, decisions, and actions aimed at correcting the present state. The contemplated effects of the actions are represented as a transition operator that hopefully transforms the present state into a more desirable future state. As a case study, the model is applied to the self-regulation of glycemia in type-2 diabetes. An outline for the extension of the model to multi-agent, multidimensional self-regulation is also suggested.

KEYWORDS anticipatory thinking, diabetes coping, goal-oriented behavior, illness strategy, purposeful agents, self-regulation

INTRODUCTION

Self-regulation refers to “processes such as exertful control and orienting that function to modulate reactivity” (Rothbart and Bates 2006, p. 99) and may be considered a synthesis of two earlier models: cybernetic control and emotion regulation (Magen and Gross 2010). In addition to affective capacities, it includes metacognitive skills; that is, memory, attention, and problem solving.

Several models of self-regulation of health and illness behavior have been suggested (Wing et al. 1986; Hamera et al. 1988; Cameron and Leventhal 2003). Most of these models conceive self-regulation as “a dynamic motivational system of setting goals, developing enacting strategies to
achieve those goals, appraising progress, and revising goals and strategies” (Baumeister and Vohs 2004, p. 180).

The role of the patient’s behavior in the evolution of the disease cannot be neglected. This is particularly true in chronic diseases (e.g., diabetes, hypertension, and so on) where the day-to-day control is almost exclusively in the patient’s hands.

However, usually the patient does not know the exact physiopathological mechanisms underlying the disease and the effects of drugs and treatments. Thus, she or he is forced to resort to a naïve interpretation of the events in order to anticipate the future events, and cope with his or her illness. In fact, an illness self-regulation strategy can be conceived as the output of a naïve narrative meaning-making process carried out by an individual who tries to arrange events, actors, times, purposes, and causality into a coherent plot (Bal 2009).

The naïve interpretation of the events could be conceived as a means for understanding the past in order to explain the present, and generate expectations about the future. From this point of view, self-regulation can be conceived as “the ability to detect an undesirable forecasted future, select the actions that hopefully will promote an alternative desirable future, and monitor the actions’ progress toward the alternative future” (Beach 2009, p. 13). If the forecasted future is undesirable, human beings construct plans that guide actions designed to promote a more desirable future.

From this point of view, naïve illness self-regulation is a sort of anticipatory thinking (Kelly 1963) where the undesirability of the anticipated possible futures generates emotional–cognitive evaluations of the situation, which, in turn, trigger plans, decisions, and actions aimed to correct the present in order to drive the events towards a better future.

According to Beach (2009), there are essentially two kinds of anticipatory rules: The noncontingent rules allow predicting the possible futures (i.e., the natural course of social, psychological, and/or physical events) if no action is taken, whereas the contingent rules generate expectations about what could happen as the result of deliberate actions. A comparison of the desirability of these two futures leads to the choice of the “best” course of action.

Thus, illness self-regulation is aimed to attain a set of goals in different domains—for example, psychological, physical, and social well-being—in a more or less remote future.

Usually the individuals’ self-regulation rules are inferred by means of thinking-aloud protocols, which can be affected by several psychological biases; for example, memory distortion, self-deceiving artifacts, and so on.

The present article attempts to develop a formal model of single-actor illness self-regulation based upon the direct analysis of the patient’s behavior, without any referral to verbal accounts. As a case study, the self-regulation process of patients affected by type 2 diabetes is carried out. Finally, an
outline for the extension of the model to multi-agent, multidimensional self-regulation is suggested.

MATERIALS AND METHODS

It was assumed that human beings “constantly” monitor their current health state over a set of relevant health state features; that is, a multidimensional array of variables, $\Theta(t)$, describing the physical, psychological, and social aspects of their health state at the time $t$. These variables and their relationships define the individual’s personal semantics of health and disease.

The desirability, $D(\Theta(t))$, of the present state, $\Theta(t)$, can be represented as a decreasing function of the discrepancy, $\Delta_r \theta(t)$, between $\Theta(t)$ and a desired target state or goal, $\Theta_\delta(t)$:

$$D(\Theta(t)) = f(\Delta_r \theta(t)),$$

where the reference value (goal or target) is dynamic in nature and can also depend on the present state $\Theta(t)$.

The discrepancy generates different emotions in different dimensions and hence different actions and plans aimed at reducing or eliminating that discrepancy. Assuming that $\Theta(t)$ is a measurable multidimensional variable, the discrepancy in the $i$th dimension, $\theta_i(t)$, has directionality: if $\theta_i(t) > \theta_i(t)$, then the actions should decrease $\theta_i(t)$, and vice versa.

