Smart Augmented Reality mHealth for Medication Adherence

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Abstract. The aim of this paper is to introduce a smart mHealth application based on the augmented reality (AR)-paradigm that can support patients with common problems, related to management of their medication. This smart mHealth application is designed and implemented as a medication coach intelligent agent, called *Medication Coach Intelligent Agent (MCIA)*. The *MCIA* will have to manage different types of information such as the *medication plan (medication regime)* of the patients, medication restrictions, as well as the patient's preferences and sensor input data from an AR-headset. Considering all this information, the *MCIA* leads with holistic decisions in order to offer personalized and unobtrusive interventions, in an autonomous way, to the patients. From a long term perspective, the *MCIA* should also evaluate its performance over time and adapt in order to improve its interventions with the patients. To show the feasibility of our approach, a proof-of-concept prototype was implemented and evaluated. The results show a high potential for using the *MCIA* in real settings.

1 Introduction

Medication adherence is a global problem [9], which can be defined as the "extent to which a patient acts in accordance with the prescribed interval, and dose of a dosing regimen" [10]. Lack of medication adherence leads to patients not achieving sufficient health outcomes [18], and about 25-50% of the patients do not follow their prescriptions correctly [16]. Non-adherence has been estimated to a cost of 100-289 billion dollars a year for the U.S healthcare system [22].

Several attempts have been made in order to address this problem such as different mHealth-applications[3] and different types of robots. Even though some interesting robots are on its way such as *Pillo* [4], robots have by nature, the limitation of being more or less fixed in its location.

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[3] Practice of medicine and public health using mobile devices, apps, smart devices and smartphones

[4] https://www.pillohealth.com

Some of the critiques towards current mHealth- applications is that they lack several basic adherence attributes [13], as well as persuasive techniques to engage people in the digital management of their disease [12].

Non-adherence can be either intentional or unintentional [8]. Unintentional non-adherence could, at least in theory, easily be addressed by sending reminders to patients. This may work very well for mHealth-applications, but it is more difficult when using robots since the user may not be close enough to the robot at all times. Intentional non-adherence is more challenging since sending a reminder can be seen as a useless attempt since, it will most likely not change the mental state of the patient. There is a conflict of interest between the system/agent and the patient in this situation. Persuasive techniques may play an important role when dealing with intentional non-adherence, but as mentioned many mHealth-applications lack this feature. AR[5]-headsets open up for a seamless interaction and brings a new approach for dealing with the problems of non-adherence.

Against this background, this paper introduces a novel solution to lead with the medication adherence problem based on the AR-paradigm and intelligent coaching systems. In particular, we introduce the so-called *Medication Coach Intelligent Agent (MCIA)*. The *MCIA* has *proactive* and *reactive* behavior in order to support the medical management of patients. Moreover, the *MCIA* has autonomous reasoning capabilities that allow the *MCIA* to lead with long-term goals in the settings of medication plans. As part of the results of this paper, an architecture of the *MCIA* is introduced. This architecture aims for a technologically scalable solution based on an AR-headset and multi-agent systems. We also present a usability evaluation of a proof-of-concept prototype of the *MCIA*.

The rest of the paper is organized as follows. In Section 2, different issues regarding medication management are discussed. In Section 3, a theoretical framework regarding the *MCIA* is presented. In Section 4, an implementation of the *MCIA* in the settings of the *Microsoft HoloLens* is presented. In Section 5, an evaluation of our proof-of-concept prototype is described. In Section 6, a short review of the related work is presented. In the last section, conclusions and future work are outlined.

2 Medication Scenario

The research in this project was developed as nurses from home healthcare brought attention to several patients having problems maintaining medication adherence through self management. Self management includes strategies and activities a person performs to live well with illness and it can be performed by the individual or in collaboration with a significant other [4, 7, 23]. Patients who are unable to perform health- and medication related activities as self management, for example handling and taking prescribed pills and following a medication plan, can get professional help in their homes, so called home healthcare [4]. A common reason for patients over age 70 to enroll in home healthcare is they are no longer able to handle their medication through self management and need professional help.

