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Motivating Machines: The Potential of Modeling Motivation as MoA for Behavior Change Systems

Fawad Taj [1,2,*], Michel C. A. Klein [1] and Aart Van Halteren [1,3]

[1] Social AI, Department of Computer Science, Vrije Universiteit Amsterdam, 1081 HV Amsterdam, The Netherlands; michel.klein@vu.nl (M.C.A.K.); a.t.van.halteren@vu.nl (A.V.H.)
[2] Department of Computer Science, University of Swabi, Swabi 94640, Pakistan
[3] Philips Research, High Tech Campus 34, 5656 AE Eindhoven, The Netherlands
* Correspondence: fawadtaj1@gmail.com

Abstract: The pathway through which behavior change techniques have an effect on the behavior of an individual is referred to as the Mechanism of Action (MoA). Digitally enabled behavior change interventions could potentially benefit from explicitly modelling the MoA to achieve more effective, adaptive, and personalized interventions. For example, if 'motivation' is proposed as the targeted construct in any behavior change intervention, how can a model of this construct be used to act as a mechanism of action, mediating the intervention effect using various behavior change techniques? This article discusses a computational model for motivation based on the neural reward pathway with the aim to make it act as a mediator between behavior change techniques and target behavior. This model's formal description and parametrization are described from a neurocomputational sciences prospect and elaborated with the help of a sub-question, i.e., what parameters/processes of the model are crucial for the generation and maintenance of motivation. An intervention scenario is simulated to show how an explicit model of 'motivation' and its parameters can be used to achieve personalization and adaptivity. A computational representation of motivation as a mechanism of action may also further advance the design, evaluation, and effectiveness of personalized and adaptive digital behavior change interventions.

Keywords: AI-powered behavioral change support systems; motivation; computational modeling; behavior change techniques; AI in health; pervasive health system

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1. Introduction

In medical sciences, the mechanism of action of a particular medicine enables physicians to understand the correct dosing better. It helps identify which patients are likely to respond to that medicine. There are also different models and evidence-based theories available for health behavior change. These theories/models identify the key constructs and processes of behavior change. However, serious discussion and research are still going on about these constructs and their mechanism of action. The fundamental disagreement is on the causality of Behavior Change Techniques (BCTs) for various theoretical psychological constructs. For example, one might argue that BCT "information about health consequences" changes behavior by changing one's belief about health consequences. The most common term used for this connection between BCTs and the modifiable factors is a Mechanism of Action (MoA), defined broadly as 'the processes through which a behavior change technique affects behavior. In comparison, others call it the process of operational manipulation of psychological constructs [1].

One of the challenges identified in the international workshop on developing and evaluating digital interventions is that digital behavior change interventions often lack clarity around the mechanism through which they have their effect [2]. It is recommended to develop and specify the circumstances in which the proposed mechanism of action would generate a targeted effect and represent the resulting knowledge as a behavior change ontology [2]. Moreover, the limited collaboration between technology designers and health behavior experts typically leads to poorly developed technologies or applications in which the choice of health behavior theories is not suitable. The theory and models chosen are not sufficiently versatile to cover all aspects of the target behavior [3]. We consider digital health change intervention as the interventions that use digital technologies to promote and facilitate behavior change through specific context and information, for example, mobile apps, web-based, etc. Due to the latest advancement in digital technologies and their capacity to collect extensive user data, these interventions consider variations in an individual's characteristics, contexts, and changes over time [4].

To account for the knowledge of health psychology, recently, the Human Behavior Change Project established a link between the BCTs and their mechanism of action [5,6]. For example, the BCTs goal-setting, feedback and reward, work by manipulating the motivation of the target. So, if motivation is chosen as the theoretical construct to be targeted in any intervention development phase, the effective and agreed BCTs can be selected from this project [6]. To effectively use BCTs in digital interventions, the parameters of the BCTs and the mediating factors need to be explicitly defined. The 'motivation' cannot work as a black box (every human is different). By creating an explicit model of the underlying MoA, in this case 'motivation', we can accommodate individual characteristics and provide the mediating feedback loop to both BCTs and the targeted behavior.

Therefore, in this paper, we present an extended version of the temporal causal network model of motivation [7] that will describe how the high-level BCTs can be made adaptive and personalized via a lower-level process of 'motivation.' The temporal causal network modeling technique gives us the flexibility to represent any complex problem having time and causality dimensions between states more efficiently and easily. The low-level process (motivation) and its components are modeled based on the observations from the neuro-reward system and represented through the temporal causal network modeling technique. More detail about the temporal modeling technique and the representation of 'motivation' is provided in Section 3.1. Furthermore, Figure 1 depicts how the model will be used in the intervention and how different BCTs can be used to affect various components of the model. So, rather than studying the manipulating effect of psychological constructs, we are modeling the mediating role of motivation and its core components for BCTs and the targeted behavior. This model will serve different purposes and illustrates the work's novelty. Firstly, using this model allows digital intervention designers to report the mechanism of action in their interventions properly. Secondly, the intervention can be made more adaptive and personalized. For example, goal-setting and feedback can be customized based on the model outputs for different personalities like introversion, extraversion, neuroticism, conscientiousness, etc.