A plan can be conceived as a more or less complex contemplated action, $\pi(t) \in \mathcal{A}$, where $\mathcal{A}$ is the set of the available actions, that hopefully will transform the actual state into a more desirable future state.

The contemplated action $\pi(t)$ can be conceived as an application of a potential transition operator, $\beta(t)$:

$$\pi(t) : \beta(t) \theta_i(t) = \theta_i(t + T),$$

which could transform the present state $\theta_i(t)$ into a future state $\theta_i(t + T)$, where generally $\beta(t) = g(t, \theta_i(t))$; that is, it is a function of time and the state itself. In the following the index, $i$ will be dropped for sake of simplicity.

The nearness of the forecasted and desired future state, $T$, could also depend on the present state itself, $\theta(t)$. For example, at the beginning of an illness, the temporal horizon could be limited to the nearest future because it is necessary to cope with a new and urgent situation, whereas in chronic states, such as cancer, the patient can be forced to replan the entire life horizon. Moreover, the desired future, $\theta_\delta(t + T)$, can also depend on the actual state itself. For example, at the beginning of chronic obstructive respiratory diseases the patient would pursue the goal of having a short walk in the garden but, subsequently, as the health state worsens, she or he will
be happy just to walk in a room, simply rest without dyspnea, and so on; that is, the patient adapts his or her desired future to a new realistic one, given the present state.

Thus, a *purposeful agent* could behave according to the following rules:

1. If \( \theta(t)/\theta_0(t) < 1 \), then choose an action \( x(t) \) such that \( \beta(t) > 1 \), so that \( \theta(t + T) > \theta(t) \).
2. If \( \theta(t)/\theta_0(t) > 1 \), then choose an action \( x(t) \) such that \( \beta(t) < 1 \), so that \( \theta(t + T) < \theta(t) \).
3. Else: do nothing so that \( \beta(t) = 1 \) and \( \theta(t + T) = \theta(t) \).

The last condition means that the patient is satisfied with the present state, which has the maximal desirability. Moreover, the higher the discrepancy between the actual state and the desired one, the more intense the corrective action should be.

When the future becomes the present—that is, at the time \( t + T \)—a new assessment and new forecasts are settled. If the forecasted discrepancies are acceptable, then no action is implemented; otherwise, other actions and plans are developed. The discrepancies are monitored continuously on different domains.

Thus, according to this model, in order to choose the best action, the subject has to compare the forecasted future without any particular action, \( x_0 \), with the forecasted future with an action \( x_j \) picked up from a set of actions \( \{ A \} \), available at time \( t \). The best forecasted improvement coincides with the contemplated action that brings the ratio \( \theta(t + T)/\theta_0(t) \) as close as possible to 1.

Now, one can assume that the change of the state from the time \( t \) to the time \( t + T \), \( \theta(t + T)/\theta(t) \), is due both to the consequences of the chosen action and to some random effects \( \varepsilon \). Thus, the transition operator can be estimated as

\[
\frac{\theta(t + T)}{\theta(t)} = \beta(t) \pm \varepsilon
\]

(1)

The intensity and the directionality of the correction at time \( t \) can be inferred from the temporal series of \( \beta(t) \), and the goal of the patient can be inferred by setting:

\[
\beta(t) = \beta(t + T) = 1.
\]

(2)

because the corresponding value of \( \theta(t) \) for which Eq. (2) holds has the maximal desirability, and hence no corrective actions are required.

Type 2 diabetes provides a simple naturalistic context for evaluating the proposed model of single-actor self-regulation.
In fact, the goal of these patients is to keep their glycemia around a target value that depends on the severity of the disease and its stage. Thus, there is just one variable, $\theta(t)$—that is, the day-to-day blood glucose level—to be monitored. Moreover, some patients are on a fixed schedule of insulin dosage, so they have to control just the caloric intake. Thus, there is only one available action.

Furthermore, often patients keep a written diary of their glucose levels one or more times per day, and long time series of daily measurements can be analyzed. Finally, one can assume that the patient’s forecasting horizon is just one day—that is, $T=1$—and that the goal is to keep a constant glycemic level, $\theta(t) = \theta_\delta$. Thus, long time series of postprandial glycemia, $\{\theta(1), \theta(2), \theta(3), \ldots\}$ can be analyzed in order to capture the logic of patients’ self-regulation coping strategies.