[5] Augmented reality

2.1 Patient Groups

From a medication management perspective, patients who use medicine regularly can be categorized into three conceptual groups. **Group 1** is independent and do not rely on help from others for managing their medication. **Group 2** is partly independent, receives help from relatives or friends, but do not get professional help. **Group 3** is in need of professional help.

The target group for the research in this project are patients from groups 2 and 3. The purpose is to investigate if AR-technology (using an AR-headset) may be used as a tool to increase their ability to improve and maintain medicine-related self management, thereby contributing to them staying independent for a longer time, delaying need for home healthcare and facilitate medication adherence.

2.2 Rules for Interchangeable Medicines

Many patients have several different medicines, as a strategy to simplify handling pills they use pill dispensers, where the medicine is distributed on a weekly basis. A common problem for the target group, and a reason why many patients need help managing their medication, is the continuous variation regarding their medicines, names of medicines and the visual appearance of pills and packages. This leads to patients and their non-professional helpers being confused when handling medication and preparing pill dispensers, which in turn leads to needing a nurse to come to their homes on a regular basis, preparing the dispenser for them.

What actually causes the variation is that the pharmacies can deliver different brands for the same type of medicine. The names and boxes varies with the brand and this makes the patients insecure and afraid of preparing their dispensers. The underlying reason for the frequent exchange of medicine brands are the rules for interchangeable medicines which are applied in most European countries. According to the rules, if a patient gets prescription for a particular medicine, the pharmacy always has to offer the brand with the lowest price if the medicines are interchangeable[6].

One of the main aims of the *MCIA* is to make patients and their helpers confident enough, using an AR-headset, to prepare their dispensers and therefore remove or delay the need of home healthcare (nurse). Another priority of the *MCIA*, in order to consider a long term experience, will be to help the patients to follow their medication plans through self management.

2.3 Prescription and On Demand Medicines

For this project a characterization of medicines has been made since there are differences in how different types of medicines should be managed by the *MCIA*. All medicines comes with prescription from a doctor. Prescriptions include adherence information about how the medicine should be taken regarding dose and time schedule. Adherence information is personalized for each patient, printed on adhesive labels at the pharmacy and attached to each package of medicine.

[6] `https://www.apoteket.se/kundservice/receptlakemedel-sa-fungerar-det/`

Medicines to be taken on a Regular Basis: The prescription label on these medicines state dose and the specific times each dose of the medicine should be taken. The goal of the *MCIA* is to make sure that the patient takes these medicines at the times they are specified.

Medicines to be taken On Demand: This type of medicines are medicines that the patient can take when he or she feels the need. Examples of common on demand medicines are pills to decrease pain or anxiety. The information on the prescription label states strength per dose, minimum time interval between doses and maximum amount of doses allowed in 24 hours. The goal of the *MCIA* will be to make sure that the user does not exceed the maximum dosage per day and occasion.

3 Theoretical Framework

The aim of this section is to formally introduce both data sources and a multi-criteria decision making approach for supporting the decision making processes of the *MCIA*.

3.1 Data Modeling

Let us start introducing the basic definition of a time point. A time point is a time stamp $\langle Date, time\_clock \rangle$. $\mathcal{T}$ denotes all the possible time points. Now let us introduce the basic definition of a medicine. A particularly interesting attribute of a medicine is its Anatomical Therapeutic Chemical (ATC)-code. The ATC-classification is an internationally accepted classification system, based on active ingredients and their therapeutic, pharmacological and chemical properties[7]. By ATC_codes, we denote a finite set of ATC-codes. Hence, a medicine is defined as follows:

Definition 1. ***Medicine***
A medicine m is a tuple of the form $\langle \epsilon, \varsigma, p, \delta, \alpha \rangle$, such that $m \in ATC\_codes \times \mathbb{R} \times [0,1] \times\ I \times Active\_ingridients$, where $\varsigma \in \mathbb{R}$ denotes a substance concentration in milligrams, $p \in [0,1]$ denotes a priority degree, $\delta \in I$ denotes a time interval such that $I = \mathcal{T} \times \mathcal{T}$. $\mathcal{M}$ denotes the set of all possible medicines.

