# Anthropomorphic Virtual Assistant to Support Self-care of Type 2 Diabetes in Older People: A Perspective on the Role of Artificial Intelligence

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Abstract: The global prevalence of diabetes is escalating. Attributable deaths and avoidable health costs related to diabetes represent a substantial burden and threaten the sustainability of contemporary healthcare systems. Information technologies are an encouraging avenue to tackle the challenge of diabetes management. Anthropomorphic virtual assistants designed as relational agents have demonstrated acceptability to older people and may promote long-term engagement. The VASelfCare project aims to develop and test a virtual assistant software prototype to facilitate the self-care of older adults with type 2 diabetes mellitus. The present position paper describes key aspects of the VASelfCare prototype and discusses the potential use of artificial intelligence. Machine learning techniques represent promising approaches to provide a more personalised user experience with the prototype, by means of behaviour adaptation of the virtual assistant to users' preferences or emotions or to develop chatbots. The effect of these sophisticated approaches on relevant endpoints, such as users' engagement and motivation, needs to be established in comparison to less responsive options.

## 1 INTRODUCTION

The global prevalence of diabetes is escalating (Karuranga *et al.*, 2017). Across the globe 90% of diabetic adults suffer from type 2 diabetes (T2D); the disease or its complications are the 9$^{th}$ major cause of death (Zheng, Ley and Hu, 2018). Recent Portuguese data estimated a total diabetes prevalence of about 13%. In Portugal more than one out of four persons aged between 60 and 79 years old have diabetes (Sociedade Portuguesa de Diabetologia, 2016).

Hyperglycaemia control in T2D involves lifestyle changes, including an adequate diet and physical activity and, where needed, regular medication. Difficulties in adhering to diabetes management, which requires sustained behavioural change, is associated with poor glycaemic control in more than half of the patients (García-Pérez *et al.*, 2013). Long term hyperglycaemia results in life-threatening complications, including cardiovascular disease, neuropathy, nephropathy and retinopathy. These complications represent an economic burden to health care systems, in addition to the clinical and humanistic burden posed to diabetes sufferers and their families (Karuranga *et al.*, 2017). Improving adherence to T2D management is therefore critical, as it will delay or avoid diabetes complications whilst relieving the



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financial pressure on healthcare systems overwhelmed by the demands of an ageing population.

Information Technologies (IT) are a promising avenue to help T2D patients self-managing their condition sustainably and without time or place restrictions. Mobile applications are regarded as cheaper, more convenient and more interactive than other IT-based interventions, such as short message services and computer-based interventions (Hou *et al.*, 2016). They have demonstrated a positive effect in improving glycaemic control in T2D patients. For example, Cui and co-workers (2016) conducted a systematic review of 13 randomised controlled trials on the effect of mobile applications on the management of T2D. Six studies provided data for meta-analysis, with a total of 1022 patients (average age from 45.2 to 66.6 years). They found that mobile applications were associated with a significant reduction in HbA1c by -0.40% (Cui *et al.*, 2016). One issue meriting debate is whether older people with T2D will have a benefit comparable to their younger counterparts, as trials included mostly younger samples (Cui *et al.*, 2016; Hou *et al.*, 2016). Mobile applications for older adults should be designed considering the needs of this population group.

Relational agents, which are virtual characters capable of establishing long-term relationships with users, emerge as an encouraging approach to engage older people.

The VASelfCare project aims to develop and test a prototype of a relational agent application to facilitate self-care of older people with T2D. In this paper we discuss ideas on the role of artificial intelligence to enhance functionalities of the VASelfCare prototype; this falls under one of the conference topic areas (interactive environments). Our position paper builds on an international collaboration between the VASelfCare team and a researcher experienced in behaviour adaptation of social robots in cognitive stimulation therapy for older people. The ideas put forward are discussed in light of experimental and bibliographic evidence.

The core of this paper is comprised by three key sections. Firstly, section 2 provides a broad overview of published work on relational agents, including a brief description on the use of artificial intelligence. Section 3 describes our relational agent prototype (VASelfCare). Together, these sections set the scene for the proposed ideas about the role of artificial intelligence to enhance functionalities of our prototype.

## 2 RELATED WORK

Studies resorting to relational agents have been conducted in several areas. The importance of incorporating an artificial intelligence component in these agents has been recognized for some years now (Cassell, 2001).

