

# A Semantic Model for Proactive Home Care Systems

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**Abstract.** In proactive computing, systems can act to eliminate, mitigate or take advantage of previous knowledge to manipulate situations of interest in advance. Such behavior is critical for Ambient Assisted Living Systems. In this paper, we present semantic models to design and implement proactive systems to Home Care environments implemented with devices and sensors. These models support semantic interoperability between the physical environments and different software levels allowing the identification of the user context. Proactivity is then obtained by the construction of the most suitable action's plan that results from the consumption of services provided by these devices and services. One challenge is to model a high-level situation and select the particular device that best meets users' needs, considering their context, location, and disabilities. The paper describes the steps required to create a generic, flexible and modularized model that can be extended to incorporate new domain knowledge regarding the specific requirements of different Ambient Assisted Living Systems.

**Keywords:** Proactive behavior · Ambient modelling · Assisted living · Ontology

## 1 Introduction

According to the Department of Economic and Social Affairs of the United Nations [1], life expectancy is augmenting. Such fact indicates that Home Care will receive strong attention, stimulating the development of new products and services in the next few years. It is expected that AAL will enable environments to support people, being sensitive to their needs and capable of predicting behaviors [2]. Systems for AAL, Home Care Systems (HCS), in particular, are emerging. According to Auvinen et al. [3], HCS can be defined as a technology to support the accomplishment of tasks, providing the means to collect, distribute, analyze and manage information related to human care.

Currently, there is a variety of devices to support people's interactions in living environments. To assist users that may be in specific and dangerous situations, we can integrate HCS with these devices. To achieve a good level of efficacy, HCS must be context-aware and present proactive behavior. Therefore, in our approach, we have a

particular interest in turning HCS into proactive systems that consider users' needs. It is important to state that "proactive behavior" means being aware of a situation and learning from it. In particular, to learn from recurrent situations so that the system can predict them and act in advance to eliminate, mitigate or take advantage of previous knowledge when situations of interest emerge.

One of the main challenges to model the proactive behavior is the complexity of the representation of semantic relationships among the things of the real world with a degree of uncertainty. This situation is easily understandable by humans but difficult to be interpreted by automated systems. Therefore, it is necessary to model the environment's semantics. The main challenge is to provide support to HCS at the semantic level so that it can recognize and predict situations of interest and choose the most suitable action to manipulate a specific situation.

In the ontology model developed and presented in this paper, ontology networks are applied to represent the contextual knowledge that is implicit in a situation, creating a classification of context-sensitive concepts and their relationships. One aspect to consider is the identification of the user's situation in different contexts, which helps the adaptation of the system to the features of the individual environment. Our goal is to obtain an ontology to support semantic interoperability between the physical environment and the software environment, allowing the identification of the users' context identifying the most suitable plan of actions. One significant challenge in this model is to represent situations in a more abstract level. This representation must allow the selection of specific device's functionalities to manipulate the situation, while, at the same time, best meet users' needs based on their context, location, and disabilities.

This paper is organized as follows. Section 2 discusses background and related work. Section 3 presents the Systems for Ambient Assisted Living. In Sect. 4 presents the Ontology Network, Sect. 5 presents reasoning over AAL Ontology. Finally, in Sect. 6, we present and discuss our conclusions and future works.

## 2 Background and Related Work

AAL characterizes an automated domestic ambient in its different user's interactions with physical objects involved in home context (e.g., patient, relatives, nurses, doctors). Thus, before we move on, we need to define 'context', 'situation' and 'proactivity'. Among a large number of existing definitions, we adopt the one of Ye, Dobson, and McKeever [4], in which context is "*the environment in which the system operates*". Events can be detected in the context, so systems need to verify the current user's contextual state and act upon it or on its changes. According to Etzion and Niblet [5], "*an event is an occurrence within a particular system or domain, it is something that has happened or is contemplated as having happened in that domain*". Events can change the state of the environment, producing new situations.

