# Towards a Generic Framework for a Health Behaviour Change Support Agent

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Abstract: Agent-oriented solutions form a useful paradigm to design intelligent systems. For health-related behaviour change, this is also a promising approach. Designing an agent for lifestyle change interventions is a difficult task because socio-ecological models are involved that represent many conflicting desires and goals. Different types of cognitive architectures are available to design this type of health behavior agents but they are rarely used. In this paper, we used the BDI model to design a health behavior agent that will execute behavior change intervention for a better healthy lifestyle. We explain the working of the architecture by the example of an agent which uses adaptive goals-setting and a percentile scheduling technique for increasing physical activity.

## 1 INTRODUCTION

One approach to build real-world complex systems is using the agent-oriented paradigm. In this paradigm, software components are tightly connected with one another and they all function autonomously. Artificial intelligence provides a major contribution to the agent development paradigm due to the required properties of autonomy, cognitive thinking, sociability and learning (Girardi, 2001). Cognitive agents in artificial intelligence are among the most developed and studied topics, which explicitly maintains the model of the environment perceive the external environment, do rational thinking and make a plan to act on the environment to fulfil one or more of its goal (Wooldridge, 1995). Agent-based modelling is common and brings significant advantages to systems when the environment is complex, the interaction between agents is nonlinear, discontinuous or the population is heterogeneous (Bonabeau, 2002).

Health-related systems are complex, due to some hard topics like patient life, data privacy, legal and technical issues. For example delay or misinterpretation between different entities/agents could cost someone life (Datta et al., 2010)(Iqbal et al., 2016). The use of agent systems in healthcare setups has increased in the last decade and the usage ranges from patient-centred applications to the organizations-centred, multi-agent system (Isern & Moreno, 2016). Drawing on (Datta et al., 2010)(Iqbal et al., 2016), recent reviews about agents applied in health-care, categorized the agents both on the basis of intended users and functionality. The applications are mainly patient-centered, staff-centered or healthcare organization-centred and with respect to functionality basis, they can be designed for planning and resource management, decision support system, data management, self-care systems and can be multifunction systems that can integrate some of the earlier describe systems to make a complete healthcare system. Another subset of health-care systems is behavior change support systems, which could benefit from agent-based intelligent models to facilitate rational and on-time decisions in a heterogeneous environment.

An approximate 60% of the risks associated with chronic diseases such as diabetes and cardiovascular disease are associated with health habits and these conditions account for 1.5%-3% of direct costs to the UK National Health Service (NHS) (GC et al., 2016). It is becoming critically important to question the creation and implementation of effective methods to improve healthy behavior. With a change in lifestyle and prevention techniques, we can significantly

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decrease the impact of non-communicable diseases, which are some of the greatest challenges facing modern society. Some of the key unhealth behaviors, such as physical inactivity, unhealthy eating, smoking, obesity, sexual behavior, and alcohol misuse are among the most common causes of disease and premature deaths in both developed countries (Ding, Lawson, & Lancet, 2016).

While this prior research on improvements in health behavior is critical in defining pragmatic approaches that could lead to changes in health behaviour, the theories developed in it are insufficient to support the development of quantitative delivery methods. Furthermore, the proposed theory-based models consider health behavior as a function of constructs such as motivation, attitude as opposed to a product of a dynamic cognitive system that is influenced by physiological, affective, environmental, social, and experiential states (Riley et al., 2011). Agent-based modelling, in contrast, provides the opportunity to define simple reflexive agent up to more complex cognitive learning agents.