In the area related to our work, healthcare, substantial research has been conducted by Bickmore *et al.,* namely in approaches tackling mental conditions. For instance, Bickmore *et al.* (2010) evaluated how patients with a high-level of depressive symptoms responded to a computer animated conversational agent in a hospital environment. Another publication describes the use of relational agents in health counselling and behaviour change interventions in clinical psychiatry (Bickmore and Gruber, no date). Ring *et al.* reported a pilot study based on an affectively-aware virtual therapist for depression counselling (Ring, Bickmore and Pedrelli, 2016). Still in mental health, Provoost *et al.* (2017) reviewed the use of embodied conversational agents in clinical psychology, mostly focusing on autism and on social skills training. The benefit of relational agents in patients with lower health literacy was demonstrated (Bickmore *et al.*, 2010). It has also been showed that interventions based on relational agents are well accepted by older people (Bickmore *et al*. 2005; Bickmore *et al*. 2013).

Devault and co-workers developed a conversational agent deploying artificial intelligence techniques for natural language understanding and dialogue management to establish an engaging face-to-face interaction. The goal was creating interactional situations favourable to the automatic assessment of distress indicators (Devault *et al.*, 2014).

The role of emotions and the importance of establishing rapport between a virtual agent and the human user, coupled to the relevance of nonverbal behaviour in affective interaction, have been studied, for instance, by Gratch *et al.* (2007), Bickmore *et al.* (2005) Bickmore, Gruber and Picard (2005), and Paiva *et al.* (2017).

One of the more explored subareas of artificial intelligence in other fields of research on virtual assistants is natural language processing, which intends to achieve a more believable interaction. For example, (Hoque *et al.*, 2013) developed a virtual agent for social skills training that reads facial expressions and uses natural language processing techniques to understand speech and prosody, responding with verbal and nonverbal behaviours in real time. Also, Rubin, Chen and Thorimbert (2010), surveyed the use of language technologies in the development of intelligent assistants in libraries.

The importance of virtual assistants in healthcare as well as the relevance of incorporating machine learning techniques is also reported in a work by (Shaked, 2017), where the authors identify a set of key features for the design of this kind of applications when interacting with older people.

The use of relational agents in people with T2D has been little explored. One exception is an Australian study, which described the development of an intelligent diabetes lifestyle coach for self-management of diabetes patients (Monkaresi *et al.*, 2013). However, this study lacks data on usability or the effect on endpoints of interest. More recently, an on-going study in the USA has used a relational agent as a health coach for adolescents with type 1 diabetes and their parents (Thompson *et al.*, 2016).

# 3 VASELFCARE PROTOTYPE

Our application targets medication adherence and lifestyle changes (physical activity and diet) in a stepwise fashion by means of an anthropomorphic virtual assistant, named Vitória. As previously mentioned, the virtual assistant was designed as relational agent. This is expected to increase engagement and long-term use (Bickmore, 2010), and to facilitate the interaction with people with lower literacy. Development of the application was guided by usability principles for older people (Arnhold, Quade and Kirch, 2014).

## 3.1 Interaction with the Application

When opening the application Vitória is depicted in a 3D living room scenario. When clicking on the button "Enter", users with T2D are directed to a menu where several choices are available, including talking to Vitória (Dialogue view – Figure 1).

### 3.1.1 The Dialogue View

Vitória communicates with users both verbally, by means of a synthetic voice, and non-verbally through facial and body animations. The latter depend on users' responses. The 3D scenario in which this virtual assistant is depicted changes according to the dialogue context (e.g. the kitchen scenario is presented when talking about the diet), the time of day (i.e. the view from the window in the background) and the season (e.g. the window view with sunshine or rain).


Figure 1: Dialogue view in the evaluation phase (version 1.00).

Another design option tailored for older people includes subtitles in Vitória's speech, which may overcome hearing difficulties.

Users communicate with Vitória using buttons or recording values, such as the daily number of steps, and medication taken. The latter data are plotted into graphs or other visual representations (Figure 2), used by Vitória to give feedback during the interaction.