Ye, Stevenson, and Dobson [6] define situation as "*the abstraction of the events occurring in the real world that are derived from the context and hypotheses about how the observed context relates to factors of interest*". Therefore, we consider the current state of the user environment as a situation.

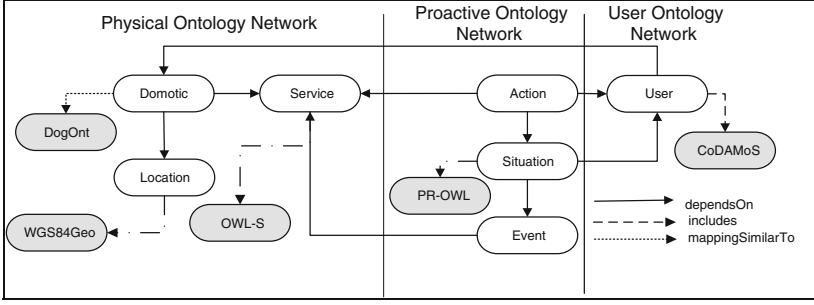
Engel and Etzion [7] describe proactivity as “*the ability to mitigate or eliminate future event of interest, identifying and taking advantage of future opportunities by applying prediction and automated decision-making technologies*”. For that class of systems, the main characteristic is the ability to predict a situation and act in advance; therefore, these systems need to manipulate uncertainty. Probability theory is a natural candidate to represent uncertain phenomena.

Multi-Entity Bayesian Networks (MEBN) can be used to generate expressive models because they combine first-order logic and probability. MEBN is a collection of MEBN fragments (MFrag) organized into MEBN Theories (MTheories). An MFrag represents a conditional probability distribution for instances (ontology instance) of its random resident variables, given their parents in the fragment graph and the context nodes. An MTheory is a set of MFrag that collectively satisfies consistency constraints ensuring the existence of a unique joint probability distribution over instances of the random variables represented in each of the MFrag. In fact, a template can be repeatedly instantiated to form *Situation Specific Bayesian Network* (SSBNs). SSBNs are regular BNs that are formed, usually in response to a query, to address a particular situation of domain knowledge [8].

Researchers [9–11] have modeled these concepts using ontologies to describe existing knowledge, and this facilitates the semi-automation of situations and actions. In this context, the concept of ontology network emerges. Ontology network is based on the integration of existing ontologies favoring modularization, reuse and re-engineering of knowledge resources as well as collaborative and argumentative ontology development [12]. The work of Pernas et al. [13] proposes a semantic modeling of adaptive Web-based learning systems. Díaz et al. [14] describe the role of an ontology network within a Semantic Educational Recommender System. The model proposed in this paper is very similar to the ones of Pernas et al. [13] and Díaz et al. [14] in terms of current situation and reactive actions. However, we added a predictive situation model using aspect of uncertainty and advanced actions. Our model also adds support for proactive behavior, thus being different from other studies.

### 3 Ontology for Ambient Assisted Living

The proposed AAL Ontology Network is shown in Fig. 1, where different arrows represent different kinds of meta-relationships. In this network, some ontologies are related to other ontologies of their domain. We refer to these as intra-relationships (intra-domain relationships). For instance, in Fig. 1, the dependence (*dependsOn*) among User and Domotic ontologies occurs as users use devices. The Device ontology also *dependsOn* Services and Location ontologies as the devices are contextualized in the physical space according to the services provided by them in specific locations. A proactive action consists of automatic executions of an action in the environment. Actions of type *dependsOn* need a particular situation to be detected or predict; they interact with the environment consuming services offered by devices. Events *dependsOn* services that are consumed by actions, and, when that happens, events are generated and the information about the environment is updated; this update may describe a new situation.



