Accepted Manuscript


# Virtual Personalities: Using Computational Modeling to Understand Within-Person Variability

Stephen J. Read, Benjamin Smith, Vitaliya Droutman, Lynn C. Miller

PII: S0092-6566(16)30173-8
DOI: http://dx.doi.org/10.1016/j.jrp.2016.10.005
Reference: YJRPE 3609

To appear in: *Journal of Research in Personality*

Received Date: 19 October 2015
Revised Date: 4 May 2016
Accepted Date: 9 October 2016

Please cite this article as: Read, S.J., Smith, B., Droutman, V., Miller, L.C., Virtual Personalities: Using Computational Modeling to Understand Within-Person Variability, *Journal of Research in Personality* (2016), doi: http://dx.doi.org/10.1016/j.jrp.2016.10.005

# Virtual Personalities:

# Using Computational Modeling to Understand Within-Person Variability

Stephen J. Read, Benjamin Smith, Vitaliya Droutman, and Lynn C. Miller

University of Southern California

Research reported in this publication was supported by the National Institute Of General Medical Sciences of the National Institutes of Health under Award Number R01GM109996. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Abstract

How can the same underlying psychological/neurobiological system result in both stable between-individual differences and high levels of within-individual variability in personality *states* over time and situations? We argue that both types of variability result from a psychological system based on structured, chronic motivations, where behavior at a specific point in time is a joint function of the current availability of motive affordances in the situation, current motivationally relevant bodily or interoceptive states, and the result of the competition among alternative active motives. Here we present a biologically-based theoretical framework, embodied in two different computational models, that shows how individuals with stable personality characteristics, can nevertheless exhibit considerable within-person variability in *personality states* across time and situations.

Keywords: Virtual Personalities, Within-person variability, Between-person variability, Social computational modeling

Virtual Personalities:

Using Computational Modeling to Understand Within-Person Variability

Personality *traits* are typically assumed to be relatively stable over time. However, recent research (e.g., Fleeson, 2001; Fleeson & Gallagher, 2009; Sherman, Rauthmann, Brown, Serfass, & Jones, 2015;) has shown that the short-term variability in personality *states* is at least as large as the between subject variability in stable trends or dispositions (*traits)*. How is it possible that the same underlying psychological/ neurobiological systems can on the one hand result in stable between individual differences, while also resulting in high levels of within individual variability in personality *states* over time and situations?

Here we present a theoretical framework, embodied in two different computational models, that shows how individuals with stable personality characteristics, can nevertheless exhibit considerable variability across time and situations in personality-related behaviors. We argue that such variability is to be expected in a psychological system based on structured, chronic motivations, where behavior at a specific point in time is a joint function of the current availability of motive affordances in the situation, current motivationally relevant bodily or interoceptive states, and the result of competition among alternative active motives. As the result of variations in these factors over time and situations, personality *states* will also vary considerably.

These models extend our previous work (Read et al., 2010; Read & Miller, 2002, in press), which argues that both the structure of personality (e.g. the Big Five) and the dynamics of personality-related behavior arise from the behavior of structured motivational systems interacting with the motive affordances of the different situations that individuals encounter over time. This work has evolved from our earlier work on goal-based models of personality (e.g., Miller & Read, 1987; Read, Jones, & Miller, 1990; Read & Miller, 1989). In that work, we argued that personality traits can be viewed as configurations of goals and motives, plans, resources, and beliefs, and that goals and motives were central to traits. In more recent work on Virtual Personalities (e.g., Read et al., 2010; Read & Miller, in press, 2002) we have argued that a personality model based on structured motivational systems allows us to provide a unified account of both the structure and the dynamics of human personality. As a number of researchers have noted (e.g., Funder, 2001), research on the structure of personality (e.g, the Big Five (John, Naumann, & Soto, 2008), HEXACO(Ashton & Lee, 2007; Lee & Ashton, 2004)) and research on personality dynamics have tended to proceed independently. However, there is growing interest in developing an account of personality that integrates the two approaches. We have argued that our Virtual Personalities model provides such an account. The current paper extends the model presented in Read et al. (2010) in several different ways, as outlined below.

## The Virtual Personality Model

Given the dynamic complexities of personality, it is not surprising that over the last decade there has been growing interest in using computational tools to model that complexity. For example, Shoda and Mischel's (Mischel & Shoda, 1995; Shoda & Mischel, 1998) CAPS model of personality is implemented as a general parallel constraint satisfaction neural network model, in which individual differences are represented in terms of the connections from a situational features layer to a highly bi-directionally connected set of nodes that represent the goals, strategies, and beliefs of an individual, and then to behavior. However, each individual is proposed to have their own unique network, which is relatively unstructured. This makes integration with work on the structure and dynamics of personality, and links to underlying biological systems, difficult.

Revelle and Condon (2015) have recently presented their CTA (Cues, Tendencies, Actions) computational model, which is based on Atkinson and Birch's Dynamics of Action (DOA) Model. In their model, Cues in the environment send activation to Tendencies and then Tendencies send activation to Actions. Actions have inhibitory links and compete with each other for activation. An enacted Action then sends inhibitory activation back to the Tendencies, representing consummatory forces. Although their model does provide the mechanisms for the different CTA systems to interact, this interaction is not organized in any particular way, such as the current model's organization into separate Approach and Avoidance systems. Moreover, there are no parameters to capture stable individual differences in the chronic importance of the corresponding Tendency.

In contrast to the CAPS and CTA models, the Virtual Personality model (Read et al., 2010) assumes that individuals' have structured motivational systems and that all individuals share the same basic structure. Individual differences arise in the parameters of components of the systems. At the broadest level, people's motivational systems are organized into two broad systems, an Approach and an Avoidance system (Carver, 2006; Carver & White, 1994). The Approach system governs sensitivity to rewards, whereas the Avoidance system governs sensitivity to punishment. Moreover, there are strong individual differences in the sensitivity of the Approach and Avoidance systems. This notion is the key foundation of Grey's Reinforcement Sensitivity Theory of personality (Gray, 1982; Gray & McNaughton, 2000). The basic distinction between Approach and

Avoidance systems and tendencies has a considerable amount of support, including biological support for this distinction across species from reptiles to humans, and has been usefully applied in a wide variety of domains (Elliot, 2008).

Within each of these two broad systems are a number of more specific motives. Information about the nature of these different motives comes from a variety of areas, such as evolutionary analyses of the tasks that individuals must pursue in order to survive and reproduce (e.g., Bugental, 2000; Kenrick & Trost, 1997), and work on taxonomies of human motives (e. g, Boudreaux & Ozer, 2013; Chulef, Read, & Walsh, 2001; Talevich, Read, Walsh, Chopra, & Iyer, 2015). There are also important individual differences between individuals in the strength and importance of each of these major motives.

In addition, the VP model makes clear predictions about the nature of situations. Sherman et al. (2015) have argued that most models of the role of situations in personality-related behavior do not provide an explicit model of what is meant by a situation. However, in our work we have long provided an explicit account of what we mean by a situation (Miller & Read, 1991; Read & Miller, 1989). We have argued that situations can be conceptualized as motive or goal-based structures, where, consistent with Argyle, Furnham, & Graham (1981), situations can be viewed in terms of the motives afforded by the situation, the physical attributes of the situation, and the typical roles and scripts that can be enacted in the situation. In our earlier computational work (e.g., Read et al., 2010) and in the current work situations are operationalized in terms of features that directly activate relevant affordances.

These motive affordances are among the major factors that activate the motives in the model. For example, a situation that affords academic pursuits provides various affordances for achievement and will activate motives related to achievement, whereas a situation that affords romantic pursuits provides very different affordances. One implication of this conceptualization of situations is that it strongly implies that one major factor underlying variability in personality-related states over time and situation is variability in the motive affordances provided by different situations.

Sherman et al. (2015) have recently provided information that supports the idea that affordances will vary considerably over time. Using the DIAMONDS (Rauthmann et al., 2014) measure of situations in an ambulatory assessment study of personality characteristics, situations, and behaviors, they found that within-subject variability in the kinds of situations encountered was considerably higher than between-subject variability. We note that the DIAMONDS taxonomy and measure of types of situations seems to overlap with our focus on the role of motive affordances in conceptualizing situations. For example, major dimensions of the DIAMONDS measure include Sociality (social interactions required or desired), Adversity (external threats), and Mating (sexually or romantically charged situation), all of which seem to tap into important motive affordances.

Our model has been implemented as a neural network (Read et al., 2010; Read & Miller, in press). See Figure 1 for a representation of that neural network model.

