Adaptive Data-Driven Persuasive Communication for a Conversational Agent to Support Behavior Change

Nele Albers
Willem-Paul Brinkman
n.albers@tudelft.nl
w.p.brinkman@tudelft.nl
Delft University of Technology
Delft, The Netherlands

Mark A. Neerincx
mark.neerincx@tno.nl
Delft University of Technology
Delft, The Netherlands
TNO
Soesterberg, The Netherlands

ABSTRACT

A human therapist continuously adapts how they persuade a client to adhere to a behavior change intervention based on theoretical expertise, past experience with the client as well as other clients, and the client's current situation. We aim at incorporating these elements into the persuasive communication of a conversational agent that acts as a virtual coach for smoking cessation and physical activity increase. The focus thereby is on investigating how three coaching elements, goal-setting, data-monitoring and the assignment of activities, can be designed to enhance treatment adherence. A first experiment is currently finished to 1) get user input for the interaction design based on interaction scenarios, 2) gather data for and test a reinforcement learning-approach to persuading people to do small preparatory activities for smoking cessation and increasing physical activity, and 3) gain insights into the acceptance and perceived motivational impact of the virtual coach used to persuade people.

CCS CONCEPTS

• **Applied computing → Health informatics**; • **Human-centered computing → Human computer interaction (HCI)**; • **Computing methodologies → Intelligent agents**; **Reinforcement learning**.

KEYWORDS

Conversational agent, virtual coach, persuasion, reinforcement learning, personalization, behavior change, smoking cessation

ACM Reference Format:
Nele Albers, Willem-Paul Brinkman, and Mark A. Neerincx. 2021. Adaptive Data-Driven Persuasive Communication for a Conversational Agent to Support Behavior Change. In *ACM International Conference on Intelligent Virtual Agents (IVA '21), September 14–17, 2021, Fukuchiyama City, Kyoto, Japan.* ACM, New York, NY, USA, 3 pages.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
IVA '21, September 14–17, 2021, Fukuchiyama City, Kyoto, Japan
© 2021 Association for Computing Machinery.

1 INTRODUCTION

Imagine you have a coach that helps you to quit smoking. Let's suppose the name of this coach is Hannah. How does Hannah decide how to persuade you to stick to your intervention? Hannah probably draws upon her theoretical expertise, experience with other and especially similar clients, and knowledge about what motivated you in the past. Furthermore, she will consider your current situation - have you had a terrible day at work or are you excited about the sudden onset of summer? And finally, Hannah will keep adapting her strategy over time as she gains more experience. Now, let's suppose that you have another coach, Sam. In contrast to Hannah, Sam is a virtual coach. Sam is available at all times, scalable, cost-effective and can facilitate tailoring [15]. However, can Sam do what Hannah can, or even more?

Changing personal behavior such as by quitting smoking is one of the most promising ways to improve health and reduce premature death, with almost 40% of deaths in the United States being caused by behavior [24, 31]. To support such behavior change, there have been numerous eHealth interventions for various domains [1, 8, 18]. Yet, adherence to these interventions remains low [1, 14]. The aim of our work thus is the design and development of persuasive communication in form of a virtual coach to help people in adhering to their intervention. Personalized data-driven advice has been shown to effectively support people during interventions, for example by tailoring motivational messages to people's gender, personality and stage of behavior change [6]. Rather than just considering certain characteristics of people, however, we go a step further by adapting the persuasion to each individual based on learning which ones they respond favorably to. Such persuasive profiles have been shown to be effective with regards to reducing snacking behavior, increasing uploads of sensor data, and yielding higher rates of clicking through for commercial emails [12]. Yet, little work has explored how continuously adapted, data-driven persuasive profiles can be used to improve adherence to an entire behavior change intervention by addressing different coaching elements such as goal-setting, data-monitoring, and activity assignments [1, 9].

2 RESEARCH PLAN

The overarching question we aim to answer is how persuasive communication for computerized coaching can serve to enhance treatment adherence in the context of smoking cessation and physical activity increase. Smoking and physical inactivity are chosen as target behaviors, as both are important preventable risk factors of cardiovascular disease [21], which is a main cause of mortality in

Europe [37]. Notably, while our research is conducted in the context of two specific behaviors, generalizability to other behaviors is an important guideline for our work. Our design process consists of 1) getting input from stakeholders, 2) designing and testing persuasion components, and 3) empirically evaluating the acceptance and motivational impact of the virtual coach. We discuss the three resulting sub-questions subsequently.