**Fig. 1.** Ambient assisted living network ontology

The intra-relationship *includes* occurs between different ontologies: (i) *User* and *CoDAMoS* [15], since the last has a set of concepts from the user ontology (i.e., profile, mood, role); (ii) *Domotic* and *DogOnt* [16], as *DogOnt* describe where a domotic device is located, its capabilities, technology-specific features needed for interfacing with it, and the possible state configurations it can assume; (iii) *Location* and *WGS84*, since the last defines all concepts and relations needed to define the localization of some point [17]; (iv) *Services* and *OWL-S* [18], as *OWL-S* is a top-level ontology having a set of concepts that are important for the semantic description of Web services; and (v) *Situation* and *PR-OWL* [17], which provides an upper ontology based on Multi-Entity Bayesian Network (MEBN) [18] theories. The last one allows us to express a probability distribution on interpretations providing support to reasoning over uncertainty using first logic order and probability. Each of these ontology networks has their internal structure, and they do not interfere with the others except by the inter-relationships. Each network is described in the following sections.

### 3.1 User Ontology Network

In this work, users are the persons who live in an AAL. The context of an environment is represented by a set of entities that surround or interact with the user. Their semantic relations  $\{R\}$  that form the context are represented by triples  $\langle Es, p, Eo \rangle$ . In these triples, the subject  $Es$  and the object  $Eo$  represent environment entities instances, which could belong or not to the same domain [10]. We also use semantic relations  $\{R\}$  to describe the User Ontology. There, a *Person* is categorized into several sub-concepts. Besides, a *Person* has associated *Devices* to interact with the environment. Therefore, the AAL system uses these *Devices* to interact with the user.

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<Person, hasSubClass, Non_Patient, Patient > ; <Non_Patient,
hasSubClass, Doctor, Caregiver, Visitor, ... > ;
<Person, hasPatientStatus, Patient > ; <Person, hasDevice,
Device > ;
<Person, hasDisability, Disability > ; <Disability,
hasSubClass,

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Visual, Auditive, Motor, Cognitive, ... > ; < Disability, hasLevel, Level > ;

< Person, hasLocation, Location > ; < Patient, hasDisease, Disease > ;

Users' location can be detected by one RFID sensor or through their interaction with a device that is located in a place inside the house. Disability is an incapacity that the person may have, and affects how devices can interact with this person. It has the *datatypeProperty* Level, which indicates the degree of disability. It is subdivided into four categories: (i) visual, where people may have difficulty to understand written text and graphic content; (ii) auditive, meaning that the user has a decreased ability to hear certain or all frequencies levels, which affect the reception of auditory information; (iii) motor: people may have limited use of their hands, or cannot use them, which affects their interaction with a device; (iv) cognitive, which involves a broad range of memory, perception, problem-solving and conceptualization of change and could affect any interaction with the person since information must be repeated more often.

### 3.2 Physical Environment Ontology Network

The physical environment ontology network is a structure of the domotic domain concepts. This domain includes the *DogOnt* ontology, which comprises device/network independent descriptions of *Building Environment*, *Building Thing*, *Controllable*, *Uncontrollable*, *Functionality*, and *State* [16].

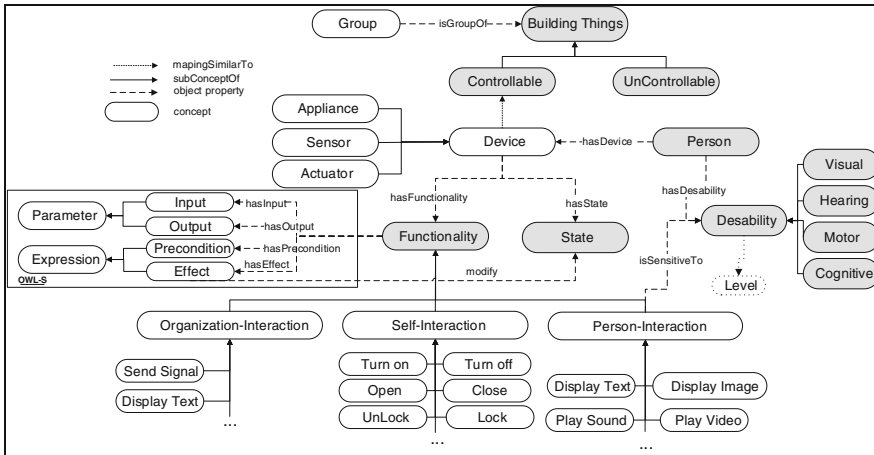


Fig. 2. Physical ontology network (adapted from Silva et al. [20])