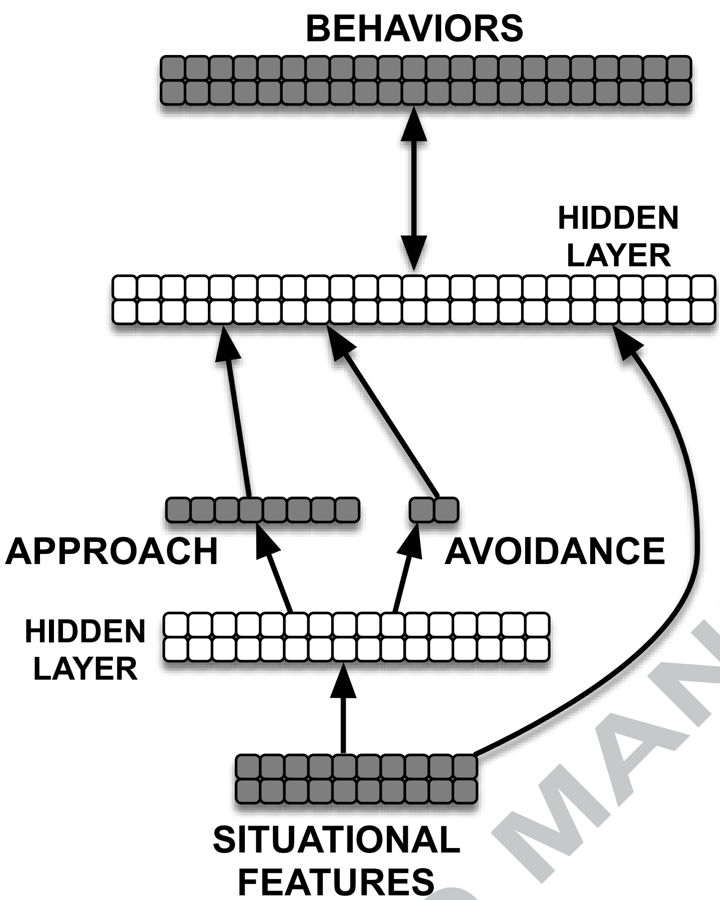


*Figure 1.* Basic structure of the Read et al. (2010) Virtual Personalities model

In the Read et al (2010) neural network model situational features, indicated by individual nodes in the Situational Features layers, send activation to the Hidden Layer, which learns patterns of situational features that define different kinds of situations (e.g., party, work cubicle). Activation then goes to the nodes corresponding to the different possible motives in the appropriate Approach and Avoidance Layers. Motives within the Approach and Avoidance layers compete with each other for activation. Activation from the motives then feeds into a Hidden layer and from there into the Behavior layer, where the different behaviors compete with one another for which behavior is enacted at that time step. The Approach and Avoidance layers have independent gain functions, which capture the idea of individual differences in sensitivity to rewards and punishments. In addition, the motive nodes within the Approach and Avoidance layers have independent baseline activations, which capture individual differences in the relative importance of different motives.

In a recent paper using this version of the model, we (Read & Miller, in press) simulated how the Big Five personality structure can arise from the behavior of these structured motivational systems. We simulated the behavior of a large number of different virtual individuals who shared the underlying motivational structure we outline above. We then randomly varied their underlying motivational parameters (e.g., the gains on the Approach and Avoidance layer, and the baseline activation of nodes) and then exposed them to a wide range of situations. We then factor analyzed the resulting patterns of behavior and showed that something like the Big Five structure would arise in the behavior of a large number of different virtual personalities, who varied in the characteristics of underlying motivational structures organized in the way our model proposes. These sets of simulations focused on personality structure and how it can arise from the dynamics within structured motivational systems.

In the current paper we focus on the dynamics of personality-related behaviors over time and situations and use an expanded version of the model to show how the same kind of model can, exhibit high levels of within-subject variability in personality-related behavior over time and situations. Below, we discuss advances in the virtual personality model that leverage additional personality dynamics considerations (e.g., the role of interoceptive state, consummatory behaviors, and satiety behaviors), and how this revised virtual personality model provides insight into within-person variability as well as between-person variability.

**Factors Responsible for Within-person Variability in Personality-related behavior**

Recently, we (Read & Miller, in press) have added the role of information about interoceptive or bodily state to the model. Based on work by Berridge and his colleagues (e.g., Berridge, 2012; Berridge & O'Doherty, 2013)(also see Bechara & Naqvi, 2004) we argue that the strength of wanting to approach or avoid an affordance in the environment is a multiplicative function of the strength of the cue (the affordance) and the current interoceptive or bodily state relevant to that cue. More concretely, wanting food is not simply a function of the strength of the food cue, it is also a function of how hungry you are. Or wanting social interaction is not simply a function of how attractive other people are, it is also a function of how lonely you are, how much you need social contact.

But, why does an organism's need for food or social contact vary over time? As is perhaps most apparent with hunger, eating can reduce the strength of a dominant action tendency (seek food) and allow alternative action tendencies to emerge. Similarly, as many of us have experienced at conferences, after a great deal of social stimulation, the strength of our desire to seek out others can be considerably reduced. Conversely, going without food or social contact for a period of time increases one's need for food or contact. Computational models such as Atkinson and Birch's (1970) Dynamics of Action and Revelle and Condon's (2015) CTA model have analyzed such within-person changes in personality-related behaviors over time. The major focus in their simulations has been on changes in Action Tendency and competition for control of behavior over time, including a consideration of how consummatory behaviors can reduce dominant action tendencies, and activate alternative ones. Although the CTA model only postulates a single effect of consummatory behaviors on Action Tendencies, we argue that a typical consummatory behavior can have two potential effects. First, a consummatory behavior such as eating or drinking can reduce the availability of the corresponding affordance in the environment (cue strength). Second, it can change bodily or interoceptive state. For example, eating reduces hunger or hanging out with friends can reduce loneliness. In our model, we treat these as two separate factors.

The conceptualization of strength of wanting as a multiplicative function of cue strength and interoceptive state identifies two separate sources of variability in behavior over time: (1) the strength of the cue (or affordance), and (2) interoceptive state. Both play a role in how much you want to do something and in variability over time and situation. A further consideration is that when there is a multiplicative relationship between two variables, as in the present case, each factor can play a gating role in controlling behavior. So if there is attractive food, but you aren't hungry you are far less likely to eat. Or if there are interesting people, but you don't particularly need social contact, you may not talk to them.

Another important factor in understanding variability is that choice of a behavior is often the result of a competition among alternative motives. Thus, the choice of a behavior is not simply a function of how strong a particular motive is; it is also a function of how strong that motive is **compared to** the other active motives. For instance, in one situation Motive A of moderate strength will not be pursued because an alternative motive is more strongly activated, whereas in another situation where Motive A has the exact same moderate strength, it will be pursued because no other motive is as strongly activated.

Although there are undoubtedly other factors that affect variability over time, the preceding analyses point to three major factors that can influence the variability of personality *states* over time: (1) the availability of relevant affordances, (2) current interoceptive state, and (3) the results of competition among multiple motives. In the following simulations we examine the impact of each of these factors on variability in personality relevant behavior across time and situations.

The current version of the model (see Figure 2) has four key additions compared to Read et al. (2010). First, it explicitly represents current interoceptive or bodily state. Second, the activation of the motives is a multiplication function of the interoceptive or bodily state of the individual and the situational cues. Third, the behavior that is enacted can modify the situational features (e.g., *consummatory*: eating food). Fourth, the behavior that is enacted can modify the current bodily state (*satiety*).

In this model flow of activation proceeds as follows: First, situational features and bodily state or interoceptive state information, indicated by individual nodes in the two layers, jointly feed into the nodes corresponding to the different possible motives in the appropriate Approach and Avoidance Layers and are multiplicatively combined. Activation from the motives then feeds into the Behavior layer, where the different behaviors compete with one another for which behavior is enacted at that time step. Once a behavior is enacted it then can have a consummatory effect on the affordances in the Situational Features layer (representing the Environment) and a satiety effect on the Bodily state.

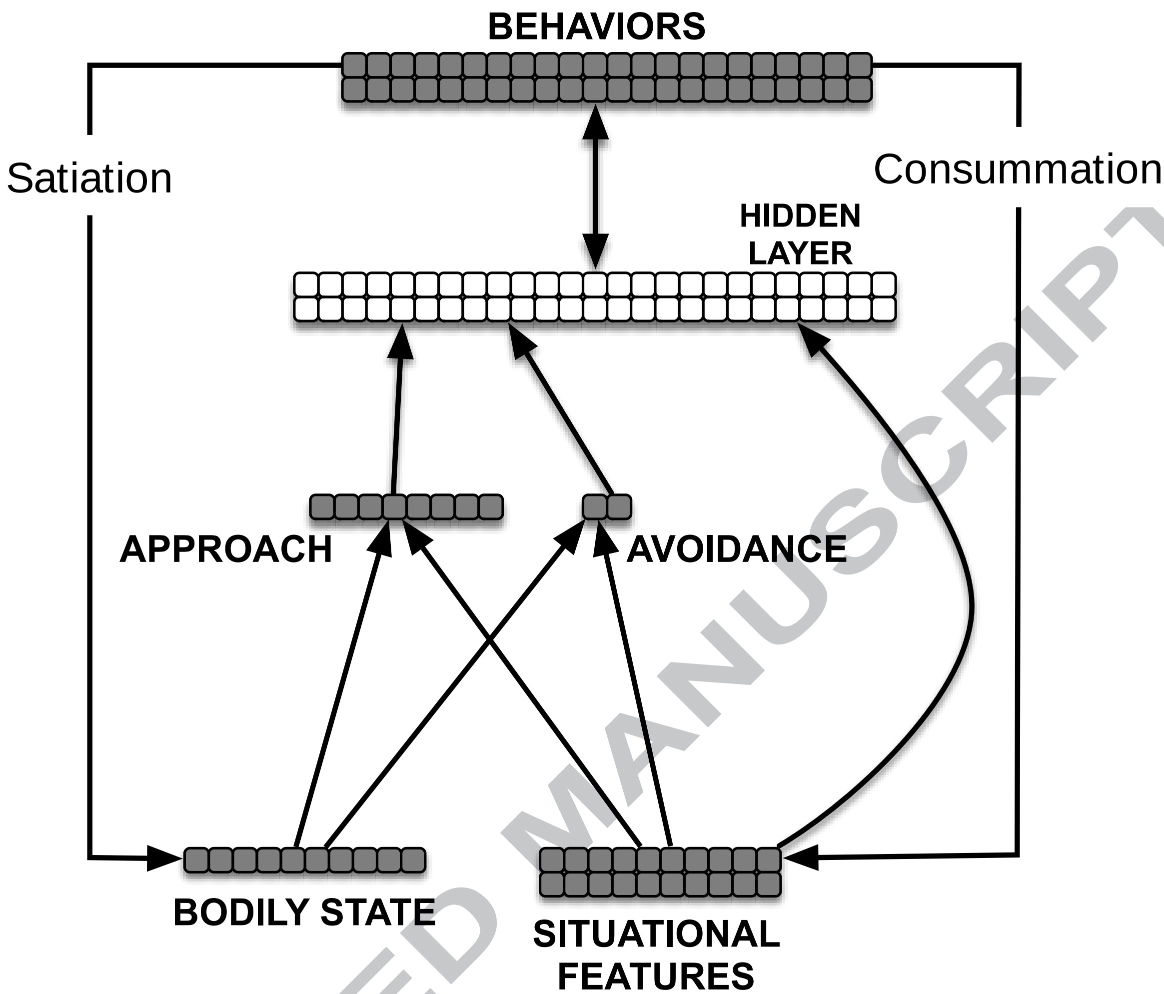


*Figure 2.* Basic structure of the revised Virtual Personalities model used in this chapter