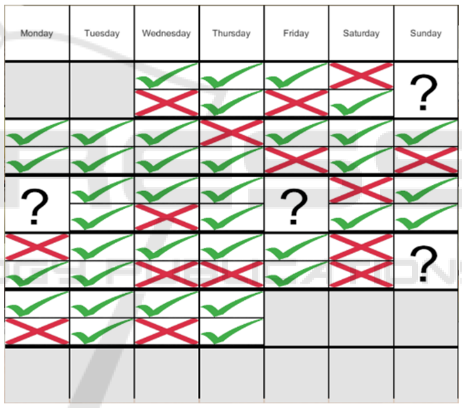


Figure 2: Medication-taking feedback (scenario: one oral antidiabetic, two daily doses; question mark means no self-reported data) (version 1.0.5).

The first daily interactions for medication adherence and lifestyle changes collect data on pertinent variables, with the purpose of tailoring the intervention to users' characteristics. For example, behaviour change on medication adherence considers users' knowledge about antidiabetic agents, their usual behaviour and the perceived self-efficacy in managing their medication. This phase is designated "evaluation phase". In the subsequent "follow-up phase", the behaviour change intervention is informed by theory and users' characteristics.

Based on the literature (Bickmore, Schulman and Sidner, 2011), each daily interaction is structured in sequential steps. Interactions in the evaluation phase have six steps: opening, social talk, assess, feedback, pre-closing and closing. The “opening” step, which consist in greeting the user, is followed by a social dialogue, including inquiries about users’ general emotional and physical state (“social talk”). Questions on a variable of interest, such as knowledge about antidiabetic medication, are then posed (“assess”), followed by feedback on the answers collected previously. Finally, contents of the next interaction are described (“pre-closing”) and a farewell is delivered (“closing”).

Daily interactions in the follow-up phase are also structured in repeated sequential steps: opening, social talk, review tasks, assess, counselling, assign tasks, pre-closing and closing. The first and last two steps are similar to those described above. In the “review tasks” step, information is collected about previously agreed tasks or behaviours. Then, information is provided about the reported task or behaviour, including reward talk or a discussion of behaviour(s) determinants (“assess”). In the counselling step, users receive information on strategies to achieve the desirable behaviour (if applicable) and on specific educational topics. After, users negotiate new behavioural goals and tasks with Vitória (“assign tasks”).

A rule-based component has been implemented in the application, to convey a more flexible dialogue flow in the follow-up phase.

The Behaviour Change Wheel (BCW), a comprehensive and evidence-based theoretical framework of behaviour change, was chosen to inform the intervention design (Michie, Atkins and West, 2014). The BWC is underpinned by the COM-B model. This model posits that engagement in a behaviour (B) at a given moment depends on capability (C) plus opportunity (O) and motivation (M). Analysis of a given behaviour in relation to COM-B allows the identification of determinants, which must be addressed to achieve change. The BCW entails also the selection of interventions functions (broad strategies for inducing the target behaviour) and behaviour change techniques (active replicable elements that promote change).

Suitable and effective behaviour change techniques (BCT) were incorporated in different steps of the interactions, guiding the dialogue creation (Michie *et al.*, 2013). For example, “Self-monitoring of behaviour” was applied in the “review tasks”; it consists of recording medication taken or steps count. In the “Assess” step, information on medication-taking is provided by means of a calendar, a technique entitled “Feedback on behaviour”. In this step users also identify potential determinants of non-adherence, which allows the selection of ameliorating strategies in the “counselling” step. This BCT is designated “problem solving”. Educational topics addressed during “counselling” encompass the “information about health consequences” BCT.

Dialogue creation in the assessment and follow-up phases employs a helpful-cooperative communication style (Niess and Diefenbach, 2016).

### 3.1.2 The Other Views

In its current version, the application has six views in addition to the dialogue view (“Main menu”, “Recording”, “My diary”, “My data”, “Information” and “About the application”). The main menu offers several sub-menus; each sub-menu, in turn, corresponds to a view of the application.

In the “My diary” view, users can create a weekly plan. The diary automatically proposes meal times with recipe suggestions. Users can also add, remove and edit activities.

“My Data” allows users to review information on topics, such as their prescribed antidiabetic medication, anthropometric measurements (e.g. a visual representation of body mass index) and their reported behaviour, by means of the same charts used by Vitória in daily interactions.

The “Information” view consists of a glossary plus educational content about diabetes, diet, physical activity, antidiabetic medication.

“Recording” allows users to input data such as the number of steps walked per day or blood glucose levels. The application gives automatic feedback to entered data, including messages in case of potentially erroneous values. Another example of automatic feedback is depicted in Figure 3; this feedback guides the user on the treatment of a hypoglycaemic episode, when the inputted blood glucose level is below 70 mg/dl.

