Tampere University

ANITA HONKA

Personalization of Digital Health Behavior Change Interventions for Health Promotion

A User Modeling Framework and a Recommender System

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ACADEMIC DISSERTATION
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Tampere University, Faculty of Medicine and Health Technology
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Supervisor	Docent Ilkka Korhonen Tampere University Finland	
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PREFACE

The Journey

In 2009, I was an enthusiastic junior researcher at VTT Technical Research Centre of Finland, who had just received her master's degree and become a mum for the first time. I felt incredibly fortunate to be part of the digital health group at VTT. Apart from mathematics, I was intrigued by human behavior, psychology, and health already during my high school years, and the research field of digital health sat conveniently at the intersection of these disciplines. I was also fascinated by the idea of being able to contribute to the greater good, as innovations in digital health could potentially improve the well-being of countless people.

I quickly realized that if I wished to build a credible career as a researcher, I should pursue a PhD. So, on the very same year I got my master's, I enrolled as a doctoral student at Tampere University of Technology (nowadays Tampere University). My aim was to graduate in five years, before I would turn 30. Well, life didn't exactly turn out as I had expected. Especially after having our second child some years later, juggling work and family-life was a handful. Personal leisure time projects were simply out of the question for many years. At the same time, I wasn't experienced enough to have a research vision of my own for a solid dissertation topic.

This doctoral thesis was inspired by the European research project, PREVE – Prevention of diseases (2010-2011), which set me on the path to develop my own research vision. PREVE was led by Prof. Niilo Saranummi, a pioneer in the field of health technology research. Sadly, he is not among us today, but his academic legacy keeps living on in the work of the many researchers he has advised, me included. Though Prof. Saranummi made me and my dear fellow researchers at the time, Kirsikka Kaipainen and Henri Hietala, to work our butts off (at least I felt like this sometimes), it was every bit of worth it. I learned incredibly much during PREVE - about psychology, theories of behavior change, digital health behavior change interventions, critical thinking, presenting research findings, to just mention a few topics. I'm ever so grateful to Prof. Saranummi for all his guidance and for sharing his research vision, which was groundbreaking at the time and still, years later, very timely. For instance, the concept of Personal Health Guides, introduced in the first publication of this dissertation, is still relevant. Looking back from now, we managed to write this multidisciplinary review article in a relatively short time, thanks to Prof. Saranummi's excellent supervision.

However, it wasn't until 2014 that I began to actively process the research plan for my dissertation. I applied for doctoral studies the second time, now changing to a PhD program more suitable for my topic. I had now a much better picture of my research interests than five years ago. In addition, new research projects were beginning at VTT which would provide me opportunities to explore my research ideas. A year later I had my third child, but I had some room to advance the second publication for the thesis during the maternity leave. By 2017, I had all the research material that I needed, collected from three different research projects, and the final project relevant for my dissertation was officially ending. However, the data analysis for the third publication was still in the middle and the writing work hadn't even started. I was struggling quite a bit with the second and third publications, as a large proportion of the required data analyses and writing took place after the related research projects had ended. I had to constantly seek for opportunities to advance the publications amid the demands of the on-going unrelated research projects and other publications, which was exhausting. In addition, finding a clear focus for the publications wasn't easy due to their multidisciplinary nature and the versatile study results at hand.

In 2018, I was offered an exciting opportunity to visit the Digital Health Lab at Flinders University, Adelaide, Australia. The 6-month period that me and my family got to spend in Adelaide was in many ways a significant experience for us all. It was meaningful also for the dissertation, as I was able to finalize my updates to the second paper, and get it accepted for publication. The fourth one, a short conference paper, got also published, which I presented at the EMBC conference in Hawaii between the Australia visit. Oh boy, I was happy! Now I had only one publication (the third) left to work on.

However in 2022, I decided to take a leap of faith and switch from academia to the well-being technology industry. After 14 years of research, I felt that perhaps my passion for improving people's well-being could be channeled more effectively, if I could directly contribute to the solutions that people use in their everyday life. My painful experience with writing scientific papers did also play some role in my decision. Nevertheless, I was still committed to finish the paper that was left in the middle, mostly because so much time and effort had been already invested in it and I hated to give up. I did have some serious thoughts, though, of forgetting the dissertation altogether as I hadn't even started to write the summary part of the thesis. I believe that it was my family and other close relatives who eventually convinced me to keep going – and here we are! Looking back from now, I'm happy I finally reached the goal I had set for myself many years ago, and it actually feels quite nice to have a book written.

More Acknowledgements

I have had the privilege of having two wonderful supervisors, Prof. Mark van Gils and Docent Ilkka Korhonen, who are highly respected professionals in the field of digital health. Both have been very encouraging and understanding throughout this long process. Prof. van Gils was always there for me when I was writing the thesis summary. If he didn't hear from me for some months, he would discreetly inquire how I had been doing without putting extra pressure on me. For some reason, he seemed confident that I'll finish the work in a decent timeframe, when I myself was not. He was also my closest mentor during my early years as a researcher, when he was the team lead of the digital health group at VTT. Mark, I thank you for believing in me and helping me to build my confidence as a researcher. I look up to you, how you've always stayed humble, kind, and true in your research despite your great academic success. My other supervisor, Docent Korhonen, provided me valuable and practical advice in terms of writing publications efficiently, planning my doctoral studies, and applying for personal grants. I am especially grateful to him for reminding me to focus more on the broader picture instead of spending too much time in seeking for perfection in minor details.

Next, I would like to express my gratitude to my follow-up group members, Docent Marja Harjumaa and Dr. Miikka Ermes. I love Marja's inspiring personality! Her positive mindset is catchy, which boosted my confidence in terms of finishing the dissertation. I always knew that I could contact her if I needed help in sorting my thoughts out. Miikka became an important mentor to me while he was in the role of a Principal Scientist at VTT. Not only did he support me in the development of my research career, but he also encouraged me to achieve personal development goals beyond academia. He was always very supportive when it came to writing research publications and paved me the way for visiting the Digital Health Lab at Flinders University.

I also thank the pre-examiners of my dissertation for their constructive in-depth feedback: Prof. (assistant) Keegan Knittle, University of Jyväskylä, an expert in health psychology and digital health interventions, and Prof. (assistant) Helma Torkamaan, Delft University of Technology, the Netherlands, an expert in health recommender systems. Furthermore, I extent my warmest thanks to Prof. (emeritus) Anthony Maeder, Flinders University, Australia, who has diverse expertise of digital health systems, for agreeing to take on the task of an opponent and being happy to come to Finland in the middle of the winter. I'm sure he will keep the conversation interesting during the doctoral defense – also for the audience.

I have been privileged to work with so many talented and wonderful individuals when conducting the research and writing the publications for my dissertation. I am grateful to all my co-authors for the easy and fruitful collaboration: Dr. Kirsikka Kaipainen, Henri Hietala, Prof. Niilo Saranummi, Dr. Elina Helander, Prof. Misha Pavel, Prof. Holly Jimison, Dr. Pekka Mustonen, Docent Ilkka Korhonen, Dr. Miikka Ermes, Dr. Hannu Nieminen, Dr. Heidi Similä, Jouni Kaartinen, Prof. Mark van Gils, Sari Vainikainen, Dr. Elina Mattila, Timo Kinnunen, and Juha Leppänen. I worked especially closely with Kirsikka, Hannu, and Heidi. With Kirsikka I shared many new and exciting experiences as we both happened to join VTT as research trainees at the same time. I have so many heart-warming memories of us working together, being roommates during work trips around Europe, exploring new cities, and sharing our worldviews. Hannu has always been fun to work with as he is such an easy-going personality whose often full of ideas. It's easy for others to catch his enthusiasm. I also enjoyed working with Heidi who knew how to be efficient but relaxed at the same time. Niilo, Ilkka, Miikka, and Elina M., you had the essential role of teaching me the art of writing publications. Elina H. had a crucial role in the second publication as she advised me on several statistical analysis related questions. Special thanks go to Timo and Juha for their high-quality work regarding the technical implementation of the digital applications that were designed and specified during the research projects relevant for my thesis. Without your contributions, the empirical studies presented in this work would have not been possible.

Apart from co-authors, there are many other colleagues and collaborators whom I've worked with regarding the topics relevant to this dissertation or who have supported me during the process: Salla Muuraiskangas, Juho Merilahti, Mikko Lindholm, Anna-Leena Vuorinen, Johan Plomp, Johanna Närväinen, Jari Ahola, Theresa Meneu, Vicente Traver, Marco Nalin, Monica Verga, Tuomas Lehto, Heimo Langinvainio, Ulla-Maija Junno, Hannu Mikkola, Tero Myllymäki, and Harri Honko. – I thank you warmly for your contributions that have had an impact on this thesis.

I want to also thank my current colleagues at Garmin Jyväskylä, who have been very supportive of this academic hobby of mine and have welcomed me to the gang. Special thanks go to my closest colleagues, the data science team members. You are amazing!

The research work and publications presented in this dissertation were supported by VTT Technical Research Centre of Finland; European Commission in the 7th Framework Program under the ICT theme; Finnish Funding agency for Technology and Innovation (Tekes) under the SalWe Research Program for Mind and Body and the Digital Health Revolution Initiative; Academy of Finland; and Advanced Research and Technology for Embedded Intelligent Systems Industry Association (ARTEMIS-IA) within Europe. Writing the summary part of the dissertation was supported by the Finnish Cultural Foundation and the Orion Research Foundation sr., which I gratefully acknowledge. Without these personal grants, finishing the thesis would have been impossible.

Kiitokset

Lopuksi haluan kiittää rakasta perhettäni, puolisoni lähisukua, sekä vanhempiani ja ihania pikkusiskojani. Kun muistelen kaikkea sitä tukea ja kannustusta mitä olen teiltä saanut, sitä väkisinkin herkistyy. Väitöskirjatutkimus on ollut prosessina pitkä ja vienyt paljon vapaa-aikaani, minkä vuoksi olen varmasti ollut välillä poissaoleva tai hajamielinen vaimo ja äiti. Kiitän omaa Henkkaani kaikesta ymmärtäväisyydestäsi ja kärsivällisyydestäsi. Et ole antanut minun luovuttaa, sillä olet aina halunnut, että vien työn maaliin kaikesta huolimatta. Marvel, Isabel, ja Paulus, olette tuoneet käsittämättömän paljon iloa ja sisältöä elämääni. Olen kiitollinen siitä kaipaamastani tasapainotuksesta ja tauotuksesta, jota olette tuoneet arkisen työ- ja väitöskirja-aherrukseni keskelle. Odotan innolla tästä harrastusprojektista vapautuvaa aikaa, jota tulen viettämään enenevissä määrin perheeni kanssa. Seija, kiitän sinua lämpimästi niistä lukuisista kerroista, kun olet hoitanut lapsia erityisesti loma-aikoina, ja näin ollen tarjonnut minulle mahdollisuuksia edistää väitöstyötäni. Tukesi on ollut korvaamatonta. Sinä ja Hannu olette myös kannustaneet minua jatkamaan niinä heikkoina hetkinäni, kun olen epäröinyt koko projektin järkevyyttä. Erityiskiitokset myös isälleni sekä Riinalle ja Sampolle.

Vesilahti, December / joulukuu 2023,

Anita Honka

ABSTRACT

About 90% of the disease burden in the European Union is attributed to chronic, non-communicable diseases (NCDs) such as cardiovascular diseases, cancer, type-II diabetes, and mental disorders. The social and healthcare costs of these diseases are substantial. Major risk factors for NCDs are lifestyle-related, hence, a significant proportion of NCDs could be avoided, or at least delayed, with a healthy lifestyle. However, adopting and maintaining healthy habits can be very challenging. Digital health behavior change interventions (DHBCIs) have the potential to offer cost-effective, accessible, and affordable public health promotion that empowers and guides individuals to improve their lifestyles. However, many DHBCIs have failed to engage users sufficiently to induce lifestyle changes, which have reduced their effectiveness. Personalizing interventions to the needs and capabilities of individuals is a promising approach for improving the user engagement with DHBCIs. Transparency of the decision-logic and data behind personalization is also relevant for user engagement, as this can enhance users' trust in the intervention content and help with conveying a personalized user experience.

The doctoral dissertation aims to advance the development of transparently personalized DHBCIs that are effective for public health promotion by 1) providing a methodological review on the theoretical foundation of behavior change support and on the personalization approaches employed in DHBCIs, 2) providing insights into the possible role of personal values in personalization based on an explorative analysis of a large retrospective, cross-sectional survey dataset regarding self-reported values, well-being, and health behaviors, 3) implementing a multidomain health recommender system (HRS) for personalizing behavior change actions for occupational health and studying the suitability of the recommendations as part of a pilot randomized controlled trial (RCT), and by, 4) suggesting visual well-being profile summaries for improving the transparency of personalization based on a small concept evaluation study.

As a result, a conceptual user modeling framework, the virtual individual model (VIM), was proposed, which specifies a comprehensive collection of promising user features for serving the personalization of effective DHBCIs, backed by behavioral science. According to the analysis results of the survey dataset, commitment to

values is positively associated with happiness. In addition, several value-congruent behaviors were reported, which confirm the motivational role of values in determining behavior as postulated by value theories. Considering values in the personalization of DHBCIs may be relevant, thereby, also the VIM incorporates values. The introduced HRS implemented a subset of the proposed VIM features, i.e., behavior change needs and intentions, and was able to generate multidomain recommendations suitable for a real-life health behavior change intervention. Finally, the investigated well-being profile visualizations were perceived as interesting, easy-to-interpret, and useful by the study participants.

The VIM provides ideas about different personalization aspects and the user features to test when searching for the most important features for effective personalization. The user features implemented in the HRS can be considered as the minimum set of features required for the personalization of multidomain interventions, and the RCT results provide a reference point for studying the impact of additional features. Finally, the preliminary results indicate that the introduced visual well-being profile summaries seem feasible for improving the transparency of DHBCIs.

TIIVISTELMÄ

Krooniset sairaudet, kuten sydän- ja verisuonitaudit, syövät, II-tyypin diabetes ja mielenterveyshäiriöt, selittävät noin 90% Euroopan Unionin alueen sairastuvuudesta ja kuolleisuudesta. Kroonisten sairauksien aiheuttamat sosiaali- ja terveydenhuollon kustannukset ovat huomattavat. Terveelliset elintavat vähentävät sairastumisriskiä merkittävästi, joten suuri osa kroonisista sairauksista olisi estettävissä, tai vähintäänkin niiden puhkeamista voi viivästyttää. Terveellisten elintapojen omaksuminen ja ylläpitäminen voi kuitenkin olla elämätilanteesta ja olosuhteista riippuen hyvin haastavaa.

Digiteknologia mahdollistaa kustannustehokkaiden ja edullisten, kansalaisten saavutettavissa olevien terveyden edistämisen palveluiden tuottamisen. Erityisesti voitaisiin hyödyntää digitaalisia terveyskäyttäytymisen muutosinterventiota (digiterveysinterventiota) kansalaisten voimaannuttamisessa ja ohjaamisessa terveellisten tottumusten omaksumisen suhteen. Monet aiemmat digiterveysinterventiokokeilut eivät ole kuitenkaan onnistuneet sitouttamaan kansalaisia niiden käyttöön elintapamuutosten edellyttämällä tavalla, mikä on heikentänyt niiden vaikuttavuutta. Interventiosisällön räätälöinti yksilön tarpeita ja kykyjä vastaaviksi on osoittautunut lupaavaksi keinoksi digiterveysinterventioiden käyttöön sitouttamisessa. Myös läpinäkyvyys räätälöinnin taustalla olevasta päätöksentekologiikasta sekä sen hyödyntämistä henkilökohtaisista tiedoista on oleellinen osa käyttäjien sitouttamista. Tämänkaltainen läpinäkyvyys voi lisätä luottamusta interventiosisältöön ja edesauttaa henkilökohtaiselta tuntuvaa käyttökokemusta.

Väitöskirjatutkimuksen tavoitteena on edistää sellaisten yksilölle räätälöitävissä olevien digiterveysinterventioiden kehitystä, joilla on kansanterveydellistä vaikuttavuutta. Tutkimuksen ensimmäisessä osassa esitellään metodologinen katsaus elintapamuutoksen tukemisen käyttäytymistieteelliseen teoriapohjaan sekä digiterveysinterventioissa hyödynnettyihin räätälöintimenetelmiin. Toisessa osassa kartoitetaan tilastollisin menetelmin yhteyksiä suomalaisten raportoimien arvojen, koetun hyvinvoinnin ja terveyskäyttäytymisen välillä laajan retrospektiivisen poikkileikkauskyselyaineiston pohjalta. Havaittujen yhteyksien nojalla esitetään näkemyksiä siitä, kuinka tietämystä yksilön arvoista voisi hyödyntää interventioiden

räätälöinnissä. Tutkimuksen kolmannessa osassa kuvataan työhyvinvoinnin edistämiseen toteutetun digisterveysintervention sisältämä suositteluagoritmi (suosittelija), joka räätälöi interventiosisältöä ehdottamalla yksilön tarpeisiin soveltuvia käyttäytymismuutostehtäviä useilta hyvinvoinnin osa-alueilta. Suositusten soveltuvuutta tutkittiin työterveyden asiakkailla osana puhelimitse tarjottua hyvinvointivalmennusta satunnaisesti kontrolloidulla tutkimusasetelmalla. Väitöskirjatutkimuksen neljännessä ja viimeisessä osassa visualisoidaan digiterveysintervention prosessoimia hyvinvointitietoja räätälöintianalytiikan läpinäkyvyyden lisäämiseksi. Visualisointien ymmärrettävyyttä tutkittiin pienimuotoisessa konseptitutkimuksessa.

Väitöskirjatutkimuksen ensimmäisenä tuloksena syntyi kattava käsitteellinen malli erityyppisistä käyttäjän ominaisuuksia kuvailevista muuttujista (ns. käyttäjämalli), joiden huomioiminen digiterveysinterventioiden räätälöinnissä voi lisätä niiden vaikuttavuutta. Kyselyaineistossa havaittiin omien arvojen tiedostamisen ja niihin sitoutumisen olevan yhteydessä onnellisuuden kokemukseen. Lisäksi raportoitiin omien arvojen mukaisia terveystekoja, mikä tukee arvoteorioiden esitystä arvojen roolista käyttäytymistä motivoivana tekijänä. Arvot sisällytettiinkin osaksi käsitteellistä käyttäjämallia. Väitöskirjatutkimuksessa kehitetty käyttäytymismuutostehtävien suosittelija toteutti käyttäjämallista yksilön käyttäytymismuutostarpeita ja muutosvalmiutta kuvaavia muuttujia. Suositukset osoittautuivat soveltuviksi ja hyödyllisiksi hyvinvointivalmennuskontekstiin. Tutkimuksen viimeisessä osassa tuotetut visualisoinnit räätälöintianalytiikan hyödyntämistä hyvinvointitiedoista olivat konseptitutkimuksen osallistujien mielestä kiinnostavia, selkeitä ja hyödyllisiä.

Väitöskirja viitoittaa digiterveysinterventioiden tärkeimpien räätälöintimuuttujien tunnistamisen jatkotutkimusta; koostettu käyttäjämalli kirvoittaa ajatuksia erityyppisistä räätälöintitavoitteista ja esittää kullekin tavoitteelle soveltuvia käyttäjämallinnusmuuttujia kokeiltavaksi räätälöinnin pohjalle. Käyttäytymismuutostehtäväsuosittelijan toteuttamat käyttäjämallinnusmuuttujat asettavat minimitason eri hyvinvoinnin osa-alueita kattavien digiterveysinterventioiden räätälöinnille, ja tulokset suositusten soveltuvuudesta tarjoavat vertailukohdan lisämallinnusmuuttujien vaikutusten tutkimiselle. Lopuksi alustavien tulosten perusteella vaikuttaa siltä, että esitetyt visualisoinnit digiterveysintervention prosessoimista hyvinvointitiedoista soveltuvat räätälöintianalytiikan läpinäkyvyyden edistämiseen.

CONTENTS

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ABBREVIATIONS

BCT	Behavior Change Technique
DHBCI	Digital Health Behavior Change Intervention
FHFS	Finnish Happiness-Flourishing Study
HRS	Health Recommender System
HRV	Heart Rate Variability
ICM	Integrated Change Model
JITAI	Just-In-Time Adaptive Interventions
NCD	Non-Communicable Disease
PA	Physical Activity
PCA	Principal Component Analysis
PVQ	Portrait Value Questionnaire
RCT	Randomized Controlled Trial
RQ	Research Question
SCT	Social Cognitive Theory
SD	Standard Deviation
SVS	Schwartz Value Survey
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TTM	Transtheoretical Model
VIM	Virtual Individual Model
WHO	World Health Organization

N/n	Number of participants in a study
part r^2	Squared semipartial correlation
Q1/*Q4*	First/fourth quartile of a distribution

ORIGINAL PUBLICATIONS

Publication I	**Honka, A**., Kaipainen, K., Hietala, H., & Saranummi, N. (2011) Rethinking health: ICT-enabled services to empower people to manage their health. *IEEE Reviews in Biomedical Engineering*, 4, 119-139, doi: 10.1109/RBME.2011.2174217.
Publication II	**Honka, AM**., Helander, E., Pavel, M., Jimison, H., Mustonen, P., Korhonen, I., Ermes, M. (2019) Exploring associations between the self-reported values, well-being and health behaviors of Finnish citizens: Cross-sectional analysis of more than 100,000 web-survey responses. *JMIR Mental Health*, 6(4):e12170, doi: 10.2196/12170.
Publication III	**Honka, AM**., Nieminen, H., Similä, H., Kaartinen, J., van Gils, M. (2022) A comprehensive user modeling framework and a recommender system for personalizing well-being related behavior change interventions: Development and evaluation. *IEEE Access*, 10, 116766-116783, doi: 10.1109/ACCESS.2022.3218776.
Publication IV	**Honka, A**., Vainikainen, S., Similä, H., Mattila, E., Leppänen, J., Kinnunen, T., Ermes, M. (2018) Citizen-centric web-based health profiling service: A service concept and a profiling method. *40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Honolulu, HI, USA, 5749-5752, doi: 10.1109/EMBC.2018.8513535.

AUTHOR'S CONTRIBUTION

The author (AH) was the first author on the author list in all the original publications. Thus, she had a major contribution and responsibility to all of them. In particular, she had the following contributions to the original publications:

I AH, KK, and HH contributed equally to the publication. AH and KK were equally responsible for the section concerning health behavior change (Section II). KK reviewed theories of behavior change, whilst AH reviewed the frameworks of behavioral economics and social marketing from the perspective of health behavior change support. Together, KK and AH synthesized the review results into a framework describing the determinants of health behavior. AH and KK were also responsible for writing the section about health behavior change support technologies (Section III). AH was responsible for reviewing the user profiling and personalization methods utilized at the time and interpreting the review results (parts E-F of Section III). Both AH and KK contributed to the introductory and concluding parts of Section III. AH contributed also to the introductory and concluding sections of the whole publication together with KK, HH, and NS. HH was responsible for the section concerning the business value of health technologies (Section IV).

II AH was the main contributor to the data analysis plan, though supported by the co-authors. She also conducted most of the data analyses and the interpretation of results. EH provided guidance in selecting the appropriate statistical methods and in interpreting the statistical results, and she conducted also one of the statistical analysis tasks. AH was responsible for writing the article, which was reviewed by the co-authors.

III AH and HN worked closely on ideating the introduced HRS and its components, though AH had a leading role in designing its concrete functionalities and user-interface. She was also responsible for specifying the details of the HRS's profiling and recommender algorithms. AH contributed together with HN and JK to the specification of the profiling questionnaire and the intervention library, to the design of the conducted RCT as well as to the participant selection. AH specified the data analysis plan for evaluating the HRS and interpreted the analysis results. She also conducted the data analyses, though HS helped with the data preprocessing. AH was responsible for writing the article, but HN and HS helped with writing the section about related work. All the authors reviewed the manuscript draft.

IV AH participated in designing the content and functionalities of the introduced health profiling service together with HS, EM, and ME. AH had a significant contribution to the design of the profiling visualizations and to the specification of the analysis algorithms. SV had a leading role in the concept evaluation of the service, although AH contributed to the evaluation plan. AH had the overall responsibility for drafting the article, but EM and ME helped in defining its focus, SV provided content regarding the evaluation methods and results, and EM described the use case scenarios.

1 INTRODUCTION

1.1 Motivation

About 90% of the disease burden in the European Union is attributed to chronic, non-communicable diseases (NCDs) such as cardiovascular diseases, cancer, type-II diabetes, and mental disorders (European Commission, 2021a). The socioeconomic burden of NCDs is high, and most of the healthcare costs in middle- and high-income countries are caused by these diseases (European Commission, 2021b). The key risk factors for NCDs are lifestyle related, the most important ones being unhealthy dietary habits, smoking, physical inactivity, and alcohol use (European Commission, 2021a; Peters et al., 2019). For mental health, protective lifestyle factors include stress management, sufficient restorative sleep, and positive interpersonal relationships (Arango et al., 2021). Therefore, leading a healthy lifestyle is a multidomain effort and crucial for the prevention of NCDs.

Digital applications have the potential to offer easily scalable and affordable, hence cost-effective, behavior change interventions for public health promotion that empower and support individuals to improve their lifestyles (Spanakis et al., 2016; Vandelanotte et al., 2016). However, the user engagement with digital health behavior change interventions (DHBCIs) has been generally too low to produce beneficial behavioral or health outcomes (Baumel et al., 2019; Böhm et al., 2020; Van Der Mispel et al., 2017). Tailoring or personalizing interventions to the needs and capabilities of individual users is considered a promising solution for improving the effectiveness of DHBCIs, as tailored interventions tend to produce better outcomes than non-tailored ones (Couper et al., 2010; Krebs et al., 2010; Lustria et al., 2013; Tong et al., 2021; Vandelanotte et al., 2016; Wang & Miller, 2019). Furthermore, with the prevalence of mobile interventions, studies indicate that dynamic adaptation to users' momentary states (e.g., mood, availability for interruptions, high risk situations for unhealthy behavior) can provide additional value to traditional tailoring, which is based on rather stable characteristics such as demographics or health risks (Tong et al., 2021; Wang & Miller, 2019). However, there is no common understanding of the important personalization aspects required for effective

DHBCIs (Hors-Fraile et al., 2018). Moreover, conducting advanced personalization is futile if the user experience of DHBCIs does not *feel* personalized, regardless of what happens under the hood, or users do not trust the intervention content. Improving the *transparency of personalization* by revealing the decision-logic and data behind personalization in a user-friendly manner can help avoid these issues and lead to an improved user engagement (Cheung et al., 2019; Tintarev & Masthoff, 2015).