To summarize, the objectives of this article are:

- To propose a formal description of the dynamics of motivation and a computational implementation to show its working as a 'mechanism of action' component in digital behavior change intervention.
- To illustrate the relevance of the model for the study of digital behavior change interventions, specifically for generating and maintaining motivation, and how this can be used for personalization and adaption of interventions.

The paper is organized as follows: Section 2 shows the role of motivation in health behavior change and, more specifically, how we can generate and maintain motivation. Section 3 explains the term 'mechanism of action' and explains different possible ways that can be used to define/present a psychological construct as a mechanism of action. Section 4 describes the extended version of the motivation model for digital health behavior change based on the neuro reward pathway. Motivation is a mechanism of action with its mathematical formulation for health behavior change. Section 5 further represents an example intervention with simulation for increasing physical activity behavior in office employees. The paper concludes with remarks and future work.

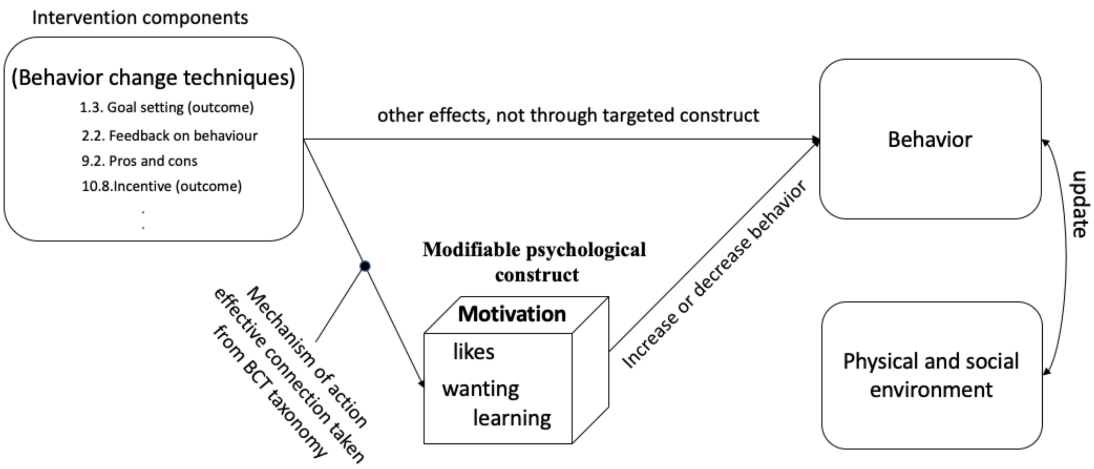


Figure 1. The model postulates the 'motivation' as the mechanism of action for a behavior change intervention.

2. Health Behavior Change and Motivation

This section of the article aims to understand the motivation construct from a neurosciences perspective and its possible role in health behavior change. Most cognitive health theories describe the potential relationships between psycho-social factors and healthy behaviors. For example, the Social Cognitive Theory, Health Belief model, and Theory of Planned Behavior are examples of theories that describe the role of individual beliefs, experiences, social factors, and environmental factors on individual health behaviors. Conversely, the widely used Transtheoretical model (TTM) and Health Action Process (HAPA) define the stages through which individuals go through to change their behavior [8,9]. Similarly, self-determination theory (SDT) explains the process of intrinsic motivation with three basic psychological needs: autonomy, competence, and relatedness [10].

Motivation in the neurosciences refers to neurotransmitters, or brain networks, which are collectively involved in different processes like releasing a chemical named dopamine, reward/punishment anticipation processing, reinforcement (learning), storing and updating a reward value, and decision-making drive human behavior. Together, these processes and chemical reactions control motivational behavior that leads to achieving a specific goal or reward. The details of all these brain networks and processes are discussed in Section 4 below. Here the mechanism of motivation concerning health behavior change is explained as two separate processes, i.e., motivation generation; how value-based anticipation of stimulus can generate 'motivation', and what can be the possible techniques for it? Similarly, to sustain a healthy behavior, how is motivation maintained or regulated, and what are the possible techniques?

2.1. Motivation Generation

Humans do or refrain from doing particular behaviors based on the calculated value of reward or punishment. To elicit approach behavior (motivation), the first step is to make the anticipation of reward from that behavior or actions. Anticipating reward means any object, event, or activity can be a reward if it motivates us, causes us to learn, or elicits pleasurable feelings. Humans are pre-programmed with certain behaviors like food or sex because they are naturally rewarding and necessary for the survival of a species. In the case of secondary reward, a specific brain area first registers the stimulus as a reward or punishment, then stores its relative value for future decision making. Before exploring different techniques that can make the stimulus rewarding and elicit pleasure feelings, there are two essential aspects of the reward mechanism in neurosciences, i.e., liking vs. wanting, and action control systems that need to be understood. The reason for presenting the differentiation between these two aspects is to be able to select an appropriate technique that can either activate liking or wanting sub-systems. Moreover, both 'wanting' and 'liking' are interchangeably used for rewards, whereas the brain circuity for both mechanisms is dissociable [11].