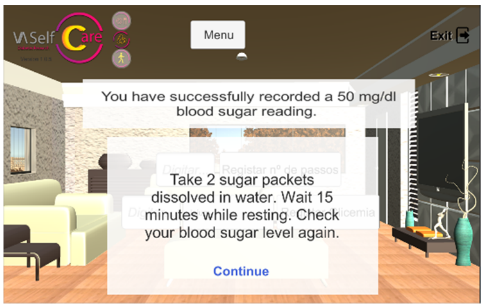


Figure 3: Example of an instant response to the recording of a low blood sugar level (version 1.0.5).

Finally, the “About the Application” view includes information about the application development, security and privacy policy.

While the dialogue view is restricted to one interaction per day, the aforementioned views can be freely accessed.

### 3.2 The Application Architecture

The components of our prototype are depicted in Figure 4. The VASelfCare Core comprises the scripts responsible for the user interface and the logic of the application; it is implemented inUnity3D with C# scripts. This core component resorts to services provided by two external elements: the **Dialogue Creator** and the **Speech Generator**.

**VASelfCare Core** comprises several modules with distinct responsibilities: the **Application Controller**, the **Dialogue Controller**, the **Speech Controller**, and the **Data Controller**.

The **Application Controller** is responsible for the logical sequence of the application and communicates with the other modules of the VASelfCare Core.

The **Dialogue Controller** decides the correct order of the dialogues, choosing the dialogue files that are used in a specific moment of the interaction.

The **Speech Controller** is the module that allows Vitória to speak, searching and activating the audio and viseme files that correspond to the on-going dialogue. Finally, the **Data Controller** module has the responsibility of exchanging data with the embedded local database. In this database the application stores clinical information entered at the time of registration and all the relevant data concerning the flow of interaction with older patients.

The application runs in tablets with Android system without Internet connection, which is intended to facilitate access at users' homes, where Internet is not always available. When an Internet connection is detected the application backs-up the database up onto the project server.

## 4 THE ROLE OF ARTIFICIAL INTELLIGENCE IN THE VASELFCARE APPLICATION

The architecture of the VASelfCare prototype presented in section 3 offers multiple opportunities for machine learning to further enhance the capabilities of the virtual assistant. This section provides a brief background on reinforcement learning and discusses the potential use of artificial intelligence methods in the VASelfCare application.

### 4.1 Reinforcement Learning

Generally, reinforcement learning is a learning method which determines how to map situations to actions and also tries to maximize a numerical reward signal. The actions performed by the agent are not identified explicitly, they have to be discovered through exploration in order to get the most reward (Sutton and Barto, 2018).

The agent can sense its environment and take actions which can change the state of the environment to reach a given goal. The formulation of the task includes the following three aspects: sensation, action and goal.

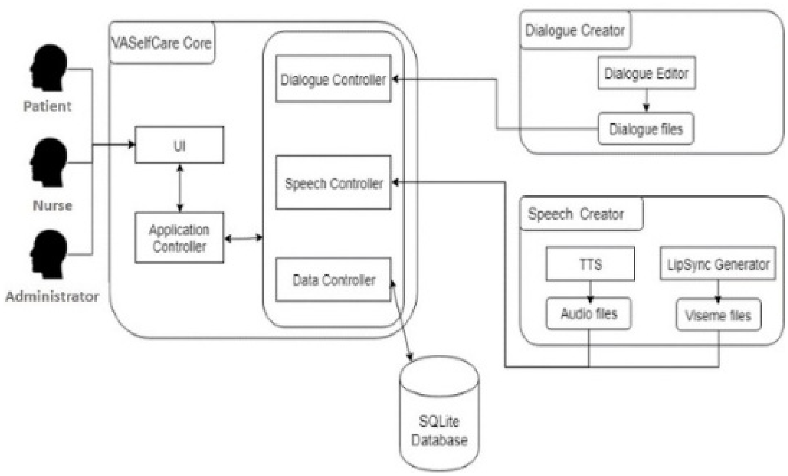


Figure 4: VASelfCare architecture.

In addition to the aforementioned concepts of reinforcement learning, there are three other key elements to correctly define a reinforcement learning problem: policy, reward function and value function and (Sutton and Barto, 2018).