When designing and developing agent-based systems, an important question is to choose or develop the decision-making process of agents. There are around 15 famous decision-making models in the literature, each based on different literature studies (Balke & Gilbert, 2014). The main inspiration for these decision-making systems are the human psychological and neurological systems. A widely used way to formalize the internal architecture of such complex agents is the BDI (Belief-Desire-Intention) paradigm. This paradigm allows to design expressive and realistic agents, yet, it is rarely used as an intelligent health behavior change agent. We argue that health-behavior coaching – helping people to develop helpful health-related behaviors and to curtail harmful ones – is a challenging as well as a fruitful domain to conduct human-aware AI research. The domain requires that a health coach understand the cognitive, emotional, physical, situational, and other aspects of a coaches' health behaviors. The possible interventions vary from providing informational support, encouraging the practice of helpful behaviors in different contexts, helping to remember behaviors when the right context arises, etc. To be impactful, these agents need to make a more personalized decision and gradually adapted for their specific circumstances. This paper presents a generic framework for a health behavior support agent, inspired by the BDI paradigm.

This article is structured as follows: section 2 will discuss the concept of health behavior change and the guidelines to define healthy behavior intervention. Section 3 discusses agent architecture based on BDI. Section 4 will define the components based on the discussion in section 2. This section will discuss the working of the model with the help of physical activity scenario and discusses agent-based programming algorithm. Finally, section 5 will discuss future work and draw a conclusion on earlier sections and will discuss the future directions.

## 2 BACKGROUND

In this section, we describe the theoretical components of a health behaviour support agent. Before defining the goals and plans for the agent, we should determine the desired results of the agent in detail. First, we have to decide the goal and plan occurring in a different context. It is recognised that any behavior that needs to be changed occurs in several different contexts (e.g. at home, at work) and have many different influences (e.g. personal, interpersonal and environmental). Therefore, different intervention results for each context and level of influence were therefore defined. For this purpose different taxonomies and planning guides can be consulted (Kok, 2014). Using the steps defined in these planning guides we can identify the context, the performance outcome, and select the right behavior change strategies.

Certain behaviors can be targeted with different behavior change techniques (BCTs), which acts as an active ingredient in any behavior change intervention. Each BCT use a different mechanism of action to target certain behavior (Michie & Johnston, 2012). The interventions are usually delivered by expert humans through a prolonged interaction with the people they coach. According to (Taj, Klein, & van Halteren, 2019), these BCTs are poorly reported and the most used technique is the goal-setting irrespective of target health domain. Each of these behavior change techniques is differently modelled and mathematically represented. For example, the goal-setting technique is represented as the staircase model to set an adaptive goal for coachee (Mohan, Venkatakrishnan, 2017), whereas in another example the adaptive goals are calculated with percentile schedule method (Adams, 2009). Based on this background knowledge we defined different parameters for our physical activity agent in section 4.

# 3 BDI ARCHITECTURE

## 3.1 Overview

The BDI approach in artificial intelligence represents the way agents can do complex reasoning based on folk psychology (Bratman, 1987). The three main mental states around which the BDI model is centred are belief, desire, and intentions. A typical BDI agent represents all the information that it has about the environment in the form of beliefs and these beliefs can be represented by modal logic language. These beliefs can be either true, false or outdated. The agent has some desires that it wishes to accomplish. Not all but for some desires that the agent actively wants to achieve turns to become intentions and the agent is equipped with a pre-defined set of plans which are recipes for achieving its intentions (Visser et al., 2016).

An agent architecture shown in figure 1 is a software computational solution to a problem showing how the component parts of a system interact, thus providing an overview of the system structure. It encodes its sensory perceptions into a state representation of its environment. It also represents the plans it can execute to manipulate its sensors, effectors, and the environment in pursuit of goals.

The basic logic components of a BDI agent are belief, desire and intention. In our model we follow the conventions adopted in the GAMA-platform- a control architecture, which in turn are based on PRS (Procedural Reasoning System). The vocabulary of the key terms of the architecture can be summarized as follows.

## 3.2 Vocabulary

### 3.2.1 Knowledge States

The agent must represent the environment by capturing information that is necessary to not only formulate a beneficial goal state but also to decide over its action space. All the information about the environment is represented in the different representation states. For example, the affective states can be represented as a different scale, whereas the preference value can be represented as logical predicates. These states will not only be used to update the belief of the agent but also will help in defining the algorithm of behavior change techniques. In figure 1 a few of possible knowledge states are mentioned; however, any number and types of states can be considered depending on the behavior the agent is targeting.

