Towards Profile and Domain Modelling in Agent-based Applications for Behavior Change

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Abstract. Health support programs play a vital role in public health and prevention strategies at local and national levels, for issues such as smoking cessation, physical rehabilitation, nutrition, or to regain mobility. A key success factor in these topics is related to the appropriate use of behavior change techniques, as well as tailored recommendations for users/patients, adapted to their goals and the continuous monitoring of their progress. Social networks interactions and the use of multi-agent technologies can further improve the effectiveness of these programs, especially through personalization and profiling of users and patients. In this paper we propose an agent-based model for supporting behavior change in eHealth programs. Moreover, we identify the main challenges in this area, especially regarding profile and domain modeling profiles for healthcare behavioral programs, where the definition of goals, expectations and argumentation play a key role in the success of a intervention.

Keywords: MAS, behavior change, profiles, domain models

1 Introduction

Personalization is a key factor for succeeding in changing the behavior of users, especially in the context of health support programs. In concrete use-cases like smoking cessation, nutrition, or physical rehabilitation, the profile of the user (or patient) can help defining different strategies and approaches to attain the desired goals, which may significantly differ from the ones tailored for other peers. Modeling the different interactions between users and health professionals, and/or support personnel, is a fundamental step towards the digitalization of these processes. The advantages of using IT solutions to support these interactions are manifold: it allows providing streamlined support to participants, it facilitates the implementation of guidelines and best practices, it can increase the effectiveness of the program, and it can potentially reduce interaction costs.

Agent-based models are a particularly promising technology in this context. Agent models allow representing not only the type of actions and behaviors of participating entities, but also their assumptions, goals, background knowledge, and plans. These elements can relate to both users following a behavior change program (e.g., patients) and those supporting the program (e.g., caregivers), whose interactions can partially be assumed by a software agent. However, existing agent-based models focus on different aspects and it is generally difficult to adapt them to specific characteristics of health-support programs. More specifically, most of these models do not fully address the elements relevant for behavior change, or require extensive adaptation and mapping to profile models.

In this paper, we identify key challenges for health support applications targeting behavior change, and we describe key requirements for implementing systems that can effectively address those challenges. We then propose a novel agent-based model for behavior change, exploiting existing persuasion and comportment models in eHealth [25, 19], and incorporating the development of domain models, and user profiles. In particular, we discuss how this model can be adapted to a real use case, in the domain of smoking cessation. This model leverages well studied behavior change research [13], incorporating as added value the usage of multi-agent systems that can encapsulate user-agent interactions, coaching, mediation, and personalized interactions, also including aspects related to argumentation and domain-specific context [11].

The paper is organized as follows. In Section 2 we introduce the smoking cessation example use case, in Section 3 we describe the challenges of behavior change in eHealth. Section 4 details the requirements derived form the challenges while Section 5 presents the propose model. Related work is discussed in Section 6 before concluding with a proposed road-map.

2 Use-case: Smoking Cessation

Smoking is a public health concern, as it produces chemical, routinary and social addiction [14]. Different measures have been adopted through the years to counter this issue, including prevention and media campaigns, increasing tobacco prices, or the introduction of smoke-free policies [3]. Given the proven benefits of stopping to smoke [3], there are many approaches for quitting this habit, although the hardest addictions to fight are related to routine and social behaviors. Smoking cessation interventions, backed up by health professionals and providing continuous support, can help individuals attaining this goal. However, they are often costly in terms of time and resources, with mitigated results if they do not consider the personal context of the participants. Hence, a personalized eHealth support system has the potential to achieve comparable results to those provided by a traditional clinic-based intervention, with the low cost associated with a public health approach. In the literature, there have been a number of approaches to address this issue, such as using expert systems [24], which provides cost-effective means of intervening in smoking cessation. However, there has also been evidence that the impact of smoking cessation support can substantially increase in social scenarios [23].

In this paper we use smoking cessation as a running example of a behavior change issue, given the omnipresence of this issue worldwide, and considering the availability of prevention and public health programs supporting this type of initiatives in Switzerland. Concretely, we take the example of the smoking cessation program named «J'arrête de fumer» (JDF), launched in 2015 in the canton of Valais and soon expanded to all the French-speaking cantons in Switzerland. The program was implemented as a Facebook community consisting of individuals willing to quit smoking on the same day. It allowed participants to share their approaches and techniques, and to support each other throughout the difficult periods of smoking cessation. After six months, out of 7000 participants, 13.5% definitely stopped smoking [9]. From the experience of this program, we can identify some of the advantages and opportunities of a social network eHealth intervention, while also considering the numerous challenges, as we will see next.