The work described in this doctoral thesis aims to advance the development of effectively personalized and transparent, multidomain DHBCIs that are designed for the *prevention* of NCDs. Hence, disease management systems (for diagnosed conditions) are not in the scope of the thesis. With *multidomain* DHBCIs, the author refers to digital interventions that are capable of supporting different lifestyle aspects. Such interventions can serve the varying health behavior change needs of individuals, which is imperative for succeeding in delivering health impact at the population level. Furthermore, *effectively personalized* DHBCIs refer to interventions that can automatically adjust to individuals' personal needs, capabilities, and life situations in such a way that they succeed in empowering people to lead a healthy lifestyle. The thesis focuses on similarity- or neighborhood-based algorithms for conducting personalization, since such techniques are easy to manage and they scale efficiently to a multitude of tailoring variables, which make them especially suitable for DHBCIs (Ning et al., 2015; Sadasivam, Cutrona, et al., 2016). Neighborhood-based personalization techniques are well-known from various online commercial recommender systems, such as Amazon and Netflix, which can match a vast database of items to the needs of millions of different users. DHBCIs that apply neighborhood-based personalization are referred to as *health recommender systems* (HRSs) (Sadasivam, Cutrona, et al., 2016; Sezgin & Özkan, 2013). The author also acknowledges the importance of user experience design when aiming at developing engaging DHBCIs. Nevertheless, this area of research is scoped out from the dissertation as it would warrant a separate thesis of its own.

1.2 Definition of central concepts

Well-being and health: In the Constitution of the World Health Organization (WHO) implemented in 1948, health is defined broadly as a "state of complete physical, mental, and social well-being, and not merely the absence of disease and infirmity" (Nutbeam & Muscat, 2021). Diener *et al.* (1999) defines well-being as subjective experiences of the quality of life, aka *subjective well-being*, which comprise three components: positive affect, low negative affect, and life satisfaction (general and domain specific). Subjective well-being has been considered a scientific term for *happiness* (Griffin & Ward, 2016). Even though it may be unrealistic to achieve a complete state of health as defined by WHO, in this thesis, the introduced definitions for health and subjective well-being are used as aspirational goals for health promotion.

Health behaviors: Any activities undertaken by a person that contribute to health outcomes can be regarded as health behaviors (Institute of Medicine, 2001). In this thesis, the focus is on habitual behaviors that help in the prevention of lifestyle-related NCDs and promote subjective well-being. These include sufficient physical activity, healthy diet, nonsmoking, reduced alcohol consumption, stress management, sufficient restorative sleep, and good social relationships (Arango et al., 2021; Diener et al., 2017; Peters et al., 2019).

Health promotion: According to WHO, health promotion "is the process of enabling people to increase control over and to improve their health" (Nutbeam & Muscat, 2021). It involves actions directed at improving individuals' knowledge, attitudes, and skills regarding health behaviors, as well as creating social, environmental, and economical circumstances that encourage individuals to make healthy choices. In this thesis, the scope of health promotion is limited to actions targeted directly to individuals, which encourage the formation of healthy habits for the prevention of NCDs and the enhancement of subjective well-being.

Multidomain health interventions: Interventions that target two or more health behaviors either simultaneously or sequentially are usually regarded as multidomain health interventions, e.g., (Salzman et al., 2022). However, in this thesis, a stricter definition is used, having the requirement of targeting *more than two* health behaviors, to correspond better to the variety of lifestyle-related NCD risk factors that ought to be considered by health promotion interventions.

Digital health behavior change interventions (DHBCIs): In this thesis, DHBCIs refer to desktop or mobile applications which aim to persuade and empower individuals to engage in actions that lead to a healthy lifestyle and promote well-being. The encouraged actions can be of various types, related to, for instance, evoking positive attitudes towards behavior change, acquiring relevant and reliable health knowledge, goal setting and action planning, self-monitoring, or performing physical, social, or cognitive tasks (e.g., buying healthy groceries at a weekly basis, doing mindfulness exercises each morning, starting a new exercise hobby with a friend). Various names have been used for these kinds of digital interventions beginning from *persuasive technologies*, introduced in the late 1990's and studied in detail by Fogg (1998), followed by *behavior change support systems*, introduced by Oinas-Kukkonen (Oinas-Kukkonen, 2010), and *ecological momentary interventions* (Heron & Smyth, 2010). Simultaneously, the terms *eHealth*, *mHealth,* and *digital health* interventions have been used (Bashshur et al., 2011; Murray et al., 2016).

User engagement: User engagement with DHBCIs can be considered from behavioral, emotional, and cognitive aspects (Short et al., 2018). The behavioral aspect has generally been described by the extent of intervention usage, whereas the emotional and cognitive aspects are related to user experience in terms of the experienced level of interest, attention, and enjoyment during the use of intervention (Perski et al., 2017). Sufficient user engagement is required for the intervention to be effective, i.e., to succeed in engaging the user in the actual behavior change process (Short et al., 2018).

1.3 Outline of the thesis

In this work, a multitude of personal characteristics that may be useful for the effective personalization of DHBCIs are explored by reviewing the theoretical foundation of behavior change support and the personalization approaches employed in HRSs. In addition, the relevance of personal values in personalization is discussed based on the results of a retrospective, cross-sectional survey study including over 100,000 responses regarding values, well-being, and health behaviors. Furthermore, a HRS is introduced that recommends behavior change actions from various lifestyle domains (e.g., dietary habits, physical activity, stress management, and sleep) according to a restricted set of user features that are considered crucial for the adequate personalization of multidomain interventions. Evaluation results regarding the suitability of the recommendations, assessed in the context of a real-life health coaching program, are presented. Finally, a few concrete visual suggestions are given for improving the transparency of personalization based on a small user study that evaluated the interpretability of the visualizations.

In Section 2, the state-of-the-art research relevant to the topics of the thesis is presented, followed by conclusions on the research gaps that the thesis aims to address. In Section 3, the research questions that guide the present work are introduced, and an overview of the original publications included in the thesis is provided. In Section 4, a summary of the utilized research materials and methods are presented, which covers the employed literature review methodology (Publication I), the research settings, participants, and the investigated outcomes for the conducted studies (Publications II-IV), the conducted statistical analyses (Publications II and III), and the implementation details of the introduced HRS (Publication III). In Section 5, the results of the original publications that address the defined research questions are presented. Finally, the results as well as the implications and limitations of the present work are discussed in Section 6, and the research conclusions are presented in Section 7.

2 RELATED WORK

In this section, the state-of-the-art research relevant to the topics of the thesis is presented as background knowledge. First, an overview of the theories that aim to explain human behavior is provided. Then, the main personalization approaches utilized in DHBCIs are introduced, which range from the first generation of digital interventions, computer-tailored interventions, to more sophisticated and recent approaches. Particularly, the methods used in HRSs are covered and discussed in detail. Finally, the section is concluded with the identified research gaps in the HRS research field, which will be addressed by the remaining sections of the thesis.

2.1 Theory of health behavior change: requirements for personalization

Social and behavioral scientists generally agree that theories of behavior and behavior change are useful for the development of effective health behavior change interventions (Glanz & Bishop, 2010; Kok et al., 2016; Michie et al., 2005; Rhodes et al., 1997), although the evidence for theory-based interventions being superior compared to non-theoretical interventions is still inconclusive (Dalgetty et al., 2019; Teixeira & Marques, 2017), and more empirical evidence is needed to validate many of the theories (Lippke & Ziegelmann, 2008). Behavioral theories define the cognitive and social factors that influence and explain the behavior of individuals, i.e., the *determinants of behavior* (Glanz & Bishop, 2010; Lippke & Ziegelmann, 2008). Hence, they inform about the factors that should be considered when attempting to elicit behavior change and help to identify appropriate behavior change techniques (BCTs) or methods (Kok et al., 2016; Michie et al., 2013; Rhodes et al., 1997; Willmott & Rundle-Thiele, 2021). BCTs are intervention components, the smallest active ingredients of an intervention (e.g., goal setting, self-monitoring, coping planning, and behavioral guidance), which aim to modify the factors that influence behavior (Michie et al., 2013). Furthermore, developing and reporting interventions according to theory-based common practices is imperative for intervention evaluation, replication, and evidence synthesis. Utilizing common practices advances the understanding of the active components of effective interventions. (Willmott & Rundle-Thiele, 2021)

There are multiple theories that aim to explain reasoned (health) behavior and predict behavior change (Davis et al., 2015; Michie et al., 2005). *Reasoned behavior* refers to actions that people undertake with deliberate intention; hence, it involves conscious decision making. Davis *et al.* (2015) have identified 82 different behavioral theories applied in health promotion interventions in the fields of psychology, sociology, anthropology, and economics. The most commonly utilized theories include the transtheoretical model of change (TTM), the theory of planned behavior (TPB), social cognitive theory (SCT), information-motivation-behavioral skills (IMB) model , and health belief model (HBM) (Davis et al., 2015; Glanz & Bishop, 2010; Rhodes et al., 1997), which all explain reasoned behavior. As many of the theories have overlapping constructs (Davis et al., 2015; Michie et al., 2005), behavioral scientists have attempted to achieve a consensus of the key determinants of (reasoned) behavior. Fishbein *et al.* (2001) and Michie *et al.* (2005) have reported the results of two different expert group workshops, which arrived at somewhat similar conclusions of the key determinants. The latter workshop resulted in the theoretical domains framework (TDF), which synthesizes the central constructs across 33 theories (Cane et al., 2012). The constructs identified by both expert groups (Fishbein et al., 2001; Michie et al., 2005) include the 1) *intention* or readiness to perform a given behavior, 2) *skills* to perform the behavior, 3) *self-efficacy*, i.e., the belief in one's capability to perform the behavior, also in the presence of obstacles, 4) *social influence* regarding the behavior, 5) *attitude* towards the behavior resulting from *outcome expectations* (whether the perceived benefits outweigh the costs) and other beliefs about the consequences of performing the behavior, 6) *environmental resources or constraints* facilitating or hindering the behavior, 7) the consistency of the behavior with one's *self-image* or identity, and 8) the *emotions* attached to the behavior. However, the TDF defines also the 9) *knowledge* or *awareness* of the importance to perform the behavior (e.g., perceived health risks), 10) *information processing* abilities (memory, attention, decision processes), and 11) *optimism* as factors influencing behavior (Cane et al., 2012; Michie et al., 2005). In addition, the framework includes behavioral regulation, goals, and reinforcement, which, however, are also regarded as BCTs (Michie et al., 2013). Hence, they may be considered primarily as methods to modify behavior instead of constructs explaining behavior as such.

In addition to the abovementioned determinants of behavior, *values* and *personality* also play a role in explaining behavior. Particularly, they influence the formation of attitude towards the desired behavior, which is one of the factors determining the intention to change behavior, as postulated by the theories of reasoned action and planned behavior (Ajzen & Fishbein, 2005). Values and personality traits are distinct, but somewhat related psychological constructs (Parks-Leduc et al., 2015), which both motivate behavior but via supposedly different mechanisms: the motives emerging from values are mostly conscious, whereas traits define one's natural tendencies to think, feel, and act (Bilsky & Schwartz, 1994; Roccas et al., 2002). In addition, unlike traits, values are not always reflected in one's behavior (Roccas et al., 2002).

Values are generally regarded as broad life goals, i.e., guiding principles in life that determine what is personally important (Rokeach, 1973; Schwartz, 1992). According to Schwartz and Bilsky (1987), "values (a) are concepts or beliefs, (b) about desirable end states or behaviors, (c) transcend specific situations, (d) guide selection or evaluation of behavior and events, and (e) are ordered by relative importance." Schwartz value theory (Schwartz, 1992) defined originally ten broad value types based on the basic human needs, which represented different motive orientations organized in a circumplex continuum (Schwartz, 1992). This value classification system has been verified across different cultures in more than 65 countries (Schwartz, 2011). Later, Schwartz and colleagues (Schwartz et al., 2012) introduced a refined version of the original value structure with 19 value types, which was recently validated in 49 cultural groups (Schwartz & Cieciuch, 2022).

While intention is regarded as the strongest predictor for behavior change (Fishbein, 2008), conflicting habits can prevent good intentions from translating into desired actions (Verplanken & Wood, 2006). Habits are *automatic behaviors* that develop when actions are repeated in the same context and, thus, become cued by the environment, situation, or internal state (e.g., time of day, location, mood, or activity). Habits are easy to maintain as they require minimal decision making, but also hard to break as they are automatically triggered by recurring contextual cues. The key to disrupting existing habits is to remove the cues that trigger them, e.g., by modifying the physical environment or avoiding certain social situations. Developing new habits requires establishing incentives and stabile contextual opportunities that encourage the desired action and promote repetition. Significant life changes, such as moving to a new location, changing jobs, or starting a family, provide opportunities to break old habits efficiently and learn new ones, as these types of changes involve modifications also in one's physical and social environments. (Verplanken & Wood, 2006)

The theories of behavior and behavior change should be considered when personalizing DHBCIs (Riley et al., 2011). Being aware of the behavioral determinants and their states at the individual-level facilitates intervention mapping, i.e., the identification of the appropriate behavior change techniques or methods that are likely to be effective for the person (Kok et al., 2016; Michie et al., 2013) (e.g., making changes to the environment for breaking unhealthy habits, raising consciousness of health risks when lack of awareness, or providing practical behavioral guidance for improving skills). Indeed, Webb *et al.* (2010) found in their review of web-based DHBCIs that interventions which utilized theory extensively and incorporated a variety of BCTs were associated with larger effect sizes than interventions incorporating fewer techniques. However, behavioral theories have been criticized of being inadequate to explain or predict behavior at the level of detail required by modern mobile-based DHBCIs that can gather intensive contextual and longitudinal data from a person and provide (near) real-time guidance (Hekler et al., 2016; Riley et al., 2011; Spruijt-Metz & Nilsen, 2014). The current theories are linear and static, designed to explain behavior at the group-level. They need to be expanded to explain individual variation and changes over time, and in different contexts, in order to truly inform the development of personalized, real-time digital interventions. (Hekler et al., 2016; Riley et al., 2011) Hekler *et al.* (2016) provide recommendations for the development of precise and quantifiable computational models of behavior change, which specify "when, where, for whom, and in what state of a person an intervention will produce a targeted effect".

2.2 Personalization approaches in DHBCIs

In personalized DHBCIs, the intervention components (i.e., behavior change goals and actions, educational or motivational messages, feedback, and reminders) can vary considerably between different individuals. Depending on the extent or *coverage of personalization* in terms of the variety of tailoring variables considered (Cena et al., 2019), there may be as many different intervention programs as there are individuals. Tailoring variables may range from basic demographic variables to the multitude of personal and contextual determinants of health and behavior (de Vries & Brug, 1999). Another important dimension of personalization is the time-varying aspect, i.e., *dynamic adaptation* (Spruijt-Metz & Nilsen, 2014), where the interventions are updated to individuals' changing needs and circumstances in a timely manner. In the following, these two dimensions of personalization are elaborated further by introducing the main personalization methods utilized in DHBCIs. In Figure 1. the methods are located along a continuum of dynamic adaptivity.

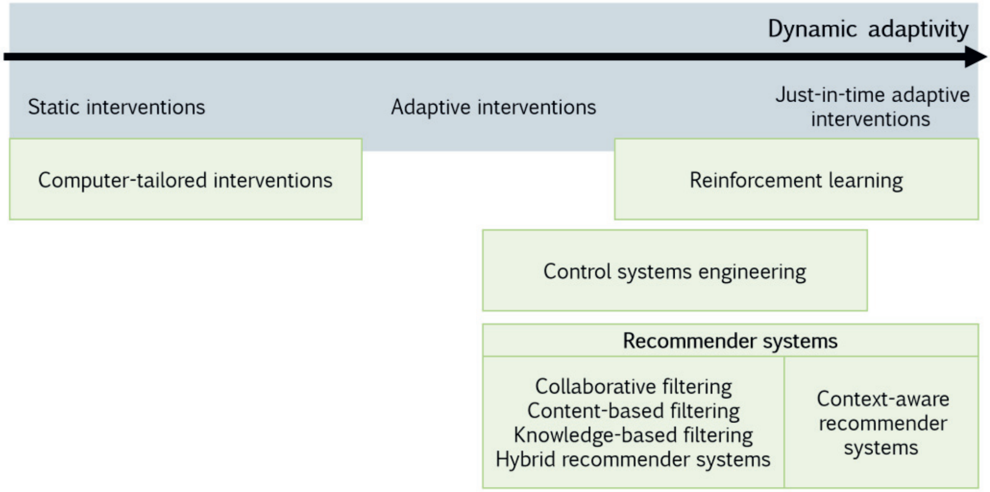

Figure 1. Common personalization methods in DHBCIs

Traditionally, computerized if-then statements have been used to adapt the content of interventions, particularly printed or desktop application materials, to the selected characteristics of individuals (Brug et al., 1996; Dijkstra & De Vries, 1999; Krebs et al., 2010; Lustria et al., 2009). These systems are commonly referred to as *computer-tailored interventions* (de Vries & Brug, 1999; Krebs et al., 2010; Lustria et al., 2009, 2013). Computer-tailored interventions have typically been designed by health behavior change experts based on their prior knowledge of the target population and the theories of behavior change. Hence, personalization is based on predefined tailoring variables, measured typically via questionnaires, and the related decision rules. (De Cocker et al., 2015; Dijkstra & De Vries, 1999; Etter, 2005; Sadasivam, Cutrona, et al., 2016) However, the development and maintenance of rule-based systems become quickly costly and complex when the aim is to conduct extensive personalization, since the number of if-else rules grows exponentially with the number of tailoring variables and intervention options (Sadasivam, Cutrona, et al., 2016; Sezgin & Özkan, 2013). In addition, computer-tailored interventions have not been designed to support (real-time) dynamic adaptation. Although, adaptation can be conducted based on the iterative or repeated assessments of tailoring variables, the adaptation schedules employed in such interventions have been infrequent, taking place at most at a monthly frequency (Krebs et al., 2010). Many conduct personalization only at the beginning of the intervention to determine the most suitable, but static, intervention path for a person (Krebs et al., 2010). Infrequent adaptation may be suboptimal for the delivery of effective behavior change support, as one's progress and the critical moments when one is in need for support can be easily missed with occasional assessment points.

Alternative personalization methods have been introduced to overcome the shortcomings of computer-tailored interventions, sparked by the tremendous development of mobile and wearable technologies during the past decade. For instance, a variety of machine learning models have been used for the personalization of health interventions (Triantafyllidis & Tsanas, 2019). *Just-in-time adaptive interventions* (JITAIs) are mobile intervention that focus on delivering support at opportune moments, when the person is susceptible to unhealthy activities or adverse health outcomes but also receptive to an intervention (Nahum-Shani et al., 2015; Spruijt-Metz & Nilsen, 2014). These interventions aim to dynamically adapt to individuals' changing internal states (e.g., stress level), behavior, or environmental and social contexts (e.g., location, activity). The adaptation is enabled by continuous data streams, measured by wearable devices or smartphones, and momentary user inputs, i.e., ecological momentary assessments (EMA) (Shiffman & Stone, 1998).

Algorithms based on reinforcement learning (Liao et al., 2020; Tewari & Murphy, 2017) and control systems engineering (Conroy et al., 2020; Rivera et al., 2018) have been suggested for JITAIs. These methods can map the values of momentary tailoring variables to the intervention options (content or dose) that are likely to maximize the intervention effectiveness, and even find the relevant tailoring variables, for each individual (Lopes dos Santos et al., 2020). In reinforcement learning, the optimal mapping function is automatically learned from the measured data based on a defined reward signal that the mapping seeks to maximize (R. S. Sutton & Barto, 2018). The appropriate moment to intervene can be learned by finding out the intervention content that maximizes the desired immediate outcome, e.g., the 30-minute step count after sending a walking prompt (Liao et al., 2020), given a certain context. In control systems engineering, the optimal intervention dosage (e.g., the intensity of guidance for exercise or eating) is identified by solving a numerical optimization problem, which minimizes the error between the desired outcome's target value (e.g., a daily step or weekly weight goal) and the predicted value, while taking into account the expected mediating influence of tailoring variables (e.g., stress level, weather conditions) on the relationship between the intervention and outcome (Rivera et al., 2018). This requires the training of a dynamical system model that characterizes the relationships between the tailoring variables, intervention dosages, and outcomes, which is used to predict the effect of an intervention dosage on the outcome(s) (Hekler et al., 2018; Lopes dos Santos et al., 2020). When developing the system model, theories of behavior change can be utilized to model the relationships between psychosocial tailoring variables and behavioral outcomes, see e.g., (Downs et al., 2021; Hekler et al., 2018). However, both the reinforcement learning and control systems engineering approaches require a considerable amount of training data or learning iterations for the algorithm to learn the optimal mapping functions for an individual (Hekler et al., 2018; Liao et al., 2020), which can cause the user to lose interest in the DHBCI already in the beginning (Liao et al., 2020). Perhaps, this explains why pre-specified adaptation rules are used in many JITAIs instead of the sophisticated ones, e.g., in (Adams et al., 2013; Gustafson et al., 2014; van Dantzig et al., 2013), or why JITAIs often include relatively simple intervention content, such as walking prompts, goal setting for daily steps, or suggestions for physical activities (Conroy et al., 2019; Hardemanet al., 2019; Liao et al., 2020; Rivera et al., 2018). In addition, reinforcement learning and control systems engineering share a similar limitation with computer-tailored interventions: they do not scale well to a multitude of tailoring variables or intervention options.

As an efficient solution to conduct extensive personalization, methods used in *recommender systems* have been suggested to be applied also to DHBCIs (Sadasivam, Cutrona, et al., 2016; Sezgin & Özkan, 2013). This has led to the research and development of health recommender systems (HRSs), which has gained a lot of speed during the recent years (Cheung et al., 2019; De Croon et al., 2021; Pincay et al., 2019; Prajapati & Brahmbhatt, 2022). The next subsection is devoted to HRSs, which are at the focus of this doctoral research.

2.3 Personalization in health recommender systems

Recommender systems were originally introduced for the purpose of information filtering (Ricci et al., 2015). In the mid-nineties, they gained popularity especially in commercial online platforms, which sought to personalize their service offering regarding, for instance, movies, music, books, and news to consumers' preferences and interests (Aggarwal, 2016; Ricci et al., 2015). A few decades later, applying recommender methods to the health domain started to gain research interest, and health recommender systems were introduced (Sezgin & Özkan, 2013). HRSs have been used for medical decision support and rehabilitation, for searching healthcare services and medical information, and for health promotion (Anderson, 2018; De Croon et al., 2021; Ghanvatkar et al., 2019; Pincay et al., 2019; Prajapati & Brahmbhatt, 2022; Yue et al., 2021). Regarding health promotion, the majority of

HRSs have focused on either physical activity (PA), healthy diet, or smoking cessation (Anderson, 2018; De Croon et al., 2021; Ghanvatkar et al., 2019; Pincay et al., 2019; Prajapati & Brahmbhatt, 2022). Some HRSs have addressed mental well-being (De Croon et al., 2021), alcohol consumption (Colantonio et al., 2015), or sleep (Pandey et al., 2020). Typically, HRSs address only one or two health behaviors; hence, they do not take a multidomain approach towards health promotion. The HRS introduced by Pandey *et al.* (2020) provides an example of addressing more than two behavioral domains, namely, PA, dietary habits, circadian rhythm, and sleep quality, but such a variety is generally uncommon.

The item types recommended by HRSs vary considerably depending on the purpose of the system (Cheung et al., 2019; De Croon et al., 2021; Ghanvatkar et al., 2019; Lattar et al., 2018; Yue et al., 2021). HRSs that promote PA have recommended activity types (e.g., running, walking, gym), PA intensities or durations (Alcaraz-Herrera et al., 2022; Ali et al., 2016; Dharia et al., 2018; Ferretto et al., 2020; Lim et al., 2017; Rabbi et al., 2015), personalized PA goals in terms of weight loss and calorie expenditure (Ali et al., 2016; Rabbi et al., 2015), exercise buddies (Dharia et al, 2018), and the time or place for exercise sessions (Dharia et al., 2018; Lim et al., 2017; Rabbi et al., 2015). HRSs focusing on healthy eating have provided nutritional advice and have recommended recipes or meal plans, restaurants, or healthy items from restaurant menus (Alcaraz-Herrera et al., 2022; De Croon et al., 2021; Ribeiro et al., 2022; Starke et al., 2021). For smoking cessation, HRSs have been used to select motivational messages for users (Hors-Fraile et al., 2022; Sadasivam, Borglund, et al., 2016). For mental well-being, particularly stress management, the recommendation space has included relaxation and cognitive exercises, physical activity, social engagement, and enjoyable activities (Clarke et al., 2017; Torkamaan & Ziegler, 2022).

2.3.1 User modeling

To conduct personalization, recommender systems need to collect and maintain user-specific data that describe the personal and contextual characteristics required for personalization. This process is generally known as *user modeling* or *user profiling* (Brusilovsky & Millán, 2007; Gauch et al., 2007; Ricci et al., 2015). The type and structure of the collected user-specific data is defined by a *user model*, whereas a *user profile* is a data instance of the user model (Gauch et al., 2007).

Different user model structures have been used to represent user-specific data in recommender systems. *Vector space models* are the most used structures. For instance, user ratings regarding different items available in the recommendation space, representing users' interests, are commonly maintained in vectors (Aggarwal, 2016). Keyword- and concept-based vectors can also be used to represent users' interests by maintaining weights for different terms or concepts that describe the item properties of interest (de Gemmis et al., 2015). Furthermore, feature vectors or attribute-value pairs have been used to represent a variety of different user characteristics, in addition to user interests (Aggarwal, 2016; Felfernig et al., 2015). According to the review of Pincay *et al.* (2019), using attribute-value pairs has been the most common form of knowledge representation in the user models of HRSs.

Simple vector space models are not always sufficient for user modeling, as vectors do not allow to specify connections between concepts. Modeling the relationships between concepts enables knowledge propagation through inference, which is especially useful when the available user data is sparse (Brusilovsky & Millán, 2007; Gauch et al., 2007). The two common types of *connected models* are tree-like concept hierarchies and network models (Brusilovsky & Millán, 2007). Hierarchical concept structures represent how broad, high-level concepts are divided into lower-level sub-concepts. In network models, the connections can be arbitrary, and they can be either semantic relationships, such as 'is-a' and 'part-of' relations, or prerequisite relationships. *Domain ontologies* refer to a sophisticated form of network models, where domain knowledge is represented as concept hierarchies, concepts can be described with attributes, and the relationship types between concepts can vary (de Gemmis et al., 2015). For instance, an ontology-based modeling system has been developed for representing 14 distinct relationship types between the constructs of 76 theories of behavior and behavior change (Hale et al., 2020). Finally, in *layered models*, concepts can be described with several values representing different estimates obtained from different sources (e.g., explicit user-provided values, observed user behavior, or inferred values) (Brusilovsky & Millán, 2007).