Policy in general defines the agent's way of behaving in a given situation. More precisely it serves for mapping from perceived states of the environment to actions which must be executed when in those states.

The reward function defines the goal of the reinforcement learning problem. It is responsible for mapping the perceived state of the environment or state-action pair to a number (reward) which defines the desirability of the given state. The agent's goal is to maximize this reward during the learning process.

Contrarily to the reward function, which indicates what is good or bad for the agent in the immediate sense, the value function defines what is good for the agent in the long run. In general, the value function is the maximal value of reward which can be expected by the agent during the learning process.

Traditional methods of machine learning, such as reinforcement learning, were used successfully in many areas. However, they were not primarily designed for learning from real-time social interaction with humans. This encompasses challenges, such as dealing with limited human patience or ambiguous human input. To address these challenges socially guided machine learning was designed (Thomaz and Breazeal, 2006).

In reinforcement learning the reward signal is represented by human feedback (e.g. facial emotion, gesture, verbal expression). Such a system is designed to efficiently learn from people with no experience in reinforcement learning. This learning method can be used to further enhance the cognitive capabilities of Vitória, the VASelfCare virtual assistant.

## 4.2 Applying Reinforcement Learning to the Prototype

### 4.2.1 Behaviour Adaptation based on Users' Evaluation

One of the possibilities is changing Vitória's facial and body animations based on users' preferences. The task of the learning agent in this case is to find what kind of pre-defined animations are desired by users (e.g. fast or slower movements, more expressive versus more neutral facial animations). To increase the learning speed animations can be labelled; the ones which have the same label and are not accepted by the user can be excluded from the learning right away. Nonetheless, to ensure variability of the virtual assistant behaviour these can show up with low probability in future interactions. The reward for the agent could be provided by users' ratings of Vitória's animations.

An additional possibility pertains to the fifth step of the evaluation stage: counselling. As mentioned in section 3.1, one of the goals of this step is to educate users on different topics. Reinforcement learning can help to create a personalised counselling step, which builds on existing knowledge and provides new information. The actions of the learning agent can be the descriptions of the new concepts and the reward can be provided by testing the newly acquired knowledge of the user; this step is already included in the evaluation stage.

For the sake of discussion, we can consider a scenario in which Vitória does not have information about the existing level of knowledge of a new user. Firstly, this construct must be evaluated, to determine what is already known about a topic (e.g. diabetes or the prescribed medication). In the follow-up interactions the virtual assistant can then address more often topics where knowledge is absent or limited. Employing this mechanism provides a tailored approach whilst ensuring that users will have comprehensive knowledge about diabetes management.

### 4.2.2 Behaviour Adaptation based on the Assessment of Users' Facial Emotions

In recent years many emotion recognition services were made publicly available. Due to the complexity of facial emotion assessment, these cloud services facilitate the development of emotion recognition systems. In practice, users upload an image or provide an URL address to the service, which returns information about emotion assessment, usually in the form of numerical data, representing the probability of the presence of a given emotion in the image.

Selected examples of emotion recognition services are Face++ Cognitive Services' Emotion Recognition which can detect anger, disgust, fear, happiness, neutral, sadness, and surprise. Google Vision detects four emotional states on the face: anger, joy, sorrow, and surprise. The Microsoft Face API an detect eight emotions: anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. The Sighthound Cloud API can recognize anger, disgust, fear, happiness, neutral, sadness, and surprise.

In a recent work we combined the above-mentioned services and trained a machine learning model to increase the overall accuracy of face emotion assessment (Magyar *et al.*, 2018). The resulting system was tested on different face emotion datasets and was able to increase accuracy from an average of 70 – 75% to approximately 95%. In the VASelfCare prototype such an emotion recognition system can be used to gather data about the overall emotional state of users, therefore detecting and preventing unwanted states (e.g. distress, pain). A pilot study for assessing elderly patients' emotions in a cognitive stimulation therapy session with a robot already showed that such information can be valuable when adapting the agent's behaviour (Takac *et al.,* 2018***).***

As an example, we can consider the second step of the daily interaction: social talk. In this step Vitória initiates small talk with a user on various topics (e.g. family, music, daily news, etc.). By combining reinforcement learning and emotion recognition, the virtual assistant can explore topics associated with positive feelings (e.g. expressing happiness when talking about grandchildren) and with negative feelings (e.g. expressing sadness when talking about a late spouse). Using this information and a history of previous conversations, the social interaction can be personalised, to ensure a positive mood during the interaction.