At the same time, these models can also capture stable individual differences (*traits)* or general behavioral tendencies. Stable individual differences are captured in terms of differences in: (1) reward and punishment histories over time, which lead to different strengths of the weights between affordance cues and motives, (2) sensitivities to reward and punishment, represented by differences in gains for the Approach and Avoidance layers, and (3) baseline activations and/or gains for different motives.

We create simulations of individuals with stable personality characteristics or stable behavioral tendencies over time and show how these individuals can exhibit considerable within individual variability across time and situation. In examining variability across time we study the role of three different factors: (1) changes in the availability of motive affordances across time and situation, either because the individual's actions change the availability of the affordances (eating all the ice cream) in the current situation, or because the individual moves to a new physical location with different affordances, or because other actors change the affordances, (2) changes in individual's interoceptive or bodily state (e.g., Hunger, Thirst, Boredom, Loneliness) that moderate the attractiveness or aversiveness of affordances, and (3) competition between multiple motives that lead to different behaviors.

## Overview of Simulations

In the following we describe and demonstrate two related computational models of the motivational dynamics we have discussed in the preceding. Although they share common theoretical assumptions there are differences between them. One is a neural network model implemented in the Leabra neural network architecture within the program *emergent* (Aisa, Mingus, & O'Reilly, 2008) and the other is implemented in the programming language Python. Two different architectures are used to highlight the general value of social computational models for providing insights into personality, rather than the need to use a specific type of architecture. Our goal was therefore to demonstrate that when implementing computational models *with the same or similar underlying theoretical assumptions*, similar results should be produced.

### Neural Network Model of Variability in Personality States

The network in Figure 3 provides a simplified version of the environmental affordances and potential behaviors of a college student, to provide a simulation that is easier to follow, but which still captures the basic implications of our analysis. The Environment layer represents different situations, with different affordances: Friend, the Library, Food, Social situation (SocSit), and Physical Danger. The Interoceptive State layer (InteroState) represents the current Interoceptive States: need for affiliation, need for achievement, Hunger, Social Anxiety, and Fear.

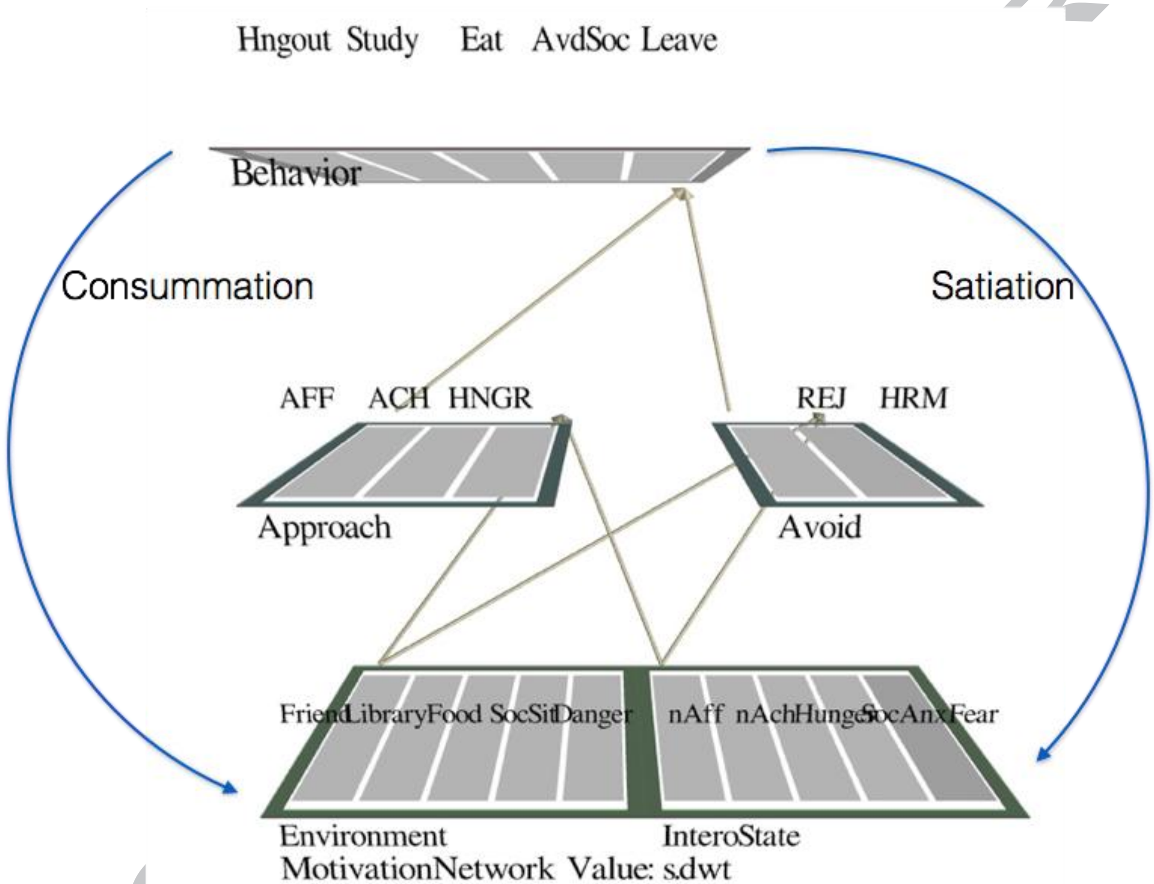


*Figure 3.* Simple version of the Virtual Personalities model used in current simulations. Based on a screenshot from the emergent neural network modeling system used to perform the current simulations. Layers in the model and the name of the nodes are: Environment: Friend, Library, Food, SocSit (social situation), and Danger. InteroState: nAff-need for affiliation, nAch-need for achievement, Hunger, SocAnx-Social anxiety, and Fear. Approach: AFF-affiliation, ACH-achievement, and HNGR-hunger. Avoid: REJ-social

rejection, HRM-physical harm. Behavior: Hngout-Hang out with friends, Study, Eat, AvdSoc-avoid socializing, and Leave.

The inputs from these two layers are then sent to the motives in the appropriate Approach or Avoidance layer, where they are multiplied together. The two layers can have different gains: This makes it possible to model the two systems as having different sensitivities to their inputs. For example, the Avoid layer can be given a higher gain than the Approach layer to capture the notion that people are more sensitive to negative events or losses.

The activation from these nodes is then sent to the Behavior layer, where the different behaviors compete with one another and the most active behavior is the one that is enacted. The particular Behavior that is chosen can then modify both the Environment and the current Interoceptive states that will then serve as input for the next step. For example, Eating can both change the environment (reduce food available) and reduce Interoceptive state. Socializing for a while can reduce Loneliness or need for others. Leaving the situation may eliminate the presence of Danger.

Figure 4 provides an overview of the flow of control in the model. Information about cues to affordances in the environment and current Interoceptive state flows to the Motive/Action Tendency layer, where they are multiplicatively combined. This activation then flows to the Behavior layer, where the activated behaviors compete to be enacted. Once a behavior is enacted it can have consummatory effects on affordances in the environment and satiety effects on the Interoceptive States.

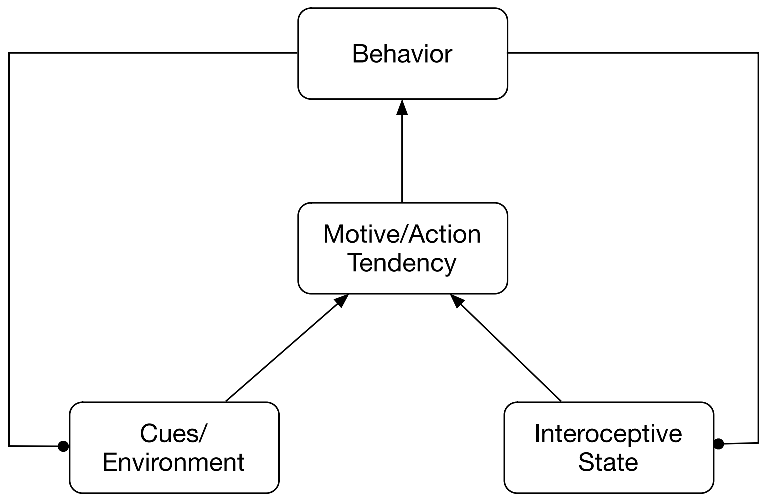


*Figure 4.* Flow of control in the current Virtual Personalities simulation

Several characteristics of the model are important for modeling fluctuations in personality *states*.