Typically, the user models of HRSs that focus on health promotion include heterogenous data, which is collected via questionnaires and user-evaluations, e.g., (Alcaraz-Herrera et al., 2022; Hors-Fraile et al., 2022; Torkamaan & Ziegler, 2021), or inferred based on the objective monitoring of behavior via wearable activity and heart rate monitors (Ali et al., 2016; Clarke et al., 2017; Lim et al., 2017; Pandey et al., 2020; Prajapati & Brahmbhatt, 2022). Environmental sensors (e.g., for humidity, temperature, or air quality) have also been utilized in a few HRSs (Pandey et al., 2020; Rist et al., 2015). In addition, the included user features vary considerably between different HRSs, which indicates a lack of common understanding of the most essential ones.

The most prevalent user features in HRSs describe user characteristics relevant for identifying health behavior change needs. These include basic demographics, such as age and gender, health behaviors, and health risks, e.g., (Alcaraz-Herrera et al., 2022; Ali et al., 2016; Dharia et al., 2018; Ferretto et al., 2020; Hors-Fraile et al., 2022; Ribeiro et al., 2022; Torkamaan & Ziegler, 2022). Many HRSs also monitor context-related features for determining the opportune moments to prompt users with recommendations. Location and the time of day are the most widely used contextual features, e.g., (Dharia et al., 2018; Hors-Fraile et al., 2022; Lim et al., 2017; Rabbi et al., 2015; Torkamaan & Ziegler, 2021). In a few cases, users' calendar availability (Dharia et al., 2018) and momentary activities (Lim et al., 2017; Rabbi et al., 2015) have also been used for detecting opportune moments. It is also relatively common to gather data about the usefulness or effectiveness of recommendations (Ferretto et al., 2020; Rabbi et al., 2015; Ribeiro et al., 2022; Sadasivam, Borglund, et al., 2016; Torkamaan & Ziegler, 2022; Yom-Tov et al., 2017) as well as user preferences regarding PA or diet (Alcaraz-Herrera et al., 2022; Ali et al., 2016; Dharia et al., 2018; Ghanvatkar et al., 2019; Lim et al., 2017; Ribeiro et al., 2022; Starke et al., 2021). In addition, social ties (Dharia et al., 2018; Hors-Fraile et al., 2022), environmental conditions (Pandey et al., 2020; Rist et al., 2015), or mental states (e.g., stress level, mood) (Clarke et al., 2017; Rist et al., 2015; Torkamaan & Ziegler, 2021) are represented in some HRSs.

However, the theory-based determinants of behavior, introduced in Section 2.1, are rarely considered by HRSs (Cheung et al., 2019; Hors-Fraile et al., 2018), or only one or two constructs are included in the user models. For instance, intention to quit smoking has been used to tailor smoking cessation messages (Hors-Fraile et al., 2016, 2022; Sadasivam, Borglund, et al., 2016), and users' self-efficacy and skills have been used to personalize stress management activities (Torkamaan & Ziegler, 2022). A unique example of a HRS, which leverages behavioral determinants extensively for personalization, is the Quit and Return smoking cessation application (Hors-Fraile et al., 2019). The application addresses several constructs of the Integrated-Change Model (de Vries, 2017), i.e., attitude, intention to quit, self-efficacy, social support, action planning, and skills.

2.3.2 Recommendation methods

Various recommendation methods have been employed in HRSs (Cheung et al., 2019; De Croon et al., 2021; Pincay et al., 2019; Yue et al., 2021). *Collaborative filtering* and *content-based filtering* are the classical methods used for recommendation. They use past user ratings for items in the recommendation space, which reflect user preferences, to predict user ratings for unrated items or to rank the top-*k* most interesting items for the user. User ratings can be either explicit (e.g., ratings from one to five stars or binary like/dislike) or implicit, where user preferences are deduced by observing user behavior (e.g., by observing user-selected items in online applications, or by monitoring real-life actions such as the steps taken). In *knowledge-based systems*, the recommendations are based on the explicit knowledge about a user (e.g., health risks and habits) instead of item-specific user preferences in the form of ratings. *Demographic* and *context-aware recommender systems* leverage particularly demographic and context-related features. *Hybrid systems* combine different recommendation methods to overcome the shortcomings of a single method. Traditionally, the abovementioned recommendation methods have been implemented by using neighborhood- or similarity-based techniques, but also machine learning, data mining, and deep learning methods have been used for improved accuracy. (Aggarwal, 2016; Ricci et al., 2015) In the following, the different recommender methods and the related neighborhood-based techniques are introduced in more detail.

In **collaborative filtering** (Aggarwal, 2016; Koren & Bell, 2015; Ning et al., 2015), user ratings provided by multiple users are utilized to make recommendations. Ratings are maintained in a user-item matrix, where columns denote items and rows include user-specific ratings for the items. Typically, recommendations are generated based on neighborhood algorithms, where similarity metrics, such as cosine similarity or Pearson correlation, are utilized for determining users similar to a target user (user-based) or items similar to a target item (item-based) according to the available user ratings. In the user-based approach, the missing ratings for a user are predicted based on the weighted average of ratings provided by the users who share a similar ratings profile with the target user. In the item-based approach, missing ratings are predicted by identifying items similar to the given item and computing the weighted average of ratings provided by the target user for the identified items. For sparse matrices, where many of the items are rated only by few users, the performance of neighborhood-based techniques will be poor. In addition, with huge matrices, the computational complexity (i.e., time and memory requirements) of similarity computations can become quite significant. However, clustering and dimension reduction techniques have been successfully used in conjunction with neighborhood algorithms to overcome these problems, thus improving both the quality and efficiency of recommendations. In addition, machine learning and data mining methods, such as latent factor models, association rules, graph models, decision trees, and Bayesian methods have been used as standalone techniques for collaborative filtering. Nowadays, latent factor models are considered the state-of-the-art technique for collaborative filtering due to their high accuracy and efficient performance with sparse data.

In **content-based filtering** (Aggarwal, 2016; de Gemmis et al., 2015), the aim is to recommend items similar to the ones rated positively by the user in the past. The items are described with attributes, and user-specific profiles are maintained to relate item attributes with user ratings. Items that match the attributes in the user profile are recommended. The items and user profiles can be represented with vector models or connected models (Gauch et al., 2007). As for collaborative filtering, neighborhood-based algorithms are commonly used for recommendation in content-based systems. Neighborhood-based techniques work especially efficiently with user profiles that maintain so-called prototype vectors for each possible value of user ratings. In such cases, the system needs to compare the similarity of item vectors to the user profile's prototype vectors. Cosine similarity is often used as the similarity metric for sparse keyword-based vectors that are typically used for representing textual items, but depending on the data type, other similarity metrics, such as Euclidean or Manhattan distances, may be more appropriate (Aggarwal, 2016). In addition to prototype vectors, a common approach is to maintain in a user profile the complete history of items rated by the user. In this case, the rating for a given item is predicted by averaging the ratings of similar items found in the user profile. However, the computational complexity is high for this kind of neighborhood computations, and applying machine learning methods (e.g., Bayesian methods, association rules, or support vector machines) in recommendation may be more appropriate in such cases.

In **knowledge-based filtering** (Aggarwal, 2016), explicit knowledge about user characteristics is derived, for example, from questionnaires, interactive dialogs, or wearable devices. In addition, expert-knowledge of the item domain is exploited. Like in content-based filtering, the goal is to match item properties to the user profile attributes or features but in a more direct manner, based on the actual values of user features instead of inference through user ratings. Typically, the input data is highly heterogenous and specific to the domain of interest, whilst collaborative and content-based methods function with somewhat similar type of input data across domains. User models maintaining attribute-value pairs can be used to represent such heterogenous data (Felfernig et al., 2015; Pincay et al., 2019). Knowledge-based recommenders can be classified into *case-based reasoning* and *constraint-based* approaches. In the former approach, recommendations are determined according to similarity metrics, whereas in the latter, explicit rules are predefined to relate user profiles' feature values with item properties. In case-based systems, the user profile specifies target values for the features, and the system seeks to find items that are described with these target values. This is analogous to the type of content-based filtering where user profiles are represented as prototype vectors. However, domain knowledge is required to determine the similarity function(s) appropriate for the user profile attributes. In constraint-based systems, the user profile specifies certain constraints or requirements for items, and filtering rules are used to find the items that satisfy all the constraints. As with computer-tailored interventions, constraint-based filtering often requires experts to plan the recommendation logic manually and, thus, can be error-prone and hard to maintain (Felfernig et al., 2015).

Knowledge-based filtering is appropriate for recommending complex items, which require a deeper understanding of user characteristics and item properties than merely user interests and simple user ratings. It is particularly suitable for use cases, where user profiles' feature values evolve over time, and the past values should not be used to predict the future, unlike in collaborative- and content-based filtering. (Aggarwal, 2016) According to the recent review of De Croon *et al.* (2021), the majority of the HRSs focused on health promotion utilized knowledge-based filtering.

Context-aware recommender systems (Adomavicius & Tuzhilin, 2015) take into consideration the contextual situations of users (e.g., temporal aspects, location, social situation), in addition to users' personal characteristics and item attributes. Mobile recommender systems are often context-aware. Typically, the contextual information is maintained in hierarchical data structures (e.g., concept hierarchies) or in multidimensional data models. In multidimensional models, users, items, and different types of contextual features are represented in separate dimensions.

Knowledge-based systems can incorporate contextual features directly into the user profiles; hence, they can recommend items that fit to a given context. In collaborative- and content-based methods, contextual pre-filtering or post-filtering is applied to the item space. In contextual pre-filtering, the user ratings provided in the past, in a given context, are selected, and this subset of ratings is used to generate recommendations. In contextual post-filtering, initial recommendations are produced using the entire data, after which the results are filtered out to include only those items that were rated in the past in the given context. Hence, the traditional recommendation methods functioning in a two-dimensional space of users and items can be applied for context-aware recommendations. However, recommender techniques functioning directly on a high-dimensional space, such as n-dimensional similarity metrics and machine learning techniques, have also been used to predict user ratings.

Demographic recommender systems leverage the demographic information about a user to recommend items. Either neighborhood-based algorithms are used, where one's demographic peer or stereotypical group is identified, and the items preferred in the group are recommended to the target user, or a machine learning model is learned that maps specific demographics directly to user ratings (Aggarwal, 2016; Tintarev & Masthoff, 2015). Demographic filtering as a standalone method may not deliver the best results, but it can provide significant additional value when combined with other recommender methods (Aggarwal, 2016), e.g., via the pre-filtering and post-filtering approaches used in context-aware recommenders. In knowledge-based filtering, demographic information can be easily leveraged by including demographic features into the user profile and item attributes.

In **hybrid recommender systems** (Aggarwal, 2016), different filtering methods are combined to compensate the shortcomings of a single method. For instance, collaborative filtering suffers from the so-called cold-start problem, where a significant number of user ratings is required from multiple users before useful recommendations can be delivered, and items that have not been rated by anyone will not be included in the recommendation space. In content- and knowledge-based filtering, it is enough to have data of the target user only, and unrated items can be recommended. However, these two methods usually generate recommendations that lack diversity and novelty, whereas collaborative filtering can recommend serendipitous items that surprise the user positively. Cheung *et al.* (2019) propose based on their review into HRSs to combine knowledge-based, collaborative and demographic filtering. They foresee that this type of a hybrid HRS has the potential to improve user engagement and intervention effectiveness by generating recommendations that are highly relevant for the user, but also diverse and interesting. Indeed, the most of the HRSs aiming at health promotion utilize hybrid methods (De Croon et al., 2021).

2.3.3 Evaluation of recommendations

The methods used to evaluate the performance of HRSs are versatile. According to the review of De Croon *et al.* (2021), most validation studies have been conducted with simulated or existing datasets, i.e., "offline" without the involvement of real users. Alternatively, single-session user surveys or interviews have been used. It is less common to study HRSs "in the wild", where study participants use the system for a real-life purpose and interact with it in real-time. The scarcity of real-life studies has been considered a major short-coming for the field (De Croon et al., 2021; Schäfer et al., 2017).

In offline studies, standard error metrics (precision, accuracy, recall, F1-score, etc.) are generally used to evaluate the performance of recommendation algorithms (De Croon et al., 2021). These metrics require users to rate all the items in the recommendation space for identifying, for instance, the true negative and positive recommendations. In real-life studies, such an approach would hamper the natural study setting, while posing also a significant response burden to users. Instead, the suitability of recommendation in the wild has been investigated by collecting user ratings for the recommended items, only, (Hors-Fraile et al, 2022; Sadasivam et al, 2016; Alcaraz-Herrera et al, 2022), or by monitoring users' explicit or implicit compliance to the recommendations (Starke & Trattner et al, 2021; Torkamaan & Ziegler, 2022; Yom-Tov et al, 2017). Some studies have also measured changes in health outcomes (Sadasivam et al, 2016; Hales et al, 2016), although, in such cases, the study objective has been to evaluate the effectiveness of the overall intervention instead of the validity of the recommendation technique. In survey and interview studies, a variety of self-report scales have been used to assess the usability, user experience, user satisfaction, or perceived usefulness of HRSs (De Croon et al., 2021).

2.3.4 Transparency of recommendations

Transparent recommendations aim to explain to users the reasoning and data behind the recommendations (Tintarev & Masthoff, 2015). Introducing transparency in HRSs could have a positive impact on user experience and motivate users to follow the recommendations. Transparency can influence users' *perceived effectiveness of personalization* by explaining the extent to which personalization has been conducted and the quality and personal relevance of recommendations (Cheung et al., 2019). Transparency can also improve users' *trust* in recommendations, if a clear explanation is provided about the data and logic behind them to help users understand how the system selects recommendations (Tintarev & Masthoff, 2015). Perceived effectiveness and trust are factors (among others) influencing *user acceptance* (Cheung et al., 2019; Sekhon et al., 2017), which is a multi-faceted construct reflecting how appropriate a service or technology is considered by its users (Sekhon et al., 2017). User acceptance is directly related to users' intent to use a HRS and to the system's ability to persuade users to follow the recommendations (Tintarev & Masthoff, 2015).

Transparent recommendations are useful also from an ethical perspective, as they can provide users concrete visibility to the utilized personal data and its usage purposes. This kind of visibility supports the ethical principles of *privacy* and *autonomy*. Privacy refers to users' ability to control access to their personal data, and autonomy allows users to decide how and for what purposes the data is used (Ikonen et al., 2009). However, to meet these principles, it is not enough to only provide visibility, but also tools that enable users to truly manage their data are needed.

For HRSs, transparency of recommendations is especially important, as inappropriate recommendations can lead to adverse health effects, the complexity of health behavior change introduces additional uncertainty to the inference process, and the nature of the data is sensitive and private (De Croon et al., 2021; Herrmanny & Torkamaan, 2021). Thus, it is imperative that users can rely on the system and trust the recommendations. Providing transparency helps in integrating users into the reasoning and decision-making process of HRSs, which can improve users' trust and engagement with the system (Herrmanny & Torkamaan, 2021). If users understand why certain recommendations were given, they can assess the correctness of the data behind the recommendations and whether it is safe to follow them. Furthermore, intrinsic motivation for behavior change requires the experience of autonomy and competence, which can be strengthened by allowing users to influence the recommendation process (Herrmanny & Torkamaan, 2021; Ryan & Deci, 2000).

Herrmanny & Torkamaan (2021) have introduced a conceptual framework of design strategies for integrating users in the reasoning process of HRSs. The core aims of the user integration framework is to *empower* users to understand the system's result generation logic and interpret the results, *encourage* users to reflect and verify the results, and *engage* users to interact with the system and influence the reasoning process. The framework specifies both abstract (high-level) and concrete strategies to achieve these goals. According to the framework, providing *transparency of result generation* is a (high-level) strategy to empower users, and providing *transparency of the* *limitations* of the reasoning process can be used to encourage users to influence the recommendation outcomes, given that the system enables users to interact with the recommendation process.

2.4 Research gap

The considerable variation in the user model features of HRSs, designed for health promotion, indicates a lack of common understanding of the important features required for the effective personalization of DHBCIs. In the user models, particularly the theories of behavior change are under-utilized. Effective health promotion also requires taking a multidomain approach, as personal health and well-being are influenced by several lifestyle areas. Health impact can be delivered at the population level, only if interventions can serve the behavior change needs of different individuals. However, this is hardly the case with HRSs. Therefore, research that accrues knowledge of the important user features for the effective personalization of DHBCIs is needed, but also technical examples of such systems are required for identifying the best practices for user modeling and personalization, especially from the multidomain viewpoint. Likewise, as transparency of personalization and data privacy are particularly relevant for the health domain, investigating practical solutions to support these goals (e.g., in terms of user-interface design or application functionalities) is also an important area of research.

3 RESEARCH AIM AND OVERVIEW

Two premises, relevant for this doctoral thesis, can be concluded from the state of prior research regarding DHBCIs: a) advanced but transparent personalization is important for improving the effectiveness of DHBCIs, and b) the techniques used in HRSs are promising for conducting such personalization efficiently. This thesis aims to advance methods that enable the effective and transparent personalization of multidomain DHBCIs. The research aim is pursued by studying the following research questions (RQs):

1. What kind of personalization purposes can different personal characteristics (user model features) serve in DHBCIs? (Publications I-III)
2. How should personal information be quantified, structured, and interpreted to form a user profile that facilitates the personalization of multidomain interventions? (Publication III)
3. Is a HRS, which conducts personalization according to users' health behavior change needs and intentions, able to produce multidomain recommendations suitable for real-life health behavior change coaching? (Publication III)
4. How can the transparency of personalization be improved in DHBCIs? (Publication IV)

Already a decade ago in Publication I, personalized DHBCIs that empower individuals to lead a healthy lifestyle were identified as a promising solution for preventing the "tsunami" of chronic, non-communicable diseases in public health. In the publication, such personalized systems were envisioned to assist users in making healthy decisions throughout the day, analogous to a GPS-based navigator, and were referred to as "personalized health guides": "Personalized HealthGuides (PHGs) would locate users on their individual health map, calculate the possible routes to improve one's health, and continuously monitor and recalculate the route if users are not on the intended track." Hence, Publication I sets the background for the topic of the thesis. It provides a review into the theoretical foundation of behavior change support and analyzes the user modeling and personalization methods employed in DHBCIs and other user-adaptive software systems at the time.

The business environment of DHBCIs is also discussed, but this is not part of the scope of the thesis. The review results revealed that the personalization capabilities of DHBCIs were inadequate for empowering individuals to adopt a healthy lifestyle, especially in terms of delivering multidomain support at the moment of need. The findings inspired the author to study the topic of personalization further and consider improvements, which led to Publications II-IV. In the following, the publications are presented in terms of the research questions they address and summarized in Figure 2.

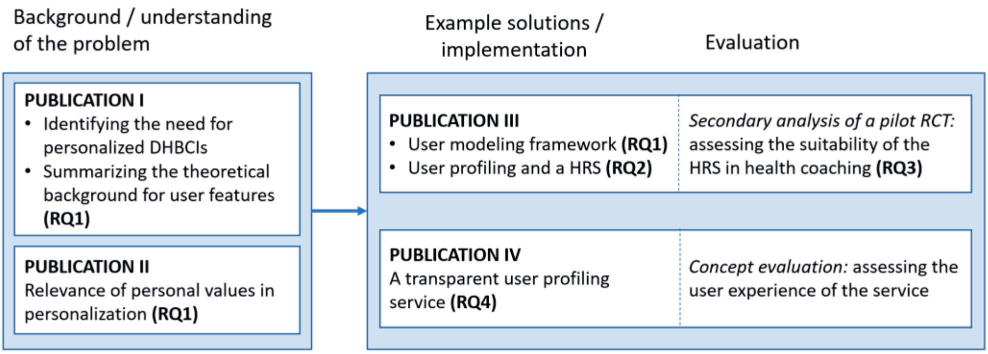

Figure 2. Key contributions of Publications I-IV to the thesis, coupled with the research questions (RQs)

Publications I-III address RQ1. In Publication I, the conducted review of behavior change theories resulted in identifying various personal and contextual factors that influence behavior, which may be useful for personalization. In addition, the review into user modeling methods revealed which user features were used for what kind of personalization purposes at the time. Publication II tackles RQ1 from the perspective of personal values by exploring the relations of self-reported values to self-reported well-being and health behaviors in a large cross-sectional dataset collected from Finnish citizens. The findings of the study can be used to formulate educated hypotheses about the relevance of personal values in personalization. Publication III, which is the most recent one of the four publications, updates the literature background provided in Publication I regarding the user features used in HRSs, proposes a comprehensive user modeling framework for supporting the advanced personalization of DHBCIs, and identifies various personalization purposes that can be served with the proposed user modeling framework.

Publication III addresses also RQ2 and RQ3 by presenting the implementation of a web-based HRS (With-Me HRS) that provides multidomain recommendations for health behavior change actions, personalized to users' behavior change needs and intentions, and by evaluating the performance of the HRS. With-Me HRS utilized a standard recommendation method (knowledge-based filtering) and implemented user features related to behavior change needs, derived from well-being and lifestyle factors, and the intention to change behavior. The implemented feature set was considered to serve the minimum requirements of personalizing multidomain DHBCIs, since in such interventions, the first step is to identify the appropriate behavior change objectives for a person (Kok, 2014), and intention to change is considered to be the single best predictor for behavior (Fishbein, 2008). The objective of the evaluation study was to investigate the suitability of the recommended behavior change actions, which were generated by the standard recommendation method that utilized the minimum set of user features. The evaluation was conducted in the context of a real-life health coaching program, where health coaches provided coaching in various lifestyle domains (e.g., dietary habits, physical activity, stress management, sleep) via telephone for the customers of occupational healthcare.

Finally, Publication IV addresses RQ4 by introducing a standalone web-based health profiling service (MyProfile), which was designed to provide personal feedback on one's lifestyle and behavioral determinants regarding different well-being topics and to be used for personalizing 3rd party DHBCIs when authorized by the user. At the time of writing the publication, MyProfile included profiles only for weight and stress management, but afterwards it was expanded with additional well-being topics, such as exercise and work well-being profiles. The profiles were designed to aggregate and present knowledge about one's health behavior change needs and determinants efficiently via simple metrics and visual summaries for the following two purposes: 1) to raise users' awareness of the relevant and realistic health behavior change targets for themselves, and 2) to provide transparency of the decision-logic behind the personalization of 3rd party applications. An open application programming interface (API) was implemented to the aggregated well-being profile data to enable the personalization of 3rd party health promotion interventions. In addition, a concept evaluation study was conducted to investigate the feasibility of the MyProfile service concept and the user experience of the implemented well-being profile views.

The work presented in Publications I-IV was carried out during three research projects. The literature reviews presented in Publication I were conducted in a 12-month, PREVE – Prevention of diseases, project (2010-2011). PREVE was a support action funded in part by the European Commission via the 7th Framework

Program under the ICT theme (FP 248197), which aimed to identify technological research directions for the empowerment of citizens in lifestyle-related disease prevention. The With-Me HRS (Publication III) stems from the WITH-ME project (2013-2016), where the aim was to develop an "European platform to promote healthy lifestyle and improve care through a personal persuasive assistant". The project was supported in part by the European ARTEMIS Industry Association and the Finnish Agency of Technology and Innovation (332885). The explorative data-analysis regarding personal values, health behaviors, and well-being (Publication II) and the development of the MyProfile service (Publication IV) were carried out in a Finnish research project (609/31/2014, 2895/31/2015) called "Digital Health Revolution" (2014-2017). A central topic for the project was the development of MyData based digital health solutions that enable citizens to govern their own health data.

4 MATERIALS AND METHODS

The methods used in the present research are mixed. Publication I is a literature review and Publications II-IV report research studies of which II and III were quantitative and IV was qualitative. Thus, methods regarding the study setting, participant recruitment, and outcome measures are relevant for all publications but the first one. For the quantitative studies, the employed statistical methods are also relevant. In addition, the recommendation algorithm implemented for With-Me HRS is a central methodological aspect (Publication III) for RQ3. In this section, a summary of the abovementioned topics will be covered.

4.1 Review methodology

Publication I provides a methodological review about the theoretical foundation of behavior change support and the maturity of DHBCIs at the time. Methodological reviews are performed for synthesizing the evidence of state-of-the-art methodological practices related to the design and conduct of research studies in a substantive field or topic (Chong & Reinders, 2021; Munn et al., 2018).

In Publication I, the behavioral theories and frameworks that had been utilized in health behavior change interventions were investigated, and a synthesis of the determinants of reasoned behavior was formed to summarize the factors that ought to be considered when personalizing DHBCIs. The review was guided by the following two study questions:

- Which theories are the most useful in explaining behavior and behavior change?
- Which are the main factors that influence behavior?

Reviews and meta-analyses regarding health promotion interventions were examined for identifying the common behavioral theories and frameworks applied for health behavior change support. Knowledge about the theories and frameworks was gathered from scientific articles and book chapters. The review included theories explaining the reasoned and automatic behavior of an individual as well as the theories of the stages of behavior change. Specifically, the following theories were selected for a detailed inspection:

- Social Cognitive Theory (SCT)
- Health Belief Model (HBM)
- Theory of Reasoned Action (TRA)
- Theory of Planned Behavior (TPB)
- Integrated Change Model (ICM)
- Transtheoretical Model (TTM)
- Precaution Adoption Process Model (PAPM)
- Health Action Process Approach (HAPA)

In addition, the frameworks of social marketing and behavioral economics, and theories on personal values and life stages were examined.

The constructs of the selected theories and the principles of social marketing and behavioral economics were analyzed thoroughly. First, knowledge about the main constructs (or principles) and their mutual relationships were extracted. Then, the constructs were compared across the theories and frameworks to identify similarities and differences. Similar constructs were grouped together and named with a common name. For instance, one of the groups was named as "outcome expectations" (terminology used in SCT), which covered constructs from several theories referring roughly to the same concept, i.e., behavioral beliefs and values (TPB), pros and cons (TTM), attitudes (ICM), reinforcers and punishers (behavioral economics), and benefits and costs (social marketing). As a result, seven key determinants of reasoned behavior were identified and included in the synthesis (see the results in Section 5.1).