2.1.1. Liking vs. Wanting

It is now a widely accepted fact in neurosciences that 'wanting' is a dissociable factor from 'liking' for the same reward [11]. The more extensive brain network of the 'wanting' and the smaller one of the 'liking' systems are described in Section 4 below. Initially, it was hypothesized that brain dopamine depletion would reduce 'liking' for rewards. Still, it is experimentally proven that a lack of dopamine demolishes all motivation (wanting) while the liking remains the same [11]. This difference is vital in behavior change because the stimulus or any intervention components may influence one or another system. For example, maybe you are hungry, and your wanting-system wants to eat something, but there is broccoli available that you do not like. It is also important to mention that 'wanting' does not mean the cognitively processed desire; instead, it is a particular form of desire triggered by reward-related cues [11]. That is why recovering addicts have a genuine desire to quit drugs, but the nonconscious 'wanting' triggers when exposed to drug cues. That is why usually the best motivation is the one which is through activation of the wanting-system (either cognitively processed or subconsciously by reward cues) and pleasurable enjoying.

2.1.2. Action Control Systems

After intercepting a reward, the human brain reward system uses three different action control systems. First, (i) the innate actions system, which is the evolutionary response to a stimulus. Conversely, (ii) habitual actions develop over time through learning via interaction with different stimuli, and (iii) goal-directed actions are more cognitively processed actions toward achieving desired outcomes [12]. Generating motivation for healthy behavior change usually utilizes a goal-direction action system to achieve the desired behavior and possibly triggers other action systems that may be more effective for changing specific behaviors. The effectiveness of behavior change intervention through any action system depends on choosing the right targeted action system in the right circumstances [12]. For example, the relative effectiveness of triggering the habitual action system for smoking cessation (behavior) in a personalized intervention (population) would be greater using the social influence-based intervention.

2.2. Motivation Maintenance

This section will discuss if motivation is generated, then why it fades out and how we can maintain it. Another essential process in the neuroscientific explanation of 'motivation', i.e., reward prediction error (RPE), can be used to keep the level of motivation. RPE is the difference between received and expected rewards. This error helps humans learn about the stimulus and use it for future decision-making. Continuous interaction with the stimulus will cause learning of the reward/punishment outcome of the stimuli via reward prediction error. RPE can be used to regulate and maintain motivation, e.g., positive reward prediction means more learning of the stimulus outcome and more chances of performing the behavior often, whereas the negative reward prediction error means less learning of the stimulus-outcome association.

As mentioned earlier, the expected value of a reward is obtained through the attributes of the incentive, such as amount, type, and delay [13]. So, different techniques can be used to regulate motivation by manipulating the attribute of the reward itself. For example, increasing the incentive on a particular behavior will generate a surprise factor and cause a positive reward prediction error. Similarly, humans like instant gratification; if the unexpected reward is given before the expected time it will also cause a surprise factor and release enough dopamine to fasten the learning process. Moreover, the same type or always-expected reward will eventually be learned and will not be effective in the long term, the value of the behavior will decrease, and the frustration will grow.

2.3. Behavior Change Techniques for Motivation Generation and Maintenance

Based on Bandura's self-efficacy theory, BCTs are usually selected based on the targeted theoretical constructs; for example, *instructions on the problem* or *increasing problem-solving skills* are often used to increase self-efficacy. In this section, we will discuss some of the techniques mentioned in Table 1, taken from behavior change taxonomy [14], that can change behavior through 'motivation'. Furthermore, the techniques are discussed in the context of the two sub-processes discussed above, and the possible roles of these techniques in manipulating any of the sub-process. For example, for motivation generation, whether specific techniques would increase the reward value (or) increase pleasure feelings, etc. In the BCT taxonomy [14], the technique "10.8. incentive (outcome)", besides the effect on other psychological processes like intention and beliefs, it also has an impact on motivation. It is argued that if an external reward is promised to be delivered after achieving a specific behavior outcome, it will generate motivation by influencing the values of the outcome of the action, e.g., the monetary incentive for the employee who comes to the office by bike can ultimately have better health [15]. The motivation for cycling may be low due to the cost (fatigue) of cycling to the office and the low rewarding value. The achievement of incentive does have rewarding value itself. Still, the pleasure anticipation (expectation) in reaction to the stimulus will increase the value of cycling and ultimately give feelings of higher reward due to health improvement.

Table 1. List of the Behavior Change Techniques (BCTs) and their respective mediating purpose in our model. These BCTs are supposed to change behavior through motivation [6].

(Code). Behavior Change Techniques	Purpose	Reward System Components
1.3. Goal setting (outcome)	For planning, reduce gratification, frustration	Maintain reward prediction error
9.2. Pros and Cons	Increase wanting (pros) and not wanting (cons)	Wanting
10.8. Incentive (outcome)	Increase outcome value	Liking
10.10. Reward (outcome)	Increase outcome value	Liking

Similarly, the BCT "9.2 pros and cons" can increase motivation by reducing the cost of ignoring unhealthy behavior consequences. Likewise, with the negative reward prediction error due to the same type or always-expected reward, the motivation will decrease, and the frustration will grow. The best strategy could be to use "1.3 goal setting (outcome)". This strategy can activate cognitive control for self-regulation by providing reasonable goals and plans to overcome immediate impulses and low execution process capacity.