Facial emotion recognition can also be used in reinforcement learning as a reward for the learning agent. In this approach the behaviour of the virtual assistant will be adapted based on the emotional response of the user. This means that Vitória will likely to prefer those actions which result in boosting the users' mood and avoid those provoking sadness.

### 4.2.3 Chatbots

Another interesting possibility is applying artificial intelligence to the VASelfCare prototype by means of chatbots, which are increasingly getting more attention. As for facial emotion assessment, there are many publicly available cloud services for building chatbots. Although these are mainly used for customer support applications, they can be easily integrated in the VASelfCare prototype.

For the sake of simplicity, we provide the description of Microsoft's Q & A maker and how it can be used in interactions with older people with T2D. Nearly all cloud-based bot frameworks work on a similar principle.

To create a chatbot from scratch it is firstly necessary to gather data on relevant topics, such as medication, activities in the form of previous conversations, user manuals and product materials. Secondly these documents are processed and used to train a machine learning model, which extracts information from the documents and uses it to form answers to questions on a given topic. The model trained initially can be tested by experts to refine the system answers. The model is then ready for use and can serve the various needs of the users.

In case of updates (e.g. a new marketed drug), the model can be easily re-trained by feeding data about the product to the system.

This feature holds great potential, since questions about diabetes management can come up daily in the interactions with Vitória. By constantly updating the model with the newest information it is ensured that the virtual assistant is providing accurate information, previously checked by experts, to multiple users. This system can also work with available text-to-speech technologies, so users will not have to read the messages.

## 5 CONCLUSIONS

Artificial intelligence, and particularly machine learning techniques, represent promising approaches to provide a more personalised user experience with the VASelfCare prototype. These approaches include tailoring the virtual assistant behaviour based on users' preferences or facial emotion assessment and the use of chatbots.

Scholten *et al*. (2017) reviewed the capabilities of relational agents to fulfil users' needs in eHealth interventions. They made a distinction between non-responsive and responsive relational agents. The former are not designed to respond to emotionally expressed users' needs in real time. Research shows that non-responsive relational agents can engage users. Although their development is simpler, there is a higher risk of a worse user experience (Scholten, Kelders and Van Gemert-Pijnen, 2017).

Responsive relational agents, designed to detect frustration and to empathically respond to it, have shown a positive effect on users' attitudes. However, this effect has not been demonstrated in clinical populations (Scholten, Kelders and Van Gemert-Pijnen, 2017). Therefore, the benefits of facial emotion assessment merit further research, particularly considering that both nonresponsive and responsive agents can provide a positive experience.

Tailoring of health information has been defined as "any combination of information and behaviour change strategies intended to reach one specific person based on characteristics that are unique to that person related to the outcome of interest and derived from an individual assessment" (Kreuter, M., Farrell, D., Olevitch, L., & Brennan, 2000). This approach demonstrated a positive effect in health behaviour outcomes in web-delivered interventions (versus nontailored approaches) (Lustria *et al.*, 2013). Our current prototype tailors the counselling step, dealing with diverse pre-existing levels of knowledge, by means of an decision system. Nonetheless, due to the nature of human-computer interaction it is nearly impossible to prepare the system for every situation using an explicit rule-based system. Reinforcement learning enables a more flexible platform for the agent to learn an appropriate behaviour based on users' preferences. It can also be used as a complementary method to the existing decision system. In this scenario the system would firstly determine what kind of action should be executed by the agent. Then reinforcement learning would be applied to determine how the action should be executed when dealing with a concrete user. By applying such a combination of machine learning methods, the application will offer a more flexible and tailored behaviour of the agent.

An open dialogue (textual or verbal) between users and the relational agent, such as the one provided by a chatbot, may support users' needs, providing a better experience and consequently improving adherence to the intervention. Ultimately, this assumption will have to be subjected to empirical trial.

We have pointed out several opportunities for research. Such research will contribute to answer a critical question posed by Dehn & Mulken (2000) about two decades ago.: "what kind of animated agent used in what kind of domain influence what aspects of the user's attitudes or performance?."