The other review topic in Publication I, relevant for the thesis, investigated how technology had been utilized for supporting health behavior change. The following study questions guided the review:

- How can individual characteristics and the context of a person be modeled, and how far have existing systems gone in personalization and tailoring?
- How can technology be used to choose suitable intervention approaches and methods?
- What is known about delivering interventions at opportune moments?

Research articles describing the implementation of health behavior change support technologies and other user-adaptive software systems were examined in terms of the employed user modeling and personalization approaches. The maturity of the technology at the time was assessed by comparing the gaps between the state-of-the-art research and the personalized health guides envisioned in the publication.

4.2 Study settings and participants

In Publication II, a cross-sectional dataset of anonymous responses to the web survey of the Finnish Happiness-Flourishing Study (FHFS) (Joutsenniemi et al., 2013) was analyzed to explore associations between values, well-being, and health behaviors. Cross-sectional studies provide a snapshot in time, where the prevalence of the outcomes or variables of interest are examined simultaneously at a particular time point (Grimes & Schulz, 2002). However, inference on causal relationships cannot be made based on cross-sectional studies, as the temporal relations between the measured variables are unknown.

The survey data were collected via a public website over a 1-year period, between 2009 and 2010, as part of the FHFS, which was a national health promotion campaign. In addition to the FHFS website that hosted the survey, the campaign included a reality TV show (of eight weekly episodes) about happiness and depression, where selected Finnish celebrities were taught happiness-related skills. The TV show attracted roughly 250,000 weekly viewers. The FHFS survey was advertised during the episodes as well as at the website of the TV production company. The survey offered people the possibility to measure their happiness levels and compare their overall score to the results of other Finns. In addition, it encouraged people to identify the key sources to their happiness (i.e., personal value items) and included a variety of questions regarding other well-being factors and health behaviors. The survey items are available (in Finnish) in the Appendix I of Publication II.

The web survey was freely available to all Finnish speaking individuals who had access to the internet. Altogether 139,462 anonymous responses were received, and after data cleaning procedures (see Publication II for details), 101,130 valid responses remained for further analysis. Of the valid responses, 62,625 responses covered personal value items. The basic background characteristics of the respondents are provided in Table 1. The age distribution in the sample was representative of the Finnish working-age population at the time of the study, but biases towards female respondents and higher education levels were present (Statistics Finland, n.d.).

Table 1. Participants' background characteristics (Publications II and III)

Characteristic		Publication II (*N*=101,130)	Publication III (*N*=50)
Age (years)			
	mean ± SD*	44.78 ± 13.82	46.40 ± 9.67
Gender, *n* (%)			
	Female	79,770 (78.88)	48 (96.0)
Education, *n* (%)			
	Comprehensive school	11,686 (11.56)	0 (0.0)
	Secondary school	23,492 (23.23)	8 (16.0)
	Bachelor's degree or equivalent	30,377 (30.04)	27 (54.0)
	Graduate degree	21,143 (20.91)	15 (30.0)
	Unknown	14,432 (14.27)	0 (0.0)
Body mass index (kg/m2), *n* (%)			
	Underweight (< 18.5)	1,687 (1.67)	0 (0.0)
	Normal (18.5 – 24.99)	50,339 (49.78)	22 (44.0)
	Overweight (25 – 29.99)	31,313 (30.96)	15 (30.0)
	Obese (≥ 30)	16,095 (15.92)	13 (26.0)
	Unknown	1,696 (1.68)	0 (0.0)
*SD = standard deviation			

The evaluation study of With-Me HRS (Publication III) was conducted as a secondary analysis of a two-armed pilot randomized controlled trial (RCT) (Muuraiskangas et al., 2022), where technology-assisted and traditional telephone coaching for occupational health were compared in terms of effectiveness and the time use of health coaches (main outcomes) in a real-life coaching context. The secondary outcomes regarding the validity and usefulness of With-Me HRS are in the focus of Publication III. The HRS was utilized for setting the action (or coaching) plans for the participants of the technology-assisted telephone coaching arm (*group with visible recommendations*), whereas in the traditional coaching arm, the recommendation generated by the HRS were not used for decision-making (*group with hidden recommendations*). Three health coaches were involved in the study, who were each assigned an equal number of participants from the two study arms.

In the beginning of the coaching program, all the participants were asked to fill out a web survey regarding well-being - including the WorkOptimum questionnaire for occupational health (Ahveninen et al., 2014) - health behaviors, and intention to modify behaviors. In addition, the group with visible recommendations conducted a 3-day Firstbeat lifestyle assessment (Firstbeat Technologies Ltd.), which is based on heart rate variability (HRV) and movement, measured via chest electrodes. The assessment was used to provide objective indicators of physical activity levels and physiological stress and recovery (well-being). The web survey answers and the objective indicators were fed to With-Me HRS for the analysis of participants' behavior change needs and intention to change. Then, based on the results, With-Me HRS generated recommendations for behavior change actions.

For the group with visible recommendations, the results of the HRS's behavior change needs analysis were examined by a health coach before the first personal contact with a participant. In addition, a PDF (portable document format) report of the Firstbeat lifestyle assessment was provided for both parties. During the first coaching call, the coach discussed participants' behavior change needs and a high-level behavior change objective was agreed upon (e.g., sleep better, manage workload, eat healthier). The participants were also asked to preselect one to three behavior change actions or tasks for themselves via With-Me HRS before the next coaching call, which was scheduled after two weeks: Participants were able to select tasks from a recommended list of 20 items (see Section 4.5.2 for details regarding the recommendation logic), or from the library of all available items, or alternatively, they could create custom actions of their choice. During the second coaching call, the preselected tasks were either confirmed by the coach or adjusted in a mutual agreement. Hence, the coaching plan was established. For the group with hidden recommendations, the coaching plan was set already during the first coaching call without the help of With-Me HRS. A PDF report of the WorkOptimum questionnaire results was the only preparatory material provided before the call.

To assess the performance of the recommendation algorithm used by With-Me HRS, coaches were asked to verify that the knowledge used as the basis for recommendations was up to date for each participant (also for the group with hidden recommendations) before any recommendations were generated. Specifically, after the first coaching call, the coaches were able to modify participants' behavior change needs, which were inferred by the HRS, and their intentions to change. In addition, coaches were asked to keep track of the final coaching tasks that were selected to the coaching plans of each participant for identifying the recommended tasks that were included.

The participants were recruited among the employees of the City of Oulu, Finland. Most of them worked in female-dominant occupations in the areas of information technology, education, culture, as well as customer, social, and health services. The inclusion criteria for participation included full-time employment, a (self-reported) decreased state of well-being, living in a relationship, and motivation to make lifestyle changes for improving well-being. Altogether, 50 participants were recruited and randomly allocated to the groups receiving visible (*N*=25) or hidden (*N*=25) recommendations. Nearly all the participants were female, a slight majority was middle-aged (58% were aged between 46 – 60 years) or overweight (56%), and most were highly educated (84% held a Bachelor's degree or higher). Details regarding the background characteristic are provided in Table 1. Further information regarding the study procedures and participant recruitment are available in Publication III and the report of the main RCT outcomes (Muuraiskangas et al., 2022).

During the concept evaluation of the MyProfile health profiling service (Publication IV), its user experience was investigated and ideas of new, appealing functionalities to the service were gathered. The evaluation was qualitative, and it was conducted via online asynchronous focus group discussions over a three-week period. The group discussion took place on a co-design platform, Owela (Friedrich, 2013), where researchers could post polls and discussion topics in a blog format and research participants could answer the polls and post comments. The participants for the evaluation study were recruited from the volunteer database of registered Owela users without any participation restrictions. The participants were first asked to register to the MyProfile service and use it freely, and then provide feedback via Owela by answering opinion polls and participating in theme discussions facilitated by researchers. The answers and comments were visible to all participants. Altogether, 29 participants took part in the focus group discussions, of which 69% were women (20/29). The mean age of participants was 57 years (range 21 – 90 years, 66% were 51-80 years).

4.3 Study outcome measures

In the following, only the outcomes relevant for the defined RQs are presented. The relevant question items from the FHFS web survey (Publication II) are provided in Table 2.

Table 2. Relevant questionnaire outcome measures from Publication II

Outcome measure	Response options
Happiness	
Happiness-Flourishing scale (Joutsenniemi et al., 2013)	10 items with a 7-point Likert scale, scoring range: 10 (very unhappy) – 70 (very happy)
Regular exercise	
On the average, how much do you exercise or strain yourself physically during your leisure time? (Wilhelmsen et al., 1972)	1. I am not very active physically in my leisure time. 2. In my leisure time, I walk, cycle, or am otherwise physically active for at least 4 hours per week. 3. I exercise at least 3 hours per week in my leisure time. 4. In my leisure-time, I practice for competitive sports regularly several times a week at a vigorous intensity. Response options 2-4 were dichotomized as "regular exercise" according to the global physical activity recommendations (World Health Organization, 2020).
Healthy eating	
On the average, how often do you eat fresh fruits or berries?	1. Less than once a week 2. 1-2 times per week 3. 3-5 times per week 4. Daily The response options for both questions were combined into a binary variable that describes the daily consumption of fruits, berries, or vegetables according to the global public health recommendations (World Health Organization, 2019)
On the average, how often do you eat fresh vegetables?	
Alcohol consumption	
How many units of alcohol do you drink per week? (accompanied with an explanation of an alcohol unit)	Integer value
Non-smoking	
How many cigarettes, cigars, or pipefuls do you smoke per day?	Integer value; the values were dichotomized with zero values referring to "non-smoking".
Commitment to values	
I have firm values that I strive to nurture.	A 7-point Likert scale: 1 = completely disagree, 7 = completely agree

In addition to these questions, respondents were asked to specify the key ingredients to their happiness via an interactive user-interface as a proxy for personal values. The respondents were exposed to a library of more than 200 different value items via a space-like animation, where items appeared and disappeared in a random order, resembling twinkling stars in the night sky. The library included words such as "ambition", "wealth", "creativity", "spending time in the nature", "kindness", "honesty", "patriotism", "self-discipline", "piece of mind", "family", "health", "stress management", "friendship", "travelling", "fortitude", and "occupation". The user-interface allowed to specify at most 20 different value items. The items could be chosen from the library of values either by clicking the appearing terms on the screen or using a search box with predictive text input. Alternatively, the respondents could enter their own free text items from outside the library.

Though the employed method for collecting value data is atypical for value research, it shares similarities with the traditionally used instruments for measuring values and can, therefore, be considered to provide a sufficiently good approximation for values. The commonly used value instruments include the 57-item Schwartz Value Survey (SVS-57), which asks respondents to rate the importance of different value items as "a guiding principle in your life" (Schwartz, 1992), and the Portrait Value Questionnaire (Schwartz et al., 2001), which measures values indirectly by asking respondents to evaluate statements that reflect the importance of the value items ("It is important to…") (Schwartz & Cieciuch, 2022). In practice, the definitions of "a guiding principle in your life" and "the key ingredients to happiness" are sufficiently similar to each other, as the concepts that produce happiness must be something that people desire to pursue in their lives, which is characteristic also to values by definition (see Section 2.1 about behavioral theories). Furthermore, in the FHFS survey, a clear indication was given about the type of information expected as the respondents were exposed to the predefined library of value items, which is the case also with SVS-57. Although, the FHFS survey did not require respondents to specifically evaluate the importance of different value items, it is reasonable to assume that the reported values were somehow personally important, since the responses were not restricted in anyway, i.e., people could decide for themselves which items were worth reporting.

In Publication III, the suitability of With-Me HRS in supporting real-life health coaching was evaluated by assessing the validity and usefulness of the recommendations. The primary outcome for validity was the proportion of participants for whom at least one of the recommended actions was included into the coaching plan. In addition, as a secondary outcome for validity, the proportion of participants in the group of visible recommendations who preselected actions from the recommended list of items as their preferred coaching tasks was investigated. Regarding the usefulness of With-Me HRS, both the coaches' and participants' perspectives were evaluated via the following question items presented in Table 3.

Table 3. Question items for assessing the usefulness of With-Me HRS (Publication III)

Outcome measure		Response options
Coaches' perspective		
	Ease of identifying participants' needs: During the coaching call, it was easy to identify the behavior change needs and objectives for the client.	A 5-point Likert scale: 1 = completely disagree, 5 = completely agree
	Ease of identifying coaching tasks: During the coaching call, it was easy to identify suitable coaching tasks for the client.	
Participants' perspective		
	Ease of explaining needs: My coach understood my well-being related needs with ease.	A 5-point Likert scale: 1 = completely disagree, 5 = completely agree
	Improved self-awareness of needs: My coach helped me realize new areas for improvement that are important for my well-being.	
	Satisfaction with coaching calls: I am satisfied with the coaching call(s).	

For the group with visible recommendations, coaches evaluated the ease of identifying participants' needs immediately after the first coaching call, whereas all the other self-reported outcomes were measured after the second call. For the group with hidden recommendations, all self-assessments were conducted after the first coaching call.

The concept evaluation study of the MyProfile service (Publication IV) included theme discussions related to the following topics: 1) user experience of the metrics and visualizations included into the weight management profile, 2) interesting profile topics (including a poll), 3) ideas of new appealing features to the service, and 4) opinions about sharing personal data between MyProfile and other health services (e.g., coaching services, healthcare sector).

4.4 Statistical analyses

In Publication II, logistic and linear regression were used to explore the associations of values and commitment to them with happiness and health behaviors. Before investigating the associations, the reported value items were classified into value types based on the Schwartz value theory of ten motive orientations (Schwartz, 1992) with the difference of having the "universalism" value divided into two subtypes: "nature" and "social concern". These categories of 11 value types have been applied also in previous research, e.g., in (Lee et al., 2008; Schwartz et al., 2012; Schwartz & Boehnke, 2004).

Altogether, 23,552 different terms or expressions were used to describe values, including the entries with typing errors. If an entry occurred less than 50 times in the sample, it was discarded to omit nonsense responses and items with typing errors from the classification. Next, synonyms and words, for which an obvious descriptive superordinate concept could be identified, were renamed with a common name by the author. For instance, the synonymous terms "buddies", "good friends", and "friendship" were renamed as "friends", and the words "wife", "husband", "spouse", "boyfriend", and "girlfriend" were renamed as "partner". After the data cleaning phase, 472 distinct terms remained in the dataset for classification.

The value classification procedure was conducted in two phases, manual and computational. In the first phase, the author manually located the distinctive terms under the 11 Schwartz value types according to the value items defined in the 57-item SVS (Schwartz, 1992). However, for many of the reported terms, a direct match could not be identified from the SVS items. Hence, additional non-Schwartz value classes were created that covered terms describing similar concepts, but for which suitable Schwartz value items could not be identified with high certainty. At this point, distinct non-Schwartz classes were defined even for rather alike concepts to minimize possible information loss, despite increasing the likelihood of highly correlated groups. As a result, 27 non-Schwartz value types were created. In the second phase of the classification procedure, several iterations of principal component analysis (PCA) were used to identify highly correlated Schwartz and non-Schwartz value types for merging. Only valid responses (55,539 out of the 62,625 available survey responses), defined as comprising four or more identifiable value items that covered at least 90% of the given terms in a response, were included in the PCA to strengthen the reliability of the classification. During the final PCA iteration, the final grouping of value items was verified, as the results did not indicate further merging needs between the value types. The final value classification included

20 non-Schwartz and 11 Schwartz value types. The details of the PCA procedure are explained in Appendix 2, and the definitions for the resulting 20 most common value types are provided in Appendix 3 of Publication II.

The associations between value types, happiness, and different health behaviors were studied for the 20 most common value types, i.e., for those reported at least in 10% of the valid value responses. Logistic regression was used to examine the relationship between a certain value type and a well-being related outcome (happiness, regular exercise, healthy eating, non-smoking, or alcohol consumption), where the value type was a binary variable (0 = "no items reported" and 1 = "at least one item reported" for the value type). The results were presented via odds ratios. For the continuous happiness and alcohol consumption outcomes, the odds ratios were computed per 10 units of change. The association between commitment to values and happiness was investigated with linear regression (see details from Publication II), and squared semipartial correlation (part r^2) was reported as the measure for effect size. All the analyses were adjusted for age and gender, and the statistical significance of the explored associations were considered at an alpha level of 0.001.

In Publication III, Mann-Whitney *U* tests were conducted to determine whether the usefulness of With-Me HRS differed between the groups with visible and hidden recommendations from the coaches' and participants' perspectives in terms of the investigated self-assessments. The group-level medians coupled with the first (*Q1*) and fourth (*Q4*) quartiles were reported for the self-assessments. The differences in group medians were considered statistically significant at an alpha level of 0.05. In addition, the Vargha-Delaney $\hat{A}$ measure of stochastic superiority (Vargha & Delaney, 2000) was reported as an indicator of the between-group effect sizes.

4.5 Implementation of With-Me HRS

4.5.1 Overview

With-Me HRS was developed to provide personalized support in determining the appropriate coaching plan for a person by considering one's behavior change needs from a multidomain viewpoint. It was designed to recommend behavior change actions from altogether 14 behavioral domains related to well-being and a healthy lifestyle (see Table 4.).

Table 4. Behavioral domains supported by With-Me HRS

Health behavior and well-being objectives (and domains)	
Reserve more time for sleep (sleep sufficiency)	Manage workload (workload management)
Improve sleep quality (sleep quality)	Practice relaxation skills (recovery from stress)
Improve eating rhythm (eating rhythm)	Practice cognitive defusion from negative thoughts (anxiety)
Improve diet quality (diet quality)	Clarify and live up to personal values (personal values)
Manage emotional eating (emotional eating)	Improve the quality of relationship with partner (quality of relationships)
Increase physical activity (physical activity)	Improve self-esteem (self-esteem)
Reduce alcohol consumption (alcohol consumption)	Cease smoking (smoking)

The behavior change actions available for recommendation were based on various BCTs (Michie et al., 2013). Some examples of the actions (with the related BCT) include: "Read an online article about the symptoms of stress and good practices for stress management" (information about health consequences), "Take a quiz for evaluating your alcohol consumption patterns" (feedback on behavior), "Find an exercise buddy" (social support), "Use Oiva to ponder the reasons that are keeping you from fulfilling your personal values in everyday life" (pros and cons), "Make a realistic list of work tasks for the upcoming work day" (action planning), "Keep a diary about eating habits for three days"(self-monitoring), "Keep fruits in sight and vegetables easily accessible at home" (restructuring the physical environment),"Wake up at the same time every day" (habit formation), and "Practice mindfulness skills with Oiva exercises" (behavioral practice). As revealed by these examples, some of the actions directed the person to utilize a 3rd party service, the Oiva web portal (oivamieli.fi), which was developed to promote mental well-being via short acceptance and commitment therapy exercises (Mattila et al., 2016).

With-Me HRS was integrated with two 3rd party online modules: Movendos health coaching service (v1.27, Movendos Ltd.), used by the coaches and participants for communication and progress monitoring, and LimeSurvey survey tool (www.limesurvey.org), used to gather the participant information required for generating personalized recommendations. Together, these modules formed a digital health coaching system, which functionalities are described in detail in (Muuraiskangas et al., 2022). With-Me HRS itself was composed of two database components, the Personal profile and Intervention library, and of two functional components, the Profiler and Recommendation engine. Figure 3. describes the technical architecture of With-Me HRS and its connections to the other modules of the health coaching system.

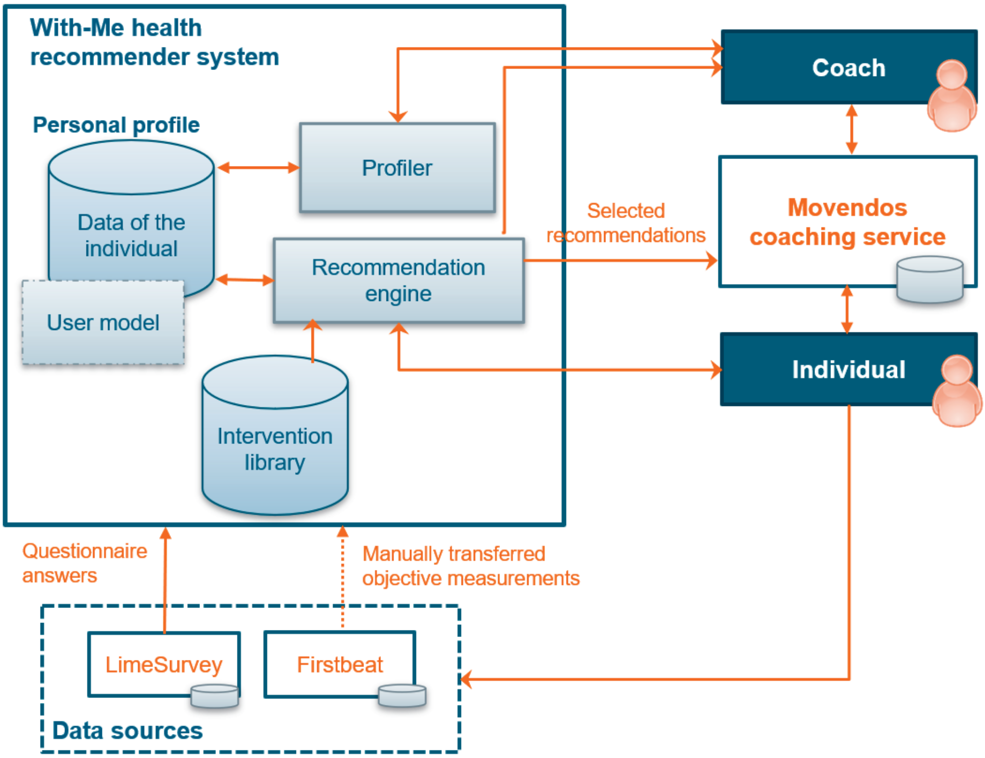

Figure 3. The technical architecture of With-Me HRS and its connections to the other digital health coaching modules (published in Publication III)

The Personal profile included a database of feature values that was specified and structured according to a conceptual user model that defined features related to well-being, health behaviors, and intentions to change lifestyle (see Section 5.2 for the user modeling details). The Profiler component created and maintained the Personal profile based on the data collected via LimeSurvey or provided by the Firstbeat lifestyle assessment. The Profiler was also in charge of analyzing the behavior change needs of a person in terms of each of the 14 behavioral domains based on one's perceived well-being and the comparison of their lifestyle habits to public health recommendations. In addition, the Profiler categorized one's intentions to change per behavior according to the TTM's stage of change construct (pre-contemplation, contemplation, preparation, action, maintenance) (Prochaska & Velicer, 1997). These analysis results were stored in the Personal profile. The Profiler provided also a user-interface for coaches to examine the participants' behavior change needs and intentions for each behavioral domain and to modify them. The knowledge maintained in the Personal profile was utilized by the Recommendation engine, which recommended behavior change actions accordingly (see the next section). The item space for recommendations was specified by the Intervention library database. The Recommendation engine provided also a user-interface for presenting the recommendations and the content of the Intervention library. The behavior change actions selected by a participant were stored in the Personal profile, but also transferred to the Movendos health coaching service.

4.5.2 Recommendation engine

With-Me HRS used the case-based reasoning approach of knowledge-based filtering (introduced in Section 2.3.2). It retrieved the Intervention library items (or cases) that matched the behavior change needs and intentions of a person, i.e., the features of the Personal profile (the target case). The Personal profile included vectors $\boldsymbol{b^i}$ specific to a behavioral domain $i \in \{1, \dots, 14\}$, which described the strength of the change need $b^i_{\text{str}} \in [0,1]$ (0: no need, 1: high need), and the intention to change $b^i_{\text{stg}} \in \{1, \dots, 5\}$ in terms of TTM's stages of change (1: pre-contemplation, 5: action). The Intervention library covered over 100 behavior change actions, which were described by features similar to the Personal profile: for each action j, the subset of behavioral domains and the stages of change that the action was designed to address were specified. Actions were matched to TTM's stages based on earlier examples of stage-matched interventions and the related research evidence, e.g. (Kim et al., 2004; Norcross et al., 2011). Actions that involved identifying the benefits or costs of a habit or raised awareness of one's current behavior (information of consequences, feedback) were associated with the pre-contemplation and contemplation stages. Actions that involved planning, solving obstacles, or creating supportive conditions for the target behavior (e.g., via seeking social support or restructuring the physical environment) were mapped to the preparation stage, whereas the action and maintenance stages were matched with repetitive tasks of practicing the target behavior or actions for relapse prevention. Self-monitoring actions were specified to match any of the TTM stages.

The employed case-based recommendation method used two Manhattan distance based similarity metrics: $\text{sim\_need}^j \in [0,1]$ and $\text{sim\_stage}^j \in [0,1]$, which together determined the suitability, $\text{sim\_total}^j \in [0,1]$, of an action j for recommendation (0: low similarity, 1: high similarity). The sim_need^j metric described the similarity between the behavior change needs $\{b^i_{\text{str}}\}$ identified in the Personal profile and the behaviors addressed by an action j. The sim_stage^j metric described the similarity between the TTM stages $\{b^{i'}_{\text{stg}}\}$ identified in the Personal profile for the behaviors i' relevant for action j, and the stages addressed by the action j. If $b^{i'}_{\text{stg}}$ belonged to the subset of stages defined for action j, $\text{sim\_stage}^j = 1$. The formulas for the similarity metrics are specified in Publication III. The recommendation method can be summarized via the following four key steps:

a) **Compute similarity metrics for each action** j, regarding the behaviors i' it focuses on:
    a. $\text{sim\_need}^j \in [0,1]$: the similarity between the behaviors i' and the Personal profile's behavior change needs $\{b^i_{\text{str}}\}$,
    b. $\text{sim\_stage}^j \in [0,1]$: the similarity between the TTM stages addressed by the action j and the stages $\{b^{i'}_{\text{stg}}\}$ identified in the Personal profile for the relevant behaviors i',
    c. total similarity, $\text{sim\_total}^j \in [0,1]$: if $\text{sim\_need}^j \geq 0.5$, then $\text{sim\_total}^j = mean(\text{sim\_need}^j, \text{sim\_stage}^j)$; otherwise $\text{sim\_total}^j = 0$. Hence, only the actions that target the behaviors for which the person has at least a moderate need for change are considered for recommendation.

b) **Preselect a list of candidate actions** $\boldsymbol{A}$ for which $\text{sim\_total} \geq 0.5$.

c) **Sort** $\boldsymbol{A}$ in a descending order according to sim_total after randomizing the order of actions. Randomization prevents the actions that target the same behaviors from clustering together in the list.

d) **Select the top-20 items** from the ordered list A for recommendation.