3 Challenges

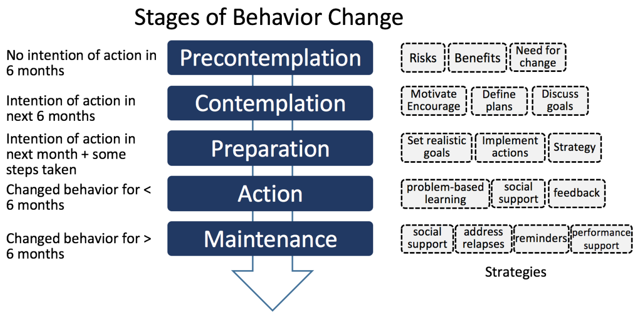

Fig. 1. The Trans-theoretical model of behavior change [19].

Behavior change is a challenging problem, especially regarding health-related issues and lifestyle. There are different factors that need to be taken into account in order to achieve effective outcomes, including the attitude, emotional issues, social pressure, self-perception, etc [13]. Given that each person has a particular background and context, even if the behavior change goals are similar, the strategies and techniques need to be personalized. As it can be seen in classic behavior change models such as the Trans-theoretical model (Figure 1) of stages of change [19], participants may fall under different states, for which intervention may require completely different strategies. The use of digital solutions for supporting behavior change holds the promise of providing higher effectiveness, increasing the level of personalization, allowing massive outreach, and reducing intervention costs. In the following, we identify the main challenges that digital behavior change applications face, in the context of health support programs.

- *Communication.* Interactions with participants require the use of appropriate means of communication, adapted to their needs, in terms of technology (e.g., usage of audio, chatbots, messaging), frequency, length, etc. A poor choice of communication technologies can lead to early abandon, or to misuse of the health support application.
- *Engagement.* Participants may quickly abandon a health program if it looses focus, if it does not provide any tangible or meaningful response, or if it deviates from the expected goals. Even if results in the very short term

are not usually possible, the participant at least expects useful interactions, motivations, rewards, or support aligned with the initial objectives.

- *Personalization.* Behavior change actions will increase effectiveness if they are tailored to the user context and situation. Health programs need to model the user, or at least the relevant factors that play a key role in the scope of the targeted behavior. At least, it is important to elaborate a basic profile of the user, and determine at which stage she is, and how to track her changes and progress during the intervention in order to tailor future actions.
- *Continuous learning.* Humans interactions and behaviors are dynamic, and require to be updated constantly. An automated health support system must deal with these changes and learn from them, potentially building patterns and user models that exploit previous interactions in order to match and predict future activities.
- *Argumentation.* Changes in activities and behavior can be motivated in different ways, and arguments supporting or opposing an idea or an action, can be part of a strategy in order to persuade a participant. Argumentation needs to be built around knowledge in the area, and must be directed depending on the state of the participant and her context. Computational argumentation theories [13] need to be adopted in order to automatize the establishment of argument construction and dialogue.
- *Domain specifics.* Persuasion, argumentation and personalization require relevant knowledge of the domain of application. This knowledge needs to be organized and modeled so that it can be used for building arguments, adapting to context, or to elaborate strategies for personalization. These domain models [5] also require the participation and validation of experts, and the usage of existing ontologies and metamodels.

4 Requirements

The challenges described previously lead to the elicitation of requirements for a behavior change support system. To illustrate the process we take as example the smoking cessation use case. The requirements can be summarized as follows:

1. *Structured & instantaneous interactions.* Participants must interact with the system through instantaneous messaging, with constrained interactions. It is important to limit the dialog length in order to avoid tiredness and losing the focus of the intervention. The usage of instantaneous messaging is convenient as it allows for multi-platform interactions, including the use of mobile devices, and integration with existing messaging systems through chatbots.
2. *Symmetric/Asymmetric communication.* In many scenarios, participants may interact with the system primarily through asymmetric dialogues [12], allowing for structured, shorter and targeted input from the user [5]. This mechanism provides more control to the system, as it can pose the arguments that the user may confirm, answer, and/or react to. For example, for asking about cigarette consumption, the system may pose questions about the context (is

the cigarette necessary, is the user alone, at work, what is the mood, etc.), allowing predefined response sets. This makes the interaction quicker, less error-prone, and more focused. Conversely, in other scenarios (e.g., emotion and feedback processes), less constrained dialogues can be allowed, possibly relying on natural language processing, polarity and sentiment analysis.
3. *Social interactions.* Participants must be able to interact with their peers, establishing virtual connections. A fundamental added value of an intervention is the network of social connections with other participants that can support, provide advice, reflect on their own goals, etc., through the duration of a health program. For example, successful smoking quitters may provide tips to other participants about dealing with morning anxiety, or how to cope with the temptation of cigarettes during social events. It has been shown in the literature that this type of social support has an important impact on behavioral change success [22].
4. *State-dependent interactions.* Interactions with users must be adapted to the stages of the program in which they currently are, characterised as states during the behavior change process (as in Figure 1). The system should keep track of the stages that a certain participant has passed, and use the corresponding strategy depending on that. For example, during contemplation the interactions may focus on the definition of plans and goals for quitting smoking, during maintenance the emphasis will be on addressing relapse events and performance support. Moreover, during each stage, the system may establish fine-grained states, e.g., during the preparation stage for smoking cessation the participant may be: assessing her level of dependence, registering smoking patters, tracking cigarettes, defining short term goals, etc.
5. *Profile learning.* The system must build a profile of each participant, based on the states that she passed through, and the data acquired through asymmetric dialog interactions, and feedback loops. The profile will constitute part of a local knowledge base for each participant, subject to privacy protection. For instance, a profile for smoking cessation may include the demographic information entered at the start of the program, a nicotine dependence assessment through the Fagerstrom test, cigarette consumption, mood and desire level according to hour-of-day, and contextual situations, etc.
6. *Behavior analytics.* Every participant may be addressed considering her behavior history, as recorder during the program, and also according to the behavior of other participants. Based on the analysis of the dialogue interactions, the system should identify behavior patterns that will have an impact on the personalization of the intervention for her. For example, based on sentiment analysis of the interactions, or on the tracking of cigarettes (e.g., recent relapse, or anxiety episodes), the system may opt to strengthen motivation factors, which would have more impact than for another participant with different behavior patterns. Furthermore, the system may cluster similar participants according to their behavior.
7. *Persuasive argumentation.* The system must use domain-modelled arguments in order to attempt to persuade the participant using suitable arguments, matching both her context and profile. Arguments can be structured

as concepts surrounding a certain problem/solution: e.g., its causes, benefits, associated risks, opportunities; or linked to goals, factual information, evidence, preferences, and opinions. For example, a smoker during a cessation phase may be suffering a motivation crisis after a month of quitting. An appropriate argument to boost motivation to sustain the cessation may be to point out that evidence shows that after the first month the relapse crisis decrease substantially. However, for a participant that just started the process this argument might have little effect. The usage of computational persuasion techniques [13] needs to be included to power this type of features.

8. *Scalability.* The support system must scale to large numbers of participants, potentially reaching thousands of users simultaneously, without degrading the quality of experience.

5 Design Principles

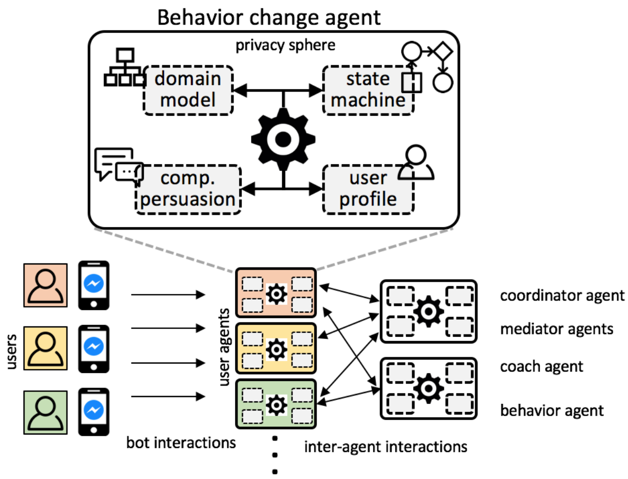

Fig. 2. A model for agent-based behavior change support applications.