3. Why and How to Model 'Mechanism of Actions'

This section aims to show the number of possible methods for representing different psychological constructs or processes that usually or possibly can act as mechanisms of action between behavior change techniques and targeted behavior. The term 'MoA' evolved with the increasing need to improve the effectiveness of behavior change interventions. The major problem is that the MoAs are not mentioned for the active ingredient, i.e., BCT, in any intervention [3]. So, a clear understanding of the processes through which individual BCTs have their effects (i.e., their Mechanisms of Action) will allow us to make more effective interventions by making intervention personalized and making replicable components in any intervention. These mechanisms of actions are defined as a range of theoretical constructs that represent the processes through which a BCT affects behavior, and these constructs specified in theories of behavior and behavior change that can be seen to 'mediate' intervention effects, such as 'beliefs about capabilities', 'knowledge', and 'behavioral regulation'. They can be characteristics of the individual (i.e., intrapersonal psychological processes) and characteristics of the social and physical environment (e.g., social support). Moreover, another challenge for digital intervention is to represent these MoAs as an explicit model and the acquired knowledge as behavior change taxonomy of that construct. Below, we discuss some possibilities to model these constructs as MoA when the respective effective BCTs are chosen in any behavior change intervention.

3.1. Temporal Causal Network Models

The mechanism of a particular construct at the psychological or neural level could be defined as a temporal causal network model. Each node on the network represents the behavioral constructs, and the arrow shows the causal impact of one construct on another. For example, in [7], a temporal causal network model for the motivation generation and maintenance process is presented based on the dopaminergic reward pathway. The model shows the casual relationship between external incentives and internal body feeling for change in a targeted behavior. The external incentive state has a causal impact on the feeling state, and feeling better about the action increases motivation. Using this type of model to change sedentary behavior is given in [16]. Similarly, emotion regulation techniques are modeled as a temporal causal network, which shows how and when specific strategies can be activated for more effective behavior change intervention [17]. So, according to our agent-based framework, any causal model for any theoretical construct that explains the causality among the behavior change components and its parameters can be plugged in as a mechanism of action [18]. This paper considers our previously published temporal causal network model for motivation [7], extending it and integrating it as the mechanism of action for digital health behavior change intervention.

3.2. Multidimensional Generalization Space

Based on [4], a state-space representation is another important way to represent when, where, for whom, and in what state intervention will produce a targeted effect for that person. The "state" is the social-psychological or environmental constructs defined based on the target populations represented as multiple variables that determine the "space" when a MoA may produce the effect [4]. For example, feedback on behavior (e.g., showing daily average steps taken) could only inspire a physical activity if the state space of the person is appropriately receptive to this intervention. The probability of a person taking 10,000 daily steps increases if the motivation is high (motivation high = yes) and if their outcome expectation is high.

3.3. Computational Agent/System Models

Computational models are often represented and validated using different statistical and mathematical models, which means the explicit specification of constructs and how constructs interact with one another. For example, in [19], the author presented a computational model based on social cognitive theory for influences on physical activity. Social cognitive theory is also modeled as dynamical systems using fluid analogies and control systems principles drawn from engineering [20]. Similarly, in [21], a computational model of behavior change, based on existing psychological theories (the transtheoretical model, social cognitive theory, the theory of planned behavior, and attitude formation theory), is proposed that describes formal relations between the psychological constructs and their role in different stages of behavior change.

4. Model Description and Formalization

This section provides an extended version of the temporal-causal network model of motivation [7], with a complete description and formalization. The earlier published model is based on the underlying neuroscientific processes (dopamine pathway and its subsystems: mesolimbic dopamine system and mesocortical dopamine system) of motivation and explains how reward is anticipated and how the brain's relative valuation system processes it. The model represents processes and psychological constructs with several different states. For example, one state represents the sensory representation of the stimulus, and the other represents its rewarding value (positive feelings). This positive feeling state influences the action state, which means the human would approach or act toward attaining the reward (called motivation generated). Furthermore, the model encoded the process of motivation maintenance through reward prediction error (RPE). RPE means the certain amount of dopamine released on either received reward is better or worse than expected. RPE plays an important role in learning (action-outcome) and provides a basis for an explanation for decreasing/increasing motivation.

Dopamine not only plays a role as the mechanism of action in motivation but also in other different human cognitive processes like movement, attention, sleep, etc. Similarly, we want to use this model as a MoA for effective, adaptive, and personalized behavior change techniques in health behavior change intervention. We now understand how motivation is generated and maintained from the neurological level, and how this mechanism needs to be exploited for healthy behavior. We aim to use to model to determine what can be done so that the user does or refrains from target behavior by *value-based reward anticipation* and how we can maintain their motivation for target behavior by *reward prediction error*. These two motivation processes need to be optimized for an effective health behavior change intervention. Before we can introduce the formal description of the model, the following questions need to be answered:

1. What strategies can be used to increase the rewarding value of a stimulus? Increasing the anticipated value of the stimulus (any behavior, goal, etc.) will be assumed that motivation is generated, and the behavior will be performed more often because of the enriching value.
2. What strategies can be used to keep the RPE as positive as possible, as the association between stimulus-reward will be learned when the RPE is positive. In the case of negative RPE, the learning would get slow or stop, and eventually, the chances are that an agent will switch to perform other behavior for greater reward.