1) Variability in Interoceptive state.

2) Variability in availability and strength of Affordances.

3) Competition between motives for control of behavior.

**Consummation and satiation.**

Once a behavior has been enacted it can have consummatory and/or satiation effects. That is a behavior can reduce or remove an affordance from the environment, such as consuming food or water (consummation), or it can modify an interoceptive state (satiation), as when hanging out with friends for a while will reduce one's need for affiliation.

Program code in the *emergent* program reads the enacted behavior and then modifies a related environmental affordance, if appropriate, and/or an interoceptive state. Then the environmental affordances and the interoceptive states are input to the network on the next time step. In addition, new cues may enter the environment, as when a friend texts you or walks up to your table in the library, and interoceptive states, such as hunger or need for social affiliation, can increase over time.

Most of the consummatory and satiation rates are set to defaults of 0.05. However, the consummatory rate for hanging out with friends or studying is set to 0 (i.e., hanging out with friends or studying never depletes the 'resource' of friends or study books); Consummatory rate for fleeing from a threat is set to 1, indicating that fleeing removes the threat.

**Neural network simulations.**

Figure 5 provides the results of one run of a simulation that demonstrates the impact of the three factors we have discussed: (1) Environmental Affordances, (2) Interoceptive States, and (3) Competition between alternative possible Action Tendencies and Actions. The different lines for the Affordances row track the level of the corresponding affordance. The level of each affordance is a function of consummatory actions by the individual, as well as environmental changes in each one over time. The Interoceptive State row tracks changes in each Interoceptive State. The Action Tendency row tracks the results of multiplicatively combining the affordances and the interoceptive states. The Behavior Activation row indicates the activation of each behavior and the result of the competition among behaviors. And the top row, Behavior Exhibited, indicates which of the possible Actions or behaviors is being carried out at each time.

First, the simulation shows the impact of changes in Affordances. At the left side of the graph, there are Friends (blue) present in the Library (red) and the individual has a high Need for Affiliation (blue) and a moderately high, but not as high Need to Study (red). The result is that the individual initially hangs out with his friends, instead of studying. But then the friends leave and with this Affordance gone, the Action tendency for Hangout drops dramatically below the Action Tendency for Study and the individual now studies. Second, the simulation shows the impact of increases and decreases in Interoceptive State. Tracking the green line in the Interoceptive States box and the Affordances box, one can see that first Food becomes present, say because a friend texts and says there is food available outside, and then Interoceptive State for Hunger becomes really high. With Affordances and Interoceptive State for Hunger now high, the Action Tendency for Eat exceeds that for Study, although there has been little drop in the Action Tendency for Study, and the individual stops studying and starts eating. But then as Interoceptive State declines, the Action Tendency for Eat decreases below that for Study and the individual begins to study again. Third, this simulation demonstrates the role of competition between Action Tendencies in behavior. Although the Action Tendency for Study stays high and does not decline very much, whether or not the individual studies is a function of the strength of the competing Action Tendency to Eat.

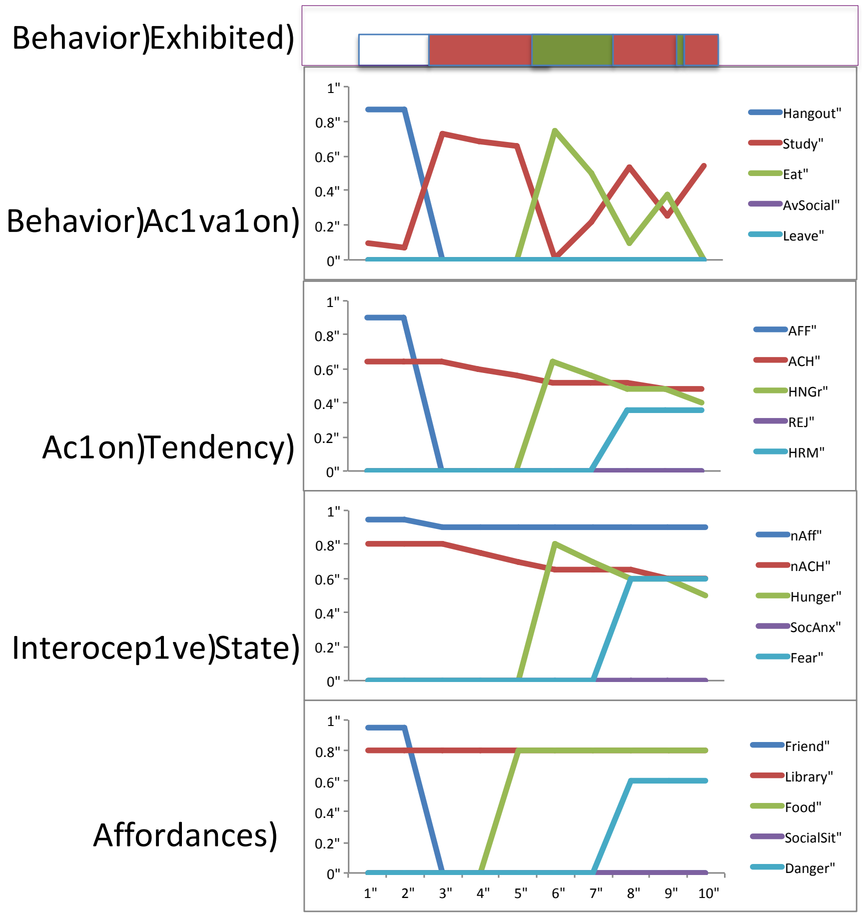


*Figure 5.* Results of simulation of the role of 3 factors over time. Affordances and Interoceptive State line graphs represent the inputs to Action Tendency in the network at each time step, where time is on the x access. The Action Tendency line graph represents the result of multiplying Affordances by Interoceptive State and the resulting activation for each corresponding Action Tendency. The Behavior Activation line graph represents the resultant activation of the different behavior nodes in the Behavior Layer, after competition between the nodes in the layer. The Action colored bar represents the winning Behavior, at each time point.

**Individual differences.**

Figures 6 and 7 provide an example of several ways in which individual differences can be captured by the model. Figure 6 presents an individual who takes longer to be sated by eating (smaller decrease in Interoceptive State for each bite of food) than is the individual in Figure 5. This can be seen by comparing the green line for Interoceptive States in the two graphs. In the second figure, Figure 6, the Interoceptive State for Hunger drops later and more slowly, than the Hunger state for the first individual in Figure 5. As a result, the Action Tendency for Eat for the second individual exceeds the Action Tendency for Study for a longer period of time, than is true for the first individual. Consequently, the second individual never goes back to studying, whereas the first person does. Although the example here involves food, the same idea could apply to things like achievement or affiliation.

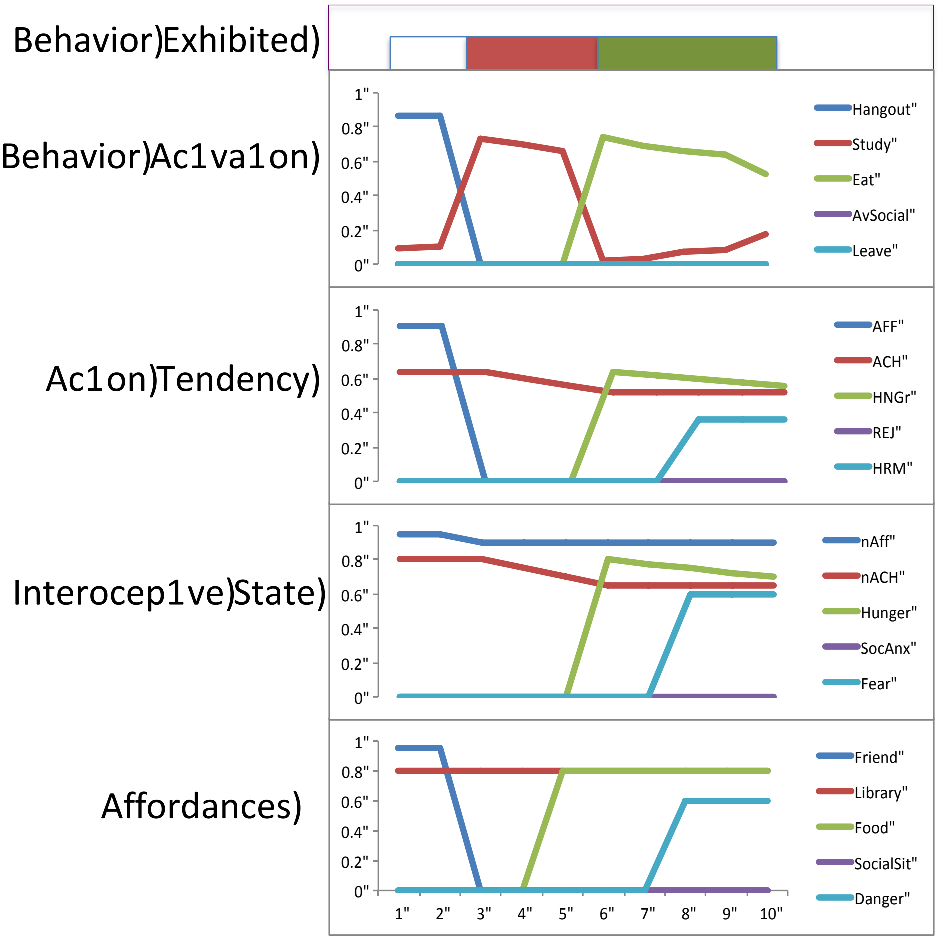


*Figure 6.* Impact of slower rates of satiation on behavior choice. Affordances and Interoceptive State line graphs represent the inputs to Action Tendency in the network at each time step, where time is on the x access. The Action Tendency line graph represents the result of multiplying Affordances by Interoceptive State and the resulting activation for each corresponding Action Tendency. The Behavior Activation line graph represents the resultant activation of the different behavior nodes in the Behavior Layer, after competition between the nodes in the layer. The Action colored bar represents the winning Behavior, at each time point.