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## REFERENCES

Arnhold, M., Quade, M. and Kirch, W. (2014) 'Mobile Applications for Diabetics : A Systematic Review and Expert-Based Usability Evaluation Considering the Special Requirements of Diabetes Patients Age 50 Years or Older Corresponding Author ':, *Journal of Medical Internet Research*, 16(4), pp. 1–18. doi: 10.2196/jmir.2968.

Bickmore, T. (2010) 'Relational Agents for Chronic Disease Self-Management', in Hayes, B. and Aspray, W. (eds) *Health Informatics: A Patient-Centered Approach to Diabetes*. Cambridge, MA: MIT Press, pp. 181–204.

Bickmore, T. and Gruber, A. (no date) 'Relational agents in clinical psychiatry.', *Harvard review of psychiatry*, 18(2), pp. 119–30. doi: 10.3109/10673221003707538.

Bickmore, T., Gruber, A. and Picard, R. (2005) 'Establishing the computer-patient working alliance in automated health behavior change interventions', *Patient Education and Counseling*, 59(1), pp. 21–30. doi: 10.1016/j.pec.2004.09.008.

Bickmore, T. W. *et al.* (2005) '"It's just like you talk to a friend" relational agents for older adults', *Interacting with Computers*, 17(6), pp. 711–735. doi: 10.1016/j.intcom.2005.09.002.

Bickmore, T. W. *et al.* (2010) 'Response to a relational agent by hospital patients with depressive symptoms', *Interacting with Computers*. Elsevier B.V., 22(4), pp. 289–298. doi: 10.1016/j.intcom.2009.12.001.

Bickmore, T. W. *et al.* (2013) 'A randomized controlled trial of an automated exercise coach for older adults', *Journal of the American Geriatrics Society*, 61(10), pp. 1676–1683. doi: 10.1111/jgs.12449.

Bickmore, T. W., Schulman, D. and Sidner, C. L. (2011) 'A reusable framework for health counseling dialogue systems based on a behavioral medicine ontology', *Journal of Biomedical Informatics*. Elsevier Inc., 44(2), pp. 183–197. doi: 10.1016/j.jbi.2010.12.006.

Cassell, J. (2001) 'Conversational Agents Representation and Intelligence in User Interfaces', *AI Magazine*, 22(4), pp. 67–84. doi: 10.1609/aimag.v22i4.1593.

Cui, M. *et al.* (2016) 'T2DM self-management via smartphone applications: A systematic review and meta-analysis', *PLoS ONE*, 11(11), pp. 1–15. doi: 10.1371/journal.pone.0166718.

Dehn, D. M. and Mulken, S. van (2000) 'The impact of animated interface agents : a review of empirical research', *International Journal of Human-Computer Studies*, 52, pp. 1–22.

Devault, D. *et al.* (2014) 'SimSensei Kiosk: A Virtual Human Interviewer for Healthcare Decision Support', in *International conference on Autonomous Agents and Multi-Agent Systems, AAMAS '14, Paris, France, May 5-9, 2014*. IFAAMAS/ACM, pp. 1061–1068.

García-Pérez, L.-E. *et al.* (2013) 'Adherence to therapies in patients with type 2 diabetes.', *Diabetes therapy*, 4(2), pp. 175–94. doi: 10.1007/s13300-013-0034-y.

Gratch, J. *et al.* (2007) 'Creating Rapport with Virtual Agents', *Intelligent Virtual Agents*, pp. 125–138. doi: 10.1007/978-3-540-74997-4_12.

Hoque, M. (Ehsan) *et al.* (2013) 'MACH: my automated conversation coach', in *Proceedings of the 2013 {ACM} international joint conference on {Pervasive} and ubiquitous computing - {UbiComp} '13*. Zurich, Switzerland: ACM Press, p. 697. doi: 10.1145/2493432.2493502.

Hou, C. *et al.* (2016) 'Do Mobile Phone Applications Improve Glycemic Control (HbA1c) in the Self-management of Diabetes? A Systematic Review, Meta-analysis, and GRADE of 14 Randomized Trials', *Diabetes Care*, 39(11), pp. 2089–2095. doi: 10.2337/dc16-0346.

Karuranga, S. *et al.* (eds) (2017) *IDF Diabetes Atlas*. 8th edn. Brussels, Belgium: International Diabetes Federation. Available at: http://diabetesatlas.org/.

Kreuter, M., Farrell, D., Olevitch, L., & Brennan, L. (2000) *Tailoring health messages: customizing communication with computer technology*. Mahwah New Jersey: Lawrence Erlbaum Associates. Available at: https://www.popline.org/node/174671 (Accessed: 4 December 2018).