In Fig. 2, the *Device* concept has the same characteristics of the *Controllable* concept of *DogOnt*, hence the existence of the triple < Device, mappingSimilarTo, Controllable > . From now on, to facilitate reading, all *Controllable*

*Things* will be referred as *Devices*. In the proposed model, there is a relationship between *Group* and *Building Thing* (either controllable or not). *Devices* are described in terms of possible configurations (*State*) and capabilities (*Functionality*). *State* refers to the internal configurations that the device can assume in a time instance, and *Functionality* refers to what the device can do to change *State* values. Appliances can be either *dumb* devices that can only be physically controlled by switching them on and off or *smart* devices able to provide complex functionalities. Actuators can control moving objects such as *Doors* and *Windows*, as suitable sensors can detect their state. Sensors also are linked to users, and they can provide variables like health, status, and location.

Based on OWL-S [18], *Functionality* has zero or more *Inputs*, *Outputs*, *Preconditions*, and *Effects*. According to Silva et al. [20], functionalities can be classified into: (i) *Person-Interaction*, when one wants to use a device to interact with a person; (ii) *Self-Interaction*, when a device needs to perform some action on itself; and (iii) *Organization-Interaction*, when one wants to communicate or ask something to an entity that is outside the house. In our model, *Person-Interaction* is a type of *Functionality*, hence it inherits certain relationships (*hasInput*, *hasOutput*, *hasPrecondition*, *hasEffects*). Thus, some characteristics of a given functionality may be previously indicated.

### 3.3 Proactive Ontology Network

This ontology describes the concepts related to proactivity in HCS (Fig. 3).

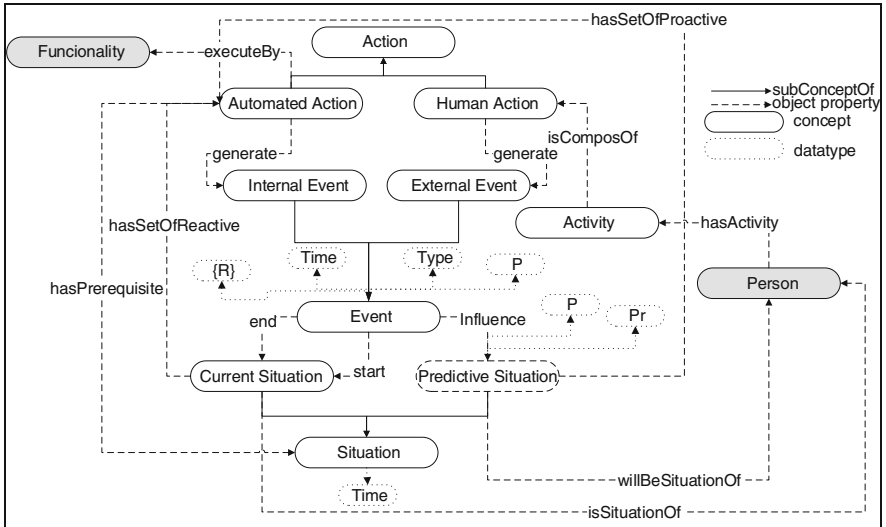


Fig. 3. Model's core (adapted from Machado et al. [10])

An *activity* represents daily activities that are made up of human actions performed by *Persons* in the home environment, like breakfasting, watching television, taking medicine or doing exercises. An *Action* is understood as something that is done willingly, executes, or entails something in an intentionally, deliberately and effortful way. In our work, *Action* is something that an entity executes, does, or performs, either manually or automated; *Automated Action* is an action that changes the status of one or more entities. It can be further classified as: *Person-focused*, referring to actions that are performed in order to communicate something to a person; *Device-Focused*, referring to actions that modify a device; *Organization-Focused*, referring to actions to inform/call an organization. *Automated Actions* are executed by the *Functionality* of a device.