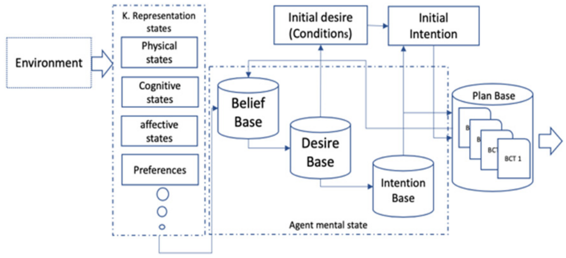


Figure 1: Conceptual diagram of BDI behavior change agent.

### 3.2.2 Beliefs

Belief is the agent knowledge about the world. The belief base always gets updated with the new information in representation states. The beliefs of the BDI is usually represented as predicates for example, Step_count (Monday, 3000)- a person steps count for Monday is 3000 steps. Belief can either be true or false.

### 3.2.3 Desire

Desires are all the objectives that the agent wants to achieve and often called the goal of the agent. It can have hierarchical links (sub/super desires) or each desire can be defined with a dynamic priority value. For example, the agent can have different conflicting desires which can be ordered according to some priority values according to the intervention. For example, for "set goal" desire will be having higher priority than giving a reward.

### 3.2.4 Intentions

Among the desires that an agent wants to achieve it select one having high priority. The intention will determine the selected plan. That is the reason that BDI based agents are usually called intention systems (Balke & Gilbert, 2014).

### 3.2.5 Plan

The agent plan base consists of actions that the agent would carry to fulfil its selected intention. In our architecture shown in Figure 1, most of the plans are the delivery or implementation of behavior change techniques. Now to define a plan for certain desire regarding behavior change the plan needs to have some pre and post conditions and the body which in our case can raise to the question that which behavior change techniques are best for which kind of health-related problem. There are a lot of randomized control trials available that can help us define our plan. For example, to implement goal-setting intention, the most used behavior change technique is the goal setting.

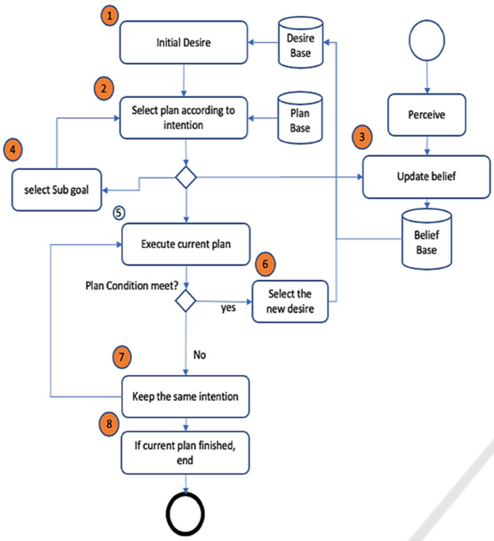


Figure 2: The flow chart of behavior change agent.

### 3.2.6 Behavior Change Techniques Algorithms

The plan base in architecture shown in Figure 1 contains behavior change techniques algorithms where all the relevant BCTs can be placed so that the agent can reason about it and select one that is relevant and feasible to the scenario. In health behavior change literature several constructs such as goal-setting, self-efficacy, reward shaping and incentives are defined and extensively studied to positively influence health behavior. The well-known hierarchy taxonomy by Susan can be considered to properly report and define the intended construct (Michie et al., 2013).

The algorithm for each of the BCT will explain post and pre-conditions, and intensity of the BCT. Currently the efficacy of different kind of BCTs are not established with regard to different behavior. Different people define each type of BCT with their unique algorithm. This is why the algorithm for BCT is shown separate than simple plans.