2.1 Needs and Values of Stakeholders

The virtual coach will be created based on the principles of human-centered design, which means that we will incorporate the needs and values of end-users. This is crucial to avoid a poor fit between the developed technology and end-users in their specific context [3, 34]. As a first step, we have designed a patient journey that captures main elements of the intervention the virtual coach is developed for [20]. Such a patient journey is a structured visualization of the user's experience [32]. Thereby, we used an iterative design process in which insights from existing interventions [19, 22, 27], relevant theories [16], and input from experts and end-user representatives were included. Based on this patient journey, we have created videos for possible interactions with the virtual coach. We show these videos to daily smokers in our current first experiment. Participants are asked to provide a rating for how likely they would engage in the shown interaction in place of the persona in the video. In addition, we ask the participants to explain their rating by means of a free-text response to understand their values and preferences. A viable future step would be to gather input from other stakeholders.

2.2 Designing Elements of Computerized Coaching to Enhance Treatment Adherence

Goal-setting, data-monitoring and activity assignments have been identified as core elements of behavior change coaching [1, 9]. The first element, goal-setting, can help people to successfully achieve a goal by providing motivation and help to stay focused on a desired outcome [7]. However, setting effective goals can be difficult [17]. The reason is that an effective goal needs to satisfy several criteria, such as aligning with other goals of the person [25] and being realistic and achievable [5]. While current behavior change applications do allow setting goals such as by choosing a smoking quit date [26, 33] or selecting a target number of steps per day [30], they do not ensure that the resulting goals meet the necessary criteria. In our research, we thus examine using a dialog with a virtual coach to support people in the goal-setting process. Such a virtual coach has the advantage that it can serve patients where traditionally clinicians would have provided guidance. This includes using information about an individual to customize the goal-setting process. Personalizing goal-setting by suggesting goals tailored to baseline physical activity has been shown in the past to significantly improve physical activity [4]. We plan to build on this work by extending the personalization to other elements of the goal-setting process. Currently, we are examining the use of personalized examples of similar people who succeeded at reaching a goal to increase a person's confidence in reaching their own goal.

The second and third core elements of the coaching process we target are data-monitoring and assigning small activities such as writing down reasons for wanting to quit smoking. More precisely, we strive to use points of interaction such as providing feedback, explaining collected data and assigning activities in a way that we are most confident to successfully motivate a specific user. Research has shown that the way people react to past persuasive attempts is a good predictor of how these people will react to those persuasive attempts in the future [12]. Moreover, the behavior of all other [12, 13] or similar people [10] can be employed as guidance. In addition, we plan to consider a person's current situation - is the person already very motivated to begin with, or is the person's confidence very low? - and to continuously learn over time based on the data we collect. One framework that integrates these elements is Reinforcement Learning (RL). RL has been successfully applied to customize the display of emotions in an argumentative dialog [36] or the politeness style of a robotic companion for elderly people [29]. Currently, we are finishing a first experiment with more than 500 people to gather data for and test an RL-approach for persuading people to do preparatory activities for smoking cessation and physical activity increase. Participants interact with the virtual coach Sam in five conversational sessions. In each of these session, participants are assigned an activity with a certain persuasion type. In the future, we plan to build on this algorithm by specifically adapting to single individuals over time and intelligently deciding when to explore new and possibly better types of persuasion.

2.3 Usability of the Persuasive Communication

Since end-users form the center of our design, we will empirically evaluate the usability of the persuasive communication. In the current RL-experiment described in the previous section, for example, we assess users' acceptance of the virtual coach [2, 28] and the perceived motivational impact of the conversational sessions.

3 METHODS

Our research methodology rests on four core pillars. First, design choices are informed by discussions with domain experts among our project partners and end-user representatives. For instance, the Dutch Center of Expertise on Health Disparities Pharos provides guidance on how to render interactions accessible to people of low socioeconomic status. Second, our research is grounded in important theories such as the COM-B model for behavior change [23] and goal-setting theory [16], as well as relevant previous work on personalizing persuasion by learning which type of persuasion works [10–13, 35, 36] such as by means of RL. Third, we use controlled experiments to test the effectiveness of individual communication components as well as qualitative studies to gain insights into the needs and values of potential end-users. Lastly, in an effort to foster reproducibility of our work, code for algorithms and statistical analyses as well as anonymized collected data will be publicly shared. Furthermore, experiments and analyses will be pre-registered in the Open Science Framework (OSF)[1].

ACKNOWLEDGMENTS

This work is part of the multidisciplinary research project Perfect Fit, which is supported by several funders organized by the Netherlands Organization for Scientific Research (NWO), program Commit2Data - Big Data & Health (project number 628.011.211).

[1] The Open Science Framework (OSF) can be found at the following address: osf.io.

REFERENCES

[1] Robbert Jan Beun, Willem-Paul Brinkman, Siska Fitrianie, Fiemke Griffioen-Both, Corine Horsch, Jaap Lancee, and Sandor Spruit. 2016. Improving adherence in automated e-coaching. In *International conference on persuasive technology*. Springer, 276–287.