Medicines will be managed in terms of events. An *event* is something that happens and which should be acknowledged by the *MCIA*. For example, if a reminder is presented to a patient whereupon the patient takes the medicines, the *MCIA* should notice that event and not present any more reminders regarding the same medicines for the same occasion. *Events* could also be things like eating food, drinking milk or other things that might have an impact, or have an effect, on the users' medication. This project however, only considers *events* regarding taking of an oral medicine, and is defined as follows:

Definition 2. ***Event***
An event e is a pair $\langle m, t \rangle$, such that $e \in \mathcal{M} \times \mathcal{T}$. $\mathcal{E}$ denotes the set of all possible events.

[7] http://www.hpra.ie/homepage/medicines/medicines-information/atc-codes

Constraints regarding medications can appear in three different ways. Firstly, it can be a medicine incompatibility, i.e. some medicines should not be taken at the same time as others, since it may have an impact on the effect of one or both of the medicines [5]. Secondly, there are time constraints. For example, if a patient takes an on demand medicine (such as regular painkillers), then a certain amount of time has to elapse until he or she can take it again. Thirdly, there can be a maximum dosage, or amount, per day. Due to lack of space, the formal definition of these constraints are not presented in this paper. The formal definition of these constrains can be found in [14]. We assume that the set of all possible constraints are denoted by $Constraints$.

A *medication plan* is the general plan which the *MCIA* wants the patient to follow. It is the foundation of the goals of the *MCIA*, and it is adherence to the medication plan that will be the primary source of feedback on how well the *MCIA* performs. The *medication plan* consists of all medicines that are prescribed, and also a set of constraints which should be considered while taking these medicines.

Definition 3. ***Medication plan***
A medication plan MP *is of the form* $MP = \langle (m_1, m_2, \ldots, m_n), \mu \rangle$ *such that* $m_i \in \mathcal{M}(1 \leq i \leq n)$, $\mu = \{C_1, C_2, \ldots, C_n\}$, $C_i \in Constraints(1 \leq i \leq n)$.

Medication adherence is the measure of how well patients follow their medication plan. This is important information for the *MCIA*, since it can be seen as the result of its actions and decisions. *Medication adherence* can be divided into two parts, overall adherence (how well the patient is following the medication plan), and the individual adherence for a specific medicine. It is not easy to measure adherence since there are many factors which it depends on, e.g. skipping one medicine one time might be fine, while skipping another is not. Elementary factors of estimating the adherence are the *priority* of each medicine, which indicates how important it is to take the medicine, and the history of the intakes (compliance to the plan). The two definitions of adherence are presented below. An *adherence function* will be used to calculate adherence.

Definition 4. ***Medication adherence for individual medicines***
Let β_m *be the medication adherence of a medicine* m *such that* $\beta_m = f_1(\gamma_m, p)$ *where* f_1 *is an adherence function for individual medicines,* γ_m *is the history for medicine* m *and* p *be its priority.*

Definition 5. ***Medication adherence in general***
Let π *be the over all medication adherence* $\pi = f_2(\sum_1^n \beta_{m_i})$ *where,* f_2 *is an overall adherence function, and* β_{m_i} *is the individual adherence for medicine* $m_i(1 \leq i \leq n)$.

Let us point out that the adherence functions f_1 (w.r.t. Definition 4) and f_2 (w.r.t Definition 5) are basically distance functions between the current state of adherence and the intended medication plan. Hence, these functions can be implemented in different ways. In our proof-of-concept prototype, f_1 was implemented as a model checking function, based on weak-constraints, following Answer Set Programming (ASP) [6], regarding the constraints of each medication in the medication plan.