## 3.3 Workflow

In the BDI practical reasoning, the agent is equipped with a library of pre-compiled plans. These plans are manually constructed, in advance, by the agent programmer. Hence in Table 1 we define performance outcomes as the goal of the agent and defined the plan as the execution of relevant BCT.

The flow of the process depicted in Figure 2 is as follow:

1. Set initial goal: The initial goal will be the behavioral outcomes that we want to achieve.
2. Plan execution: execute the relevant plan which can be either to select the sub-goal or update the belief base.
3. Perceptions are updated: For each behavioral goal, the second step is to perceive the relevant information from the environment and update agent belief base.
4. If the current goal contains a sub-goal it would hold the current goal on hold and will select the sub-goal and will select the relevant plan for it.
5. If the current goal doesn't have any sub goals and don't need to update the belief base the current plan would be executed.
6. After successful completion of the plan, the new desire with the highest priority would be selected.
7. Until the successful completion of the current plan, the current intention would still in hold and will execute until get finished.
8. The reasoning end if there is no plan and desire available for execution.



## 4 SCENARIO

Using the planning guidelines discussed in section 2,

Table 1: The behavior change performance objectives and selected methods.

| **Target population:** individual<br>**Target behavior:** Physical activity | **Determinant:1** Intention | **Determinant:2** Motivation | **Selected BCT** |
|---|---|---|---|
| **Performance outcome:** increase number of daily steps count | A resolve to act on certain way | | Goal Setting (behavior) |
| **Performance outcome:** Keep motivation for behavior outcome | | Arrange reward if and only if there is an effort to achieve the targeted behaviour | Rewards |

we will choose some specific components for our example. Table 1 shows the performance outcomes and the mechanism of action (determinants)-through which we will achieve our target in our example scenario that is presented below. The last column shows the selected BCTs that are considered best in literature for these kinds of targets. We considered adaptive goal-setting techniques for the daily recommended steps. The mathematical formulation and algorithm are defined in section 4.1.

## 4.1 Adaptive Goals and a Percentile Schedule of Reinforcement

Adaptive goals that often and uniquely adjust to the recent performance of an individual may be a more realistic approach to developing flexible yet challenging and achievable goals. The goal-setting and feedback algorithm was based on a rank-order percentile algorithm derived from recent developments in basic science around schedules of reinforcement (Adams, 2009). The percentile algorithm requires continuous and repeated measurements of daily steps count and then the algorithm work as follow:

1. The ranking of a sample of behavior (steps/day) from lowest to highest and calculation of a new goal based on a pth percentile criterion. For example, for one participant, the steps count each day for their last 9 days (ranked from lowest to highest) was 1000, 1500, 2600, 4500, 5000, 5700, 6300, 8000, 11,000.
2. The 60th percentile represents a goal of 5700 steps, which becomes the 10th day's goal. Based on (Adams, 2009), the best window to consider is of 9 window and the pth percentile 60% of the last 9 reading which is calculated with

$$=((p/100) * no\_day). \quad (1)$$

To achieve customized targets, percentile shaping capitalizes on the normal behavioral variability. Percentile shaping also generates specific, measurable goals inherently that can be explicitly rewarded. Only a handful of studies have evaluated the use of a percentile shaping strategy by changing goals to increase physical activity, and none have compared percentile shaping goals orthogonally (Adams, 2009).

In our example, the aim is to develop an intelligent agent that can provide counselling in a manner similar to a human coach. There is a need for computational methods that can not only model and predict the changes in the human physiological and cognitive system, but also for methods that can coach this human system toward a beneficial goal (Shiwali Mohan & Venkatakrishnan, 2017). The working of the agent for the given scenario below is depicted in Figure 3.