[2] Timothy W Bickmore, Suzanne E Mitchell, Brian W Jack, Michael K Paasche-Orlow, Laura M Pfeifer, and Julie O'Donnell. 2010. Response to a relational agent by hospital patients with depressive symptoms. *Interacting with computers* 22, 4 (2010), 289–298.

[3] Linda D Breeman, Mike Keesman, Douwe E Atsma, Niels H Chavannes, Veronica Janssen, Lisette van Gemert-Pijnen, Hareld Kemps, Wessel Kraaij, Fabienne Rauwers, Thomas Reijnders, et al. 2020. A multi-stakeholder approach to eHealth development: Promoting sustained healthy living among cardiovascular patients. *International Journal of Medical Informatics* (2020), 104364.

[4] Neel P Chokshi, Srinath Adusumalli, Dylan S Small, Alexander Morris, Jordyn Feingold, Yoonhee P Ha, Marta D Lynch, Charles AL Rareshide, Victoria Hilbert, and Mitesh S Patel. 2018. Loss-framed financial incentives and personalized goal-setting to increase physical activity among ischemic heart disease patients using wearable devices: the ACTIVE REWARD randomized trial. *Journal of the American Heart Association* 7, 12 (2018), e009173.

[5] Anne Conzemius and Jan O'Neill. 2009. *The power of SMART goals: Using goals to improve student learning*. Solution Tree Press.

[6] Roelof AJ De Vries, Cristina Zaga, Franciszka Bayer, Constance HC Drossaert, Khiet P Truong, and Vanessa Evers. 2017. Experts get me started, peers keep me going: comparing crowd-versus expert-designed motivational text messages for exercise behavior change. In *Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare*. 155–162.

[7] Tracy Epton, Sinead Currie, and Christopher J Armitage. 2017. Unique effects of setting goals on behavior change: Systematic review and meta-analysis. *Journal of consulting and clinical psychology* 85, 12 (2017), 1182.

[8] Ahmed Fadhil and Silvia Gabrielli. 2017. Addressing challenges in promoting healthy lifestyles: the al-chatbot approach. In *Proceedings of the 11th EAI international conference on pervasive computing technologies for healthcare*. 261–265.

[9] Jane Greene and Anthony M Grant. 2003. *Solution-focused coaching: Managing people in a complex world*. Pearson Education.

[10] Santiago Hors-Fraile, Shwetambara Malwade, Francisco Luna-Perejon, Claudio Amaya, Antón Civit, Francine Schneider, Panagiotis Bamidis, Shabbir Syed-Abdul, Yu-Chuan Li, and Hein De Vries. 2019. Opening the Black Box: Explaining the Process of Basing a Health Recommender System on the I-Change Behavioral Change Model. *IEEE Access* 7 (2019), 176525–176540.

[11] Yilin Kang, Ah-Hwee Tan, and Chunyan Miao. 2015. An adaptive computational model for personalized persuasion. In *Proceedings of the 24th International Conference on Artificial Intelligence*. 61–67.

[12] Maurits Kaptein, Panos Markopoulos, Boris De Ruyter, and Emile Aarts. 2015. Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles. *International Journal of Human-Computer Studies* 77 (2015), 38–51.

[13] Maurits Kaptein, Richard McFarland, and Petri Parvinen. 2018. Automated adaptive selling. *European Journal of Marketing* (2018).

[14] Saskia M Kelders, Llewellyn Ellardus Van Zyl, and Geke DS Ludden. 2020. The concept and components of engagement in different domains applied to ehealth: a systematic scoping review. *Frontiers in psychology* 11 (2020), 926.

[15] Yanhui Liao, Qiuxia Wu, Jinsong Tang, Fengyu Zhang, Xuyi Wang, Chang Qi, Haoyu He, Jiang Long, Brian C Kelly, and Joanna Cohen. 2016. The efficacy of mobile phone-based text message interventions ('Happy Quit') for smoking cessation in China. *BMC Public Health* 16, 1 (2016), 1–11.

[16] Edwin A Locke and Gary P Latham. 2002. Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American psychologist* 57, 9 (2002), 705.

[17] Edwin A Locke and Gary P Latham. 2015. Breaking the rules: a historical overview of goal-setting theory. In *Advances in motivation science*. Vol. 2. Elsevier, 99–126.

[18] Kien Hoa Ly, Ann-Marie Ly, and Gerhard Andersson. 2017. A fully automated conversational agent for promoting mental well-being: a pilot RCT using mixed methods. *Internet interventions* 10 (2017), 39–46.

[19] Eline Meijer, Janneke S Korst, Kristiene G Oosting, Eline Heemskerk, Sander Hermsen, Marc C Willemsen, Bas van den Putte, Niels H Chavannes, and Jamie Brown. 2021. "At least someone thinks I'm doing well": a real-world evaluation of the quit-smoking app StopCoach for lower socio-economic status smokers. *Addiction science & clinical practice* 16, 1 (2021), 1–14.