Different behavior science, health psychology, and neuroscience literature are approached to find answers to the above questions. The collected literature helped us define a simple motivation framework, given below, which structures our understanding of the phenomena associated with reward-seeking and motivation. The proposed formalization describes the computation of the valuation system (costs and benefits), and outcome values are formulated to define a human's current motivation state. We will use this process of *value-based reward anticipation* to **generate** motivation. This will be described in the next Section 4.1. Section 4.2 will look into the *reward prediction error* process for **maintaining** or improving the current motivation level.

4.1. Value-Based Reward Anticipation for Motivation Generation

To answer the first question, the net expected reward is calculated according to the utility function, taken from neurocomputational science literature [22], see Equation (1). The equation will determine the rewarding value for the action to be taken at a certain point in time (t). The net rewarding value is the subtraction of the expected reward (pleasure, health, food, etc.) from the costs (negative consequences, fatigue, etc.) associated with that action. The cost and expected values are subjective, and it means everyone would have different reward expectations for the same behavior. The calculated expectations of rewards (or punishment) during value-based decisions are updated based on experiences in the surrounding world.

$$\text{Net expected reward}_{(t)} = \sum \text{reward}_{(t)} - \sum \text{costs}_{(t)} \tag{1}$$

In the original temporal causal network model, we considered this expected reward ($\sum$reward) in Equation (1) as the expectation of pleasure associated with the action, called "*liking*" or the *positive feelings*. Let us assume that we are only measuring *liking* or *positive feelings* as an expected reward, and the total costs are a weighted sum of all different subjective costs. Then Equation (1) can be expanded as given below:

$$\text{Net expected reward}_{(t)} = \text{liking}_{(t)} - (\text{costs}_{1(t)} + \text{costs}_{2(t)} + \text{costs}_{3(t)} \ldots) \quad (2)$$

As mentioned earlier in Section 2.1.1, this net reward value determines the motivation or the "wanting". So, motivation is directly proportional ($\propto$) to the outcome of net reward [22]. We can rewrite the Equation (2) as follows:

$$\text{Motivation}_{(t)} \propto \text{liking}_{(t)} - \gamma_1 \times \text{costs}_{1(t)} - \gamma_2 \times \text{costs}_{2(t)} - \gamma_3 \times \text{costs}_{3(t)} \ldots \quad (3)$$

A new term is introduced in Equation (3); the term temporal discounting (γ) is the inclination for a person to see a desired outcome in the future as less important than one in the present. It is considered a good characteristic in prediction for the maintenance of healthy behavior. For example, the temporal discounting rate is strongly associated with body mass [23]. Despite the potentially high cost of different behavior, they develop over a more extended period and are thus not immediately noticed, for example, weight gain. This type of cost is usually discounted and sometimes to a negligible level. As the cost and expected reward are subjective matters, similarly, every cost variable has different discounting rates.

This formalization of motivation and the different involved factors can be used to generate motivation.

4.2. Reward Prediction Error for Motivation Maintenance

To maintain motivation, we exploit the reward prediction error. The association between behavior and the outcome is learned over time. The strength of this connection is dependent on the reward prediction error and is represented as follows:

$$\text{RPE}_{(t)} = \beta\ (\text{Received Reward}_{(t)} - \text{Net expected reward}_{(t)}) \quad (4)$$

where Received $\text{Reward}_{(t)}$ denotes a received reward at time t for a certain action or behavior, and net expected reward shows the predicted/expected reward at time t. This error value is responsible for dopamine release, and it determines the learning of the action-outcome connection, whereas β is a learning rate parameter that determines how much weight of the error is registered or, in simple words, it shows the neuron's firing rate. Every human is different; that is why with the same trail of the experiment, some learn more quickly than others.

To summarize, we will use Equation (2) to generate motivation and Equation (4) to regulate or maintain the motivation. Figure 2 shows the schematic representation of the whole motivation process and the links of its components with other components in behavior change intervention.