5 RESULTS

5.1 User modeling framework for personalizing DHBCIs

Publications I-III address RQ1: "What kind of personalization purposes can different personal characteristics (user model features) serve in DHBCIs?" To answer this question, it is important to first understand what kind of factors determine behavior, as interventions should tackle the discouraging and strengthen the supportive factors of behavior change. In Publication I, the key determinants of reasoned behavior and their relationships were identified based on the analysis of the theoretical foundation of health behavior change. The results are depicted in Figure 4. as a high-level conceptual model, which summarizes the central constructs over several behavioral theories.

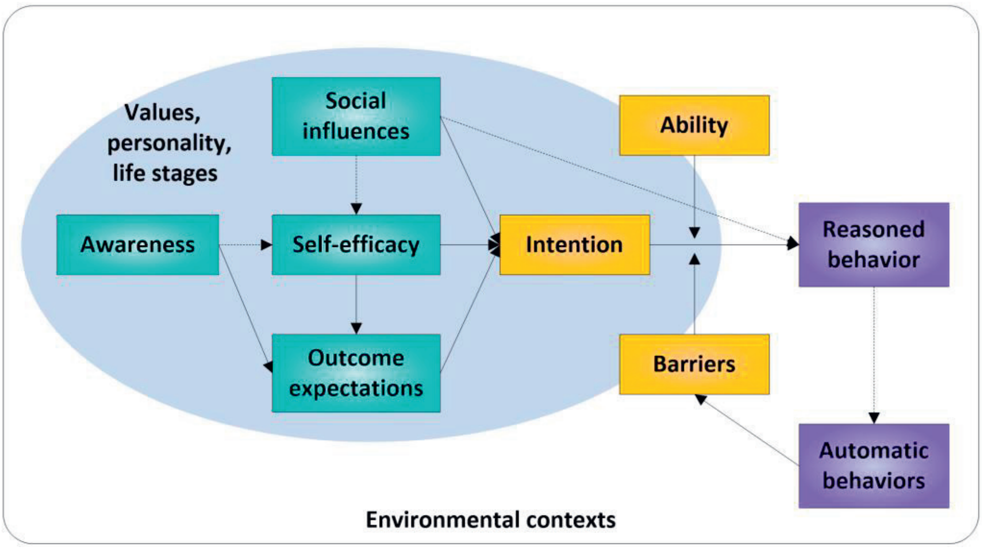

Figure 4. The determinants of reasoned behavior and the relationships between them (published in Publication I, © 2011, IEEE)

In the beginning of a behavior change process, reasoned behavior is required, as desired behavioral changes rarely take place without deliberate intention and conscious actions. However, long-lasting changes require that the new behavior becomes as automatic as possible, i.e., becomes cued by a certain context and forms into a habit. The immediate determinant of reasoned behavior is intention, which refers in this context to the level of motivation and commitment one has towards performing the behavior. Though the stages of behavior change are not explicitly illustrated in Figure 4. the intention determinant comprises these stages which can vary from no intention to intending to act and to taking action. The abilities to perform and the barriers constraining or discouraging the behavior determine whether intention can be translated into maintained behavior change. Abilities and barriers can be related to one's internal resources such as self-regulation skills (e.g., action planning and self-monitoring), personality traits, psychological abilities, or physical capabilities, or to the available environmental resources such as the social influence of peers, access to services and products, or time and money. Conflicting unhealthy habits and biases in thinking act also as barriers to the new behavior, as old habits are hard to break. The main determinants of intention include awareness, social influences, self-efficacy, and outcome expectations, which are influenced by one's personality, values, and life stage. Finally, individuals constantly interact with their immediate physical and social environment, which sets the limits and possibilities for actions and personal development. The details about the determinants of behavior were provided in Section 2.1.

In Publication III, the theoretical foundation of behavior change, the principles of evidence-based intervention planning for health promotion (Fernandez et al., 2019; Michie et al., 2005; Willmott & Rundle-Thiele, 2021), and the knowledge of the common user model features used for personalization in DHBCIs (presented also in Section 2.3) were utilized to identify a) the user-specific knowledge required for the advanced personalization of DHBCIs and b) the user model features that could provide this knowledge. The user-specific knowledge that was identified as relevant for personalization was described by the following questions:

1) What are the risk behaviors to be addressed (e.g., unhealthy eating rhythm, insufficient sleep, lack of exercise)?
2) How motivated is the person to modify these behaviors? Are they aware of the need to change behavior?
3) Which determinants of behavior should be addressed for increasing motivation and eliciting behavior change?
4) What are the factors (abilities / barriers) that facilitate or impede behavior change?
5) What motivates and interests the person? How should intervention materials and messages be framed to increase motivation towards behavior change,

e.g., elicit emotions vs. stick to facts, or use negative vs. positive framing (Hornik et al., 2016; Josekutty Thomas et al., 2017; Salovey, 2005)?

6) What are the opportune moments to provide support?
7) What kind of behavior change techniques (Kok et al., 2016; Michie et al., 2013) and activities are effective for the person?

In this work, a user model that is able to represent knowledge that provides answers to the abovementioned questions is referred to as the *virtual individual model* (VIM). This term was originally introduced in Publications I and III to emphasize the need to describe user needs and characteristics comprehensively in the user models of DHBCIs for delivering effective behavior change support. The VIM was envisioned to cover all the relevant features required for the adequate personalization of DHBCIs.

The first attempt to specify the elements and user feature types of the VIM was made in Publication III based on the identified knowledge needs. As a result, a comprehensive user modeling framework, the VIM framework, was designed. The core feature types included in the VIM framework are categorized under four high-level elements: 1) health and well-being, 2) resources, 3) motives and preferences, and 4) behavior change needs and determinants. These elements were designed to provide answers to the questions 1-5. Therefore, they include features which help identify the appropriate behavior change plan (or action plan) for a person. In addition to the core elements, the VIM includes feature types related to momentary context, intervention items, and progress evaluation, which provide answers to the remaining questions 6 and 7 and, therefore, support the execution of the defined behavior change plan. Figure 5. presents the VIM elements and the related feature types (concrete feature examples are provided in Appendix 1 of Publication III). Two additional blocks are visible in the figure, which are not part of the VIM framework but closely related: The intervention library defines the available items for constructing the personalized intervention, for instance, the variety of behavior change objectives, techniques, and actions that can be recommended to individuals. Thus, the intervention library determines the space for personalization (or recommendations). In addition, keeping track of the intervention items appropriate for other individuals similar to the target person can provide added value for personalization, when the personalization methods of collaborative and demographic filtering are applied.

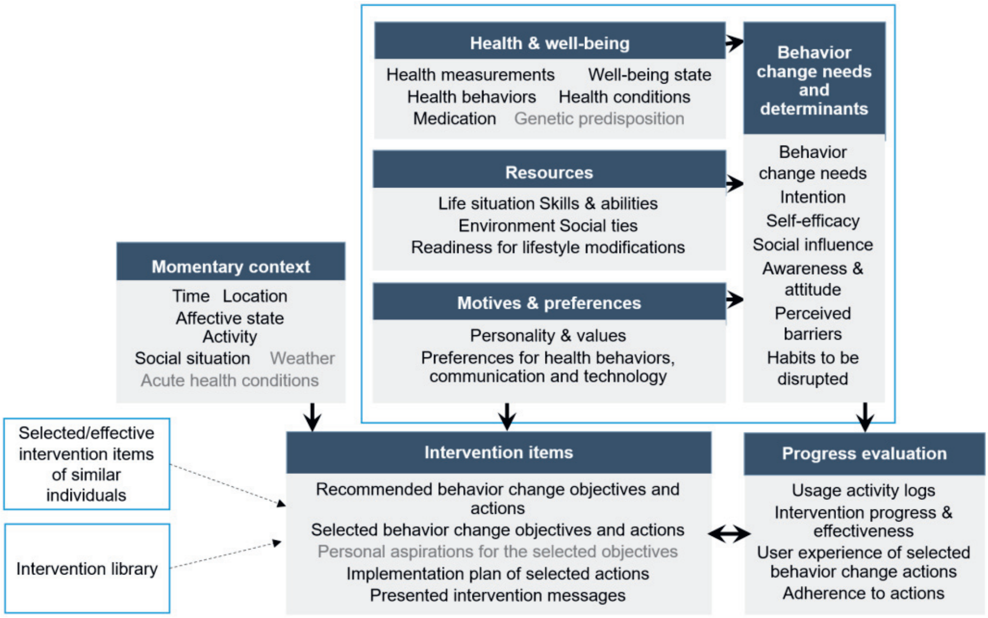

Figure 5. Elements of the VIM framework and the related feature types (updated from Publication III)

The VIM includes also certain feature types that seem promising for personalization but lack a solid theoretical background or a proven practical value. These features are presented with a grey font in Figure 5. The figure has been modified from Publication III by changing the color of the activity and social situation features under the momentary context element from grey to black. Though, these features are rarely used in recent HRSs (see Section 2.3.1), the review results in Publication I reveal that they can be useful for identifying the opportune moments to interrupt a person.

Finally, the following personalization purposes can be served by the identified VIM feature types (described per VIM element):

- **Health & well-being** features help determine individuals' behavior change needs and their relative importance in terms of health benefits. The features reveal one's risks to develop lifestyle-related diseases or mental health issues and indicate the behaviors aggravating the risks.
- **Behavior change needs and determinants** enable to identify appropriate behavior change objectives for a person, to adapt recommended actions to one's intentions and capabilities to change behavior, and to identify the behavioral determinants to target and the appropriate BCTs to apply in the recommendations. The features can be partially inferred based on the health & well-being, resources, and motives & preferences elements.

- **Resources** facilitate the recommendations of behavior change actions that are achievable with a reasonable effort by considering one's general abilities and barriers for behavior change. For instance, the features inform about one's everyday routines, the facilities readily available, psychological abilities, and close social ties, which could be leveraged by the recommendations. In addition, the features indicate whether certain personal abilities or skills need to be strengthened before the person can successfully engage with a target behavior.
- **Motives & preferences** enable to use persuasive message framing and the tone of communication that is perceived as appealing and credible by the user, to consider users' preferences regarding alternative options for behavior change actions, and to associate recommended objectives and actions with personally meaningful life goals (i.e., value-based aspirations) to increase user engagement.
- **Momentary context** features enable to identify the opportune moments for disrupting the user with an intervention message or prompt and delivering recommendations and support (when in need of and receptive for support), as well as to identify the type of support appropriate for a particular moment. This is especially important when attempting to provide real-time support and guidance.
- **Intervention items** and **progress evaluation** features facilitate the dynamic adaptation of intervention content and providing feedback to users. They inform when the selected intervention items (behavior change objectives and actions) need to be updated and what kind of items are inappropriate for the person by keeping track of the recommended and selected items, the adherence to the set behavior change plan, the progress towards objectives, and the effectiveness of the completed actions in terms of health benefits.

Publication II focused on values (located under the "motives & preferences" element of the VIM) and provided ideas on how values could be utilized in personalization for increasing user engagement with DHBCIs. The motivational role of values in guiding behavior, especially in terms of health behavior, was supported by the observed associations between self-reported values and health behaviors. For instance, reporting value items related to "health" (a non-Schwartz value) was associated with several healthy behaviors (regular exercise, healthy eating, and non-smoking with increased odds of 71.71%, 39.96%, and 26.76%, respectively); valuing the nature part of "universalism" was associated with regular exercise and healthy eating (increased odds of 26.09% and 13.94%, respectively); and "tradition" (commitment to traditions or religion) was related to a reduced alcohol consumption (an increased odds of 29.30%). However, unhealthy behaviors (smoking, unhealthy eating, and irregular exercise) were associated with valuing "power" (dominance, social status; increased odds of 27.80%, 27.78%, and 24.66%, respectively) and "mental balance" (striving for self-acceptance, non-Schwartz; increased odds of 20.79%, 16.67%, and 15.37%, respectively). "Power" was also associated with an increased alcohol consumption (an increased odds of 17.35%), and both, "power" and "mental balance", were associated with decreased happiness levels (increased odds of 20.69% and 24.12%, respectively). In addition, "conformity" (restraint of violating social norms) was related to smoking and unhealthy eating (increased odds of 20.48% and 19.46%, respectively). "Power", "mental balance", and "conformity" values express deficiency and self-protection needs, which are related to avoiding or controlling anxiety and threat (Sortheix & Schwartz, 2017). Further definitions and exemplary value items for the investigated value types are provided in Appendix 3 of Publication II. Finally, being aware of one's values and committing to them had a strong, positive association with happiness (part r^2=0.28).

As values motivate behavior (Rokeach, 1973; Schwartz, 1992; Schwartz & Bilsky, 1987), the knowledge of the values one holds as important could help in identifying motivational or attitudinal reasons for the lack of intention in terms a healthy lifestyle change. Particularly, people who have a high priority for values reflecting deficiency and self-protection needs may not have the required mental resources to focus on health behaviors due to having more pressing needs to attend to, which could explain the observed findings. In such cases, it may be wise to focus the intervention on strengthening mental abilities. The knowledge of personal values could also provide means to engage individuals who do not find health benefits particularly motivating: values could be used to associate the health behavior change objectives with one's aspirations (located under the VIM's intervention items element), thereby reframing the objectives in a personally appealing way and supporting the development of positive outcome expectations for health behaviors. For example, presenting a healthy lifestyle as a means for increasing productivity and professional influence at work might appeal to people valuing "power". For an individual who highly prioritizes one's immediate family ("loved ones" was the most reported value type in the study sample), introducing healthy habits as a way to gain energy for spending more quality time with one's children/grandchildren could be motivating. Finally, the observed relations between commitment to one's values and happiness support previous research findings which suggest that being conscious of one's values and living up to them is beneficial for subjective well-being (Sagiv & Schwartz, 2000; Sheldon & Elliot, 1999). Since value-congruent behavior seems to be important for well-being, including value clarification exercises and support for value-congruent behavior as intervention topics would be an improvement to the offering of DHBCIs. Indeed, the domain of personal values was supported by With-Me HRS, as mentioned in Table 4.

5.2 User modeling in With-Me HRS

Publication III addresses RQ2, "How should personal information be quantified, structured, and interpreted to form a user profile that facilitates the personalization of multidomain interventions?", by describing the implementation of the Personal profile component of With-Me HRS, which provides an example of such a user profile. In the publication, the term *personal profile* is used to refer to a digital representation of an individual, created by populating the VIM elements with an individual's personal data. Thus, a personal profile is a specific type of a user profile that entails sensitive personal information for the purpose of personalizing DHBCIs.

The With-Me user model, underlying the Personal profile component, implemented the following VIM feature types:

- "health measurements" comprised of HRV-based recovery during sleep and awake,
- "well-being state" comprised of perceived sleep quality, stress, and work well-being, social well-being, and psychological well-being (e.g., life satisfaction and mood),
- "health behaviors" including, for instance, sleep and eating habits, as well as the objective and subjective measures of physical activity level,
- "behavior change needs" (or objectives, see Table 4) derived based on the features related to health measurements, well-being state, and health behaviors, and
- "intention" to change behavior regarding each supported behavior change need.

These features were used for personalizing the recommendations of behavior change actions. However, as the available actions were designed for office workers who lived in a relationship and were willing to make lifestyle improvements, as mentioned in Section 4.2, knowledge about the "life situation" (demographics, occupation, work situation), "social ties", and "readiness for lifestyle modifications" feature types (located under the VIM's "resources" element) was also available for the With-Me user model. The questionnaires and Firstbeat lifestyle assessment indicators that were used to populate the user model are explained in Appendix 2 of Publication III. Furthermore, the user model covered VIM features related to the recommended and selected behavior change objectives and actions, which were used to evaluate the suitability of the recommendations. This involved storing the identifiers (ids) of the recommended and selected Intervention library items to the Personal profile.

The With-Me user model specified how to quantify the selected VIM features and the common properties used to describe them as follows:

- *original value:* the so-called raw value of the feature received directly from the data source (not available for derived features such as behavior change needs),
- *harmonized value:* a transformation of the original feature value to a unified 5-point scale, describing a user's situation with values ranging from 1 (poor) to 5 (good); available for features related to well-being and health behaviors,
- *timestamp:* the time and date of acquiring the feature value,
- *confidence:* an indication of the accuracy of the feature value presented with a continuous scale ranging from 0 (low) to 1 (high),
- *source:* denotes the origin of the feature value (self-report, Firstbeat lifestyle assessment, or derived by the Profiler).

Harmonized values were used to simplify the computations of derived features. Examples of such features include sleep quality determined based on perceived sleep problems and the objectively measured recovery during sleep, and the behavior change needs determined based on various well-being and lifestyle-related features. Confidence values were utilized to determine whether the behavior change needs, analyzed by the Profiler, were accurate, and therefore, could be used for the basis of recommending behavior change actions.

The With-Me user model specified also a three-layered hierarchical structure for the features, comprising "original features", "integrated features", and "aggregated features" (Figure 6. The original feature layer formed the bottom level of the hierarchy, and it hosted the "raw" values provided directly by the available data sources (in addition to the harmonized values). The features based on single-item self-reports were assigned a confidence value of 0.8 to acknowledge the typical bias observed in self-reporting (Bauhoff, 2011), whereas the ones based on validated questionnaire scales were given the value of 0.9. The confidence of the Firstbeat lifestyle assessment indicators were determined based on the percentage of missing heart rate values provided by the assessment. On the integrated layer, original features that measured the same concept but from different perspectives were integrated (e.g., stress level was determined by integrating the harmonized values of the subjective and objective measures of stress). Confidence values were determined based on the agreement between the harmonized values of the features to be integrated; the higher the similarity between them, the higher the confidence for the resulting, new feature. In addition, original features that were closely related to each other were combined to form a higher-level concept (e.g., sleep sufficiency was inferred based on the personal need and the time reserved for sleep) with a confidence value taken as the minimum of the original features' confidence values. Finally, the aggregated top-most layer summarized knowledge across different concepts based on the features residing on the other two layers.

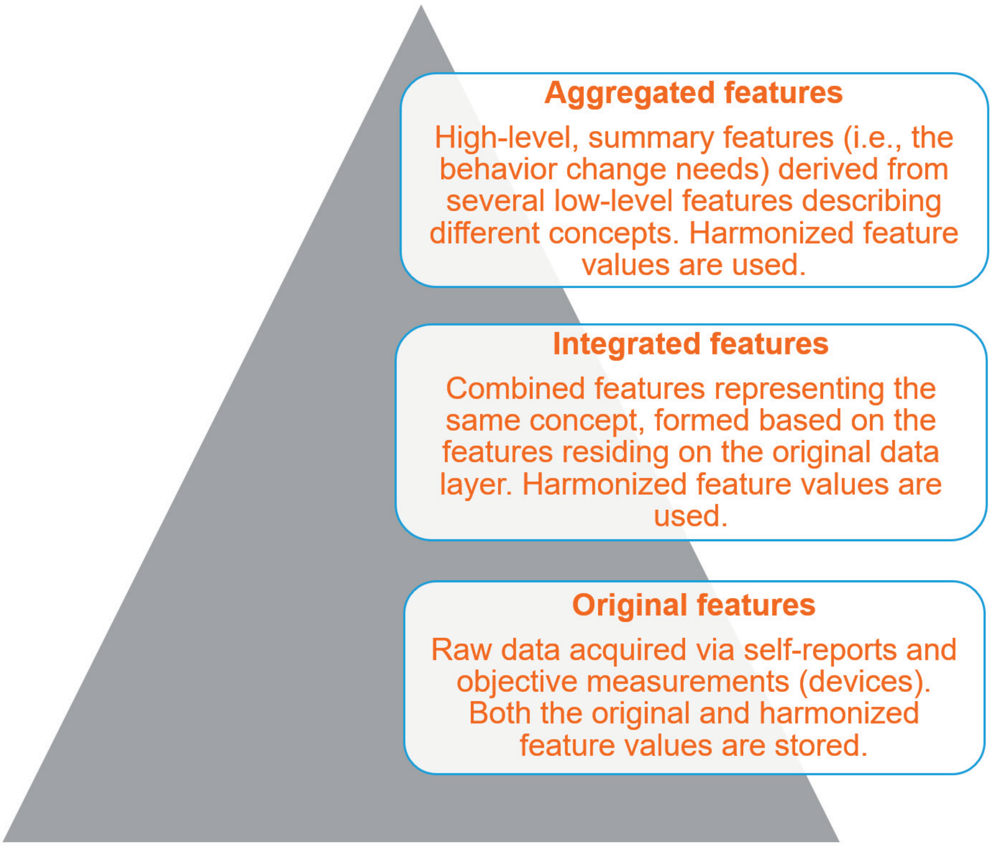

Figure 6. The hierarchical data layers of the With-Me user model (based on Publication III)

The VIM's "behavior change needs" was the only feature type residing on the aggregated feature layer of the With-Me user model. Deriving these needs involved the interpretation of information over several well-being and lifestyle factors residing at the lower data layers. The needs were represented in a format that could be directly utilized by the recommendation algorithm (see Section 4.5.2). For each of the 14 behavioral domains supported by With-Me HRS, the behavior change need was evaluated by comparing the similarity between an object and a reference vector which included a subset of the user model features, relevant to the specific domain. For instance, the need to clarify personal values was determined based on life satisfaction and the perceived sufficiency of time for important life areas, and the need to practice relaxation skills was derived based on stress level (an integrated feature), perceived ability to relax, irritability, work efficiency, and sexual desire. The object vector was based on the Personal profile values, whereas the reference vector included the ideal values for the features in terms of well-being. Hence, the reference vector represented a situation in which behavioral changes were not required (strength of change need = 0). Normalized, weighted Manhattan distance was used as the similarity metric for comparing the reference and object vectors; the smaller the distance between the two vectors, the weaker the change need. The confidence values for the analyzed needs were determined based on the confidence values of the need-specific user features. In addition, missing feature values in the object vectors decreased the confidence. The well-being and lifestyle-related features implemented by the With-Me Personal profile, and the rules used to harmonize feature values, compute derived features, and determine confidence values are described in detail in Appendix 2 of Publication III.

5.3 Evaluation of With-Me HRS

Publication III seeks to answer RQ3, "Is a HRS, which conducts personalization according to users' health behavior change needs and intentions, able to produce multidomain recommendations suitable for real-life health behavior change coaching?", by assessing the validity and usefulness of With-Me HRS in a health coaching context.

The validity of the recommendations could be assessed for the participants for whom the coaches had recorded the final coaching tasks and verified that the knowledge stored in With-Me HRS regarding the behavior change needs and intentions were up to date. Complete and valid data were available for 41 (out of 50) participants. For 73% (30/41) of the participants, at least one of the recommended behavior change actions was included into the coaching plan. For the group with visible recommendations (85% or 17/20), this proportion was higher than for the group with hidden recommendations (62% or 13/21). However, also the number of tasks included into a participant's coaching plan was higher for the group with visible recommendations (median 3.0 [*Q1* 2.8; *Q4* 3.0] vs. 1.0 [*Q1* 1.0; *Q4* 2.0]). Of the participants having two or more tasks specified, 53% (10/19) and 43% (3/7) had at least two of the recommended tasks included into the coaching plans for the groups with visible and hidden recommendations, respectively. Furthermore, in the group with visible recommendations, 90% (18/20) of the participants preselected at least one of the recommended actions as their preferred coaching task and 50% (10/20) wished to select all three coaching tasks (the maximum number of possible tasks) from the list of recommended items.

The usefulness of With-Me HRS was evaluated by comparing the coaches' and participants' perspectives between the two groups (Table 5. The coaches considered it considerably easier to identify appropriate coaching tasks for the participants with visible recommendations than for the other group. However, between-group differences were not observed in coaches' perceived effort regarding the identification of participants' behavior change needs, although the participants with visible recommendations were considerably more satisfied with the coaches' abilities to understand their behavior change needs. In addition, the participants with visible recommendations were moderately more satisfied with the coaching call(s) and with the coaches' abilities to help them realize personally relevant behavior change needs that they were unaware of before.

Table 5. Between-group differences regarding the usefulness of With-Me HRS (based on Publication III)

Outcome	Visible recommendations median (*Q1*; *Q4*)	Hidden recommendations median (*Q1*; *Q4*)	$\hat{A}^{a}$	*P*-value
Coach				
Ease of identifying participants' needs	4.0 (3.0; 4.0)	4.0 (3.50; 4.0)	0.57	.390
Ease of identifying coaching tasks	4.0[b] (4.0; 5.0)	4.0 (3.0; 4.0)	0.71	.005**
Participant				
Ease of explaining needs	5.0 (4.25; 5.0)	4.0 (4.0; 5.0)	0.71	.004**
Improved self-awareness of needs	4.0 (4.0; 4.0)	4.0 (3.0; 4.0)	0.69	.01*
Satisfaction with coaching call(s)	5.0 (4.0; 5.0)	4.0 (3.50; 5.0)	0.67	.023*

The items were measured with a 5-point Likert scale (1 = completely disagree, 5 = completely agree).
Unless otherwise stated, *N*=24 and *N*=25 for the groups with visible and hidden recommendations, respectively.
[a]Vargha-Delaney $\hat{A}$ measure of stochastic superiority for the effect size of between-group difference. Limits for interpretation: 0.56 (small), 0.64 (medium), 0.71 (large) (Vargha & Delaney, 2000)
[b]*N*=25
**P* < .05, ***P* < .01

5.4 Well-being profile views

Publication IV addresses RQ4, "How can the transparency of personalization be improved in DHBCIs?", by introducing the visualizations and metrics of the well-being profile views in the MyProfile service as an example of communicating the reasoning behind behavior change recommendations (transparency of result generation). In addition, the user-interface of With-Me HRS's Profiler serves as an example of providing transparency to the limitations of reasoning.

The well-being profile views in MyProfile explained users' behavioral determinants and behavior change needs. In Figure 7. the key visualizations and metrics used in the profiles are presented for the weight management profile. In the weight management profile, one's eating, exercise, and sleep habits were analyzed based on questionnaires. On the left side of the figure, the states of different behavioral determinants that impact one's capabilities for modifying a behavior are summarized for the three behavioral domains. The nature of a determinant in terms of either supporting or hindering behavior change is denoted by colors; yellow refers to a barrier (challenge) factor and dark green refers to an ability (strength) factor. The visualization on the right side highlights the most and least potential behaviors to target according to the behavior change need and capabilities to change behavior. Behaviors located towards the upper right corner of the graph should be the most potential to target due to the expected health benefits and one's strong motivation and abilities for improving behavior. Users could also download the personal data behind the profile views, i.e., the original questionnaire answers and the derived profile metrics, in a PDF or a machine-readable JSON (JavaScript object notation) file format.