Lustria, M. L. A. *et al.* (2013) 'A meta-analysis of web-delivered tailored health behavior change interventions', *Journal of Health Communication*, 18(9), pp. 1039–1069. doi: 10.1080/10810730.2013.768727.

Magyar, J., Magyar, G., Sincak, P. 2018. A Cloud-Based Voting System for Emotion Recognition in Human-Computer Interaction. *2018 World Symposium on Digital Intelligence for Systems and Machines*, pp. 109-114.

Michie, S. *et al.* (2013) 'The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: Building an international consensus for the reporting of behavior change interventions', *Annals of Behavioral Medicine*, 46(1), pp. 81–95. doi: 10.1007/s12160-013-9486-6.

Michie, S., Atkins, L. and West, R. (2014) *The Behaviour Change Wheel*.

Monkaresi, H. *et al.* (2013) 'Intelligent Diabetes Lifestyle Coach', *Fifth International Workshop on Smart Healthcare and Wellness Applications (SmartHealth'13) - Adelaide, Australia*, p. s/p.

Niess, J. and Diefenbach, S. (2016) 'Communication Styles of Interactive Tools for Self-Improvement', *Psychology of Well-Being*. Springer Berlin Heidelberg, 6(1), p. 3. doi: 10.1186/s13612-016-0040-8.

Paiva, A. *et al.* (2017) 'Empathy in Virtual Agents and Robots: A Survey', *ACM Trans. Interact. Intell. Syst.*, 7(3), p. 11:1–11:40. doi: 10.1145/2912150.

Provoost, S. *et al.* (2017) 'Embodied conversational agents in clinical psychology: A scoping review', *Journal of Medical Internet Research*, 19(5). doi: 10.2196/jmir.6553.

Ring, L., Bickmore, T. and Pedrelli, P. (2016) 'An affectively aware virtual therapist for depression counseling', *ACM SIGCHI Conference on Human Factors in Computing Systems (CHI) workshop on Computing and Mental Health*. doi: 10.1128/JB.01951-12.

Rubin, V. L., Chen, Y. and Thorimbert, L. M. (2010) 'Artificially intelligent conversational agents in libraries', *Library Hi Tech*, 28(4), pp. 496–522. doi: 10.1108/07378831011096196.

Scholten, M. R., Kelders, S. M. and Van Gemert-Pijnen, J. E. W. C. (2017) 'Self-guided Web-based interventions: Scoping review on user needs and the potential of embodied conversational agents to address them', *Journal of Medical Internet Research*, 19(11). doi: 10.2196/jmir.7351.

Shaked, N. A. (2017) 'Avatars and virtual agents – relationship interfaces for the elderly', *Healthcare Technology Letters*, 4(3), pp. 83–87. doi: 10.1049/htl.2017.0009.

Sociedade Portuguesa de Diabetologia (2016) *Diabetes: Factos e Números - o ano de 2015*.

Sutton, R. S. and Barto, A. (2018) *Reinforcement Learning: An Introduction*. MIT PRESS. Available at: https://mitpress.mit.edu/books/reinforcement-learning-second-edition (Accessed: 13 November 2018).

Takac, P. *et al*. (2018). Cloud Based Affective Loop for Emotional State Assessment of Elderly. In: G D'Onofrio, ed.. *Active & Healthy Aging: Novel Robotic Solutions and Internet of Things*. Avid Science, ISBN 978-93-86337-71-9

Thomaz, A. L. and Breazeal, C. (2006) 'Reinforcement learning with human teachers: Evidence of feedback and guidance with implications for learning performance', *AAAI Conference on Artificial Intelligence*, 6, pp. 1000–1005. doi: 10.1039/C3EE 43707H.

Thompson, D. *et al.* (2016) 'Use of Relational Agents to Improve Family Communication in Type 1 Diabetes: Methods', *JMIR Research Protocols*, 5(3), p. e151. doi: 10.2196/resprot.5817.

Zheng, Y., Ley, S. H. and Hu, F. B. (2018) 'Global aetiology and epidemiology of type 2 diabetes mellitus and its complications', *Nature Reviews Endocrinology*. Nature Publishing Group, 14(2), pp. 88–98. doi: 10.1038/nrendo.2017.151.