Thus, when the *Acting* is *Person-Focused*, it will be executed by a *Person-Interaction Functionality*; similarly, *Organization-Focused* and *Device-Focused* will be processed by their corresponding *Functionalities*. Agents (humans or devices) carry out actions to achieve a goal. When an action does or does not achieve its objective, it may generate events, which return the status of an entity. An event has a name and is characterized by an internal or external type, a timestamp and a set of contextual semantic relations  $\{R\}$  (described in Sect. 3.2). Events can be linked to one or more contexts. For instance, a pattern that defines that an event must be detected if a particular sequence of events happens within a given window of time involving the “user” in his/her living room. In this work, events can determine the evidence of the beginning and the ending of a situation. Thus, events change the state of the environment and characterize a new current or predictive situation [10]. To describe health situations, we need the knowledge of experts in the application domain to indicate which events can produce relevant situations.

The current situation has a set of events that characterize its beginning and ending, and the time attribute of these events that characterize the valid time window of this situation, shown in Fig. 3. Also, the current situation has a set of triggered reactive *Automatic Actions*  $\{a\}$  that are detected during a valid time for handling the current situation. In this model, the presence of events determines the current situation. The event evaluation can lead the system to find out that a situation has a probability of happening in the future. Predictive Situations are characterized by a set of influence *Events*, a *pattern*  $(p)$ , which is a MEBN theory implemented in PR-OWL to describe some form of correlation among events that shape a situation in the future, a timestamp (time during which they may occur), and a set of proactive *Automatic Actions*.

## 4 Reasoning Over AAL Ontology

This section presents the employment of the proposed model in a HCS scenario, in which reasoning is used to detect and predict situations and select the most appropriate actions to deal with these situations. HCS must manipulate events that characterize situations of interest and trigger reactive and proactive actions. This case study aims to demonstrate the use of the model in scenarios where the necessity of a mechanism that acts in a proactive way is emphasized.

Imagine John, a 78 years old citizen without the need for hospitalization but having diseases such as diabetes, hypertension, and lightweight memory problems. Therefore, John requires continued treatment, and his house was configured as a smart environment with a Home Care System (SIaaS middleware) to manage situations that involve him. Based on this scenario, his doctor identified he is presenting agitation behaviors. This situation causes problems for his health. Thus, there is an embedded infrastructure in John's residence that provides Automated Actions. In this context, a pervasive application, called *appPervAgitation*, was developed, and it manages agitation situations in patients with Alzheimer disease. The application provides the current and predictive situation for the middleware manipulate. The Current Situation is started when the Event (HeartbeatMore101) that represent the Heartbeat Sensor collects values greater than 101 and is ending (HeartbeatLess101) when the value's sensor produces value less than or equals 100.

Current Situation		
Event	Type	Rule
Start	External Event HeartbeatMore101	Patient (John) $\wedge$ SensorHeartbeat (Sensor_Heartbeat1) $\wedge$ hasValue (Sensor_Heartbeat1, CollectValue) $\wedge$ swrlb:greaterThan(CollectValue,101) $\rightarrow$ isSituationOf (John, Emergency_Situation)
End	External Event HeartbeatLess101	Patient (John) $\wedge$ SensorHeartbeat (Sensor_Heartbeat1) $\wedge$ hasValue (Sensor_Heartbeat1, CollectValue) $\wedge$ swrlb:greaterThanOrEqual(CollectValue,50) $\wedge$ Aswrlb:lessThanOrEqual (?CollectValue,100) $\rightarrow$ isSituationOf (John, Emergency_Situation)