The BDI health behavior agent model function as follows: our agent aims to assist in delivering the best available BCT for increasing physical activity and keep the motivation high to maintain the behavior. To make it simple we considered simple physical activity guidelines of 10000 steps per day by the National Heart Association of Australia (Tudor-Locke et al., 2011). To achieve this goal, a number of behavior change techniques can be applied but according to the literature, the mostly applied BCT for physical activity behavior is goal-setting. The goal-setting theory by Locke and Latham (Locke & Latham, 2012) provides evidence that to be maximally effective, the goals should be difficult yet attainable. Therefore, for adherence purpose, the agent will set a new adaptive goal for the coachee each day if the coachee didn’t meet the standard guidelines. Moreover, for motivation and reinforcement purpose, if the coachee meeting the guidelines the coachee will be awarded rewards. To make it short, the main goal is to assist user to maintain 10000 steps count daily and sub goals to achieve this main goal is goal setting and reward.

According to the flow diagram discussed in Figure 2 the flow of the process of our scenario is as follows:

1. Initial goal of increasing physical activity is depicted as initial desire: **Keep_Fit**
2. To fulfil this desire the plan is to start monitoring daily steps count and update the belief base accordingly. For example, **step_count(Monday, 3000)**- a person steps count for Monday is 3000 steps.
3. while executing the monitoring plan and adding new belief about daily step count. A rule is introduced which add new sub-goal of goal setting by applying the following rule.
   Rule: with each **belief: Steps_count add New_desire: goal_setting**
4. For this new desire of goal setting the plan is to call the adapting goal setting algorithm. Which is explained in section 4.1.
5. The execution of the plan will also update the belief base of the agent.
6. Whenever the step counts would be more than 1000 per day the goal setting plan would generate a new sub-goal of reward.
   **add_sub_intention(reward)**

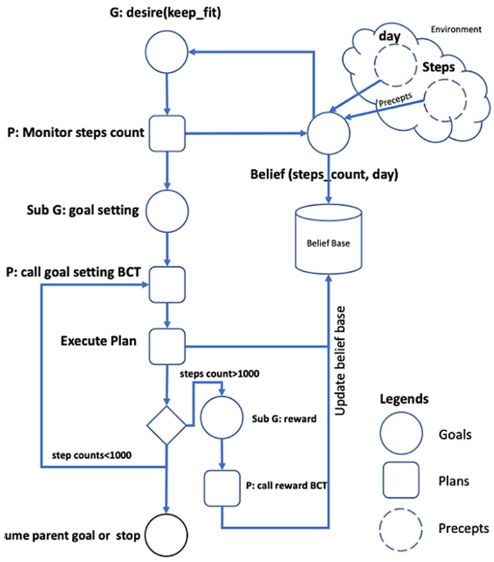


Figure 3: Flow chart of the scenario.

## 4.2 ABMS Platforms and Languages for Simulating BDI Agents

The design of its internal architecture is an important decision when developing a software agent. Several models of deliberative, reactive, and hybrid architectures have already been proposed. BDI architecture is one of the most popular agent decision-making models in the community of agents. BDI architectures have been introduced in several agent-based modelling and simulation (ABMS) platforms. For example, the BDI paradigm integrated into the GAMA modelling platform and its GAML modelling language to manipulate BDI concepts in a simple language (Taillandier, Bourgais, Caillou, Adam, & Gaudou, 2017). There also exists some middleware to connect the famous ABMS platform to BDI frameworks e.g. JACK (Busetta, Rönnquist, Hodgson, & Lucas, 1999) and Jadex (Pokahr, Braubach, & Lamersdorf, 2005).

A programming language is an essential component of agent-based technology and agent-based systems implementation. Such a language, called an agent-oriented programming language, should provide high-level abstractions and constructs for developers to implement and use agent-related concepts directly. Some of the famous languages Agent-oriented languages that support BDI architecture are AgentSpeak(L), Jason, Af-APL, 2APL, JACK(L), JADEX, GOAL etc.