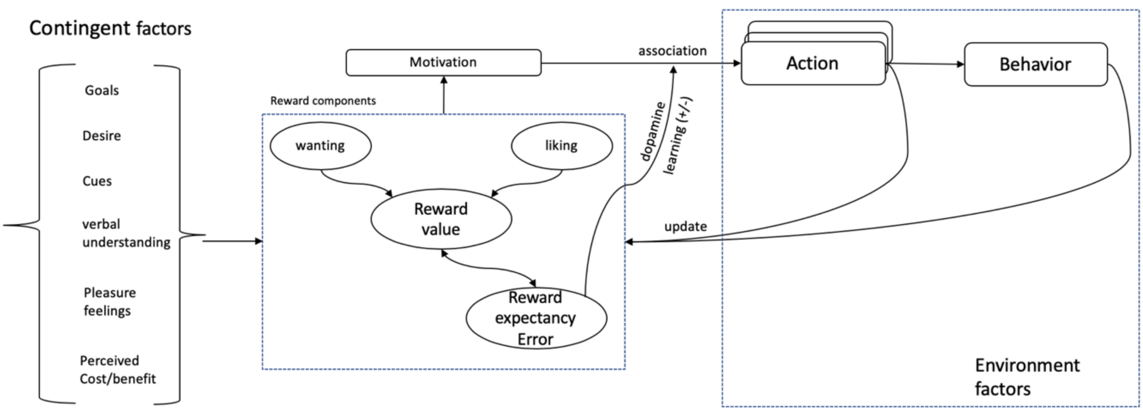


Figure 2. The schematic representation whole process of 'motivation' and its links with reward components.

5. Motivation-Based Intervention Example and Simulations

This section will illustrate integrating the above motivation model in digital health behavior change intervention. Different scenarios are simulated to show the two processes, i.e., motivation generation and motivation maintenance, with the help of the formalization of the respective process introduced above. The assumption is that chosen behavior change techniques will influence personal and environmental factors. The target population's likelihood of regularly achieving their goals means that the relevant individual changed their behavior if all plans were completed.

An intervention scenario is created for an office environment. The intervention components, i.e., target behavior, BCTs, MOA, and environment, are defined according to an agent-based framework [18], shown in Table 2. The framework is based on ontology for behavior change interventions (BCIO) [24], which defines the intervention components and explains their connection.

Table 2. Our model defines the intervention components and their relations to specific motivation processes.

Motivation Processes	Targeted Behavior	Sub-Processes in the Motivation Model	BCTs	MoA	Environmental Observations
Motivation Generation	Physical Activity	Value-Based Reward Anticipation	10.8 Incentive (outcome) 5.1 Information about health consequences	Motivation	Step count, feelings (hedonic pleasure)
Motivation Maintenance		Reward-Prediction Error	1.3 Goal setting (outcome)		

Let's suppose a scenario given below:

"The office management announced a 3-month program for employees to make them physically active. The organization targeted motivation as a core psychological construct for changing behavior. The employees are asked to subscribe, and they are provided digital wearable devices that can count their daily physical activities. The program is designed to use performance-based incentives to activate the dopamine reward pathway. When the stimuli (physical activity) are cognitively processed, it becomes a goal. The first technique to generate motivation is to give incentives for goal achievement. For this reason, after every 15 days, the incentive will be given according to the choices toward the goal. The goal is to increase the rewarding value of physical activity and overcome its costs. Furthermore, the reward prediction error will be calculated to maintain motivation to change strategies and determine the motivation level. Every component and process of the intervention is described in the concerned sector below."

Table 2 shows all the components of an intervention scenario and how specific motivation processes correspond to the different computations and relevant, effective behavior change techniques. For example, to generate motivation, an incentive will be given. The observation would be to check whether the activity for the participant is rewarding (pleasurable) or not. Similarly, in the case of motivation regulation, the reward prediction error would be observed, and strategies will be changed accordingly.

According to our model of motivation, there is some further explanation of the scenario. Participants will be given a daily goal (steps to be taken). They will have to achieve the goal and be awarded daily points based on the performance (goal achievement). On every 15th day of the intervention, the participants will get a badge based on their points in the past 15 days. We assumed two costs associated with the target behavior (physical activity), i.e., health consequences and fatigue, for demonstration purposes.

Different personalities will take this cost differently because it is a subjective matter, and everybody has a different discounting rate. Moreover, the values of each variable are determined between 0 and 0.9 (0 being the smallest and 0.9 being the highest). Based on those parameters, motivation generation and maintenance are simulated below. Each section demonstrates what parameters are observed and how these parameters can be tuned with different behavior change techniques for effectiveness and personalization of the intervention.