3.2 Decision Making Modeling

In order to make decisions considering all of the relevant information such as the *medication plan* and the so called *information variables*, a *multi-criteria decision making-approach* has been chosen and more specifically, the *weighted sum method (WSM)* [15]. *Information variables* are used by the *WSM* for calculating weighted sums; an *information variable* is a pair of the form $\langle n, v\rangle$, where n is a propositional atom that describes what the variable represents (such as a preference or a context factor) and $v \in [0, 1]$, e.g. $\langle prefersAudioOutput, 0.4\rangle$, $\langle noisy, 0.8\rangle$.

Information variables are compensatory. Having a global rank where a good criterion can compensate for a bad criterion is usually referred to as the *full aggregation approach* [15]. This is highly desirable since the *MCIA* will deal with conflicting information and priorities.

Information availability. One of the drawbacks with *multi-criterion decision making* in general, is that a lot of information has to be specified. In this case however, the information should always be available in real time through sensors and internal values.

All desires (also called goals), which the *MCIA* has committed to achieving, are called *intentions* and for each *intention* there is a finite set of *actions* $\{a_1, a_2, \ldots, a_n\}$. *Actions* are basically different ways of achieving an *intention*. *Actions* can also be seen as the *MCIA's* means of interacting with the environment. The distinction between *intentions* and *actions* is a way of handling high level reasoning (using *intentions*), while still being able to adapt and be sensitive to the current situation (by using an appropriate *action*). An *intention* is defined as follows:

Definition 6. ***Intention***
An intention x is a pair $\langle ID, \alpha\rangle$, where $ID \in \mathbb{N}$, α be the intention to be performed.

Example 1. Let x_r be the *intention* to send a reminder to the user. Then there is a set of actions $\{a_1, a_2, a_3\}$ related the intention x_r, where $a_1 =$ use audio output, $a_2 =$ use visual output and $a_3 =$ use audio and visual output.

Before presenting the definition of decision making, a couple of related definitions are presented. *Utiliy weights* can be seen as the *priority* of the *information variable* regarding a given decision, and is defined in the following way.

Definition 7. ***Utility weights***
Let w_{xd} be the weight for information variable x regarding the decision d, then $w_{xd} \in \{L, M, H\}$ (low, medium or high importance).

An exact numeric value of the *utility weight* for the different priorities, is not defined and it may have to depend on the type of decision. However, a value between 0 and 1 will always be used for each of the different levels of importance.

The utility function $U(a)$, uses *information variables* with *utility weights* to calculate the utility of an alternative a and is defined in the following way.

Definition 8. ***Utility function***
Let a be an action, and $\sigma_1, \sigma_2, \ldots, \sigma_n$ be the positive ***information variables****, then $U(a) = \sum_0^n x_i w_i$ where, x_i is the value of the* ***information variable*** *$\sigma_i (1 \leq i \leq n)$, w_i be the weight of the information variable σ_i.*

Only *positive information variables* are used in the calculation. *Positive*, simply means that if the *information variable* has a high value, it should increase the utility for the given alternative. This is chosen for simplicity of the calculation, but it puts some requirements on what *information variables* there must be in order for the utility function to be fair. Competing alternatives should always depend on similar *information variables*, which means that they should have the same importance and have a similar purpose. This problem could be addressed by setting a weight which corresponds to the exact value of the importance of the variable, but it is hard to exactly define the importance of an *information variable* for a given decision. Instead, *utility weights* are merely a rough estimation of how important an *information variable* is.

Information which is not defined explicitly as a value (such as information in the *medication plan*), but may still be important when calculating the utility of the alternative, will be converted into an *information variable* using a separate function. This function varies depending on the type of information, but the result will be a number between 0 and 1 and will therefore be treated as a regular *information variable*.