Figure 7. MyProfile summary of the weight management profile (published in Publication IV, © 2018, IEEE)

The participants of the concept evaluation study considered the visual summaries presented in the weight management profile interesting, easy-to-interpret, and useful. For instance, one of the participants commented: *"Clear, interesting how the* [potential for] *changes are visualized. Could the target levels* [for behavior changes] *be also included in the picture as clearly?"* In addition, people liked the thought of receiving similar types of profiles and feedback on other well-being topics such as exercise, diet (including grocery shopping), stress management, and time management (e.g., for balancing work and leisure). However, a need was expressed to consider in the profiles also the current life situation, such as parenthood and work situation, and life changes, as the life situation impacts one's abilities to modify behavior, and life changes influence one's habits. Indeed, this user requirement verifies the importance of including life stages in the user model features of DHBCIs, as suggested also by the VIM (see Figure 5. Suggestions regarding additional features that were considered to improve the MyProfile service included recommendations for concrete behavior change actions, active support for behavior change, monitoring one's progress via evolving profiles, and comparing the profile results with one's peer groups. Sharing the profile results with healthcare service providers was considered beneficial, though a few participants expressed worries about the possible misuse of their personal data regarding the risk of being treated unfairly at work or by the healthcare system. In addition, one of the participants did not see any value in the service.

The Profiler component of With-Me HRS provided transparency of the uncertainty associated with the recommendation results (transparency of limitations) based on the confidence values that were computed for each analyzed behavior change need as explained in Section 5.2. The behavior change needs associated with low confidence were highlighted in the user-interface of the Profiler with a warning sign to urge coaches to check the analysis details and, if necessary, adjust the strength of the need manually by moving a value slider, visible in Figure 8. The coaches were able to inspect the features used to infer a behavior change need by clicking the name of the related behavior change area. In the feature details, the values causing uncertainty to the inference were highlighted with a lightning symbol. In addition, coaches could change the intention to change values (stage of change) for a behavior change area via a drop-down menu. Figure 8 demonstrates these user-interface indicators for the behavior change area related to recovery from stress. In this example, the confidence of the stress level feature is low due to a conflict in the subjective and objective measure of stress.

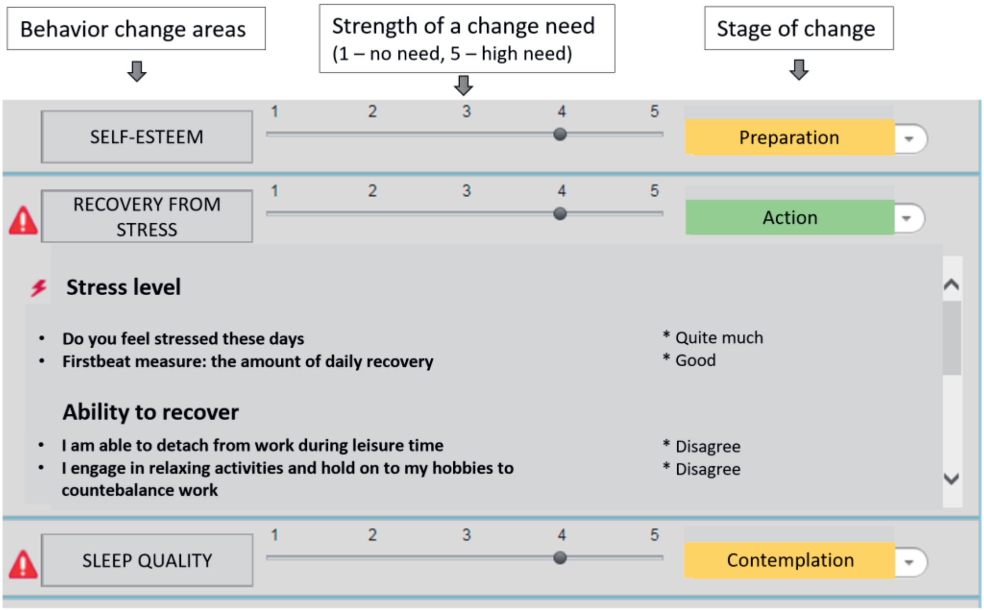

Figure 8. A screenshot of the Profiler user-interface of With-Me HRS

6 DISCUSSION

The aim of the thesis was to accrue knowledge about the effective and transparent personalization of multidomain DHBCIs for health promotion. With *effectively* personalized DHBCIs, the author refers to interventions that can automatically adjust to individuals' personal needs, capabilities, and life situations so that they are successful in empowering people to lead a healthy lifestyle and, thus, in delivering health impact. In *transparent* personalization, the reasoning and data applied for adapting the intervention content (e.g., for generating recommendations) are made visible to users. The specific research objectives were to

a) discover personal characteristics relevant for the personalization of (multidomain) interventions (RQ1),
b) provide an example of an operational user model that is able to facilitate multidomain personalization based on a subset of the identified personal characteristics (RQ2),
c) evaluate the feasibility of a HRS that recommends behavior change actions personalized according to the implemented user model (RQ3), and
d) introduce solutions to improve the transparency of personalization (RQ4).

In the following, the contribution of the thesis is discussed in terms of these objectives. In addition, the implications and limitations of the research are considered.

6.1 Accomplishment of objectives

6.1.1 Relevant personal characteristics for personalization

The personalization purposes that different personal characteristics (user model features) can serve in DHBCIs (RQ1) were discovered by diving into the research literature of behavioral science and personalized DHBCIs, particularly HRSs. A synthesis of the key determinants of reasoned behavior was constructed, which provided the theoretical foundation for different personalization requirements. Then, a comprehensive framework of user modeling features, the virtual individual model (VIM), was defined to serve the identified personalization requirements. The VIM attempts to specify relevant user features that facilitate the effective personalization of multidomain DHBCIs, i.e., features related to users' 1) health and well-being, 2) resources, 3) motives and preferences, 4) behavior change needs and determinants, and 5) momentary context. In addition, it specifies features useful for tracking the 6) intervention items that a user has interacted with and features for 7) progress evaluation. In a nutshell, the VIM feature categories provide the knowledge required for 1) identifying the appropriate behavior change plan for a person, including behavior change objectives, techniques, and actions, as well as other intervention content that are engaging, empowering, and hence effective, 2) facilitating the dynamic adaptation of the intervention, and 3) identifying the opportune moments to deliver support. Furthermore, an exploratory analysis regarding one of the VIM features, personal values, was conducted to gain understanding on how values could be utilized for increasing the user engagement with DHBCIs. In the analyzed FHFS dataset of over 100,000 web responses, several value-congruent behaviors were reported (e.g., valuing health was associated with reporting several healthy habits, and valuing nature was associated with nature-preserving behaviors), which is aligned with value theories claiming that values motivate behavior (Rokeach, 1973; S. Schwartz, 1992; S. Schwartz & Bilsky, 1987). In addition, commitment to values had a strong, positive association with happiness, which supports the previous findings indicating that fulfilling one's values can be beneficial for subjective well-being (Sagiv & Schwartz, 2000; Sheldon & Elliot, 1999).

To the author's best knowledge, the VIM represents the first attempt of gathering a comprehensive set of user model features into one framework for the purpose of serving the extensive personalization of multidomain DHBCIs. The most widely used features for personalization have been related to health status, well-being, and health behaviors, e.g., (Alcaraz-Herrera et al., 2022; Ferretto et al., 2020; Pandey et al., 2020), and recently, a health user modeling service was introduced for conducting personalization according to health needs (Polignano et al., 2023). However, knowledge about users' health and behaviors can facilitate personalization only to a limited extent. Comprehensive, general-purpose frameworks of user features have been suggested before (Cena et al., 2019; Musto et al., 2020), but they are missing features important for supporting health behavior change. For instance, the conceptual user model underlying the MYRROR user modeling platform (Musto et al., 2020) attempts to provide a holistic representation of the user for serving a variety of personalization aspects, independent of the application area. The user model includes features related to interests, affective state, personality, behaviors, social connections, and physical states, but features related to health behavior change needs and behavioral determinants are not included. The conceptual framework proposed by Torkamaan & Ziegler (2021) share many similar and important features with the VIM, particularly, health status, behavioral determinants, and contextual knowledge. However, the framework was developed to inform persuasive design requirements for DHBCIs regarding its functionalities and the available intervention item types, whereas the VIM aims to serve different personalization aspects in terms of picking the relevant intervention item for the user from a variety of options.

Some of the proposed VIM features that are presumed to be useful for promoting user engagement and intervention adherence have been utilized in previous HRSs. Of the momentary context related features, location and time (of day) are the most widely used for determining the opportune moments for selecting and delivering recommendations suitable for a particular moment, but also other contextual features (current activity, affective state, weather, and calendar availability) have been used for personalization in a few cases, e.g., (Clarke et al., 2017; Dharia et al., 2018; Lim et al., 2017; Rist et al., 2015). In one study (Hors-Fraile et al., 2016), the time lag between receiving and reading messages was used to infer the best timing for disrupting a user, which is an interesting approach. In terms of considering users' preferences, preferred PA modes and food items have been used for personalizing recommendations, e.g., (Alcaraz-Herrera et al., 2022; Ali et al., 2016; Ribeiro et al., 2022). However, utilizing values and personality traits for personalizing the tone of communication have not yet been explored in the HRS field, even though appropriate message framing has been shown to increase persuasiveness (Graham & Abrahamse, 2017; Josekutty Thomas et al., 2017; Matz et al., 2017). Likewise, making behavior change objectives personally meaningful by associating them with value-based aspirations, thus aiming at influencing personal attitudes, appears to be a fresh concept to study in DHBCIs. In consumer research, however, the impact of value-based message framing on attitudes has been studied, e.g., regarding attitudes towards meat consumption (Graham & Abrahamse, 2017).

The theory-based determinants of behavior are underutilized in HRSs designed for health promotion, even though these factors are highly relevant when determining the right kind of support to be provided, see e.g., (Kok et al., 2016; Rhodes et al., 1997). For instance, examining the VIM features related to the "resources" and "behavior change needs and determinants" categories, enables to identify when someone is not motivated to change behavior despite a clear health need. In such cases, attempting to raise personal awareness and strengthen one's capabilities may be more appropriate than trying to engage the person with the target behavior. Furthermore, most of the HRSs that consider behavioral determinants target only a single determinant. For instance, intention to change has been used for tailoring smoking cessation messages (Hors-Fraile et al., 2016; Sadasivam, Borglund, et al., 2016), users' social ties have been leveraged for promoting physical activity (Dharia et al., 2018), and users' abilities have been used for recommending stress reduction activities (Torkamaan & Ziegler, 2022). The Quit and Return mobile application for smoking cessation (Hors-Fraile et al., 2022) is a rare example of a HRS that considers several behavioral determinants for personalization.

Tracking features related to progress evaluation is relatively common in DHBCIs in terms of users' adherence to or the effectiveness of the recommendations. For instance, Torkamaan & Ziegel (2022)have introduced a HRS, which tracks users' adherence to recommendations for estimating one's abilities to follow certain recommendations, and the recommendations are adjusted accordingly. In addition, the HRS implemented by Ferretto *et al.* (2020) determines the effectiveness of the recommended PA by monitoring changes in health outcomes (blood pressure, body mass index, and waist circumference) across users, and recommends activities which have been effective for users sharing a similar demographic and health profile with the target person. Furthermore, reinforcement learning has been used to infer effective message types for different users by monitoring users' PA levels after sending motivational messages (Yom-Tov et al., 2017).

The "health & well-being" category of the VIM includes features related to genetic predisposition, although the feasibility and value of utilizing individuals' genetic profiles for personalizing lifestyle interventions remains still to be seen. Once genetic testing becomes mainstream, different approaches for utilizing genetics can be studied at a large scale. The opportunities offered by genetics are intriguing in for identifying the most effective behavioral actions (e.g., dietary habits, exercise modes, or sleep patterns) for improving the well-being of a particular person. Utilizing genetics for personalizing nutritional advice has already been experimented within a few studies (Celis-Morales et al., 2017; Coletta & Kreider, 2015).

6.1.2 User modeling for multidomain recommendations

The Personal profile component of With-Me HRS provides a practical example of *user modeling methods that quantify, structure, and interpret personal information to form a user profile that facilitates the personalization of multidomain interventions* (RQ2). The HRS was designed to support a variety of behavioral domains, namely, sleep, physical activity, eating habits, alcohol consumption, smoking, workload management, recovery from stress, anxiety, self-esteem, value-congruent behavior, and the quality of relationships. A subset of the VIM features, relevant for serving the minimum requirements for personalizing multidomain interventions, was selected for implementation by the With-Me user model, which underlay the Personal profile. At the very least, such interventions should be able to identify the behavioral area(s) to be targeted (Kok, 2014; Rhodes et al., 1997). The health risk a behavior poses is an important criterium for the identification, but just as important is the person's intention or motivation to change the behavior (Rhodes et al., 1997). Recommending actions that are of no interest for the person would most probably result in a poor user experience, which would lead to a weak user engagement and a lack of health impact. Therefore, the VIM features supporting the identification of suitable behavior change targets (and the related actions) were implemented by the With-Me user model, i.e., feature types related to health behaviors, well-being state, health measurements, and the behavior change needs and intentions.

The With-Me user model specified the features used by the system, the properties used to describe each feature (original values, harmonized values, timestamps, confidence values, and data source), and the hierarchical structure between them. The hierarchical structure included three data layers (original, integrated, and aggregated layers) of varying knowledge refinement levels. The original layer contained features acquired directly from the available data sources (questionnaires and Firstbeat lifestyle assessment), and the integrated layer combined closely related original features to form mid-level features that represented different concepts. The aggregated layer contained high-level features (behavior change needs), which combined various concepts and could be used as a direct input for the recommender algorithm. The With-Me data hierarchy shares similarities with the multilayer structure proposed by Cena *et al.* (2019) for modeling real-world user data, where the first layer contains the acquired raw data, and the last layer includes features representing the highest level of knowledge inference and the associations identified between different features.

The With-Me user features were populated by using a set of rule- and similarity-based algorithms implemented by the functional Profiler component. The Profiler maintained the rules for transforming features' raw values to harmonized values, for computing the confidence value for each feature, and for inferring new features. The choice of the appropriate user modeling algorithms depends on the available data sources, the heterogeneity and amount of data, and the complexity of the features to be derived. For With-Me HRS, well-defined, direct measures were used for the input features and the amount of data was small; hence, simple rule-based algorithms were sufficient. Furthermore, although the data were heterogenous, the harmonization of feature values to a common scale enabled to utilize a basic similarity-based approach for inferring users' behavior change needs. However, there are myriad of other user modeling approaches to select from. For instance, various machine learning techniques have been applied to infer different types of user features (e.g., interests, mood, social relations, physical activities) from web or smart phone usage data (Cena et al., 2019), linear equations have been used to compute the health impact of physical activity (Ferretto et al., 2020), and player rating algorithms and the Rasch model have been used to infer users' ability to perform stress-reducing activities (Torkamaan & Ziegler, 2022).

6.1.3 Feasibility of a multidomain HRS

The RQ3, "*Is a HRS, which conducts personalization according to users' health behavior change needs and intentions, able to produce multidomain recommendations suitable for real-life health behavior change coaching?",* was addressed by evaluating the feasibility of With-Me HRS in a real-life health coaching context. In the evaluation study, the validity and usefulness of the HRS was investigated. The behavior change actions recommended by With-Me HRS were included into the coaching plans of more than 70% of the study participants in a mutual agreement between the coach and a participant. This can be considered a reasonably good result, which is an indication of the suitability of recommendations generated based on behavior change needs and intentions, especially when only half of the participants were exposed to the recommendations. The indication of the suitability of the recommendations was even clearer from the participants' side: A large majority (90%) of the participants who were exposed to the recommendations was happy to choose recommended items as coaching tasks for themselves.

When evaluating the usefulness of With-Me HRS, it should be noted that the HRS had two purposes in the health coaching program: a) to provide an overview to the coaches of participants' behavior change needs and intentions systematically across different behavioral domains (via the Profiler's user-interface), and b) to recommend behavior change actions for participants' coaching plans. When evaluating the usefulness of HRS, these two functionalities were not separated. The RQ3 concerns only the recommendation functionality, but also the impact of the Profiler's overview is reflected in the evaluation results.

With-Me HRS appeared to be a useful tool for supporting real-life health coaching. The HRS reduced coaches perceived effort in identifying appropriate coaching tasks for participants, but not in identifying their behavior change needs or objectives. It's likely that individuals, who voluntarily participate in health promotion interventions, have a clear idea of the areas they wish to improve already beforehand, which would simplify a coaches' job in identifying appropriate objectives for the participants. However, the participants for whom the coaches could utilize the HRS for decision-making, were more satisfied with the quality of coaching than the participants who were not exposed to recommendations. Particularly, these participants were more satisfied with the coaches' abilities to understand their behavior change needs and to help them realize new, personally relevant areas for improvement, which indicates that the HRS was useful also for identifying behavior change objectives, even though this was not directly reflected in the coaches' self-reports. The Profiler's analysis results may have enabled coaches to form a comprehensive picture of participants' situations effortlessly, beyond the needs identified by the participants themselves. However, also the Firstbeat lifestyle assessment report, which was provided to the participants who received coaching supported by With-Me HRS, may have influenced the participants' perceptions of coaching quality.

The With-Me HRS study provides results "in the wild" where actual users utilize the system for a real-life problem, instead of just providing feedback about its outputs in an artificial usage context. Real-life study settings are preferred over offline studies, although most of the previous validation studies for HRSs have been conducted offline (De Croon et al., 2021). Previously, the suitability of recommendations has been evaluated in real-life settings based on user satisfaction with the recommended items, self-reported or observed adherence to recommendations, or changes in health outcomes, e.g., (Dharia et al., 2018; Sadasivam, Borglund, et al., 2016; Torkamaan & Ziegler, 2022). In the present study, the primary measure for suitability was the number of recommended behavior change actions selected to a participant's coaching plan, which is a stronger indicator for suitability than measuring mere user satisfaction, but not as good as measuring the adherence to recommendations.

Knowledge-based filtering with case-based reasoning was chosen as the recommendation method for With-Me HRS. Knowledge-based filtering is appropriate for recommending complex items which requires a deeper understanding of user characteristics and item properties than merely the inference of user preferences from user ratings (Aggarwal, 2016). Knowledge-based filtering allows to personalize recommendations directly to the specific characteristics of a person, facilitates transparent recommendations, and can handle highly heterogenous input data. These are all important properties for health-related applications (Cheung et al., 2019; De Croon et al., 2021; Sadasivam, Cutrona, et al., 2016). Indeed, knowledge-based filtering can be considered a standard approach for generating recommendations in HRSs, and it is widely used in the field (De Croon et al., 2021). Another important advantage of knowledge-based filtering for HRSs is that the past is not used to predict the future, which is typical for collaborative and content-based filtering, but the recommendations adapt to users' evolving characteristics (e.g., improved skills) (Aggarwal, 2016).

In general, the neighborhood-based recommendation techniques traditionally used in recommender systems are efficient, scalable, and easy to maintain compared to many other personalization approaches. Neighborhood-based techniques do not require costly training phases as opposed to reinforcement learning and many other machine learning based approaches (Ning et al., 2015). Furthermore, the computationally simple similarity metrics scale much better to high-dimensional user models than rule-based personalization techniques, used in computer-tailored interventions and constraint-based recommenders, which makes case-based filtering especially interesting for personalizing behavior change interventions. While computing the neighborhoods in high-dimensional data can be computationally complex, especially when the number of users and items is vast, most of these computations can be done offline and maintained in a low-memory storage ready for recommendations per request (Ning et al., 2015). Similarity functions are also easy to maintain. For instance, the addition of a user model feature for case-based reasoning involves the addition of the respective (weighted) term to the function, while in computer-tailored interventions, this would require manual re-assessment of all the existing mapping rules, which usually increase substantially in number as the set of input features is expanded (Sadasivam, Cutrona, et al., 2016; Sezgin & Özkan, 2013). In control systems engineering, the dynamical system model would need to be re-trained with the new features (Lopes dos Santos et al., 2020). However, the bottleneck for the scalability and maintenance of case-based recommenders is that descriptive feature values need to be assigned to the available intervention items, which often requires manual work. Just like with computer-tailored interventions, the development of case-based recommenders requires intensive domain knowledge. Particularly, the accuracy of case-based reasoning depends on whether the users and items have been described with the essential features.

Finally, even if machine learning, data mining, or deep learning approaches may achieve more accurate results than neighborhood-based approaches (Aggarwal, 2016; Koren & Bell, 2015), seeking for the best accuracy is not the highest priority when recommending behavior change actions. In such cases, providing the top-k items, which all meet user characteristics reasonably well, is more than sufficient and even preferable for a good user experience, as the user is provided more freedom of choice.

6.1.4 Transparent recommendations via well-being profiles

The well-being profiles of the MyProfile service provided an example solution *for improving the transparency of DHBCIs* (RQ4). The profiles included visual summaries of metrics that described users' behavior change needs and behavioral determinants analyzed based on questionnaire responses. As explained earlier, knowledge of such user characteristics is essential for personalizing multidomain DHBCIs; hence, the well-being profiles could serve as a basis for generating health behavior change recommendations. According to the conducted concept evaluation study, the well-profile summaries were perceived as interesting, easy-to-interpret, and useful by the study participants who tried out the MyProfile service. Furthermore, associating concrete suggestions and guidance for lifestyle improvements with the well-being profiles was desired. Thus, the introduced profile summaries may be feasible for explaining the rationale and data behind behavior change recommendations. However, whether this truly is the case remains still to be investigated, as the utility of the well-being profiles in justifying and explaining recommendations was not directly evaluated with the employed study setting.

In terms of facilitating the transparency of reasoning, MyProfile is an upgrade to With-Me HRS, which also provided a user-interface for summarizing the well-being profiles underlying the recommendations (via the Profiler component), though it did not include behavioral determinants and its interpretability was not thoroughly investigated. However, unlike MyProfile, With-Me HRS provided transparency to the limitations of the recommendation results, which is important for enabling users to interpret the trustworthiness of the recommendations (Herrmanny & Torkamaan, 2021; Tintarev & Masthoff, 2015).

Though transparent reasoning is especially important for HRSs, due to the possibly adverse effects of inappropriate recommendations and the sensitive nature of the data, most of the existing systems do not explain why certain recommendations are presented (De Croon et al., 2021; Yue et al., 2021). In the systematic review of De Croon *et al.* (2021), only ~10% (7/73) of the investigated HRSs attempted to provide insights to the rationale behind recommendations, and at a very simplistic level. For instance, the items recommended have been associated with personal health goals or health benefits via brief textual explanations or by adding health-related tags to the items. None of the examined HRSs were reported to provide indications to users about the limitations of the employed reasoning logic.

6.2 Scientific and practical implications

This doctoral thesis contributes to the development of easily scalable, hence cost-effective solutions for health behavior change interventions, that succeed in helping people to lead a healthy lifestyle. Extensively personalized DHBCIs, particularly HRSs, are promising technologies, which can have major positive economic and societal impacts on societies.

The vast majority of HRS research has concentrated on improving the accuracy and computational efficiency of recommendation methods, see e.g., (Alcaraz-Herrera et al., 2022; Dharia et al., 2018; Starke et al., 2021; Yue et al., 2021), while evaluating the impact of different user model features on the suitability of recommendations has attracted less interest. However, both aspects are equally important when developing HRSs that strive for effective personalization, which results in increased user engagement and succeeds in delivering positive health impact. By introducing the VIM and the variety of personalization purposes it is designed to serve, the thesis aims to draw wider research attention to the role of user model features in personalization, as wisely chosen features can increase the suitability of recommendations tremendously. Particularly, the VIM specifies a comprehensive collection of promising user features in terms of the effective personalization of multidomain DHBCIs, informed by behavioral sciences.

Although the present work does not provide direct empirical evidence for the proposed VIM features, the VIM can be considered a common conceptual user modeling framework for HRSs, and other DHBCIs, that provides ideas about different personalization aspects and the user features to test when searching for the most impactful ones in terms of user engagement and health outcomes. This kind of research would help in achieving an empirical consensus of the important features for personalization, which is currently missing in the HRS field. The evaluation study of With-Me HRS provides baseline results about the suitability of recommendations generated with a minimum set of features important for multidomain interventions, i.e., behavior change needs and intentions, which can be used as a reference when testing the impact of additional features. In addition, the VIM feature categories could be used to support unified reporting practices across different user model implementations. Describing the implemented user model features with a common taxonomy enables the aggregation of empirical evidence regarding the most impactful features.

The findings of the exploratory analysis regarding personal values also provide some food for thought about interesting personalization aspects to consider in DHBCIs. Due to the motivational role of values in guiding behavior (Rokeach, 1973; Schwartz, 1992; Schwartz & Bilsky, 1987), which was reflected in the observed value-behavior associations, the knowledge of the values one holds as important could be used to reframe the identified behavior change needs as objectives that are aligned with one's value-based aspirations as an attempt to improve user engagement. In addition, the knowledge of one's values could be used to identify whether deficiency or self-protection needs form a barrier towards health behavior change, which may require a complete re-assessment of the intervention focus. Finally, as indicated by the FHFS results and previous research (Sagiv & Schwartz, 2000; Sheldon & Elliot, 1999), being conscious of one's values and living up to them seems to be beneficial for subjective well-being. Therefore, expanding the intervention libraries of DHBCIs with behavior change objectives and actions that promote value clarification and value-congruent behavior may improve the effectiveness of health promotion interventions. Value clarification was also one of the objectives supported by With-Me HRS, used as an intervention to improve subjective well-being.

In addition to introducing the conceptual VIM, this thesis describes the implementation of the With-Me user model that realizes a subset of the VIM features. Identifying the relevant user features to include in a user model is important, but equally so is identifying the appropriate methods to populate the model features with reliable and valid data, which involves making decisions on acquiring the required information and processing it to a format that can be directly used for personalization. Based on the experience of implementing the With-Me user model, a few practical recommendations, applicable to at least HRSs that use knowledge-based filtering, can be given for simplifying the data processing rules and improving the validity of user features:

- *Use a mix of objective and subjective measures as information sources.* Objective monitoring of behavior (e.g., daily activity patterns, sleep habits) via wearables should be preferred over self-reports, when feasible in terms of accuracy and costs, to reduce users' self-reporting burden and bias. Furthermore, without accurate and continuous monitoring of behavior, the assessment of users' behavior change needs and progress, which are central VIM features, becomes challenging. However, for inherently subjective features (e.g., perceived well-being, mood, personality, preferences), self-reports provide naturally the most reliable information. In addition, for concepts involving both psychological and physiological aspects (e.g., sleep quality, stress), subjective and objective measures complement each other. For instance, HRV measurements may reveal poor physiological recovery during sleep even though the person feels well rested.
- *Transform feature values to a unified scale when appropriate.* Unifying feature value scales can simplify the computation of aggregated or derived features and enables data source independent user modeling. In With-Me HRS, the same formula for deriving the strength of a behavior change need was possible to apply to different behavioral domains, since the domain specific input features were transformed to a harmonized value scale. Unified scales enable also to apply the same inference logic for transforming raw data into knowledge across different data sources, which supports flexible replacement of alternative sources. Data source independent user modeling is especially useful for the objective measures of behavior due to rapidly developing self-tracking technology and the variety of devices used by different users.
- *Associate each feature value with a confidence estimate.* Confidence estimates enable the system to discard recommendations that involve uncertainty or to communicate about uncertainties directly to users. Being transparent about the accuracy of the data behind recommendations can increase users' trust in the system and enables users to make informed decisions on whether to follow the recommendations or not. The data accuracy depends on the validity of data sources (e.g., the accuracy of tracking technology, using validated vs. non-validated questionnaires) and the choice of inference methods.