[20] Eline Meijer, Kristell Penfornis, Nele Albers, Bouke Scheltinga, Douwe Atsma, Niels Chavannes, Sven van der Burg, Willem-Paul Brinkman, and Winnie Gebhardt. 2021. Perfect Fit: een identiteitsgebaseerde virtuele coach die ondersteunt bij stoppen met roken en meer bewegen. *Nederlands Netwerk voor Tabaksonderzoek (NNvT) Congres* (2021).

[21] George Michas, George Karvelas, and Athanasios Trikas. 2019. Cardiovascular disease in Greece; the latest evidence on risk factors. *Hellenic Journal of Cardiology* 60, 5 (2019), 271–275.

[22] Susan Michie, Jamie Brown, Adam WA Geraghty, Sascha Miller, Lucy Yardley, Benjamin Gardner, Lion Shahab, Andy McEwen, John A Stapleton, and Robert West. 2012. Development of StopAdvisor: a theory-based interactive internet-based smoking cessation intervention. *Translational behavioral medicine* 2, 3 (2012), 263–275.

[23] Susan Michie, Maartje M Van Stralen, and Robert West. 2011. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. *Implementation science* 6, 1 (2011), 1–12.

[24] Ali H Mokdad, James S Marks, Donna F Stroup, and Julie L Gerberding. 2004. Actual causes of death in the United States, 2000. *Jama* 291, 10 (2004), 1238–1245.

[25] Harold F O'Neil and Michael Drillings. 1994. *Motivation: Theory and Research*. Routledge.

[26] Jeni Paay, Jesper Kjeldskov, Mikael B Skov, Nirojan Srikandarajah, and Umachanger Brinthaparan. 2015. Quittylink: Using smartphones for personal counseling to help people quit smoking. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services*. 98–104.

[27] Kristell Penfornis, Winifred Gebhardt, and Eline Meijer. 2021. Mijn toekomstige zelf is (niet) gestopt met roken: Een experimentele studie naar de effecten van een toekomstige-zelf interventie op de zelfidentiteit van rokers. *Nederlands Netwerk voor Tabaksonderzoek (NNvT) Congres* (2021).

[28] Simon Provoost, Annet Kleiboer, José Ornelas, Tibor Bosse, Jeroen Ruwaard, Artur Rocha, Pim Cuijpers, and Heleen Riper. 2020. Improving adherence to an online intervention for low mood with a virtual coach: study protocol of a pilot randomized controlled trial. *Trials* 21, 1 (2020), 1–12.

[29] Hannes Ritschel, Andreas Seiderer, Kathrin Janowski, Stefan Wagner, and Elisabeth André. 2019. Adaptive linguistic style for an assistive robotic health companion based on explicit human feedback. In *Proceedings of the 12th ACM international conference on PErvasive technologies related to assistive environments*. 247–255.

[30] Amelia Romeo, Sarah Edney, Ronald Plotnikoff, Rachel Curtis, Jillian Ryan, Ilea Sanders, Alyson Crozier, and Carol Maher. 2019. Can smartphone apps increase physical activity? Systematic review and meta-analysis. *Journal of medical Internet research* 21, 3 (2019), e12053.

[31] Steven A Schroeder. 2007. We can do better—improving the health of the American people. *New England Journal of Medicine* 357, 12 (2007), 1221–1228.

[32] Marc Stickdorn, Jakob Schneider, Kate Andrews, and Adam Lawrence. 2011. *This is service design thinking: Basics, tools, cases*. Vol. 1. Wiley Hoboken, NJ.

[33] Harveen Kaur Ubhi, Susan Michie, Daniel Kotz, Wai Chi Wong, and Robert West. 2015. A mobile app to aid smoking cessation: preliminary evaluation of SmokeFree28. *Journal of medical Internet research* 17, 1 (2015), e17.

[34] Lex Van Velsen, Jobke Wentzel, and Julia EWC Van Gemert-Pijnen. 2013. Designing eHealth that matters via a multidisciplinary requirements development approach. *JMIR research protocols* 2, 1 (2013), e21.

[35] Klaus Weber, Kathrin Janowski, Niklas Rach, Katharina Weitz, Wolfgang Minker, Stefan Ultes, and Elisabeth Andrè. 2020. Predicting Persuasive Effectiveness for Multimodal Behavior Adaptation using Bipolar Weighted Argument Graphs. In *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems*. 1476–1484.

[36] Klaus Weber, Niklas Rach, Wolfgang Minker, and Elisabeth André. 2020. How to Win Arguments. *Datenbank-Spektrum* 20, 2 (2020), 161–169.

[37] E Wilkins, L Wilson, K Wickramasinghe, P Bhatnagar, et al. [n.d.]. European Heart Network. European Cardiovascular Disease Statistics 2017.