The decision of choosing the best *action* is taken in real time by using the following definition.

Definition 9. ***Decision making***
Let D be a decision and $a_1, a_2, \ldots, a_n$ be competing actions, then $D = max(U(a_1), U(a_2), .., U(a_n))$ *such that $U(a_i)$ is a **utility function** which calculates the utility of $a_i (1 \leq i \leq n)$.*

A plan is simply a list of *intentions* which, if nothing changes, will be executed by the *MCIA*.

Definition 10. ***Plan***
Let δ be a plan $\delta = (\nu, \theta)$, $\nu = [x_1, x_2, \ldots, x_n]$ where each $x_i (1 \leq i \leq n)$ be an intention, $\theta = [l_1, l_2, \ldots, l_n]$ be a list of dependencies such that $l_i = (\pi, \beta)$, $\pi \in \{ID | (ID, \alpha)\ appears\_in\ \nu\}$, $\beta \subseteq \{ID | (ID, \alpha)\ appears\_in\ \nu\}$[8] and $\pi \notin \beta$.

4 Implementation

In this section, a proof-of-concept prototype of the *MCIA* is described. In this proof-of-concept prototype, the *MCIA* has been embodied as a smart augmented reality (AR)-mHealth application in the settings of a *Microsoft HoloLens*. This AR-mHealth application was designed as a *long-term experience application (LTEA)* [14]. The internal reasoning process of the *MCIA* follows the *beliefs-desires-intentions (BDI)*-model [24]. The *BDI* approach was chosen to handle a practical reasoning algorithm. Unity and Visual Studio were used to implement the prototype, and Vuforia was used as a plug-in to Unity in order to recognize medicine boxes. The general architecture of the system is depicted by Figure 1. The architecture consists of three major components, the *MCIA*, *external agents* and *databases*. The *external agents* and the *databases* provides the *MCIA* with the information it needs in order to supply the services to the user. The external agents, which are also *BDI-agents*, were introduced in our previous work [20]

[8] $appears\_in$ is the classical membership operator in lists.