5.1. Motivation Generation

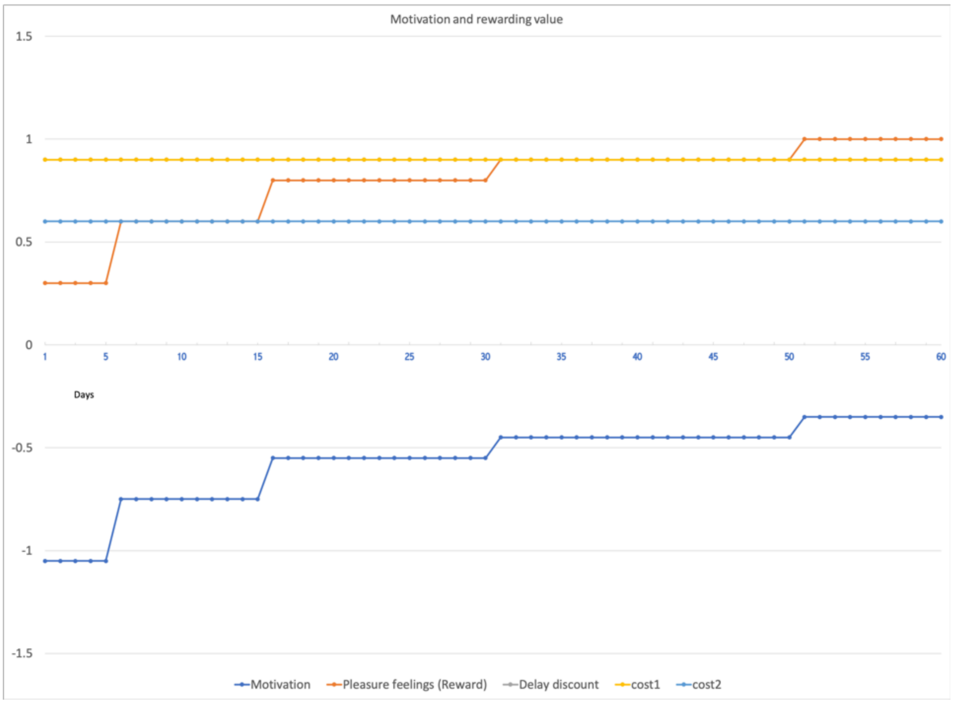
The hypothesis that motivation is generated through value-based reward anticipation can be observed by the intensity of the behavior for which an incentive is given. According to Equation (2), motivation is directly proportional to the difference between the expected reward and the cost of getting this reward. So this means that there could be several reasons that cause the difference in motivation level, and different techniques can be used to overcome these reasons. Firstly, let us consider how incentives can change the behavior, as the technique "10.8 incentive (outcome)" is the promise of external reward for performing a specific behavior. We keep the delay discounting and cost associated with the behavior constant (delay discounting 0.9, $cost_1$ 0.9, $cost_2$ 0.6), because we are giving them an incentive to increase the pleasure feeling; in other words, we are making the behavior rewarding for them. According to Equation (3), if the participant starts liking the incentive, it will increase their motivation to perform the behavior more often and achieve the reward again and again. Figure 3a shows how giving incentives during the intervention program increases the pleasure feeling (liking) and how motivation started building. This simulation gives us two insights; first, we can use incentives or other techniques to increase the pleasant feeling. Second, we can make these techniques adaptive according to different personalities. Next comes the subjectivity issue; maybe some employees will not consider points and badges as rewarding compared to the cost associated with them. We will show it with a difference in delay discounting value to simulate variability in different personalities. The health consequences of not living an active life are high (0.9), and doing daily physical activity has a moderate level of fatigue cost (0.6). Using the technique "5.1 information about health consequences," we can target the delay discounting of the associated costs. In Figure 3b, suppose all of them like it equally, but the difference in their discount rate for the related costs would make a difference in their motivation level. The employee with the highest discount rate does not know or care about the health consequences and fatigue associated with actions. So, giving awareness or information about health consequences can target the delay discounting parameter.

5.2. Motivation Maintenance

The process of motivation maintenance means maintaining the level of motivation generated earlier. This is done by calculating reward prediction error on different intervals in the model. The RPE value in the model represents the difference between received and expected rewards for performing some actions. If their expectation is met, a certain amount of dopamine gets released. The dopamine release shows the learning of the reward anticipation from that action. When this association is learned enough, the dopamine is released with stimulus cues only, not the reward itself. By performing this action more often because of the reward, it is assumed that the behavior gets habituated.

Positive Reward Prediction Error

The scenario to understand RPE calculation is depicted in Figure 4. In our design, RPE is calculated using Equation (4). The expected reward on the fifteenth day was 150 points; the positive reward prediction arose because it was the first time. Later, on the 30th day, the expected and received reward were the same and did not cause any dopamine spike because the participant learned the behavior and its outcome. The participants will wish for a bronze medal again on day 45th, and surprisingly, getting a gold badge will produce high dopamine spikes. On the 75th day, the participant expected a gold medal again (worth 300 points), but surprisingly he got no reward which means he does not meet the actual reward expectation; according to Equation (4), 0 − 100 = −100. This negative reward prediction error would cause the update of the reward value of the action to 0 and would be less likely to perform again.