The With-Me HRS provides a feasible example of a multidomain HRS, since it was successful in generating suitable recommendations from various behavioral domains in the context of a real-life health intervention. Multidomain personalization is a novel aspect for HRS research, as the majority of existing HRSs designed for health promotion support only a few behavioral domains (e.g., PA or diet) (De Croon et al., 2021; Yue et al., 2021). However, such HRSs cannot address the varying health behavior change needs of different individuals. Without multidomain HRSs, the potential of HRSs in offering effective and scalable interventions for health promotion cannot be fulfilled at the population level. However, the implementation of a HRS capable of personalizing daily, detailed guidance that specifies when to recommend what and how often may become rather complex and hard to maintain across various behavioral domains. Detailed, concrete recommendations are especially important for standalone HRSs, intended to be used without the support of human experts, contrary to the usage context of With-Me HRS. A feasible approach for integrating the multidomain perspective with concrete recommendations could be to develop HRSs modularly with two hierarchical layers, where at the first layer, a high-level HRS recommending behavior change objectives across different behavioral domains is maintained and, at the second layer, various domain specific HRS submodules focusing on recommending concrete actions are implemented. Ideally, each submodule would be independent from each other, implement distinct parts of the overall user model, and have separate intervention libraries relevant to the domain in question, which would enable a modular development of the intervention offering. With-Me HRS can be considered a prototype of the first layer of the proposed multidomain approach, which activates domain specific submodules as need arises, and therefore, orchestrates the whole system. Many of the previous single-domain HRSs can be seen as examples of such submodules, such as the HRSs that recommend PA intensities or durations, or specific food items and proportions to be included into a meal (Ali et al., 2016; De Croon et al., 2021; Dharia et al., 2018).

In multidomain DHBCIs, an additional challenge, on top of the many other personalization issues, is to identify the behavior change needs that should be addressed first. It is unrealistic to attempt to change all (or many) unhealthy habits at once (Wilson et al., 2015), as the available resources of a person, determined e.g., by one’s life situation, abilities, and the available time and energy, are typically enough for only a few behavior change objectives at a time. With-Me HRS solves this problem of choice by providing recommendations for only those behavioral domains for which the person has at least a moderate need for change (health-wise) and is motivated to act upon. The HRS also guides the person to select at most three of the recommended actions to work on. In addition, the MyProfile service provides a user-friendly way to visualize this type of a recommendation logic by guiding users' attention to the behavioral domains for which they have a high need for change as well as sufficient motivation and capabilities to modify.

Succeeding in providing appropriately personalized behavior change support is pointless without users' trust and engagement with the system. These could be achieved by integrating users in the reasoning and decision-making process of DHBCIs (Herrmanny & Torkamaan, 2021). The well-being profile views in MyProfile and With-Me HRS provide practical examples that may empower and encourage users to get involved in the reasoning process of DHBCIs, since they implement some of the concrete strategies defined by the user integration framework of Herrmanny & Torkamaan (2021), which was briefly introduced in Section 2.3.4. The MyProfile views provide transparency to the reasoning process and, thus, contribute to the user empowerment aim of the user integration framework, whereas With-Me HRS contributes to the user encouragement perspective by providing transparency to the limitations of reasoning.

The MyProfile visualization that presented users' behavior change needs and capabilities for indicating the most potential behaviors to target could be used to justify why recommendations from a certain domain are superior to the other domains (*causal explanation* – a concrete strategy of the user integration framework). In addition, the visualization enables users to interpret the extent of their behavior change needs and capabilities on a scale from 0 to 100 (*reference*) and to compare their situation between different domains (*support of quantitative assessment*). The MyProfile summary, which explained the behavioral determinants that act as personal barriers or abilities for change in a particular behavioral domain, can be used to reveal the features that the recommendations are based on (*insight into considered variables*) and to justify why certain actions are recommended instead of others within the same domain (*causal explanation*). The positive user evaluation results regarding the interpretability of the MyProfile views indicate that these types of visual summaries could be taken into wider use. Finally, in the user-interface example of With-Me HRS, the limitations of the Profiler's behavior change needs analysis were communicated to users (coaches) by highlighting the results involving uncertainty and revealing the source of uncertainty (*information about uncertainty*), thus encouraging users to verify the inference results. The user-interface also enabled users to correct the results (*opportunity for manipulation*), which is a concrete strategy to communicate to users that they can and should interact with the system to influence the recommendation results (Herrmanny & Torkamaan, 2021). These concrete examples of providing transparency to HRSs are timely, as the importance of transparent recommendations is well-acknowledged in the field of HRSs, but still underutilized (De Croon et al., 2021; Herrmanny & Torkamaan, 2021; Yue et al., 2021).

In addition to providing transparency regarding the personalization of DHBCIs, MyProfile was designed to serve as a personal health data vault, which not only provided users an easy access to their data, but also offered an open application programming interface for 3rd party health service providers to the analyzed health profiles for the purpose of supporting the adequate personalization of available digital interventions. However, 3rd party applications could access the profiles only with the permission of the user, i.e., the owner of the data. MyProfile followed the *MyData* approach (Poikola et al., 2015), which emphasizes the importance of giving citizens the right to access and use freely their personal data, as well as the power to decide which services are authorized to access their data, when, and for what purposes. Hence, the MyProfile service promotes the ethical aspects of data privacy and autonomy. An obvious benefit of such a service concentrating purely on behavior change needs profiling (or user modeling) is that it enables users to flexibly try out different 3rd party interventions and receive highly personalized recommendations immediately after taking the services into use, without having to share their raw personal data and to go through additional data collection phases. Intervention service providers may also perceive advantages as they could concentrate on providing high quality intervention content instead of having to put significant resources into the research and development of valid user modeling methods.

6.3 Limitations and future research

This thesis discusses the personalization of interventions that are targeted directly to individuals. However, the author acknowledges that such interventions are insufficient for eliciting behavior change when the required environmental resources are missing, or the social atmosphere is unsupportive. Indeed, individual-level behavioral theories such as TRA and TPB, which do not consider environmental and economical influences on behavior, are able to explain only 40-50% of intention formation and 19-38% of actual behaviors (Sutton, 1998). Sustained behavior change may also require policy changes or environmental changes in communities and organizational structures (Glanz & Bishop, 2010; Verplanken & Wood, 2006), since providing incentives and opportunities to engage in healthy actions and increasing the costs of unhealthy choices are crucial for behavior change. The decision-making contexts of people, the choice architectures, can be organized as such that it becomes easier to engage with healthy than unhealthy actions (Thaler & Sunstein, 2008). For instance, designing bicycle-friendly cities with reduced car parking opportunities would increase the appeal of commuting by bicycle instead of driving. In addition, using social marketing campaigns in different channels (e.g., schools, workplaces, TV) to address social norms is also part of a comprehensive intervention approach (Siegel & Doner Lotenberg, 2007).

The present work does not provide empirical evidence about the effectiveness of the different VIM feature types and the associated personalization aspects in eliciting behavior change. This shortcoming should be addressed by future research, since implementing the entire VIM would be rather resource-intensive, also requiring the collection of a large variety of personal data. Implementing all the VIM features becomes justified only if solid empirical evidence can be accumulated indicating that each feature has a significant and independent impact on intervention effectiveness. However, some of the personalization aspects are likely more important than others. For instance, personalizing recommendations according to users' behavior change needs and intentions may be considered mandatory (Rhodes et al., 1997), whilst identifying the opportune moments to disrupt a person with a recommendation should be considered a nice-to-have feature, if it is expected to improve intervention effectiveness only slightly. Discovering the impact of each personalization aspect requires well-defined controlled studies, which iteratively test the influence of the VIM elements and the related feature types on the quality of recommendations, user engagement, and health outcomes. The evaluation results of the multidomain With-Me HRS can be used as a reference for comparing the impact of additional user features, beyond behavior change needs and intentions, on the validity of recommendations. Likewise, the hypotheses regarding the role of personal values in personalization, derived based on the exploratory analysis results of the FHFS dataset, should be validated in the future with controlled study settings.

Though the VIM specifies various user features that facilitate the personalization of interventions, it does not provide concrete tools for the enactment of behavior change techniques, the active ingredients of an intervention. Extensive knowledge of evidence-based BCTs and intervention mapping frameworks, such as (Kok et al., 2016; Michie et al., 2013), is required to be able to fully utilize the VIM features for designing intervention libraries and defining the logic for matching intervention items to different user features. Particularly, the extensive review of Carey *et al.* (2019) provides direct indications of the BCTs most appropriate for each behavioral determinant, which can be utilized for mapping BCTs to the VIM user features.

With-Me HRS was designed to serve as an assistive tool for health coaches to be used only at the beginning of the delivered health coaching program. Some features that are particularly important for standalone HRSs, aiming at supporting long-term behavior change, were not implemented, which limits the usefulness of With-Me HRS for public health promotion in its current form. As coaches were available to provide individual guidance and support for the program participants, the HRS did not need to be highly sophisticated. The shortcomings of With-Me HRS, limiting its usefulness as a standalone HRS, include recommending actions that are not detailed enough to instruct users precisely on what to do and how (e.g., the weekly frequency, intensity, and duration for PA was not specified), considering a rather limited set of features for personalization, and being incapable of dynamically adapting to users' changing circumstances.

As suggested above, implementing standalone HRSs modularly from distinct HRS submodules, each specialized to different behavioral domains, may be a practical solution for providing multidomain yet specific recommendations. The technical feasibility of such an approach could be verified by future research prototypes. The prototypes would require a master HRS (similar to With-Me HRS) that keeps track of users' behavior change objectives and decides which submodules to activate and when, while also being in charge of populating and maintaining the user model features that are common across submodules. The approach is advantageous also from the data privacy perspective, as unnecessary collection and monitoring of personal data could be avoided by associating designated data streams with the submodules, to be activated only by active submodules. For instance, continuous monitoring of sleep quality and HRV may be required by exercise and stress management HRS submodules, but not by a submodule offering nutritional advice.

Behavioral theories suggest that, in addition to intention, personal skills (or abilities) and the contextual or environmental opportunities to engage with the behavior (e.g., time and nearby facilities) are necessary for a change to take place, see e.g., Fishbein *et al.* (2001). However, skills and barriers were not implemented by the With-Me user model, but they should be considered by (future) standalone HRS prototypes. Skills enable to recommend behavior change actions that provide health benefits but are not too challenging for the user to complete, and barriers enable to filter out recommendations that the user simply does not have the opportunity to follow. When gathering empirical evidence about the most impactful user features in the future, the next logical step would be to expand the With-Me user model with features regarding personal skills and barriers, and investigate whether the suitability of recommendations improve, accordingly. If knowledge-based filtering is used for generating the recommendations, also the intervention library items need to be labelled with the features added to the user model. Furthermore, as users' skills develop, the recommendations should adapt to require gradually increasing effort, see e.g., (Torkamaan & Ziegler, 2022) for an example implementation.

With-Me HRS was based on knowledge-based filtering, which is a straightforward method for testing the impact of user features on the quality of recommendations. However, once empirical knowledge of the most important user features is available, a hybrid method that combines knowledge-based and demographic-based collaborative filtering might be a more effective approach (Cheung et al., 2019). Utilizing collaborative filtering is appealing, as it can introduce diversity, novelty, and even serendipity to the recommendations and, thus, can foster user engagement with the system (Aggarwal, 2016; Cheung et al., 2019). These properties are not inherent to the alternative personalization methods for DHBCIs, such as control systems engineering and reinforcement learning. In the hybrid HRS approach, knowledge-based filtering could be used first to identify the subset of recommendable items that match the most critical user needs to be fulfilled (e.g., behavior change needs, intention, skills, and health restrictions), after which demographic-based collaborative filtering can be applied to select items from the subset that have been effective for or liked by the users sharing similar demographics (or life situation) with the target user. Hence, knowledge-based filtering would ensure that all the behavior change actions recommended to the user are safe and useful, while demographic-based collaborative filtering introduces diversity to the recommendations (e.g., in terms of preferences) within the set limits. The proposed hybrid method may be able to facilitate even rather extensive personalization with only a subset of the proposed VIM features.

The With-Me user model did not track and collect user data continuously or even at regular intervals. Thus, it did not support the dynamic adaptation of recommendations, and the common properties used to describe features were not optimal for describing time-series. Although new recommendations were always generated if a user re-took the well-being survey associated with the user model, past survey answers were not considered in the analysis. Particularly, users' long-term progress and other trends in the data could not be detected. For a standalone HRS, it is imperative to have the capability of adapting recommendations to users' evolving situations while also considering the effectiveness of the followed recommendations. This would require specifying to the introduced user model structure additional properties that describe the temporal aspects of different features. Certain features are valid only in short-term such as contextual features (e.g., mood, location, activity), whereas others remain unchanged in long-term and do not need to be updated often (e.g., demographics, personality traits). Furthermore, features may be aggregated over different time periods. For instance, only the most recent contextual feature values matter when detecting opportune moments for recommendations, but data over the past month would be relevant for detecting users' progress or intervention effectiveness. Therefore, it would be useful to expand the With-Me user model structure with data properties that specify features' update frequency (e.g., every minute, daily, weekly), the analysis time window (e.g., past week, past month) for aggregate features, and the minimum number of measurement points required for the reliable inference of aggregate features. These properties would also enable to identify outdated feature values that should not be used for personalization.

The user-interfaces of the Profiler component of With-Me HRS and the MyProfile service had certain limitations in terms of transparency. They did not incorporate warnings for outdated user features, which would be important for communicating to users about the limitations of personalization. In the case of With-Me HRS, the coaches had to manually review the validity of the participants' personal profiles before the HRS could proceed to generate recommendations. Ideally, the HRS would have automatically notified the participants about outdated profile data and asked them to re-answer the questionnaire used by the Profiler. In addition, neither of the profile user-interfaces included information about personal health restrictions, such as food allergies or physical limitations for exercise. Communicating clearly about the health restrictions that are considered in the recommendations would also be important, so that users could be confident about the safety of the recommendations.

The employed study method for evaluating the well-being profile views of MyProfile can provide only indicative results regarding the feasibility of the introduced visualizations and metrics in improving the transparency of behavior change recommendations. Since the service did not generate actual recommendations, the impact of the well-being profiles in explaining the recommendation could not be directly evaluated. The results should be confirmed with a research setting, where the transparency of recommendations generated with and without the well-being profile summaries would be measured quantitatively and compared to each other. However, testing the interpretability of visualizations and metrics with light qualitative studies before the actual technical implementation is generally a good practice, which supports efficient development work.

The outcome measures selected for the evaluation of With-Me HRS were somewhat limited. It would have been informative to include metrics for assessing the quality of recommendations in terms of diversity, novelty, or serendipity, as these factors are important for user engagement. In addition, the best approach for validating the suitability of the recommended behavior change actions would have been to assess the impact of the recommendations on participants' behavior, i.e., to evaluate participants' adherence to the actions that were recommended and selected. However, this would have required the continuous monitoring of behavior for the different domains supported by the HRS, which was not possible in the study. Even so, indications for adherence can be observed from the results of the pilot RCT (Muuraiskangas et al., 2022) conducted for the health coaching intervention that utilized With-Me HRS. One of the trial outcomes was participants' self-reported adherence to the selected coaching tasks, which was generally high for all the tasks, including the tasks selected based on With-Me HRS's recommendations.

Finally, the participants of the two quantitative studies included in the thesis were mostly highly educated, working-aged females. Particularly, in the evaluation study of With-Me HRS, nearly all the participants were female. Hence, the presented results regarding the validity and usefulness of With-Me HRS and the associations between values, well-being, and health behavior might not hold for other demographical subgroups, such as for males, youngsters, or the elderly.

7 CONCLUSIONS

In the doctoral thesis, HRSs were studied and discussed from various aspects related to a) the different needs for personalization, b) the user model features that may serve these needs, c) user modeling methodology, d) the suitability of HRSs for personalizing multidomain health promotion interventions, and e) improving the transparency of personalization.

The proposed conceptual user modeling framework, the virtual individual model (VIM), specifies a comprehensive collection of promising user features that can serve a variety of personalization purposes. With-Me HRS implemented a subset of these features, namely behavior change needs and intentions, and used knowledge-based filtering to recommend health behavior change actions. It was shown that such a HRS was able to produce multidomain recommendations suitable for real-life health behavior change coaching, which complements the state-of-the-art in HRS research, mostly focused on single-domain interventions. Furthermore, the implementation of the With-Me user model provides a concrete example of multidomain user modeling. Lastly, visual well-being profile summaries were introduced for providing transparency to personalization. Particularly, the visualizations and metrics of the MyProfile service were considered interesting, easy-to-interpret, and useful among users, which suggests that such summaries may be feasible for improving the transparency of DHBCIs.

This work seeks to attract wider research attention to the importance of wisely chosen user model features in personalization to complement the existing HRS research, which focuses mostly on fine-tuning personalization techniques. However, empirical studies are needed that evaluate the proposed VIM features and produce evidence of the most effective personalization aspects. The evaluation results of With-Me HRS provide a reference point for testing the impact of user features beyond the implemented behavior change needs and intentions, which can be considered the minimum set of features required for the personalization of multidomain DHBCIs.

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PUBLICATIONS

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Rethinking Health: ICT-Enabled Services to Empower People to Manage Their Health

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Rethinking Health: ICT-Enabled Services to Empower People to Manage Their Health

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Methodological Review

Abstract—**Lifestyle is a key determinant in the prevention and management of chronic diseases. If we would exercise regularly, eat healthy, control our weight, sleep enough, manage stress, not smoke and use alcohol only moderately, 90% of type II diabetes, 80% of coronary heart disease, and 70% of stroke could be prevented. Health statistics show that lifestyle related diseases are increasing at an alarming rate. Public health promotion campaigns and healthcare together are not effective enough to stop this "tsunami". The solution that is offered is to empower people to manage their health with the assistance of ICT-enabled services. A lot of R&D and engineering effort is being invested in Personal Health Systems. Although some progress has been made, the market for such systems has not yet emerged. The aim of this critical review is to identify the barriers which are holding back the growth of the market. It looks into the theoretical foundations of behavior change support, the maturity of the technologies for behavior change support, and the business context in which behavior change support systems are used.**

Index Terms—**Behavior change support, coproduction of health, ecosystem, health guides, health outreach, personal health systems, personal profile.**

I. Introduction

AFFORDABLE health care is a challenge to any government. Although most countries subscribe to the WHO Alma Ata declaration about access, equity, and quality of healthcare services, the ways health care services are organized, provided and financed vary a lot between countries. This is due to the long evolutionary process and national values that have shaped the systems. As a byproduct, the national systems have become quite rigid owing to complex sets of interdependent policies and practices and vested interests of stakeholder groups.

The need to reinvent healthcare has become obvious in the course of the past 10–15 years. During this time, several drivers have emerged that interactively push for a systemic change regarding the ways that health services are organized, delivered and reimbursed.

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On the demand side societies are graying, our lifestyles are projected to lead towards a huge increase in chronic conditions, and we are better informed of what medicine can do. On the supply side biology-based medicine has improved our understanding of diseases, their diagnostics and therapies. Parallel to these, the role of patients has changed fundamentally from passive objects of care to proactive partners and coproducers of their health and care. Finally, ICT enables the integration of data and best practices, the virtualization of certain health services and resources, and access to services anytime, anywhere.

Concerns over health outcomes and increasing health expenditure have led countries to look for ways to reform their health systems [1], [2]. Additionally, numerous reports, papers and books, e.g., by Clayton Christensen and Michael Porter [3], [4], have been produced over the years, but no consensus has emerged on how to service the increasing demand.

The *job*,[1] which is the focus of this review, relates to our current unhealthy behaviors and the disease burden that these behaviors cause for healthcare systems. The facts are clear (see e.g., [5] and [6]).

1) The most important risk factors leading to chronic diseases and premature death (high blood pressure, high cholesterol, obesity, inadequate fruit and vegetable intake, physical inactivity, excessive alcohol consumption, and smoking) are all lifestyle related [7].
2) Chronic diseases could be prevented and managed to a large extent, if people would change their health behaviors, i.e., exercise regularly, eat healthy, control their weight, sleep enough, manage stress, not smoke, and use alcohol only moderately [6].
3) We are already spending most of our health budgets directly and indirectly to the care of chronic diseases, e.g., in Europe nearly 80% of the disease burden is due to chronic conditions and diseases [8].
4) Health statistics show that lifestyle related diseases are increasing at an alarming rate [2].
5) We also need to recognize that our health is determined by a number of interacting determinants. As an example, Willet [5] suggests that the impact on premature death of quality/efficacy of healthcare services, behavioral patterns (lifestyle, environmental factors, societal circumstances), and genetic predispositions including acquired genetic changes is 10%, 60% and 30%, respectively.

[1]Christensen's book uses a metaphor "the job to be done" in discussing their ideas on "rethinking health".

6) If we accept the above estimate, then behavior is the most important health determinant, and it is also the one that we can influence/modify. Our family history (genetic predisposition) is something we inherit and cannot therefore influence.

Clearly, public health promotion campaigns and healthcare together are not effective enough to stop this "tsunami", i.e., to persuade people to pursue and lead healthy lifestyles. "The job to be done" is to lead a healthy lifestyle. The reality, however, is that most of us do not follow this. If that is the case, are there other ways to engage and motivate people to manage their lifestyle? Could ICT be used for this?

This is not a new question as the idea of using ICT to empower patients and individuals to manage their health and lifestyle has been an active R&D area for years. The objective of this review is to look beyond the current state of the art (SoA) to identify barriers that need to be overcome in order to realize the following scenario.

Today we can all benefit from the GPS navigator. It translates a problem of finding the route in the real world into a conceptual model that it uses to find the route and displays it to users in an easily understandable way. Furthermore, every time users take decisions (e.g., change the route), the system recalculates the shortest path to bring users back on track. What if we had a similar navigator to guide us through our day and assist us in making healthy decisions? Such Personalized HealthGuides (PHGs) would locate users on their individual health map, calculate the possible routes to improve one's health, and continuously monitor and recalculate the route if users are not on the intended track.

The core idea of the above behavior change scenario is that interventions must also take into account the "upstream", i.e., the environment in which people live. Therefore, creating PHGs is not enough. We need to take into account also the environment (ecosystem and its members), where we navigate our health journeys. This translates into three additional challenges: 1) how to integrate PHGs with the environment; 2) how the ecosystem members jointly create value; and 3) how society sets the policies, incentives and regulations that govern the ecosystem and set the choice architectures for its constituents (see e.g., [9] and [10]). One way to visualize this is the onion: policies form the topmost layer; underneath is the ecosystem where people navigate their health journeys in collaboration with the other ecosystem members; innermost are the PHGs.

The structure of this review stems from the above scenario: we need to bridge theories and knowledge from behavioral sciences and psychology with marketing and management research in order to create commercially viable PHG services. The paper extends the work done in the EU-funded PREVE project.[2]

The sections that follow this introduction review and discuss the SoA and the barriers in realizing PHGs, with two exceptions. First, we will not discuss policy development for healthy environments. We feel that this discussion is better suited for a health policy journal. Second, we will not discuss the safety and privacy issues. We are not excluding them because they are not important. In fact, any personalized health solution must have adequate safety and privacy arrangements in place to create trusted relationships between users and service providers. The reason for excluding them from this review is simply that in this paper we focus on the behavior change support aspects.

Section II discusses what we know of the users from the behavior and psychology viewpoint; especially how to influence health behaviors and personalize interventions. It introduces three concepts that will be further explored in Sections III and IV, namely *determinants of behavior*, *personal profile* and *coproduction of health*. In Section III, we look into the SoA of PHGs that can guide people when they navigate their health journeys in interaction with their coproducers. Section IV discusses value generation, business models and governance of the Health Outreach ecosystem. Finally, Section V brings these elements together and presents the gaps that we have identified, and that need to be filled before the scenario presented above can be realized.

II. Health Behavior and Coproduction

ICT services which help users to lead healthy lifestyles cannot be created without an understanding of what influences behavior. This section provides the theoretical frame for the subsequent sections. It introduces three concepts: determinants of behavior, a personal profile and coproduction of health.

A. Methods to Change Behavior

Behavior is the result of interactions between physical, psychological and social processes. In addition, it always takes place in a specific context that influences the available options and resources for healthy behaviors. Behavior and behavior change processes are explained by behavioral theories, which suggest effective ways to influence and change behavior [11]–[14]. Theory-based interventions produce better effects across various health behaviors than interventions without theoretical foundations [15]–[18]. Basing interventions on theory also ensures that intervention effectiveness can be evaluated [19]. Unfortunately, no one theoretical model completely predicts or explains health behaviors. Therefore, multiple theories and disciplines are needed to design effective interventions [11]–[13], [19].

Behavioral change often involves addressing several behavioral determinants, and methods for changing an individual's behavior usually need to be combined with methods for changing the environment [20]. Interventions can be downstream, i.e., targeted directly to individuals, or upstream, i.e., focusing on larger structural conditions such as organizational and environmental factors. Interventions should aim to affect also upstream conditions to achieve long-term effectiveness [11], [13]. Taxonomies of intervention methods and preconditions for their application both upstream and downstream have been created to aid intervention development [11], [21].

Since people have limited cognitive and time resources to deal with the multitude of choices they constantly face in their daily lives, one of the core issues is to improve their life management skills. Unhealthy behaviors often co-occur [22] (e.g., drinking and smoking, or stressful and sleep-deteriorating behaviors). Multiple health behavior research seeks to understand

[2]PREVE reports are available at www.preve-eu.org.