As a case study, in the present article the daily records of the postprandial glucose level (PPG(t)) of four male patients (mean age equal to 64 ± 3 years) affected by type 2 diabetes were analyzed. The patients were on a fixed insulin schedule, and their coping strategies were based upon self-regulation of eating and, to a lesser extent, physical exercise, essentially consisting of short outdoor walks. The length of the time series ranged from 340 to 420 days. The missing values (ranging from 2.5 to 4% of the number of points) were estimated by means of cubic spline interpolation.

From the day-to-day glucose level of each time series, $b(t)$, was computed as:

$$\beta(t) = \frac{\theta(t+1)}{\theta(t)} = \frac{PPG(t+1)}{PPG(t)}$$  \hspace{1cm} (3)

**RESULTS**

Because the frequency distributions were skewed to the right, the normality of the distribution of the natural logarithms of $\beta(t)$ was tested by means of the Kolmogorov-Smirnov test. The logarithms of each time series were normally distributed.

The values of $\beta(t)$ were regressed against $\theta(t)$ according to the following function:

$$\beta(t) = e^{(b_0 + b_1/\theta(t))},$$  \hspace{1cm} (4)

where $b_0 < 0$ and $b_1 > 0$. Equation (4) can be considered as a proxy of the patient’s self-regulation illness strategy. The condition

$$|b_0| > \frac{|b_1|}{\theta(t)}$$
assures that the $\beta(t)$ is a decreasing function of $\theta(t)$. Moreover, the higher the value of $b_1$, the higher the decreasing steepness of the function. Thus, $b_1$ measures the sensitivity of patients' reactions to glycemic changes, whereas $b_0$ represents the maximal theoretical correction to hyperglycemia.

Finally, one can notice that

$$|b_0| = \frac{b_1}{\theta(t)} \Rightarrow \beta(t) = 1.$$  \hspace{1cm} (5)

Thus, from Eq. (5) one can compute the target value as

$$\theta_\delta = \frac{|b_1|}{b_0}.$$  \hspace{1cm} (6)

For each time series, the best fitting regression function ($\beta(t)$ vs. $\theta(t)$) was computed. In addition, the autoregression functions were computed for each patient.

The theoretical responses to hypoglycemic (50 mg/dL) and hyperglycemic (300 mg/dL) episodes were computed by means of the equation:

$$\theta(t + 1) = \beta(t)\theta(t) = \left[ e^{(b_0 + b_1/\theta(t))} \right] \theta(t)$$  \hspace{1cm} (7)

with $\theta(t)$ respectively equal to 50 and 300 mg/dL.

Table 1 shows the best estimates of the parameter $b_0$, $b_1$; the target values for each patient ($\theta_\delta$); and the number of points ($N$).

As one can see, all but one patient showed good control of the glycemic level attained by means of the same self-regulation strategy represented by Eq. (4). For each patient, a negative autocorrelation function was found at the time lag equal to one day.

As an illustrative example, Figure 1 shows the time series of the glucose level of a 67-year-old man.

The natural logarithms of $\beta(t)$ were normally distributed with mean equal to 0.001 and standard deviation equal to 0.45.

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>Best Estimates of the Parameters and Target Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient</td>
<td>$b_0$</td>
</tr>
<tr>
<td>1</td>
<td>-0.924</td>
</tr>
<tr>
<td>2</td>
<td>-0.78</td>
</tr>
<tr>
<td>3</td>
<td>-0.80</td>
</tr>
<tr>
<td>4</td>
<td>-0.67</td>
</tr>
</tbody>
</table>

*p < 0.001.
The best fitting function of $b(t)$ vs. $h(t)$ is shown in Figure 2:

$$b(t) = e^{(b_0 + b_1/h(t))} = e^{(-0.924 + 130.2/h(t))}.$$

Thus, the goal of the self-regulation process was computed according to Eq. (5) as:

$$e^{(-0.924 + 130.2/h(t))} = 1 \Rightarrow \theta_\delta = 140\text{mg/dl}.$$

The negative autocorrelation between $b(t+1)$ and $b(t)$ is shown in Figure 3. This indicates a negative feedback aimed at regulating the level of glucose between subsequent days.
FIGURE 3 $\beta(t)$ autocorrelation function.