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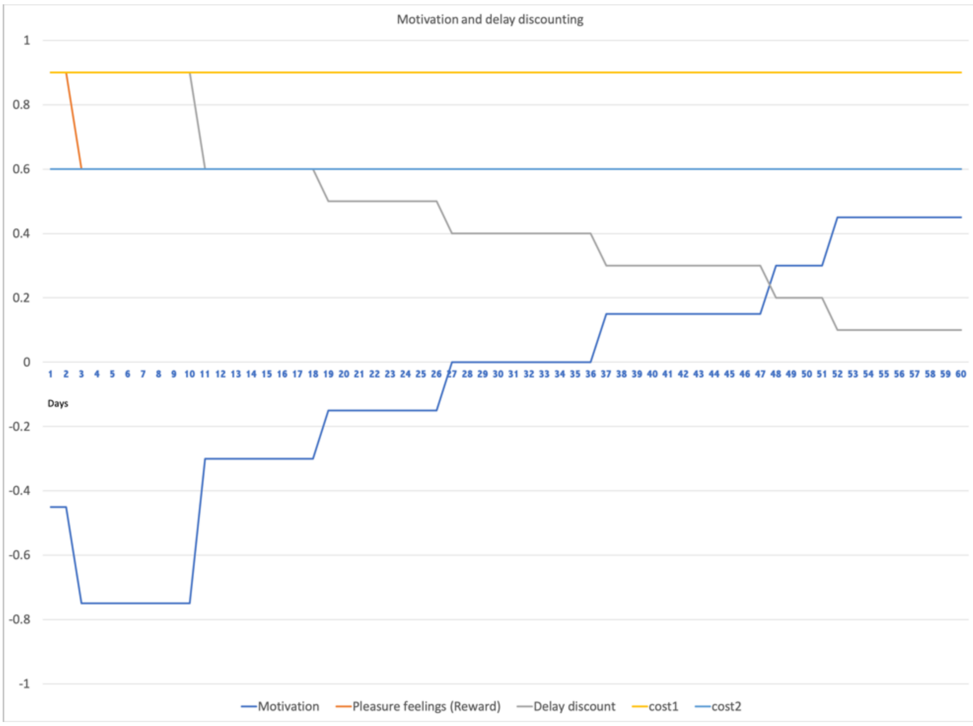

(**b**)

Figure 3. Motivation concerning different model parameters/processes through different BCTs (**a**) shows the effect of increasing liking for the activity by triggering a value-based reward system, and; (**b**) shows the effect of targeting the delay discounting characteristic of the participants.

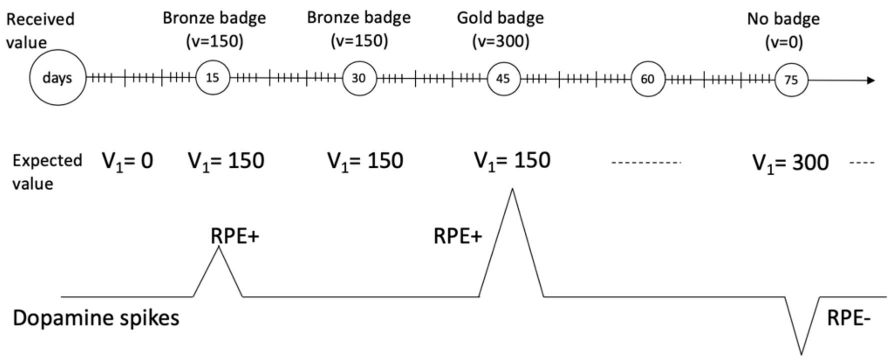

Figure 4. The timeline for incentive and the corresponding reward prediction errors.

For this reason, goal-setting techniques are primarily used to regulate motivation in different types of behavior change interventions [3]. The goal-setting helps develop a plan for maximizing the reward [12]. In addition to long-term goals (desired outcomes), it is also essential to generate short-term goals that are vivid and detectable, which allow people to monitor their progress. For this reason, small adaptive goals for daily step count and feedback based on their performance would help them monitor their progress and increase the rewards of the actions. Due to faster communication and efficient and ubiquitous seniors, these operations are pretty straightforward and precise in digital interventions.

6. Conclusions

Digital behavior change interventions usually do not report the explicit action of their techniques. If the techniques are mentioned, the mechanism of action through which these techniques have achieved their effects is not explicit. With recent consensus among health and social science researchers about the behavior change constructs and their effect pathways, we can develop theories and models that can easily be integrated into digital interventions. In this article, it has been shown how motivation can be explicitly modeled and integrated within an intervention as a mechanism of action for different behavior change techniques. Various parameters and aspects of the neuro-reward system formulated the model and presented it for motivation generation and maintenance.

An example intervention is defined and simulated to show how we can generate and maintain motivation and how the model's integration can help us achieve personalization and adaptivity through behavior change techniques. This type of research is novel and emerging. In addition to the personalization, models such as the ones presented in this paper could help digital intervention designers to properly report and use behavior change techniques by making their mechanism of action explicit.

7. Limitations and Future Work

The model proposed in this study is based on neurological observations. These observations are validated in the neurosciences to show the working of the release of different neuro-chemicals. In our work, we used these observations to propose a model of health behavior change. This type of usage requires additional validation. Preferably, a long-term experiment is performed in which data is collected about all the factors discussed in the model. In the future, we are working on designing an experiment where we can collect the relevant data to validate this model and report the result.

Another limitation is that we did not evaluate the use of this model as part of an actual intervention. We are currently working on developing such an intervention and its evaluation in a feasibility study. This intervention will use the model presented in this paper as a reasoning engine, continuously evaluating the user's current behavior and factors and using this to apply the best behavior change technique. The system will operate on mobile, web, or both. It collects real-time data from the user and uses this as input for the model, determining which necessary behavior change can be applied.

Finally, this paper only uses "Motivation" as a mechanism of action. It would also be helpful to develop models of other mechanisms of action, to evaluate the generalizability of the approach that we have presented.

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