Following the requirements detailed in the previous section, we present a multi-agent model for a behavior change system. emphasizing its main components: domain modelling, user profiling, argumentation, stage/state management, and communication. This model is based on the concept of user-dedicated agents that interact with each participant individually through conversational messaging, while being able to keep a local knowledge base composed of the user profile and behavior. At the same time, each of these agents can interact with each other directly or through mediator agents, in cases where collaboration is required, or if further coaching/information is needed. The minimal components of the model are depicted in Figure 2. Each behavior change agent is a lightweight software entity in charge of a single participant. Each of these agents manages the state of the participant through a state machine that reflects the different stages (and inner states), as the program progresses. It also progressively constructs a profile of the user, based on the interactions it has/had, and possesses a domain model that contains information relative to the behavior that is targeted (e.g., a model of smoking cessation issues/interactions). In addition, it includes a computational persuasion model that structures argumentation related to the domain model, and that chooses strategies of action according to the participant stages and profile. The data and profile information remains within the private sphere of each agent, which is not permeable to other agents unless passing through privacy preserving filters. The model incorporates the participants as users that interact with their corresponding behavior change agent through messaging. The agent responds embodied as a conversational application, and agents may interact among them depending on their different roles:

- Coordinator agent: it manages the addition/removal of participants and their corresponding agents in the program, it manages general stage changes, and regulates interactions within the system, including changes in the domain model (which can be forwarded to the rest of agents), incorporation of new program rules, enforcement of agreed regulations.
- Mediator agents: these are in charge of managing interactions among behavior change agents. For instance, if certain agent requires to share action plans with another one, a mediator will be activated to manage these interactions. Mediators are necessary, as they can forward agents to the most relevant peers, depending on their needs and profiles.
- Coach agents: these agents provide support, motivation, information and strategy resources to behavior change agents. In many occasions, the argumentation of each individual agent may not cover a specific situation, and the coach may be required to intervene, potentially connecting with a non-virtual coach, e.g., a professional in tobacco addiction.
- Behavior agents: these are in charge of building collective profiles of behavior, feeding from the aggregation of individual agent information. This allows the elaboration of common patterns that can help grouping participants or finding common strategies for increasing the success of the program. For instance, it may identify groups of users that are struggling with relapse episodes, or those who appear to have motivational breakdowns.

As depicted in Figure 3, our model and its main conceptual components can also be related to aspects found in well-known behavior change models such as the I-Change model [25]. This model also incorporates different stages (as in the model in Figure 1), although it adds different elements, such as predisposing, information, motivation and ability factors, which have incidence on several aspects of the behavior change process. Our agent-based approach has the flexibility to adapt to such behavior change models. For instance, the user profiling can be used to model motivation factors, and to characterize action plans and skills. Similarly, argumentation and persuasion can be used to confront awareness and information factors to barriers or obstacles.

In the following, we present the design principles of our approach, explaining through concrete examples how they relate to our agent-based model.

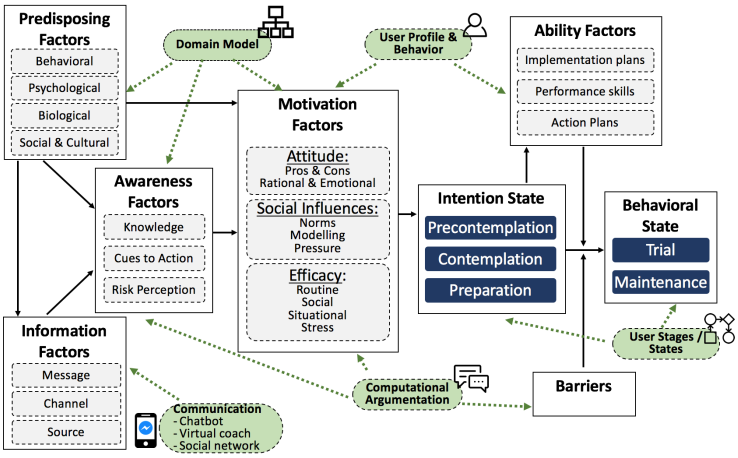

Fig. 3. The I-Change model of behavior change [25], and its relation to the different elements of our proposed agent-based model (rounded boxes).