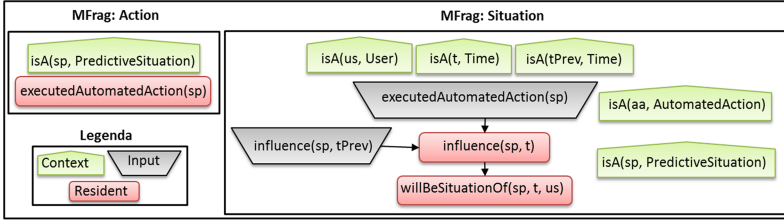
The application executes a plan with the objective of aiding an agitated patient with Alzheimer disease. The corresponding Automated Actions are: (a1) Notify caregiver; (a2) indicate the use of urgent drugs; (a3) play music; (a4) send message to the caregiver after his appointment; and (a5) request assistance from the health care provider.

These actions generate influence events managed over the time by the HCS application, and their detection generates values to the Local Probability Distribution (LPD) of the model. This knowledge must be provided by a predictive situation model specified by an expert in this particular situation.

The Predictive Situation model was developed in UnBBayes<sup>1</sup>, which is a tool for this purpose. A node in an MFrags must have a list of arguments. These arguments are placeholders for entities (instance of ontology) in the domain. For example, argument *us* in the expression *willBeSituationOf* (*ps*, *t*, *us*) is a placeholder for an entity of User while the argument *t* is a placeholder for the time step this instance represents.

Figure 4 shows the MTheory to Predictive Situations. Green nodes at the top of each figure are context nodes; darker nodes are the input nodes, and the yellow ones are

<sup>1</sup> <http://unbbayes.sourceforge.net/>.



**Fig. 4.** MEBN theory for Predictive Situation in AAL Systems

resident nodes. The MFrag Action describes the fragment that represents the incidence of Automated Actions performed by the HCS. An MFrag Situation presents the probability of an unwanted situation involving the User in the future, thus the resident node *willBeSituationOf*(*ps*, *t*, *us*) presents the probability of a Predictive Situation “*ps*” at time “*t*” be a situation of the User “*us*”. It is a resident node influenced by another resident node called *influence*(*ps*, *t*), which have the input node *executedAutomatedAction*(*ps*) and its own local probability distribution at an earlier time “*tPrev*”. In the MEBN theory for Predictive Situation of Fig. 4, the TimeStamp entity is an order variable, which represents discrete time (normally used in Bayesian Networks).

**Table 1.** Local probability distribution to MEBN theory predictive situation

<p><b>RESIDENT:</b> <i>executedAutomatedAction</i>(<i>sp</i>) [ <i>a1</i> = 0.6, <i>a2</i> = 0.1, <i>a3</i> = 0.2, <i>a4</i> = 0.05, <i>a5</i> = 0.05]</p>	<p><b>RESIDENT:</b> <i>Influence</i>(<i>ps</i>, <i>t</i>)</p> <p>if any <i>ps</i> have ( <i>executedAutomatedAction</i> = <i>a1</i> ) [   <i>HeartbetLess101</i> = 0.70,   <i>HeartbetMore101</i> = 0.30 ] else if any <i>ps</i> have ( <i>executedAutomatedAction</i> = <i>a2</i> ) [   <i>HeartbetLess101</i> = 0.40,   <i>HeartbetMore101</i> = 0.60 ] else if any <i>ps</i> have ( <i>executedAutomatedAction</i> = <i>a3</i> ) [   <i>HeartbetLess101</i> = 0.30,   <i>HeartbetMore101</i> = 0.70 ] else if any <i>ps</i> have ( <i>executedAutomatedAction</i> = <i>a4</i> ) [   <i>HeartbetLess101</i> = 0.05,   <i>HeartbetMore101</i> = 0.95 ] else if any <i>ps</i> have ( <i>executedAutomatedAction</i> = <i>a5</i> ) [   <i>HeartbetLess101</i> = 0.05,   <i>HeartbetMore101</i> = 0.95 ] else [ <i>HeartbetLess101</i> = 0.5, <i>HeartbetMore101</i> = 0.5]</p>
<p><b>RESIDENT:</b> <i>willBeSituationOf</i>(<i>ps</i>, <i>t</i>, <i>us</i>)</p> <p>if any <i>ps</i> have ( <i>influence</i> = <i>HeartbetLess101</i> ) [   true = 0.01,   false = 0.99 ] else if any <i>ps</i> have ( <i>influence</i> = <i>HeartbetMore101</i> ) [   true = 0.99,   false = 0.01 ] else [ true = 0.5, false = 0.5]</p>	