Figure 7 provides an example of an individual who has a greater sensitivity to threat than the individuals portrayed in the first two examples. In the current simulation we capture that greater sensitivity by increasing the gain on the multiplicative layer for Avoidance from 1 to 2. The effect of this can be seen by comparing the Aqua line in Figure 7 with the aqua lines in the other two figures. In those figures the aqua lines for Danger and Fear move to moderate levels after time point 7, but they are not strong enough, yet, to result in an avoidance behavior, such as Leave. Thus, the Affordance, the Interoceptive State, and the Action Tendency stay at a constant moderate level.

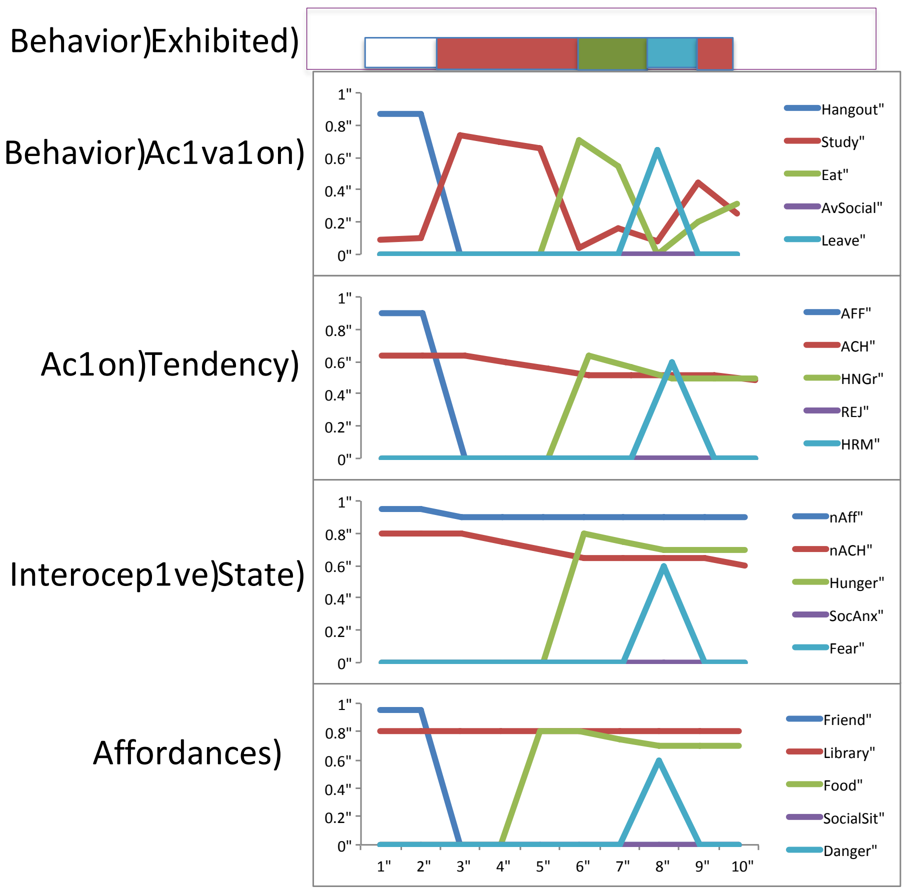


*Figure 7.* Simulation of greater sensitivity or gain to threat. Affordances and Interoceptive State line graphs represent the inputs to Action Tendency in the network at

each time step, where time is on the x access. The Action Tendency line graph represents the result of multiplying Affordances by Interoceptive State and the resulting activation for each corresponding Action Tendency. The Behavior Activation line graph represents the resultant activation of the different behavior nodes in the Behavior Layer, after competition between the nodes in the layer. The Action colored bar represents the winning Behavior, at each time point.

However in Figure 7, by time step 8, because of the higher gain on the Avoidance layer, the value for the aqua line in the Action Tendency box exceeds the values for the other action tendencies. As a result, this individual stops Studying and Leaves. However, because Leaving reduces the threat to 0, the Action Tendency for Leave immediately drops and the individual starts to Study again.

## Python Model of Variability in Personality States

Our theoretical model was also implemented in python to clearly show the underlying mathematical principles, as well as to demonstrate that the basic findings are not specific to the architecture in which we simulated our theoretical approach. The python-based simulation is available online at http://github.com/bjsmith/motivation-simulation. It is closely based on Revelle and Condon's (2015) cues, tendencies, and actions (CTA) model. This implementation extends their model by introducing "interoceptive states". Interoceptive States represent current levels of need or lack. For an action to happen, in addition to an environmental cue, there must also be an active interoceptive state present. The model also includes a learning system. Each action independently carries some expected and actual reward and punishment value, and in order for the simulated actor to take action, the expected reward for taking the action must be greater than the expected punishment.

The flow of influence in the model is reflected in the flow chart in Figure 8.

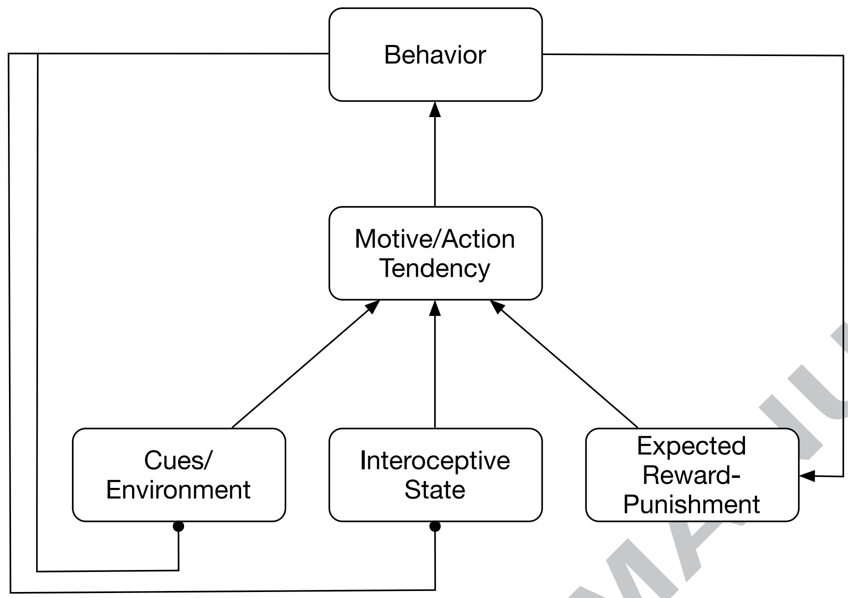


*Figure 8.* Flow of control in the Python model of personality

**Calculating action tendency.**

In this model the strength of the action tendency is a multiplicative function of current interoceptive state, environmental affordances, and the weighted difference between the positive and negative consequences of an action. Specifically, this is represented by the following equation:

$$t_i[x] = (e_{p,i} - \left[\frac{1}{\lambda}\right] e_{n,i})(\varepsilon_i \cdot E_i)(s_i \cdot \Sigma_i) + p(t_i[x-1])$$

*where $t_i[x]$ is action tendency at time x for action i*

$e_{p,I}$ is expected positive attributes and

$e_{n,I}$ is expected negative attributes

λ is the loss aversion parameters.

$\varepsilon$ is the vector representing the current presence of relevant elicitors and $E$ is the matrix representing their mapping to action $i$

$s$ is the vector representing the current presence of relevant internal states, and $\Sigma$ is the matrix representing their current mapping to action $i$.

$p$ is the persistence of action tendency from t-1 to t.

**Consumption and satiation.**

At each time step, this equation is used to calculate the current action tendency, and then the action that has the highest tendency and is also over action threshold $r$ is taken. Actions can then modify both the interoceptive state and the availability of an affordance. For example, eating can reduce hunger (interoceptive state) and the amount of food. This produces a change in elicitors and states according to whichever action is active and the amount of consummatory and satiation power, respectively.

Most consummatory and satiation power rates are set to 0.05 of the relevant elicitor or state and 0 to all other elicitors and states by default, although they can be modified as desired. However, the consummatory power of hanging out with friends or studying is set to 0 (i.e., hanging out with friends or studying never depletes the 'resource' of friends or study books); the consummatory power of a potential partner in the environment is set to 1 – i.e., approaching a potential partner in the environment to request the person's number immediately results in either acceptance or rejection – the opportunity is 'consumed'. Consummatory power for fleeing from a threat is set to 0.5, indicating that fleeing quickly removes the threat. The satiation power of fleeing on fear, on the other hand, is set to twice the default value, indicating that fear remains quite some time after the threat is removed.

**Learning.**

Finally, a learning system adjusts expected positive and negative values for an action as a function of the discrepancy between the expected and received reward and punishment values. Rewards and punishments are modeled separately, allowing for individual differences to learned values during decision-making, according to decision-making parameter $\lambda$, according to

$e_p[x+1] = l(v_p[x]) + (1-l)(e_p[x])$ **Rewards**
$e_n[x+1] = l(v_n[x]) + (1-l)(e_n[x])$ **Punishments**

*l* is the learning rated

*v* is the actual value of an action

*e* is the expected value of an action.