Conversational multi-agent ecosystem. The behavior change multi-agent model requires direct and personalized communication with the participants in the health program. Given that these interactions are crucial in order to set up behavioral goals, define strategies, implement actions, motivate and support the chosen actions, etc., the communication choices need to be chosen carefully. A chatbot-based interface has the advantage of being deployable in social networks, and that it can implement asymmetric dialogues natively. Moreover, it allows immediate responsiveness while reaching thousands of users simultaneously. In our model, each of these behavior change agents manages a single participant, keeping private their personal profile information and states, although with the possibility of sharing certain information through the mediator and behavior agents at a higher level. This multi-agent design enables both the encapsulation of per-user information/profiles, and the potential interaction among them in order to exploit the fact that multiple participants may face similar situations.

State-driven interactions. As it has been shown in the Trans-theoretical and the I-Change models, stages and participant states play a fundamental role in order to organize strategies and adapt interventions to the current context. For instance, in a smoking cessation program a key step is to quantify consumption during the preparation stage, by explicitly communicating with the agent each time a cigarette is lit. This can be modeled as a loop-repeating state of cigarette tracking during the preparation stage, which may lead to a self-consciousness state where the participant is aware, not only of how much she smokes, but also under which circumstances it happens.

User modelling. As it has been seen in the I-Change model [25], motivation and ability factors have a direct impact on the progress of the desired behavior change. In the proposed model, this is translated into a user profile that characterizes the participant, not only in terms of basic information such as demographics, or domain-specific assessments (e.g., nicotine dependence), but also in terms of plans, goals, and skills (which are particular to each individual), as well as attitudes, social factors, and efficacy. For instance, the user profile of a smoking cessation participant may establish strategies for coping with crisis, such as preferred alternatives to cigarettes: running early in the morning instead of smoking, or switching to a patch in case of anxiety. Having this information in the profile may help the behavior change agent to adapt its advice accordingly.

Domain modelling. Each domain of application for a particular health issue requiring behavior change, has its specific concepts and terminology, as well as inherent logics. The different physiological, psychological, emotional, motivational factors are different for each domain, and this specificity needs to be considered. Our behavior change model incorporate domain models that formally define these elements. A domain model identifies *problems* and *solutions*, and different concepts associated to these, e.g., the causes of a problem, risks, motivations; or the costs and side-effects of a solution, benefits, opportunities of a solution, etc. Other types of concepts can also be defined in the domain model, such as facts and evidence (e.g., verifiable information items), goals (e.g., personal, societal), opinions (subjective) and preferences [5]. This structured information, typically organized as ontologies, can be fed to the behavior change agents in order to manage awareness and motivation factors throughout the intervention.

Computational persuasion. Argumentation in an asymmetric dialogue for behavior change has the underlying purpose of implementing certain action. This requires the usage of persuasion techniques, potentially using the most suitable argumentation elements for the current situation. For example, during the action/trial stage of the I-Change model, a participant trying to quit smoking may have a moment of lack of motivation, due to a perceived weight gain during the cessation period. the behavior change agent may then use the domain model to choose the most appropriate argument to try to introduce motivation factors to the participant. Probabilistic approaches [13] can be implemented within the agent in order to determine the most suitable course of action.

Privacy. Finally, the model introduces the need for bounding the range of action of each behavior change agent to its corresponding participant. This is important in order to preserve and protect sensitive data, e.g., in the user profile, behavior data, stages/states, and other private information. In any case it is necessary to define mechanisms for sharing part/aggregated data at the macro, level, with the intention of fostering collaboration among individual agents, as well as to generate and analyze behavior patterns among groups of agents.

6 Related Work

Multi-agent systems (MAS) have been used in the past for supporting eHealth interventions in different areas, as they are able to model human-like behaviors and dynamics. Behavior change systems have also been studied extensively in the context of personalized and ubiquitous computing [17], although lacking the integration of interventions into support or coaching systems. As it is explained in a survey summarizing some of the relevant work on this topic [15], assistive technologies still need to explore potential opportunities regarding the incorporation of techniques that specialize and personalize behavior change interventions. Other lines of research include exploring strategical argumentation [21], or the formalization of preferences and arguments within NLP interactions [4].