We will illustrate our scenario using a programming language. Algorithm 1 is developed with the close syntax to GAML modelling language but it can be modelled in any agent-oriented language. Algorithm 2 shows the goal-setting algorithm and algorithm 3 keep track of the reward for achieving the goal. The algorithm uses an existing constraint solver and does not need to modify or enforce the vocabulary of the BDI.

Algorithm 1: BDI based goal-setting agent.

```
Procedure Main()
        Create agent ← goal_setting_agent ▷name of
the agent
        Target_steps:1000#day
        Reward:0                              Percentile:
p
Agent goal_agent Control::BDI

    Procedure init() {
        add Desire ← keep_fit }
    Perceive target:no_of setps var:day
        Add belief: Steps_count var: day_i
        Do remove_intention(keep_fit, false)
Rules belief: Steps_count New_desire: goal_setting
Plan record_steps_count where intention: keep_fit
    Do read_daily_steps_count
Plan set_goal where intention: goal_setting
    If current_step_count < Target_steps
    Do add_sub_intention(get_current_intention(),
find_adaptive_goal, true )
    Do current_intention_on_hold();
    Else
    Do  add_sub_intention(reward)
Plan adaptive_goal where intention:
find_adaptive_goal_perc
    Call Adaptive_percentile_goal (days,,p)▷ Goal
setting algorithm
    do remove_intention(find_adaptive_goal_perc,
true)
Plan calculate_reward where intention: reward
    Call reward()            ▷ reward algorithm
    do remove_intention(reward, true)
```

Algorithm 2: Adaptive goal based on Percentile schedule algorithm.

```
Procedure Adaptive_percentile_goal (no_days, p^th)
    Do arrange daily_steps_count in ascending order
    Compute the position of p^th percentile   /60^th
    Return  ((p/100)*no_day)
```

Algorithm 3: Reward algorithm.

```
Procedure reward ()
    Do add reward=reward+1     ▷ make sure
reinforcement
```

## 5 FUTURE WORK

In this article, we explore ways that an agent system can specify the goal for the coachee according to his previous performance which is incorporated into the BDI execution process and used to guide the choices made.

The future direction would be to implement this algorithm with any agent base modelling environment and will simulate it. The agent technology is rarely adopted in health behavior domain so there is so much opportunity to include knowledge from behavior sciences. For example, adding more personalization aspect to agent e.g. a value-based planning approach which takes into account social and ethical values that affect decision-making (Cranefield, Winikoff, Dignum Delft MVDignum, & Frank Dignum, 2017).

The health behavior agent needs to consider the causal model which can assess the failure or success of the intervention, this can be achieved by considering a causal model within the BDI architecture. The coachee may not have enough expertise or resources to conduct the behavior, may not believe they can execute the behavior effectively (low self-efficacy), may not have the right emotional state or having some social norms etc. (Shiwali Mohan & Venkatakrishnan, 2017). This kind of model is already available which can initially do reasoning about unwanted behavior (Klein, Mogles, & Van Wissen, 2011), which can likely be modelled according to BDI architecture.

Furthermore, a promising direction to equip the health change agent with a functionality that allow it to reason about the reasoning of the coachee. This topic has received significant research attention and can be explored with the help of implementing Theory of Mind (ToM). Theory of mind provides an important understanding of how human reason about other mental states (Baron-Cohen, Leslie, & Frith, 1985). There is some research which introduces a formal BDI-based agent model for Theory of Mind, which can be used or modified to reason about the coachee health-related constructs (Bosse, Memon, & Treur, 2007).

## 6 CONCLUSION

In this paper, we proposed a design of a BDI based health behavior agent model that can monitor and reason about the different psychological and physiology constructs of its user. The knowledge about the environment is represented in the form of beliefs and the intentions are fulfilled in the form of delivering the right kind of behavior change technique. The model is illustrated with the help of an example of physical activity coach which records the daily steps count of the coachee and according to the adopted goal-setting technique, the agent selects goals that are appropriate for a coachee given the past history of performance. The agent's other goal is to keep the motivation high for which the agent uses the reward-based behavior change technique.

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