FIGURE 4 Theoretical response to blood glucose discrepancy with respect to the reference goal. X-axis = time; Y-axis = glycemia; squares = response to a hypoglycemic episode (starting point 50 mg/dL); circles = response to a hyperglycemic episode (starting point 300 mg/dL) (color figure available online).
The theoretical response was computed by means of the following equation:

\[
\theta(t + 1) = e^{-0.924 + 130.2/\theta(t)} \theta(t) = \beta(t) \theta(\tau)
\]

One can see in Figure 4 that the response to a hypoglycemic episode (e.g., \(\theta(t) = 50\) mg/dL) would lead to a sort of overshoot toward hyperglycemia followed by a smooth decline toward the equilibrium point, whereas the response to hyperglycemia is an almost smooth decline toward the target goal. In both cases, the theoretical effect of the perturbation would fade out in about 4 days.

**DISCUSSION**

According to Ainslie (2004), in order to face motivational conflicts, people are prone to devalue a given future event at different rates, depending on how far away it is. This phenomenon means that individuals’ temporary and (inherently) unstable preferences upset conventional utility theory.

Our approach to the patients’ illness self-regulation is somewhat similar to the Ashby’s cybernetic “ultrastability” (Ashby 1958, p. 242). The self-regulation models of health and illness (Wing et al. 1986; Hamera et al. 1988; Cameron and Leventhal 2003) can be considered as instances of more general cybernetic models in which the feedback is the main mechanism aimed at reducing (and sometimes increasing) the discrepancy between goals and actual states. Cybernetic models can, in turn, be considered as instances of systems thinking (Gharajedaghi 2006; de Savigny and Taghreed 2009).

Moreover, our model agrees with the well-known fact that emotions and personal plans strictly intermingle (Hogan 2003). Yet, emotions can be conceived as the main motivations underlying human beings’ plans, decisions, and actions (Damasio 1994; Carver 2004; Gutnik et al. 2006). Thus, one can assume that goals and feedback are essentially based upon emotional and affective responses to the actual situation (Carver 2004), which are difficult to measure directly (Giani et al. 2007).

In the present article, self-regulation was conceived as a cognitive–emotional process that enables human beings to construct forecasted desirable futures, given the reconstruction of the past and the explanation of the present state. The main objective was to formulate a model of self-regulation based upon the direct analysis of the time series of a proxy—that is, the glycemic level—of health related behavioral variables without any referral to subjective verbal statements.
The ingredients of this self-regulation model were as follows:

- Extrapolated forecasting; that is, the extension of the present state in order to predict how it will evolve without any interference by the agent’s actions.
- Action forecasting; that is, the extension of the present in order to predict the transformative effects of the agent’s contemplated actions.
- Desired future; that is, the desire that the extension of the present state has certain characteristics.
- Comparison; that is, the evaluation of the discrepancy between the extrapolated and the desired future.

If the anticipated comparison generates “negative” emotions—for example, fear, anger, regret, and so on—the agent is forced to select some actions from a set of available options, formulate a plan in order to avoid these negative emotions, and hopefully transform the undesirable future into a more desirable one.

The main move was the assumption that a given measurable state, \( \theta(t) \), can be more or less desirable depending on its discrepancy with respect to a desired state or goal, \( \theta_{d}(t) \).

The contemplated effects of actions were represented as a transition operator, \( \beta(t) \), which would transform the actual state into a more or less near future state that would be more or less discrepant with respect to the desired future:

\[
\z(t) : \theta(t + T) = \beta(t)\theta(t).
\]

The second assumption was that the value of the transition operator at each time, \( \beta(t) \), can be inferred ex post from the sequence of observed states. Finally, it was assumed that the functional relationship between \( \beta(t) \) and the state \( \theta(t) \) allows one to infer the goal of the decision maker by setting \( \beta(t) = 1 \), which corresponds to the “no action” choice.

The results showed that the frequency distribution of \( \beta(t) \) was skewed to the right. This means that even if for the majority of the days the patients succeeded in maintaining the system around their personal goals \( \theta_{d} \), the corrections of hyperglycemia were more frequent with respect to corrections of hypoglycemia.

In order to find the value of the patients’ target point, \( \beta(t) \) was regressed against \( \theta(t) \). The rationale of this choice was that the greater the discrepancy between the actual state \( \theta(t) \) and the desired state \( \theta_{d}(t) \), the greater the correction \( \beta(t) \) needed to drive the system toward the goal.

From another point of view, \( \beta(t) \) can be considered as a sort of proxy of the cognitive and emotional reaction of the patient to the observed discrepancy between the present state and the desired one. Moreover, the inverse
exponential relation between $b(t)$ and $h(t)$ indicates that the corrective actions to decrease glycemia are stronger than the corrections to increase it. This can be due to the fact that the fear of hypoglycemia is higher than the fear of hyperglycemia and that the corrective actions of hypoglycemia are more efficient.