Concerning the utilization of social networks for supporting health and well-being programs, there have been several initiatives, although with mixed results. In particular, social networks have been used in previous attempts at providing community-based platforms for smoking cessation. Tweet2Quit is one such example [18], showing promising potential for the development of online support systems. However, these results still show no conclusive evidence on the effect of social interactions or the effectiveness of information messages. Other approaches have included WhatsApp and Facebook as social platforms, for instance targeting smoking relapse prevention [6], or smoking cessation in young adults [20]. Digital assistants have become popular in recent years, and have been used under different contexts, exploiting vocal command interfaces. A study focusing on smoking cessation advice [2] was conducted comparing Siri and Google Assistant against simple Web search, and showed that in fact, the use of these assistants is often not better than a manual search. Early attempts to design virtual coaches for smoking cessation [10] have only provided initial ideas and requirements, while concrete implementations remain to be developed. Beyond smoking-related use-cases, chatbot-based solutions and prototypes have been presented in other contexts, such as dietary & food counselling [1], healthy lifestyle programs [8], or primary care patient intake [16].

7 Road-map

In this paper we presented an abstract model that considers behavior change models as basis for developing multi-agent-based systems that automatize the support of participants in healthcare programs. This model is a starting point towards the implementation of effective and personalized support systems that are able to effectively take into account domain models and user profiles to tailor the type of intervention. Although this constitutes a first step in this direction, a significant number of future contributions are required to achieve this goal:

- *Behavior change ontologies* The inclusion of vocabularies and ontologies for description, discovery, provenance and exchange within behavior change agents is of particular importance. these ontologies can formalize the knowledge of the domain models, and help structure the argumentation graphs that can be used later for the respective computations.
- *Domain models* Specific models should be developed for each domain. The existence of public libraries of these models can help enriching agent-based

systems in areas such as physical rehabilitation, medication adherence, physical activity, sleep training, etc.

- *Agent coordination and negotiation* Although the proposed model includes the definition of goals, which can be used within the argumentation component, it remains to specify what mechanisms will be implemented in order to incorporate computational persuasion into the agent execution logic. While existing approaches [13] offer potential solutions, it remains to be studied how to incorporate the learning process (e.g., evolution of the participant, or reuse of other participants' behavior) in order to enrich the model.
- *Cooperation.* The specification of cooperation protocols for participating agents is an important topic of study, in order to enable clustering participants, finding common problems and targeting community-based interventions that focus on similar issues. This reinforces the social-nature of the proposed approach and its inherent benefits in the context MAS.
- *Implementation.* The implementation of the proposed model is challenging, both form the technical (integration of multi-agent and behavior change approaches), and the application point of view (evaluation of the system on a real environment with a concrete participants). For this purpose, we plan to apply the model presented here in the future editions of the JDF smoking cessation program in Switzerland. KPIs to evaluate implementations shall consider both technical indicators as well as persuasion metrics.
- *Privacy.* Given the potentially sensitive nature of profile and behavior information, privacy concerns need to be thoroughly studied and addressed. Ensuring privacy protection, using different approaches spanning from obfuscation to anonymity guarantees, will be expected, adopting ethics-by-design methodologies [7].

References

1. Angara, P., Jiménez, M., Agarwal, K., Jain, H., Jain, R., Stege, U., Ganti, S., Müller, H.A., Ng, J.W.: Foodie fooderson a conversational agent for the smart kitchen. In: CASCON. pp. 247–253 (2017)
2. Boyd, M., Wilson, N.: Just ask siri? a pilot study comparing smartphone digital assistants and laptop google searches for smoking cessation advice. PloS one **13**(3), e0194811 (2018)
3. Centers for Disease Control and Prevention: Quitting smoking among adults–united states, 2001-2010. Morbidity and mortality weekly report **60**(44), 1513 (2011)
4. Cerutti, F., Tintarev, N., Oren, N.: Formal arguments, preferences, and natural language interfaces to humans: an empirical evaluation. In: ECAI. pp. 207–212 (2014)
5. Chalaguine, L., Hadoux, E., Hamilton, F., Hayward, A., Hunter, A., Polberg, S., Potts, H.W.: Domain modelling in computational persuasion for behaviour change in healthcare. arXiv preprint arXiv:1802.10054 (2018)
6. Cheung, Y.T.D., Chan, C.H.H., Lai, C.K.J., Chan, W.F.V., Wang, M.P., Li, H.C.W., Chan, S.S.C., Lam, T.H.: Using whatsapp and facebook online social groups for smoking relapse prevention for recent quitters: A pilot pragmatic cluster randomized controlled trial. J medical Internet research **17**(10) (2015)