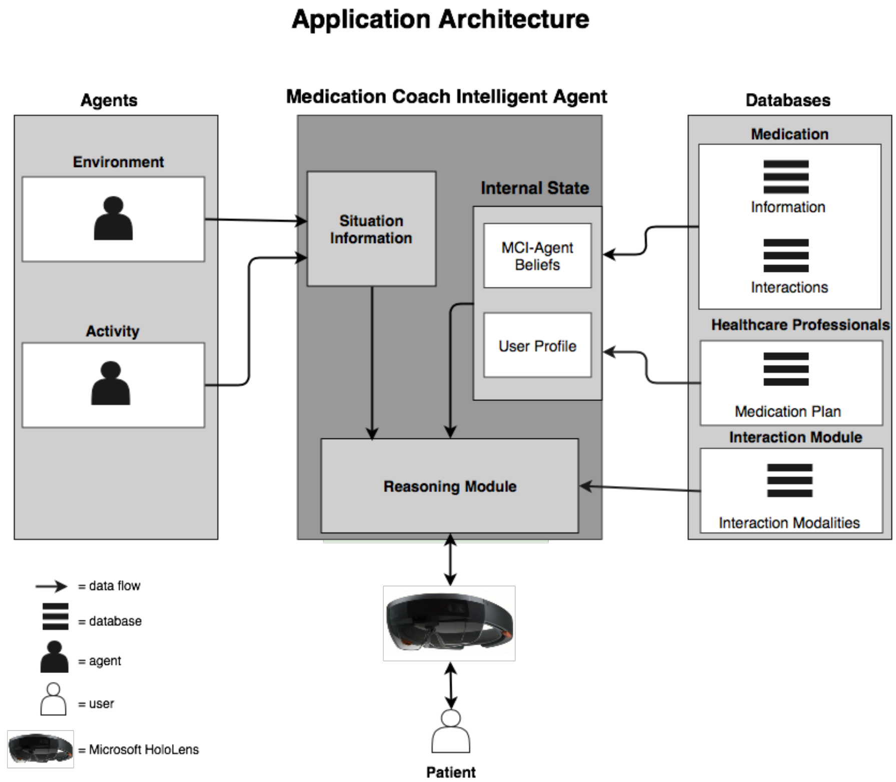

Fig. 1. Architecture

The reasoning loop of the *MCIA* can be seen in Figure 2. A *plan of intentions* (later referred to as *plan*) will be constructed using the current state, referred to as *internal state* (Figure 1, 2), and the *long-term goals*. This *plan* will be created on a daily basis and planning will take place over a specific time period. By practical reasons, it is assumed that this planning process will take place during night time. This means that when the user wakes up, the *plan* for the day has already been made and only re-planning using the *event-driven approach* is necessary. The reason why it is referred to as an *event-driven process* is that *events* can be seen as triggers that changes the *internal mental state* of the *MCIA*. Therefore, in the case of an *event*, the *MCIA* should check for interactions with the *plan* and re-plan accordingly.

Proactive behavior emerges by *actions* executed in order to achieve the *intentions* of the *MCIA*, such as sending reminders to the patient. Reminders are also context-aware regarding time, but in our proof of concept, also by simulated information from the environment. *Reactive behavior* emerges by using input to directly trigger some behavior, e.g. using voice commands and information regarding the user's vision (using the AR-headset), it is possible to display information regarding medicine boxes. *Autonmous behavior* emerges by reasoning about the *intentions of the day*. The purpose

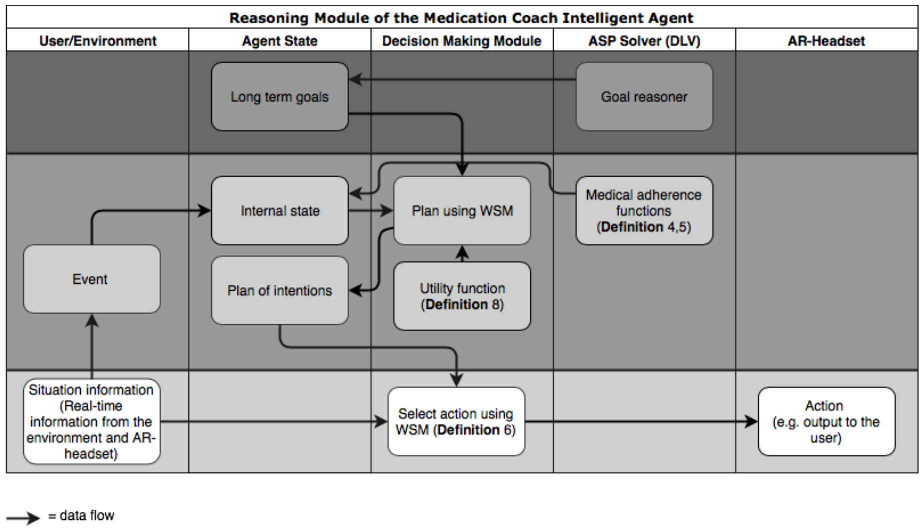

Fig. 2. Reasoning loop

of *intentions* are to improve medication adherence of the user, and by evaluating the behavior of the user, the reasoning can be adapted.

5 Evaluation

In order to show the feasibility of our approach, a usability evaluation of the proof-of-concept prototype of the *MCIA* was done. We aimed to answer the following questions:

- Is there a difference, related to age, regarding if people are willing to use an AR-headset for medication management?
- Is there a difference, related to experience of using smart technology, regarding if people are willing to use an AR-headset for medication management?