Table 1 presents local probability distributions for each resident node of the MTheory for Predictive Situation. This table shows the resident node *executedAutomatedAction*(*sp*), which describes the incidence of actions for manipulating the Predictive Situation “*sp*”, whereas 60 % of cases were *a1* (notify caregiver); 10 % - *a2*, (urgent administration of drugs), 20 % - *a3* (play music), and so on (details in Table 1).

The resident node *influence*(*ps*, *t*) means that if an Automated Action “*a1*” was performed for manipulating some Predictive Situation (*ps*), then the event *HeartbeatLess101* happens in 70 % of cases and *HertbetMore101* in 30 %, the remaining of the local probability distribution follows the same logic. The resident node

$willBeSituationOf(ps, t, us)$  means that the agitated situation is 99 % true when the Event HeartbeatMore101 is detected.

The reasoning process in PR-OWL ontology is an automatic generation of SSBN to determine the probabilities of a query. In this case, the query is “What is the probability of an agitated situation involving John happening in time T1?”. Using the MTheory for Predictive Situation in AAL systems and the Local Distribution of Table 1, the SSBN of Fig. 4 was generated. To answer the question, it was determined that the current time is “T0” and the HeartbeatMore101 Event was detected in T0. Such evidence determines that John is agitated.

In the Specific Situation Bayesian Network presented in Fig. 5, there is a probability of 58,41 % in T1 that John will be agitated. Therefore, the execution of a proactive plan of is needed for manipulating an agitated situation that may happen in the future.

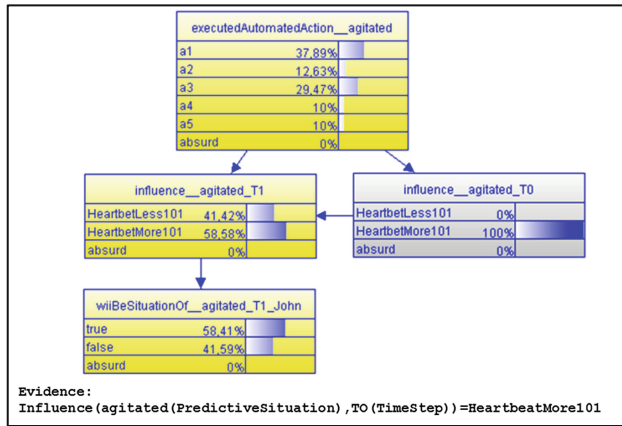


Fig. 5. Specific Situation Bayesian Network to Agitated  $willBeSituationOf$  John

## 5 Conclusion

Most of the research efforts in situation awareness are generally directed to implementation with a little preoccupation for the modeling of all the concepts involved. In the domotic application area, mainly in the complex environment of home-care for supporting elderly people with cognitive restrictions, we need models to support semantic interoperability between a smart environment and smart applications, allowing the identification of the current user situation and identifying the most suitable action to be executed. In this paper, we presented current issues in modeling for building Ambient Intelligence Systems for home-care. Our model was developed according to the methodology defined to build ontology networks. An ontology was developed, and it can be reused in several applications to improve interoperability, offering more semantics, allowing the detection of user’s current and future situations and identifying the most suitable action to be performed. After developing the network,

we conclude that this structure can be easily modified to incorporate new knowledge data, allowing to model concepts from different Ambient Intelligence environments. Our goal is to design models to describe an automated residential environment entirely controlled by a middleware. Currently, we are working on testing the situation detection over a real automated environment.

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