In summary, the patients’ self-adjusting rules seem to be the following:

1. Today there is an increase (decrease) of PPG with respect to my desired goal.
2. With no correction, the PPG will continue to increase (decrease), and there will be some risk of hyper (hypo) glycemic episodes.
3. This is an undesirable future for me.
4. Therefore, a decrease (increase) of the food intake is needed today so that tomorrow the PPG will be as close as possible to my goal.
5. The stronger the degree of the actual departure from my goal, the stronger the correction I should apply.
6. A stronger correction is needed when the departure is toward hypoglycemia.

Some limitations of the present article are worth mentioning. First, we cannot say whether the exact form of the functional relation between $b(t)$ and $h(t)$ can be generalized to the entire population of patients with type 2 diabetes. In fact, the small number of patients is essentially due to the difficulty of obtaining temporal series with a reasonable number of missing values. However, the fact that the form of best fitting function is consistent across the patients seems to indicate that this model could be generalized. In this case, each patient would be an instance of Eq. (4), according to some probabilistic joint distribution of the parameters ($b_0$ and $b_1$) where each combination of the parameters would represent a different self-regulation strategy. In particular, $b_0$ indicates the theoretical maximal correction due to a hyperglycemic episode, whereas $b_1$ represents the sensibility of the patient to the variation in glycemic level. Thus, different combinations of $b_0$ and $b_1$ describe different coping strategies and/or different characteristics of the disease.

In principle, the proposed self-regulation model could be extended to situations where the patient has to monitor an array of variables on several domains; for example, cholesterol, body weight, blood pressure, pain, psychological discomfort, social role, and so on. Gathering multidimensional observations is very difficult, and only indirect information and incomplete data can be obtained. However, one can reasonably assume that the value of each variable is a function of the other ones; that is, $\theta_i = f_i(\theta_1, \theta_2, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots)$.

In this case, one can resort to an analogy with Takens’ theorem (Takens 1981), which states that the time series of measurements of a single
observable can be used to reconstruct the qualitative features of the
dynamics of a nonlinear and complex system. Thus, one can conceive
the blood glucose level as the measurable and observable variable that
conveys information about the dynamics of the other intermingled vari-
ables of a complex system. We are trying to explore the soundness of this
assumption.

As a final objection, it is worth noticing that the proposed self-regulation
model could be an oversimplification because it is based upon the decisions
and actions of a single agent. As a matter of fact, the way in which human
beings cope with their health problems cannot be understood without con-
sidering the social network in which they are embedded. From this point of
view, an illness can be conceived as a trajectory in a social event space in
which several agents are involved in order to cope with the different aspects
of the bio-psycho-social aspects of the illness of a member of their social net-
work. Thus, even in simplest cases, such as, for example, the control of the
level of glucose, the values of the parameters of the self-regulation—for
example, $b_0$ and $b_1$—could be conditioned by the direct or indirect control
of the patient’s behavior by one or more members of the family (typically
the partner) and, more generally, the social network in which the patient
is embedded. For example, family conflict is an important, potentially clini-
cally significant influence on the glycemic control in the management of type
1 diabetes in youth (Drotar et al. 2012), and lifestyles are a sort of contagion
flowing within a network of relatives, friends, friends of friends, and so on
(Christakis and Fowler 2007).

The analysis of these more complex and realistic situations is ongoing.

In principle, self-regulation models can be applied to the increasing
number of bio-signals that can be acquired by means of modern technolo-
gies. However, these signals are usually analyzed by ignoring the emotional
and cognitive factors affecting patients’ self-regulation processes (Gutnik
et al. 2006, Giani 2011). From this point of view, a given time series contains
both physiological and psychosocial information. It is difficult to disentangle
these two kinds of information, because the temporal details of bio-signals
(e.g., the so-called glycemic-Holter) are of the order of minutes or even sec-
onds, whereas the times of human reactions and decisions are much more
slower.

This is one of the reasons why the analysis of the day-to-day time series
of postprandial glycemia obtained by means of the classical fingerstick was
carried out.

The model was applied to simple situations in order to explore its
soundness and predictive power. In this way, individuals’ coping strate-
gies—that is, $b_0$ and $b_1$—can be quantified, and different patients can be
compared in order to personalize preventive and/or therapeutic interven-
tions. Our results are encouraging, and more complex models are being
explored.
REFERENCES