7. d'Aquin, M., Troullinou, P., O'Connor, N.E., Cullen, A., Faller, G., Holden, L.: Towards an ethics by design methodology for ai research projects. In: Proc. of the AAAI/ACM Conference on AI, Ethics, and Society. pp. 54–59. ACM (2018)
8. Fadhil, A., Gabrielli, S.: Addressing challenges in promoting healthy lifestyles: the al-chatbot approach. In: Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare. pp. 261–265. ACM (2017)
9. Folly, L., Riedo, G., Felder, M., Falomir-Pichastor, J.M., Desrichard, O.: Rapport de l'évaluation externe du programme « J'arrête de fumer » sur Facebook. Sur mandat du Fonds de Prévention du Tabagisme (2016)
10. Grolleman, J., van Dijk, B., Nijholt, A., van Emst, A.: Break the habit! designing an e-therapy intervention using a virtual coach in aid of smoking cessation. In: International Conference on Persuasive Technology. pp. 133–141. Springer (2006)
11. Hunter, A.: Opportunities for argument-centric persuasion in behaviour change. In: European Workshop on Logics in Artificial Intelligence. pp. 48–61 (2014)
12. Hunter, A.: Modelling the persuadee in asymmetric argumentation dialogues for persuasion. In: 24th International Joint Conference on Artificial Intelligence (2015)
13. Hunter, A.: Towards a framework for computational persuasion with applications in behaviour change. Argument & Computation (Preprint), 1–26 (2017)
14. Jones, A.M.: Health, addiction, social interaction and the decision to quit smoking. Journal of health economics **13**(1), 93–110 (1994)
15. Kennedy, C.M., Powell, J., Payne, T.H., Ainsworth, J., Boyd, A., Buchan, I.: Active assistance technology for health-related behavior change: an interdisciplinary review. Journal of medical Internet research **14**(3) (2012)
16. Ni, L., Lu, C., Liu, N., Liu, J.: Mandy: Towards a smart primary care chatbot application. In: KSS. pp. 38–52 (2017)
17. Oinas-Kukkonen, H.: A foundation for the study of behavior change support systems. Personal and ubiquitous computing **17**(6), 1223–1235 (2013)
18. Pechmann, C., Pan, L., Delucchi, K., Lakon, C., Prochaska, J.: Development of a twitter-based intervention for smoking cessation that encourages high-quality social media interactions via automessages. JMIR **17**(2) (2015)
19. Prochaska, J.O., Velicer, W.F.: The transtheoretical model of health behavior change. American journal of health promotion **12**(1), 38–48 (1997)
20. Ramo, D.E., Thrul, J., Chavez, K., Delucchi, K.L., Prochaska, J.J.: Feasibility and quit rates of the tobacco status project: A facebook smoking cessation intervention for young adults. J of medical Internet research **17**(12) (2015)
21. Rosenfeld, A., Kraus, S.: Strategical argumentative agent for human persuasion. In: ECAI. vol. 16, pp. 320–329 (2016)
22. Tsoh, J.Y., Burke, N.J., Gildengorin, G., Wong, C., Le, K., Nguyen, A., Chan, J.L., Sun, A., McPhee, S.J., Nguyen, T.T.: A social network family-focused intervention to promote smoking cessation in chinese and vietnamese american male smokers: A feasibility study. Nicotine & Tobacco Res **17**(8), 1029–1038 (2015)
23. Velicer, W., Prochaska, J., Redding, C.: Tailored communications for smoking cessation: Past successes and future directions. Drug and alcohol review (2006)
24. Velicer, W.F., Prochaska, J.O., Bellis, J.M., DiClemente, C.C., Rossi, J.S., Fava, J.L., Steiger, J.H.: An expert system intervention for smoking cessation. Addictive behaviors **18**(3), 269–290 (1993)
25. de Vries, H., Mesters, I., Van de Steeg, H., Honing, C.: The general public's information needs and perceptions regarding hereditary cancer: an application of the integrated change model. Patient education and counseling **56**(2), 154–165 (2005)