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Effectiveness of User States, Demographics and Traits in Persuading to Quit Smoking

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This document is an encore abstract of the paper "Persuading to Prepare for Quitting Smoking with a Virtual Coach: Using States and User Characteristics to Predict Behavior" presented at AAMAS 2023 [4].

1 Motivation

Despite their frequent use in digital applications for behavior change, persuasive messages tend to have small effects on behavior (e.g., [3, 8, 13, 14]). To improve algorithms for choosing persuasive messages, user states (e.g., motivation, skills, knowledge) and demographics and traits (e.g., age, need for cognition, personality) are commonly used as algorithm components. As collecting data for many algorithm components often is costly, places a burden on users (e.g., [11, 15]), and raises privacy concerns, a more thorough understanding of the impact of different algorithm components on behavior is welcome.

2 Methods

Therefore, instead of developing a new algorithm and comparing it with existing ones, our goal is to first better understand how effective it is to consider user states, demographics, and traits when choosing persuasive strategies. This can allow us to make more informed decisions regarding the components to use. We thus used the data from a study in which daily smokers interacted with the text-based virtual coach Sam [1] in up to five sessions to study the effects of these algorithm components. Participants of the study were assigned a new preparatory activity for quitting smoking (e.g., visualizing one's desired future self) [5] together with a persuasive strategy in each session. In the next session, Sam asked participants about the effort they spent on their activity to measure their behavior. Sam further asked questions about people's capability, opportunity, and motivation to do an activity based on the Capability-Opportunity-Motivation-Behavior (COM-B) model [10] to determine people's states. In addition, we measured 32 demographics and traits as well as people's involvement in their activities. Based on the resulting 2366 state transition samples from 671 people, we compared how effective considering states, demographics, traits, and involvement is for predicting behavior after persuasive attempts. Moreover, using simulations, we assessed the long-term effects of optimally persuading people based on a Reinforcement Learning (RL)-approach that considers current and future states to maximize the effort people spend on their activities.

3 Findings

We investigated six research questions related to the (long-term) effectiveness of considering different algorithm components. Our findings suggest that states derived from the COM-B model help to predict both behavior (i.e., the effort people spend on their activities) and next states (*Q1* and *Q2*). Thus, considering such states can allow one to choose persuasive strategies that cause people to spend more effort on their next activity as well as ones that move people to future states in which they are more likely to successfully be persuaded to spend much effort on their following activity. Based on simulations, we further found that people tend to move to states with higher Q-values or stay in the state with the highest Q-value when they are persuaded optimally based on an RL-algorithm (*Q3*). However, there are always some people in states with low Q-values, which means that not all people can be persuaded to spend a lot of effort on their activities. Furthermore, it matters *how* people are persuaded. Specifically, people in our simulations tend to spend more effort on their activities if they are persuaded optimally based on the RL-algorithm than if they are persuaded based on the worst or an average persuasive strategy (*Q4*).

Besides assessing the effectiveness of predicting people's behavior based on their states, we also examined the effectiveness of considering demographics, traits, and people's involvement in their activities. Compared to using states, we obtained worse results when using only demographics and traits to predict people's behavior after persuasive attempts (*Q5*). Additionally considering people's involvement in their activities led to slightly better predictions than only using demographics and traits, but the results were still not better than for states. Using traits, demographics, and involvement *in addition* to states does offer some benefit (*Q6*). Involvement thereby again performs best.

4 Conclusion

The findings from our study provide empirical support for the integration of people's states as well as their involvement into behavior change persuasion algorithms. These insights can be directly applied to further research on smoking cessation, exploring the utilization of these components within a full application. Furthermore, both components could be employed in eHealth applications targeting behavior modification beyond smoking cessation such as physical activity [2, 12, 7] or (mental) wellbeing [6, 9]

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References

1. Albers, N.: Reinforcement Learning-based Persuasion for a Conversational Agent to Support Behavior Change: Code. https://doi.org/10.5281/zenodo.6319356
2. Albers, N., Hizli, B., Scheltinga, B.L., Meijer, E., Brinkman, W.P.: Setting physical activity goals with a virtual coach: vicarious experiences, personalization and acceptance. Journal of Medical Systems **47**(1), 15 (2023)
3. Albers, N., Neerincx, M.A., Brinkman, W.P.: Addressing people's current and future states in a reinforcement learning algorithm for persuading to quit smoking and to be physically active. PLOS ONE **17**(12), e0277295 (2022)
4. Albers, N., Neerincx, M.A., Brinkman, W.P.: Persuading to prepare for quitting smoking with a virtual coach: Using states and user characteristics to predict behavior. In: Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems. pp. 717–726 (2023)
5. Albers, N., Neerincx, M.A., Penfornis, K.M., Brinkman, W.P.: Users' needs for a digital smoking cessation application and how to address them: A mixed-methods study. PeerJ **10**, e13824 (2022). https://doi.org/10.7717/peerj.13824
6. Ciocarlan, A., Masthoff, J., Oren, N.: Kindness makes you happy and happiness makes you healthy: Actual persuasiveness and personalisation of persuasive messages in a behaviour change intervention for wellbeing. In: International Conference on Persuasive Technology. pp. 198–214. Springer (2023)
7. Ghantasala, R.P., Albers, N., Penfornis, K.M., van Vliet, M.H., Brinkman, W.P.: Feasibility of generating structured motivational messages for tailored physical activity coaching. Frontiers in Digital Health **5** (2023)
8. Kaptein, M., Markopoulos, P., De Ruyter, B., Aarts, E.: Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles. International Journal of Human-Computer Studies **77**, 38–51 (2015)
9. Ly, K.H., Ly, A.M., Andersson, G.: A fully automated conversational agent for promoting mental well-being: A pilot rct using mixed methods. Internet Interventions **10**, 39–46 (2017)
10. Michie, S., Van Stralen, M.M., West, R.: The behaviour change wheel: a new method for characterising and designing behaviour change interventions. Implementation Science **6**(1), 1–12 (2011)
11. Pommeranz, A., Broekens, J., Wiggers, P., Brinkman, W.P., Jonker, C.M.: Designing interfaces for explicit preference elicitation: a user-centered investigation of preference representation and elicitation process. User Modeling and User-Adapted Interaction **22**(4), 357–397 (2012)
12. Rabbi, M., Pfammatter, A., Zhang, M., Spring, B., Choudhury, T., et al.: Automated personalized feedback for physical activity and dietary behavior change with mobile phones: a randomized controlled trial on adults. JMIR mHealth and uHealth **3**(2), e4160 (2015)
13. Spelt, H.A., Zhang, C., Westerink, J.H., Ham, J., IJsselsteijn, W.A.: Persuasion-induced physiology as predictor of persuasion effectiveness. IEEE Transactions on Affective Computing **13**(3), 1593–1604 (2020)
14. de Vries, R.A.J.: Theory-Based and Tailor-Made: Motivational Messages for Behavior Change Technology. Ph.D. thesis, University of Twente, Netherlands (2018)
15. Yang, M.J., Sutton, S.K., Hernandez, L.M., Jones, S.R., Wetter, D.W., Kumar, S., Vinci, C.: A just-in-time adaptive intervention (jitai) for smoking cessation: Feasibility and acceptability findings. Addictive Behaviors **136**, 107467 (2023)