**Python simulations.**

In the following we provide several simulations demonstrating the behavior of the model and how it responds to changes in the factors we have outlined. The parameters and the expected and actual reward and values that are used in learning are given in the following two tables:

Table 1

*Parameters in the model*

| | Name | Value |
|---|---|---|
| Action threshold | $R$ | 2 |
| Learning rate | $0 \leq l \leq 1$ | 0.05 |
| Action tendency persistence | $0 \leq p \leq 1$ | 0.9 |
| Loss aversion | $\Lambda$ | 1.5 |

Table 2:

*Initial positive and negative expected values and actual values of the affordances or elicitors*

| | $e_p$ | $e_n$ | $v_p$ | $v_n$ | |
|---|---|---|---|---|---|
| Food | 1 | 0.25 | 1 | 0.25 | |
| Friends | 1 | 1 | 1 | 1 | |
| Potential partner | 2 | 0.05 | 2 | 4 | |
| Library | 1 | 0.2 | 1 | 0.36 | |
| Danger | 4 | 0 | 4 | 0 | |

In the following simulations we examine the impact of the same three major factors on variability in personality relevant behavior across time and situations: (1) the availability of relevant affordances, (2) current interoceptive state, and (3) the results of competition among multiple motives.

***Within individual variability.*** Figure 9 provides one run of a simulation that demonstrates the impact of the three factors we already investigated in the neural network model: (1) Environmental affordances (Elicitors), (2) Interoceptive States, and (3) Competition between alternative possible Action tendencies and Actions. The different lines for the Elicitor row track the level of the corresponding elicitor or affordance, where different colors track different ones. The level of each elicitor is a function of consummatory actions by the individual, as well as environmental changes in each one over time. The States row tracks changes in each Interoceptive state. The Action Tendency row tracks the results of multiplicatively combining the affordances, the interoceptive states, and the expected gains and losses associated with each possible Action tendency. The top row, Action, indicates which of the possible Actions or behaviors is being carried out over time.

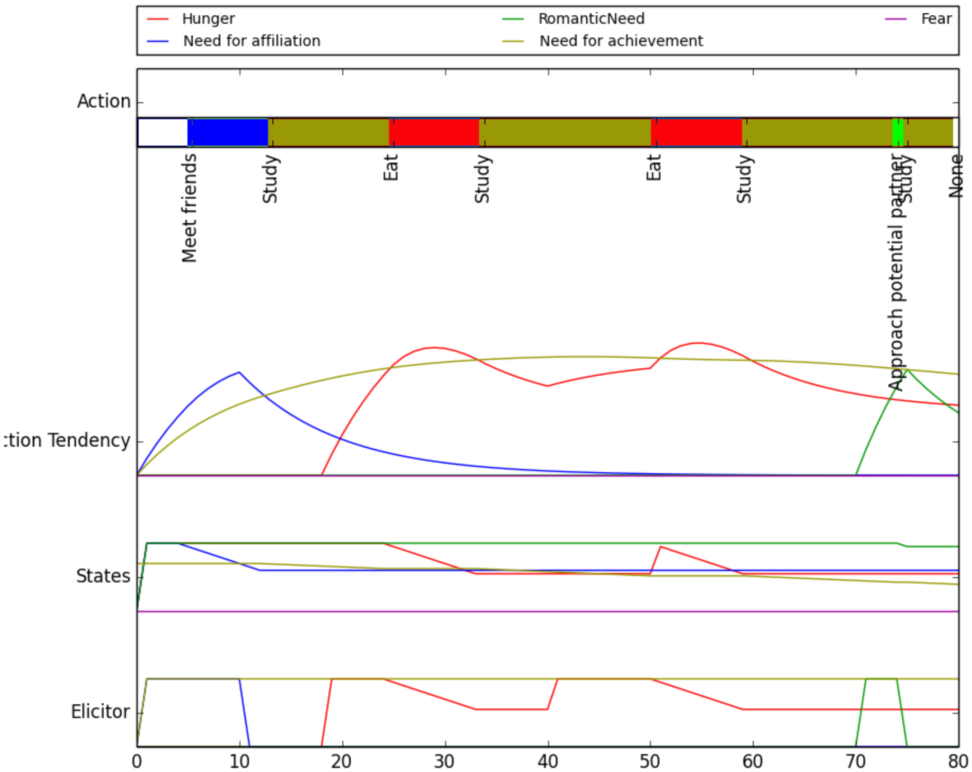


*Figure 9.* Results of one simulation of the impact of 3 factors on behavior. Elicitors and States line graphs represent the inputs to Action Tendency in the network at each time step, where time is on the x access. The Action Tendency line graph represents the result of multiplying Affordances by Interoceptive State and the resulting activation for each corresponding Action Tendency. The Action colored bar represents the winning Behavior, at each time point.

First, the simulation shows the impact of changes in affordances. At the left side of the graph, there are **Friends** present in the **Library** (Elicitor row) and the individual has a high need for affiliation and a moderately high, but not as high need to study. The result is that the individual initially hangs out with his friends, instead of studying. But then the friends leave and with this affordance gone, the Action tendency for Hangout drops dramatically below the action tendency for Study and the individual now studies. Second, the simulation shows the impact of increases and decreases in Interoceptive state. Tracking the red line in the States box and the Elicitor box, one can see that first food becomes present, say because a friend texts and says there is food available outside, and then Interoceptive state for Hunger becomes really high. With Affordances and Interoceptive state for Hunger now high, the Action tendency for Eat exceeds that for Study, although there has been no drop in the Action tendency for Study, and the individual stops studying and starts eating. But then as food declines and interoceptive state declines, the action tendency for eating decreases below that for studying and the individual begins to study again. Third, this simulation demonstrates the role of competition between Action tendencies in behavior. Although the Action tendency for Studying stays high and does not decline, whether or not the individual studies is a function of the strength of the competing action tendency to eat.

**Individual differences.**

Figure 10 provides an example of one way in which individual differences can be captured by this model. This presents an individual who has a smaller appetite and is more quickly sated than is the first individual (in contrast to the NN simulation, where the individual took longer to be sated). This can be seen by comparing the red line for States in the two graphs. In the second figure, Figure 10, the Interoceptive state for Hunger drops sooner and further, than the Hunger state for the first individual. As a result, the Action tendency for Eat for the second individual exceeds the Action tendency for Study for a shorter period of time, than is true for the first individual. As a result, the second individual spends less time eating before going back to studying, than does the first person. Although this is applied to food, this idea is generalizable to things like achievement or affiliation.

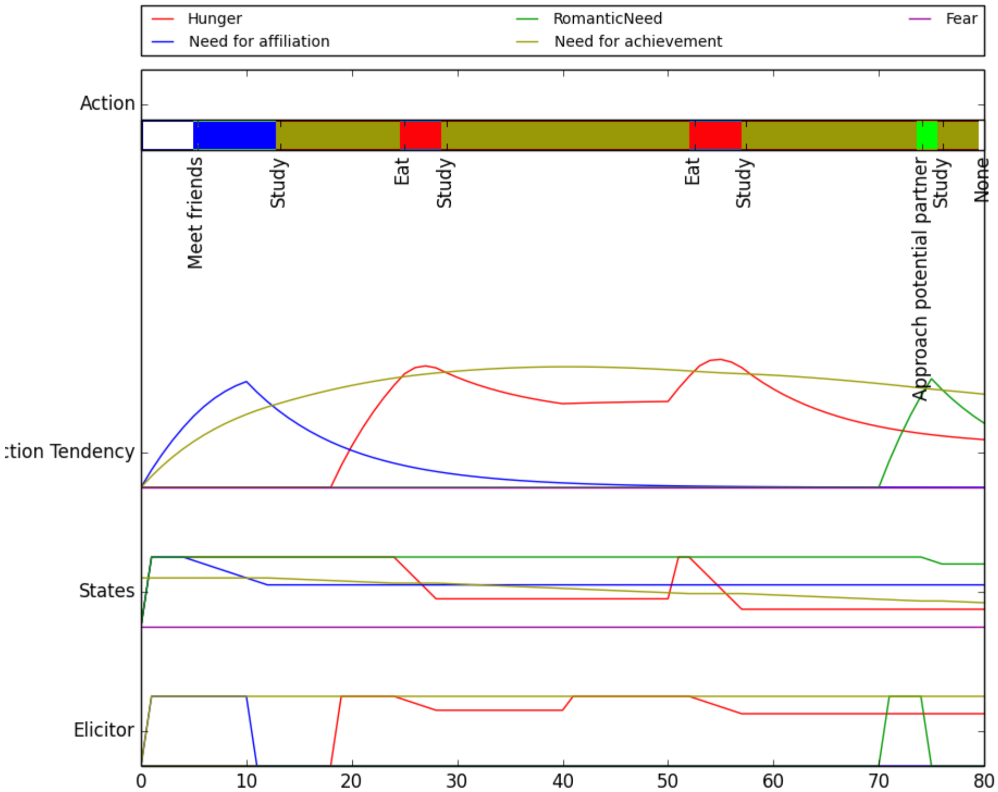


*Figure 10.* Simulation of impact of faster satiation on behavior. Elicitors and States line graphs represent the inputs to Action Tendency in the network at each time step, where time is on the x access. The Action Tendency line graph represents the result of multiplying Affordances by Interoceptive State and the resulting activation for each corresponding Action Tendency. The Action colored bar represents the winning Behavior, at each time point.