The functionality involved displaying information about medicine boxes regarding two features namely, helping the user to use a medicine at this moment and to help the user to prepare a dispenser. The evaluation involved 15 participants who were selected by using the following criteria: a.- Different levels of management of medication on a regular basis; b.- Wide range of ages (medication management in applies to people in all ages, not just elderly); c.- Different experiences using smart technology in general. The setting was a quiet and home-like environment. The participants were able to use voice, vision and gestures to interact with the system and were presented with both visual and audible output. Table 1 summarizes the visual information presented to the participants. After the test they were asked to fill in a form. Responses were on a five-point *Likert-type scale* graded from 1 (strongly disagree) to 5 (strongly agree). The lower bound to agree was made at 4 (4 or 5 = agree).

Table 1. Visual information about medicines presented to test participants

The evaluation showed that of all participants 20% perceived the technology hard to use and 13% thought that they would need a lot of training before using this technology in real life. There were a couple of vast differences regarding participants over and under 70 (4 and 11 respectively), and also between experienced smart technology users and those less experienced (8 and 7 respectively). Of the participants over 70, 50% were willing to use the technology in the future but none thought other people would appreciate the technology. For the participants under 70, the corresponding numbers were 91% and 100%. For participants over 70, 0% considered themselves as experienced smart technology users, while 73% of the people under 70 considered themselves as experienced. Of all experienced participants 100% were willing to use this technology in the future and 88% thought that most other people would appreciate the technology.

6 Related work

The possibilities of using smart-glasses (AR) within a system to assist doctors and other healthcare-personnel in emergency situations was explored in [11]. Smart-glasses was connected to different types of medical equipment and was used to display important information for the person wearing them. The smart-glasses could also be used to record video/audio and to take snapshots of the process.

Mitrasinovic *et al.* concluded that smart-glasses have evident utility to healthcare professionals [19]. A major advantage mentioned by Mitrasinovic *et al.* is that the glasses are hands-free which liberates the users from giving manual input.

A concept to send context-aware reminders to users in order to increase medication adherence was presented in [17]. They argued that sending reminders should depend on other factors than time, since there are a lot of scenarios where time-based reminders can fail. Results showed that the concept proved to be better compared to time-based reminders, which motivates the need of being context-aware.

An article about using a humanoid robot to support elderly peoples' everyday life [21], supplied similar functionality that we wish to do. Their prototype showed that there is potential in using a humanoid robot, and by using a robot (*NAO* in this case) it is possible to handle additional problem domains such as emergency situations.

General tools to increase medication adherence for patients are smart dispensers (e.g. [3]), robots (e.g. [2]) and applications to mobile devices (e.g. [1]). General functionality of these devices is to remind the patient to take the medicine and to help them with taking the right medicines. Our vision is to combine all of these common features and to add a more intelligent behavior.

7 Conclusions and Future Work

Medication adherence is a healthcare issue that affects both youth and elderly patients around the world. Until now, there is no a general solution that can support the dynamic demands that each individual requires for keeping his or her self-medication management optimal. In this regard, we argue that our approach based on intelligent coaching systems and AR-headsets shows a solid and scalable solution for leading with the complex processes of tailored services on medication management. Results from our evaluation showed that participants felt comfortable using an AR-headset during medication management procedures, such as taking pills and putting pills into pill dispensers. The evaluation indicates that the *MCIA* embodied in an AR-headset can be a useful tool in helping patients to maintain self management and medication adherence. From a societal perspective, maintained self management is likely to delay or possibly prevent, the need for professional assistance by nurses. As most western countries suffer from lack of nurses and other health care professionals the effects of the *MCIA* would potentially have a high impact on sustainability of public health resources. In our future work, we aim for a complete implementation of the *MCIA* and a long term usability evaluation of the *MCIA*.

Acknowledgements: This research has been supported by Nordic Telemedic Center (EU Interreg Botnia Atlantica), SFO-V Strategic Research Area Health Care Science and CEDAR (Centre for Demographic and Aging Research).

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