## General Discussion

We have shown how high variability in personality-related behavior can be the result of the interactions of structured motivational systems with the motive affordances of situations and the internal interoceptive or bodily state of the individual. In our simulations high levels of within-person variability in personality-related behavior can be the result of four different factors. First, as situational motive affordances change, the behavior of the individual can vary quite strongly. Second, the choice of a behavior will vary as a result of the current interoceptive or bodily state of the individual. Third, situational affordances and bodily state are multiplicatively combined to determine the degree of "wanting" or Action Tendency. Fourth, whether a particular behavior will be chosen or enacted is partially a function of the strength of alternative behaviors. Whether a behavior will be chosen cannot be predicted when taken in isolation.

A number of researchers have raised the issue of why we find high levels of within-person personality-related variability across time and situation. However, as Sherman et al. (2015) have recently argued a problem in understanding the bases of that variability is that we lack an explicit account of what a situation is and we, as a field, lack an explicit model of how persons and situations interact. Our model provides explicit conceptualizations of both personality traits and of the situations that people encounter and provides an explicit account of how they interact to create behavior that is sensitive to both the person and the situation.

## Theoretical Predictions

The model makes a number of testable predictions. Not only does it make predictions about what variables predict variability in personality related states, it also makes specific predictions about how those variables should be combined. First, the model predicts that variability in personality states is a function of the extent to which situational cues activate motives whose pursuit is afforded in that situation (situational cue strength). It predicts that this is a key aspect of situations that is critically important in predicting behavior in different situations. Thus, one can measure this activation of motives and examine the extent to which this predicts variability in behavior (McCabe & Fleeson, 2012, 2015; Sherman et al., 2015). Second, the model predicts that behavior is also a function of the current bodily or interoceptive state of the individual relevant to specific motives. In contrast, both DOA and CTA treat motivational strength purely as a function of cue strength. Third, the model predicts that the degree of motivational strength or "wanting" is a *multiplicative* function of situational cue strength and current bodily state. For example, the strength of wanting food will be a multiplicative function of current bodily state and cue strength. Motivational strength is not just an *additive* function of these two factors.

The model also predicts that the behavior of the agent can cause variability in personality related states through several mechanisms. First, behavior can change features of the situation that activate relevant motives (consummatory processes and moving to different situations). Second, behavior can change bodily state through satiety mechanisms.

The model also predicts that behavior will be the result of competition between different activated behaviors and different motives. As a result there will often be sudden changes and non-linearities in behavior. As can be seen in some of the simulations, the model predicts some of the sets of conditions that will lead to sudden shifts in behavior.

The model also makes specific predictions about the nature of motivational equilibria. Models such as Carver and Scheier's (1998) cybernetic model of goal-directed behavior or DeYoung's (2015) cybernetic model of personality argue that equilibria in behavior are due to a cybernetic or setpoint mechanism, where the system is trying to reduce the discrepancy between its current state and some target or set point, much like a heating system increases the heat to meet a particular temperature or setpoint in a thermostat. In contrast, our model (as well as Revelle and Condon's CTA (2015)) argues that equilibria, such as a particular body weight, are the result of contending forces, and not of a set-point mechanism.

## Potential Research and Applications to Data

Both computational models presented here suggest future research possibilities. Specifically, both models have clear implications for how behavioral data should be collected and analyzed. First, it makes specific suggestions about what variables should be measured: (1) the motive or goal affordances of the different situations in which people find themselves, (2) the current bodily state of the individual (e.g. hunger, loneliness, etc.), (3) individual differences in the chronic importance of different motives, (4) general sensitivity to reward and punishment (Approach and Avoidance), and (5) motive-directed behavior. It also suggests that the degree of "wanting" for a motive will mediate the relationship between the situational and interoceptive cues.

One obvious example would be to collect such fine-grained data longitudinally using experience sampling techniques (such as the use of smartphones). This should allow us to test predictions about within-person and between-person, variability of behavior over time and situations.

The model also makes suggestions about how actual data should be combined and statistically modeled. For example, it predicts that situational cues and bodily states should be multiplicatively combined, rather than combined additively. Of course, this is a testable prediction. Further, the fact that behavior is the result of competition between motives and between behaviors and that the "dependent variable" is which of many behaviors will be enacted, also has strong implications for the nature of the predictive function that should be used. In particular, one should use statistical methods, such as multinomial logistic regression that are specifically designed to handle choice among multiple alternatives or multiple classification problems.

## Related approaches

### Conceptual Models

Fleeson & Jayawickreme (2015) have argued that social-cognitive perspectives (e.g., motives, strategies, and beliefs) and trait theory can be reframed as a single theory, "Whole Trait Theory", which is a framework for explaining both individual differences and the diversity of behaviors in individuals with a given personality trait. Their theory is similar to the current approach in its emphasis on the role of motives and goals in trait-related behavior. However, their work is largely silent as to how exactly the external world, motivations, and prior learning combine to form inter- and intra- individual differences.

DeYoung (2015) has recently outlined a cybernetic model of personality, based on the idea of personality as based on goal-directed, self-regulating systems, although he has not provided a computational realization of that model. In contrast with the current model, he has strongly argued for the idea of a cybernetic model of motivation, in which the system is trying to match a set point or standard and is operating to reduce the discrepancy between the current state of the organism and the setpoint. However, Berridge (2004), following an earlier argument by Bolles (1980) has noted that current thinking about animal motivation is not consistent with a setpoint model. More consistent with the data is a system in which the system settles at a point that is an equilibrium between opposing forces. For example, the idea is that current body weight is not the result of attempting to match some kind of setpoint, but is instead the result of an equilibrium between caloric intake and caloric expenditures (as well as other processes), which are influenced by such things as the availability and access of food and exercise levels. Our model, as does the CTA model, takes this equilibrium view of motivation.

**Computational Models**

Shoda and Mischel's (Mischel & Shoda, 1995; Shoda & Mischel, 1998) CAPS model of personality has been implemented as a general parallel constraint satisfaction neural network model, in which a situational features layer feeds into a highly bi-directionally connected set of nodes that represent the goals, strategies, and beliefs of an individual. This set of highly interconnected nodes then feeds into a behavior layer. The interaction among the nodes in the intervening constraint satisfaction layer are responsible for the enactment of behaviors. However, in the CAPS model, individuals have highly idiosyncratic and somewhat ad hoc goals and motivational systems. That characteristic makes integration with prior work, on the structure and dynamics of personality, and links to underlying biological systems, difficult.

Closest in some ways to the current model is Revelle and Condon's (2015) CTA (Cues, Tendencies, Actions) computational model, which is based on Atkinson and Birch's (1978) Dynamics of Action (DOA) Model. In their model, Cues in the environment send activation to Tendencies and then Tendencies send activation to Actions, which have inhibitory links between them and compete with each other for activation and to be enacted. The enacted Action then sends inhibitory activation back to the Tendencies, representing consummatory forces. Although not implemented as a neural network model, they do note that it would be straightforward to implement CTA as a neural network model.

Their model has several key differences from our Virtual Personalities model. First, the Tendencies are not systematically organized in any way that corresponds to the general structure of personality (e.g., the Big Five). Second, the Tendencies do not have parameters to capture stable individual differences in the chronic importance of the corresponding motive. Third, a key part of our VP model is the idea that current motive strength or degree of wanting is not just a function of situational features, as in CTA, but is also a function of interoceptive or bodily state. Fourth, wanting is a multiplicative, not additive function, of cue strength and bodily state. For example, the degree of current wanting for food is a multiplicative function of the cue strength of the food and the current hunger of the individual.

## Conceptualizing Situations

One important characteristic of our model is that it is based on an explicit conceptualization of the nature of situations and what it is about situations that drives the motivated behavior of the system. As we noted earlier in the paper, our model, as well as a great deal of our earlier work (Miller & Read, 1991; Read & Miller, 1989) (also see (Argyle et al., 1981) considers situations to be goal or motive based structures, where key components of a situation are the motives that are afforded in that situation and the behaviors or scripts that can be enacted to pursue satisfaction of those motives. Because we also consider traits to be motive or goal-based structures when we consider how different individuals respond to different situations, we can think about whether and how the motives of the individual fit with the motive affordances of the situation.

## Comparing Two Architectures

Although the architectures and some of the assumptions of the two computational models examined here are different, both models were able to simulate the impact of the three major factors we examined and the impact of those factors was parallel across the two models. This suggests that the results of the simulations do not strongly depend on specific characteristics of the differing architectures of the two models. Instead, the fact that we can replicate the same basic effects across two different architectures supports the idea that the basic findings are a result of the core theoretical factors of the model.

Aside from being constructed in different architectures that differ in some of their basic assumptions, the two models also differ in two other ways. First, the python model has implemented reinforcement learning, whereas the neural network model has not. Learning in the model is apt to become increasingly important as we model longer time periods for individual personalities where the reinforcement contingencies differ. However, the absence of leaning in the present implementation of the neural network model is not a principled difference between the two architectures, but rather a result of the fact that we have simply not yet implemented learning in the current version of the Virtual Personalities model. It would be straightforward to do so and that is one of the next steps in developing that model. Second, the python model, in addition to being driven by the motive affordances of the situation and the interoceptive state of the individual is also driven by an explicit representation and weighting of the expected positive and negative consequences of a choice.

### Why Construct Two Versions Of The Model?

There are several reasons to construct two versions of the theoretical model. As we have already discussed this allows us to demonstrate that the results of the simulations are not specific to the specific architecture in which they are implemented. However, the other major reason to do so is that each architecture has strengths that the other lacks. One of the major benefits of the neural network architecture is that it allows us to more easily tie our model to findings about the neurobiology of decision-making and personality, as well as to biologically detailed models of such things as memory or semantic representation. Conversely, one of the major benefits of the python based model is that it makes the mathematical underpinnings of the model easier to understand and to follow.

## Summary, Limitations, and Future Directions

Social computational models allow researchers to examine their assumptions and better understand the dynamic implications of those assumptions. The current work helps us to understand how behavior can dynamically change within persons over time and situations as well as between persons. As we illustrated, different computational architectures with similar underlying assumptions can produce similar effects.

The current Virtual Personality model is an advance over our earlier and other models of personality by incorporating interoceptive states, closely tied to insula activity (Droutman, Read, & Bechara, 2015), into the model. Still, a great deal of additional integration with other computational models of underlying biologically-based psychological processes (e.g., involving decision-making and learning processes) is possible. In our ongoing collaborative computational work, funded by the National Institutes of General Medical Sciences (NIGMS), we are working to close that gap by integrating personality and motivational dynamics into a much more fine-grained and comprehensive computational model of the neural underpinnings of human decision-making, motivational, and learning processes.

Computational modeling offers an exciting paradigm shift in which researchers can work collectively to improve one another's models. In doing so, we can suggest where and how to not only reduce the residual error in our models of within- person and between-person variability in behavior, but how we might better work together collectively to advance a more integrated and comprehensive cumulative science of personality dynamics.

References

Aisa, B., Mingus, B., & O'Reilly, R. (2008). The Emergent neural modeling system. *Neural Networks*, *21*(8), 1146–1152. http://doi.org/10.1016/j.neunet.2008.06.016

Argyle, M., Furnham, A., & Graham, J. A. (1981). *Social situations*. Cambridge [Eng.] ; New York: Cambridge University Press.

Ashton, M. C., & Lee, K. (2007). Empirical, Theoretical, and Practical Advantages of the HEXACO Model of Personality Structure. *Personality and Social Psychology Review*, *11*(2), 150–166. http://doi.org/10.1177/1088868306294907

Atkinson, J. W., & Birch, D. (1970). *The dynamics of action*. New York: John Wiley.

Bechara, A., & Naqvi, N. (2004). Listening to your heart: interoceptive awareness as a gateway to feeling. *Nature Neuroscience*, *7*(2), 102–103.

Berridge, K. C. (2004). Motivation concepts in behavioral neuroscience. *Physiology & Behavior*, *81*(2), 179–209. http://doi.org/10.1016/j.physbeh.2004.02.004

Berridge, K. C. (2012). From prediction error to incentive salience: mesolimbic computation of reward motivation. *European Journal of Neuroscience*, *35*(7), 1124–1143.

Berridge, K. C., & O'Doherty, J. P. (2013). From Experienced Utility to Decision Utility. In P. W. Glimcher & E. Fehr (Eds.), *Neuroeconomics, Second Edition. Decision Making and the Brain.* (pp. 325–341). Academic Press.

Bolles, R. (1980). Some functionalistic thoughts about regulation. In F. M. Toates & T. Halliday (Eds.), *Analysis of Motivation Proceses* (pp. 77–102). Academic Press.

Boudreaux, M. J., & Ozer, D. J. (2013). Goal conflict, goal striving, and psychological well-being. *Motivation and Emotion*, *37*(3), 433–443. http://doi.org/10.1007/s11031-012-9333-2

Bugental, D. B. (2000). Acquisition of the algorithms of social life: A domain-based approach. *Psychological Bulletin*, *126*(2), 187–219. http://doi.org/10.1037/0033-2909.126.2.187

Carver, C. (2006). Approach, Avoidance, and the Self-Regulation of Affect and Action. *Motivation and Emotion*, 105–110.

Carver, C. S., & Scheier, M. F. (1998). *On the Self-regulation of Behavior*. Cambridge, England: Cambridge University Press.

Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS Scales. *Journal of Personality and Social Psychology*, *67*(2), 319–333. http://doi.org/10.1037/0022-3514.67.2.319

Chulef, A. S., Read, S. J., & Walsh, D. A. (2001). A hierarchical taxonomy of human goals. *Motivation and Emotion*, *25*(3), 191–232.

DeYoung, C. G. (2015). Cybernetic Big Five Theory. *Journal of Research in Personality*, *56*, 33–58. http://doi.org/10.1016/j.jrp.2014.07.004

Droutman, V., Read, S. J., & Bechara, A. (2015). Revisiting the role of the insula in addiction. *Trends in Cognitive Sciences*, *19*(7), 414–420. http://doi.org/10.1016/j.tics.2015.05.005

Elliot, A. J. (Ed.). (2008). *Handbook of approach and avoidance motivation*. New York: Psychology Press.

Fleeson, W. (2001). Toward a structure-and process-integrated view of personality: Traits as density distributions of states. *Journal of Personality and Social Psychology*, *80*(6), 1011.

Fleeson, W., & Gallagher, P. (2009). The implications of Big Five standing for the distribution of trait manifestation in behavior: fifteen experience-sampling studies and a meta-analysis. *Journal of Personality and Social Psychology*, *97*(6), 1097.

Fleeson, W., & Jayawickreme, E. (2015). Whole trait theory. *Journal of Research in Personality*, *56*, 82–92.

Funder, D. C. (2001). Personality. *Annual Review of Psychology*, *52*(1), 197–221. http://doi.org/10.1146/annurev.psych.52.1.197

Gray, J. A. (1982). *The neuropsychology of anxiety: An enquiry into the functions of the septo-hippocampal system*. Oxford: Clarendon press.

Gray, J. A., & McNaughton, N. (2000). *The neuropsychology of fear and anxiety*. Oxford: Oxford University Press.

John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm shift to the integrative Big Five trait taxonomy. In P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality: Theory and research (3rd ed.,* (pp. 114–158). New York: Guilford Press.

Kenrick, D. T., & Trost, M. R. (1997). Evolutionary approaches to relationships. In S. Duck (Ed.), *Handbook of personal relationships: Theory, research, and interventions* (pp. 151–177). Chichester, England: Wiley.

Lee, K., & Ashton, M. C. (2004). Psychometric Properties of the HEXACO Personality Inventory. *Multivariate Behavioral Research*, *39*(2), 329–358. http://doi.org/10.1207/s15327906mbr3902_8

McCabe, K. O., & Fleeson, W. (2012). What is extraversion for? Integrating trait and motivational perspectives and identifying the purpose of extraversion. *Psychological Science*, *23*(12), 1498–1505.

McCabe, K. O., & Fleeson, W. (2016). Are traits useful? Explaining trait manifestations as tools in the pursuit of goals. *Journal of Personality and Social Psychology*, *110*(2), 287–301. http://doi.org/10.1037/a0039490

Miller, L. C., & Read, S. J. (1987). Why am I telling you this?: Self-disclosure in a goal-based model of personality. In V. J. Derlega & J. Berg (Eds.), *Self-disclosure: Theory, research, and therapy*. Plenum Press.

Miller, L. C., & Read, S. J. (1991). On the coherence of mental models of persons and relationships: A knowledge structure approach. *Cognition in Close Relationships*, 69–99.

Mischel, W., & Shoda, Y. (1995). A cognitive-affective system theory of personality: Reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Psychological Review*, *102*(2), 246–268. http://doi.org/10.1037/0033-295X.102.2.246

Rauthmann, J. F., Gallardo-Pujol, D., Guillaume, E. M., Todd, E., Nave, C. S., Sherman, R. A., … Funder, D. C. (2014). The Situational Eight DIAMONDS: A taxonomy of major dimensions of situation characteristics. *Journal of Personality and Social Psychology*, *107*(4), 677–718. http://doi.org/10.1037/a0037250

Read, S. J., Jones, D. K., & Miller, L. C. (1990). Traits as goal-based categories: The importance of goals in the coherence of dispositional categories. *Journal of Personality and Social Psychology*, *58*(6), 1048–1061.

Read, S. J., & Miller, L. C. (in press). Virtual Personalities: A Neural Network Model of the Structure and Dynamics of Personality. In R. R. Vallacher, S. J. Read, & A. Nowak (Eds.), *Computation Models in Social Psychology*. New York, NY.

Read, S. J., & Miller, L. C. (1989). Inter-personalism: Toward a goal-based theory of persons in relationships. *Goal Concepts in Personality and Social Psychology*, 413–472.

Read, S. J., & Miller, L. C. (2002). Virtual personalities: A neural network model of personality. *Personality and Social Psychology Review*, *6*(4), 357–369.

Read, S. J., Monroe, B. M., Brownstein, A. L., Yang, Y., Chopra, G., & Miller, L. C. (2010). A neural network model of the structure and dynamics of human personality. *Psychological Review*, *117*(1), 61–92.

Revelle, W., & Condon, D. M. (2015). A model for personality at three levels. *Journal of Research in Personality*, *56*, 70–81. http://doi.org/10.1016/j.jrp.2014.12.006

Sherman, R. A., Rauthmann, J. F., Brown, N. A., Serfass, D. G., & Jones, A. B. (2015). The Independent Effects of Personality and Situations on Real-Time Expressions of Behavior and Emotion. *Journal of Personality and Social Psychology*. http://doi.org/10.1037/pspp0000036

Shoda, Y., & Mischel, W. (1998). Personality as a stable cognitive-affective activation network: Characteristic patterns of behavior variation emerge from a stable personality structure. In S. J. Read & L. C. Miller (Eds.), *Connectionist models of social reasoning and social behavior* (pp. 175–208). Mahwah, NJ: Erlbaum.

Talevich, J. R., Read, S. J., Walsh, D. A., Chopra, G., & Iyer, R. (2015). A comprehensive taxonomy of human motives. *Unpublished Manuscript, University of Southern California*.