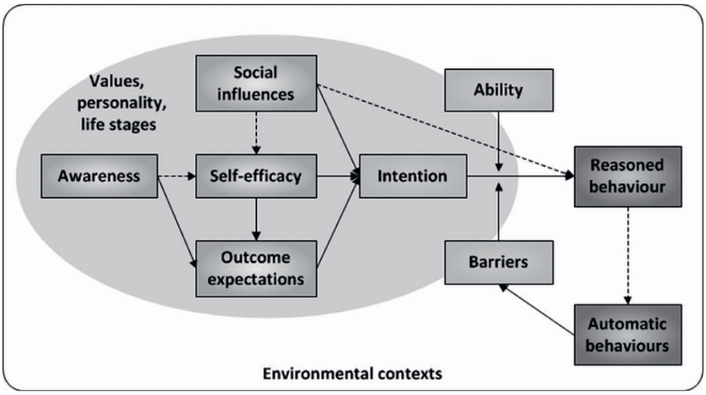

Fig. 1. Determinants of behavior and the relationships between them.

how various behaviors are related to each other and to identify common elements underlying behaviors [22]. Closely related to multiple behavior change interventions are approaches in positive psychology to enhance overall wellbeing. There is indicative evidence that positive psychology interventions, which focus on cultivating positive feelings, behaviors or cognitions, can result in significant increases in wellbeing and reductions in depression symptoms [23].

B. Determinants of Behavior and Personal Profile

Health behaviors are any activities undertaken by a person which influence health outcomes, including diet, physical activity, smoking, substance use, sleeping patterns, stress management and activities which influence mental health. As stated above, there is no single theory that completely explains behavior and the interventions needed to modify behavior. Instead, theoretical models overlap and complement each other. Fig. 1 presents a hybrid model of the key determinants of behavior, constructed by the authors. It is based on a review into the fields of psychology and motivation (e.g., [11], [12], and [19]), communication (e.g., [24] and [25]), development, social marketing (e.g., [26] and [27]), and behavioral economics (e.g., [9], [10], and [28]), as well as earlier comparisons of behavioral determinants by behavioral scientists [29], [30].

For a lifestyle change to take place, the person needs to have sufficient *intention* or *motivation* to go through with the change process, be free from any *barriers* preventing the change, and have the *abilities* required by the process. The development of motivation requires that the person acknowledges her need to change behavior (*awareness*), believes that she can succeed with it (*self-efficacy*), and has encouraging *social influences* that support the behavior change as well as positive expectations about the outcomes of the change (*outcome expectations*). *Automatic behaviors* such as habits, routines, and biases in thinking can either support or impede the behavior change. *Values* and *personality* of the individual, and the current *life stage* set the background for the determinants of behavior, and thus influence the behaviors and choices of the person.

The *environmental context* of the person determines the options and resources available for pursuing healthy behaviors. The person needs to live in an environment that does not hinder healthy decisions but makes them easy to make and maintain over time. Building such surroundings requires society and community level actions that target the education system, workplaces, food markets, personal trainers, restaurants, media etc. The role of schools is especially important in providing education and increasing awareness regarding healthy lifestyle and its benefits already from the early age.

There is strong evidence that behavior change support needs to be tailored to the individual's needs and characteristics (*personal profile*) in order to be effective and sustainable [15], [16], [31], [32]. The determinants of behavior in Fig. 1 form an essential part of a personal profile. A personal profile should comprise the individual's health behaviors and clinical risk factors, including the genetic susceptibility and family history of diseases, to identify the lifestyle areas that should be targeted; values and preferences to find solutions that motivate to engage with the behavior change process; and resources to identify the barriers that should be worked out. The personal profile is dynamic, evolving through different life stages and environmental contexts. Thus, it needs to be continuously updated with data from the individual's actions and environment. The personal profile can be utilized in the development of personalized interventions, which target the relevant behavioral determinants with appropriate methods.

Both direct and indirect means are needed in creating personal profiles. Direct means include questionnaires. Various instruments and scales have been developed and validated to measure, e.g., different aspects of physical, social and mental health, quality of life, behavioral risk factors and other determinants of behavior, and personal characteristics [33], [34] such as personal motivators and values [35], [36]. Indirect, technology-based means for more complex data interpretation (such as deriving information about habits and routines) are discussed in Section III.

C. Coproduction of Health

PHG users are surrounded by an environment comprising multiple coproducers that together with the users coproduce

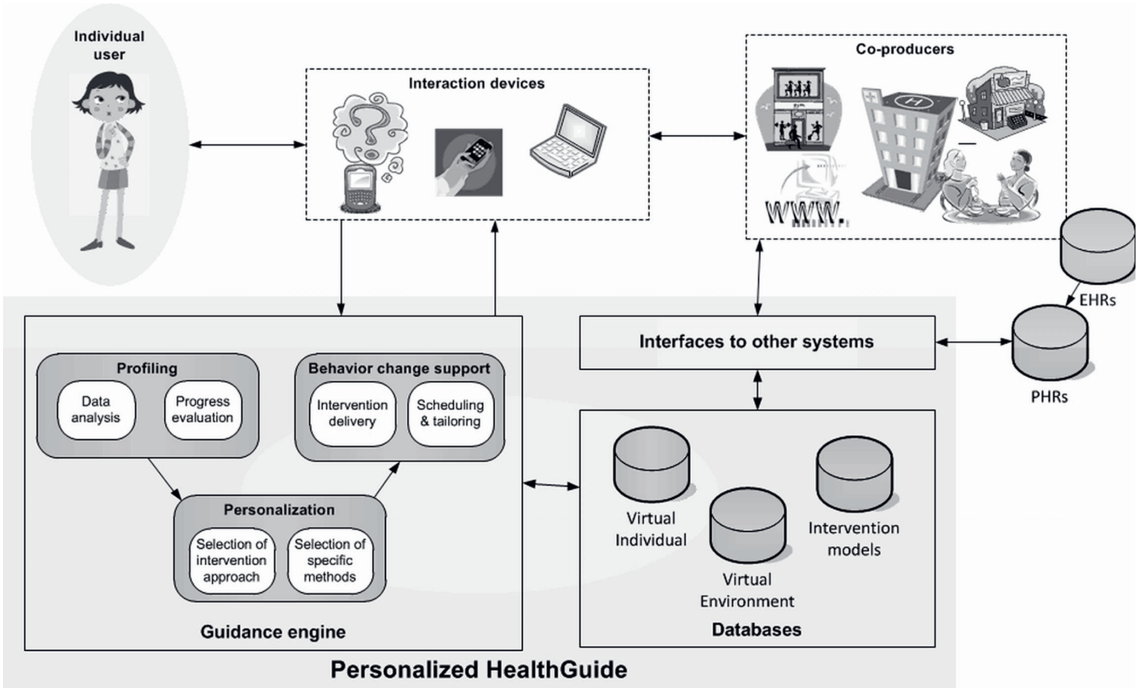

Fig. 2. Conceptual overview of a PHG.

health. These include, e.g., family, work, schools, shops, restaurants, leisure activities, and of course healthcare. All these parties, including the users, constitute a network of *coproduction of health (CPH*), where people navigate their lives and in doing so interact in the CPH network.

The CPH network can also be viewed as a *health outreach ecosystem*. It is governed by rules set by society, institutional players and other stakeholders. The rules determine how value is created and business is conducted inside the ecosystem. The reason to call it a health outreach ecosystem comes from the following two observations: 1) although healthcare providers are members in the ecosystem, there are also many other coproducers; and 2) as PHGs are used 24/7, nonhealthcare coproducers (e.g., family, work, and educational institutes) play a more important role in affecting the daily health decisions/choices of users.

III. Personalized HealthGuides

A. Introduction

Health promotion interventions have used technology for personalization and tailoring for a long time. The first generation of tailored interventions consisted of print materials such as reports and pamphlets, which were tailored to different target groups; the second generation took advantage of interactive technology, websites and desktop applications; and the third emerging generation delivers interventions with mobile and remote devices to provide tailored support in the context of everyday life [37], [38].

These third-generation tailored intervention systems, which we have named Personalized HealthGuides (PHGs), should address relevant behavioral determinants with motivating and engaging strategies, provide personalized support and guidance in everyday situations based on users' individual characteristics and needs, adapt to changing contexts, and deliver support at opportune moments, i.e., when users are both in need of and receptive to the support. A conceptual overview of PHGs is depicted in Fig. 2.

PHGs must be ubiquitous, accompanying individuals in their everyday lives, and aware of the users' current situation or context by maintaining a *virtual environment* model. They also need to be aware of the behavior change support services or intervention strategies available from different coproducers, and incorporate a *guidance engine* that selects the most appropriate methods and solutions for a given situation and user characteristics. The employed support strategies should be continuously evaluated and updated against individuals' progress in their health journeys and the changing environmental conditions. PHGs also need to coordinate interactions and data exchange with coproducers, and derive data from various sources including personal health records (PHRs), which in turn gather clinical data from electronic health records (EHRs).

Underpinning these parallel processes, PHGs need to maintain user profiles that incorporate the personal profile variables presented in Section II. User profiles are dynamic, updated whenever new information is learned about the users. We refer to this kind of comprehensive representation of a person as the *virtual individual*[3] model.

In the following, we discuss the current state of knowledge about how technology can be used to support healthy behaviors to form a picture of how far in maturity the current technology is from being able to facilitate the described ubiquitous, context-aware PHGs. We will focus on behavior change support technologies in the domain of health and wellness and on user-adaptive software systems. This section is structured through the following questions.

1) What technological methods exist to address determinants of behavior change and to promote coproducer involvement through supportive environments?
2) What is the current state of technology-enabled behavior change support (BCS) interventions, and how effective and successful have they been?
3) What is the state of the theories and frameworks of ICT-enabled behavior change? Are there established guidelines and tools to develop ICT interventions?
4) How can individual characteristics and the context of a person be modeled, and how far have existing systems gone in personalization and tailoring?
5) How can technology be used to choose suitable intervention approaches and methods?
6) What is known about delivering interventions at opportune moments?

We finish the section with a discussion of the gaps between the envisioned PHGs and current level of knowledge and of ethics and acceptability of continuously monitoring individuals in their daily activities.

B. ICT Methods to Support Behavior Change

This section provides an overview of various existing methods for technology-based behavior change support. The methods are categorized loosely based on the behavioral determinants they target (see Fig. 1).

1) Motivation and Outcome Expectations: From the viewpoint of BCS technologies, motivation has two layers: 1) how can technology be used to increase users' motivation to commit to sustainable lifestyle changes? and 2) how can people be motivated to use BCS technologies? Engagement, both initial and long-term, is a prerequisite for the other objectives of a BCS technology; if users stop interacting with the system, it can have no further impact [39], and a system which is not used does not provide value to users.

Peer and counselor support and networking, e-mail/phone contact, frequent website updates, and tailored content are related to longer website visits or a larger number of logins [40]. Periodic prompts which penetrate into users' daily lives can be used to remind and motivate them to persevere with healthy behaviors or to continue using the intervention program [41]. Follow-up prompts can be important to achieve maintenance of behavior change [42]. It appears that outcomes improve if prompts are frequent (e.g., weekly instead of monthly).

[3]We have coined this concept to complement the virtual physiological human (VPH) concept. VPH aims to comprise all the knowledge of the biology and physiology of a human ("body"). Virtual individual in turn aims to comprise the knowledge of the personal characteristics of a human ("mind").

It has been suggested that health promotion interventions should be as entertaining and appealing as the competing activities to make the target behavior intrinsically motivating—pleasurable, fun experiences for the sake of the behavior itself [13]. In the creation of engaging experiences, inspiration can be searched from game design strategies such as different types of reinforcements to maintain interest [43], [44]. Games can make learning processes enjoyable and engaging and therefore more appealing than traditional instructional media [45]. Especially schools could take advantage of this.

Designing for emotional experiences is an emerging approach which leverages knowledge about user emotions to better adapt their responses [46]. Research in affective computing and emotional responses can also provide new insights to understanding motivation [47]. Emotional design is a balance between three levels of design [48]: 1) visceral level consists of physical features such as look-and-feel which are processed automatically; 2) behavioral level involves user perceptions of the usage of the intervention; and 3) reflective level comes into play as the user's perception of the meaning of the system use. The general "feeling" and purpose of the intervention is very likely to affect users' outcome expectations. It has been suggested that developers should consider looking at their interventions through a positive lens, focusing on the positive impact of healthy lifestyle to wellbeing, happiness and life satisfaction instead of the negative aspects of unhealthy behaviors [48], [49].

2) Awareness and Comprehension: Self-management of healthy behaviors essentially requires that an individual is aware of the benefits and risks associated with various options. We are flooded with information nowadays. Therefore, messages need to be simple and concrete with tailored content to increase personal relevance [25]. Besides message content, attention needs to be paid to the characteristics of the message source, which can function as a role model or means for social learning, and as the channel to deliver the message [50].

Intervention delivery channels should be appropriate and natural to users. Adoption of new ideas generally happens most effectively through interpersonal communication [24], since people's perceptions and attitudes are strongly influenced by their social networks. With the emergence of the Social Web, information is increasingly being spread by people through their friends and acquaintances [51].

Information quality, i.e., the system's ability to convey the intended meaning to its users, significantly influences information intake and user engagement [48]. There are guidelines and techniques to improve comprehension of quantitative information [52]. On a general level, the Information Systems success model [53] may offer a good systematic approach to the design of information content of interventions. Computer agents can be used for educational purposes and they may provide additional benefits over humans in real-life settings: they have more time to explain contents, patients feel less stupid if they need to ask the agent to repeat questions, agents treat every user in the same way without bias [54], and comprehension can be evaluated [55].

3) Abilities and Empowerment: Empowerment is a process through which people gain greater control over the decisions and actions affecting their health [56]. Empowered people have sufficient skills, understanding, and self-efficacy to take the responsibility of their health in their own hands. Several studies show that empowerment can be increased with ICT applications [17], [57] and digital games [45], [58].

Decision support systems are a special category of BCS technologies, aiming to improve performance and help people make informed choices. Decision support systems related to health have thus far been mainly focused on improving the performance of healthcare professionals. It seems that there is a theory-practice gap in designing decision support for patients [59]. Until recently, decision support interventions have assumed that people are rational in their decision-making; now they are beginning to acknowledge the emotional, cognitive, environmental and time constraints that people face [59].

4) Virtual Social Support: Social influences such as support, pressure, and perceived norms have a great impact on behaviors; social learning and role models are powerful facilitators of behavior change. People often have a tendency to respond to their computers as if they were living beings, and it is possible to form warm relationships between people and technologies [60]. A shift from pure system intelligence towards social and emotional intelligence in ambient and pervasive technologies has been promoted [61]. BCS technologies can be considered as social actors, and designed to be likeable and credible [62]. For instance, relational or embodied agents can be used to enable more natural, effective and engaging interactions with users [63]; feedback, praise, and adaptation to users' choices can bring a feeling of social interaction into the usage of technology [61]; and friendship, compassion and encouragement can strengthen the bond between users and technologies [62]. Users appear to like interacting with agents or devices more when relational strategies such as empathetic responses or facial expressions are utilized [64].

5) Supportive Environments: Promoting Coproducer Involvement: People's choices are influenced not only by individuals themselves, but also by the coproducers in their environments, the organizations they are involved with, and the communities and society they live in. Systems which enable coproducer involvement would involve, e.g., data transfer between various actors, advanced data interpretation to produce decision support for each actor's needs, and sufficient value for all coproducers to participate. For example, Internet interventions could be a valuable addition to routine care, enabling practitioners to guide patients to Internet resources [65].

Social support from family members, friends, and peers is invaluable in behavior change. In general, social support interventions for a variety of health-related purposes have been reasonably successful [66], and the presence of social support can be beneficial in BCS technologies as well [40], [67]. Even though evidence is still limited, personalized guidance through an empathetic human contact seems to improve intervention effectiveness.

Online support groups and health social networks exist nowadays for almost every possible topic related to health or wellbeing [68], [69]. The emergence of online communities such as *PatientsLikeMe* [70] has created new opportunities for crowdsourcing, harnessing the power of the crowd to create new knowledge and share existing knowledge. Common features in current online communities include seeking and sharing personal experiences, opinions and answers, and exchanging social support.

Society, communities, policy-makers and organizations have the power to set regulations and incentives that influence environments and promote healthy choices and discourage unhealthy ones. Currently, policy-makers scarcely have decision support tools to assess the effectiveness and feasibility of different health promotion strategies [71]. These kinds of tools could speed up the implementation of new health-promoting policies and increase awareness among policy makers.

C. *Effectiveness of ICT Interventions*

Several reviews and meta-analyses have examined the effectiveness of ICT interventions and have found them to be feasible and efficacious in various domains of health, such as psychotherapeutic use [72], [73], disease management [74], [75], health behavior change [17], [38], [76]–[78], and mental wellbeing through positive psychology [49]. However, the results have often been somewhat mixed. The knowledge about how to design effective ICT interventions for sustainable behavior change is still limited [48], and there is a lack of universal research guidelines [79]. In the following, we present a brief overview of the most studied categories of current BCS technologies: Internet interventions, mobile technologies, and video games.

Psychotherapeutic Internet interventions have had positive effects in treatment of various mental problems such as depression, anxiety [72], [73], stress and insomnia [73]. Preventive, health-promoting interventions have focused on behaviors such as physical activity, nutrition, alcohol consumption, smoking, weight management, and mental wellbeing [17], [49], [80]. Even though the general effectiveness of Internet-based interventions is now fairly well established, understanding of the specific components and strategies, which contribute to the effectiveness, is far from complete. Recent reviews and meta-analyses [17], [73], [76], [80], [81] have attempted to uncover design elements and strategies which influence the actual impact of Internet interventions. To increase effectiveness they suggest to base interventions on a strong theoretical basis, to tailor interventions to users' needs and characteristics [17], [81], to make the program interactive and engaging [17], and to utilize multiple behavior change strategies [76].

Mobile technologies can leverage contextual information to provide personalized behavior change support at opportune moments, as health-related information can be collected and analyzed in real-time and in everyday situations. Besides mobile phones, mobile devices which measure physiological variables can be useful in providing instant and objective feedback about behaviors; for example, pedometers have been shown to increase physical activity [82]. Mobile phones are becoming increasingly sophisticated and allow tailored programs that use interactivity and multimedia [15], [83]. Mobile technologies can also narrow the gap in accessing health resources. Currently, short message service (SMS) presents a primary delivery channel for interventions as it allows personally tailored interventions at low cost and is especially suitable for scheduled intervention delivery and certain behavior change methods such as periodic prompts and reminders [84]. Recent reviews on SMS interventions for preventive health behaviors, disease management, and clinical care have found evidence for improved outcomes in the majority of studies [75], [84]–[86].

Video games are often enjoyable and engaging, which potentially leads to increased motivation and to improved health outcomes. Several studies suggest that games are effective in training healthcare professionals in knowledge and skills [87], and in improving patients' skills and empowerment in disease management and rehabilitation [88]. They are also a potential new channel for interventions for the youth [89]. Relatively few studies on the usage of games to promote healthy behaviors have been conducted, and the empirical evidence in this area is still scarce [87]. Most attention has been paid on exercise games, so-called "exergames" to combat the ever-increasing obesity epidemic. Recent reviews confirm that games increase physical activity [90], [91] and nutritional knowledge [91] in children. Game-based learning seems to be at least as effective as conventional instructional media [45].

There is some evidence that ICT-enabled health promotion is effective. However, there is not enough evidence of the effectiveness on a long-term basis, partly because of the fact that many intervention studies have fairly short follow-up times, which do not permit far-reaching conclusions about the sustainability of behavior change [92]. Another factor to consider in this context is that the majority of the applications lack a comprehensive approach towards all dimensions of an individual's life, which may be one reason for the drop in usage rates after an initial period of interest [93].

D. Technology-Enabled Behavior Change Support: Theories and Models

In the following, we provide an overview of theoretical frameworks and guidelines which have been developed thus far for ICT-enabled health behavior change interventions. We also briefly touch upon the available tools and software frameworks which aid the design and implementation of BCS technologies.

1) Design Methods for BCS Technologies: The need for models to guide intervention design has resulted in the development of several guidelines, such as design propositions for ePsychology interventions [48] and behavior change model for Internet interventions [94]. These models provide a basic framework for Internet intervention development. In the domain of mobile and ambient technologies, general design strategies for behavior change technologies to support healthy lifestyles have been proposed [95]. For ambient persuasive systems, a model has been developed which can leverage situational awareness, context awareness, and user awareness to increase their impact [62]. As for video games, guidelines to develop psychotherapeutic gaming interventions for youth have been proposed [96].

The persuasive technologies field focuses on recognizing and utilizing various strategies to design technologies which support behavior or attitude changes or improve compliance [97]. It is a multi-disciplinary approach, combining disciplines such as health promotion and communication with engineering. Its focus is now shifting from single applications towards behavior change support systems (BCSS), i.e., information systems designed to form, alter or reinforce attitudes, behaviors or compliance [98]. In the following four approaches are discussed: functional triad, behavior wizard, persuasive systems design model, and design with intent.

The *functional triad* framework presents three persuasive roles that a technology can play: tool, medium, and social actor [97]. As a tool, technology makes users' activities easier or more efficient to do, e.g., leads through processes or performs calculations (improves abilities or lowers barriers). As a medium, it provides interactive and engaging experiences, e.g., simulations of behaviors, and it can be used for boosting self-efficacy, skills learning, or improving motivation. In the role of a social actor, technology mimics a living entity by modeling its behaviors, e.g., by providing feedback or social support.

The *behavior wizard* tool [99] has been created to function as a method for choosing proper design strategies to develop BCS technologies. The method classifies behavior change targets into 15 types along two dimensions: duration and flavor. Once the desired type of behavior change has been identified, the tool helps to locate relevant studies and strategies to achieve the desired outcome.

The *design with intent* (DwI) method has been developed to provide guidance for designers in choosing among design techniques for influencing interaction [100]. The method involves using eight lenses to provide different worldviews on behavior change. Examples of these lenses include Ludic Lens (techniques derived from games and playful experiences) and Cognitive Lens (using cognitive biases and heuristics based on psychology research to influence users' decisions). DwI is perhaps most effective as a tool for idea generation in early design phases.

The *persuasive systems design* (PSD) model [101] can be used for analyzing persuasion context and persuasive techniques. It has three main constructs: the intent, the event, and the strategy, and it includes 28 different strategies divided into four categories. PSD has thus far been used only for evaluation and analysis purposes.

Persuasive technology design methods seem to have potential in guiding the development of BCS technologies. However, thus far they have been put to test only in relatively small trials. In addition, most of them have been developed in Western, individualistic cultures. They may hence be less suited for collectivist cultures with different conventions and traditions.

In summary, models and frameworks for the development and evaluation of BCS technologies are emerging. They open up new opportunities to reach users in the midst of their everyday lives and to dynamically adapt intervention methods. This has prompted the question whether current health behavior models are applicable to mobile interventions [102]. Intervention tailoring has usually been done based on pre-intervention factors [38], [81]. Theories and models typically do not address how to adapt the intervention during its course, or how to time the intervention to opportune moments. One possible solution to transform current theories into dynamic theories might come from the field of control systems engineering [102].

2) Modeling Interventions and Evidence-Based Guidelines: Vinson *et al.* [103] argue that valuable time and resources are wasted on developing new interventions from scratch, and dissemination and reuse of interventions need to be considered early on. To improve reusability, software toolkits have been developed, such as *Michigan Tailoring System*[4] and *TailorTool* for the development of tailored interventions, and *DTask* and *LiteBody*[5] for developing dialogue-based systems.

Due to the complexity of human behavior, intervention protocols are challenging to model, as they need to describe the relationships between theoretical constructs, intervention methods, and actions that should be performed with certain preconditions. Behavioral medicine ontologies would be useful as they strengthen the linkage between theory and practice, provide reusable behavioral protocol components, and improve interoperability [93], [104]. Lenert *et al.* [93] made one of the first versions of such ontology. Bickmore *et al.* [104] have proposed a "core ontology" that consists of the following models: *theory model* with relationships between theoretical constructs and behavior change techniques; *behavior model* containing knowledge of theory application to specific behaviors; *protocol model* with parameters and criteria for a specific intervention; *user model* which consists of the personal characteristics of a user affecting intervention delivery; *external data model* with data inputs and outputs from the system; and *task model* which describes how the intervention is delivered, taking all the information into account. This ontology is in close agreement with the conceptual PHG model presented in Fig. 2.

Another issue in intervention modeling is the dynamic adaptation to changing situations and individual characteristics. A conceptual framework for adaptive interventions, which determines decision rules and dosages of adaptive components per tailoring variables, has been presented in [105].

E. Personal Profile: Modeling Users and Contexts

Personal profiling is widely studied in *user-adaptive software systems*. These are systems that tailor their appearance and behavior to the needs and preferences of individual users or user groups [106]. User-adaptive systems are used in many domains, e.g., marketing and e-commerce [107], [108], social networks [109], [110], entertainment [111]–[113], and health [81], [114], [115]. Of the many types of user-adaptive systems, *recommender systems* [116], [117] are the most relevant in the context of behavior change support, as they can be used to match appropriate interventions to personal profiles.

User models were initially introduced in the context of web-based educational systems, information retrieval systems, and recommender systems [106]. Mobile, ubiquitous systems brought along a new dimension by introducing the concept of *context-awareness*, which involves data acquisition not only about users, but also about their physical and social environments [118].

User and context models are overlapping concepts, since often systems do not differentiate user features from the environmental features. Moreover, there is no definite agreement on what variables should be considered as context. Dey *et al.* [119] have provided a useful definition of context: *Context is any information that can be used to characterize the situation of entities. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves*. The definition of context has been expanded in [120] with time, physical environment and artifact entities, and the person entity is further divided into user identity, preferences and current activity.

In this section we review how far the current systems are from the envisioned virtual individual and virtual environment models. First, we explore to what extent the constituents of the personal profile derived from behavioral theories (see Section II) are included in the existing user and context models. Then, we introduce the data sources that have been used to gather profile information, and summarize how user and contextual features are represented in the user and context models.

1) Personal Profiles in Existing Systems: The most commonly modeled user features in user-adaptive web systems are user knowledge, interests, goals or tasks, background information (e.g., profession, work experience, and job responsibilities), and individual traits (e.g., personality traits, cognitive styles, cognitive abilities, and learning styles) [106]. In web-based health systems, the most common user features are the current health behaviors, e.g., exercise and eating habits, and readiness to change behavior [81]. Other tailoring variables utilized include clinical risk factors, information needs, and demographics [81], [115], [121]. In [110], a physical activity related user profile is proposed, which includes users' personal motivators, number of desired workout partners, favored activities, available time slots for exercising, and vital signs to classify fitness level.

The first models representing user contexts were created for the purpose of platform adaptation, but as the interest towards mobile and ubiquitous systems grew, more contextual variables were incorporated to the models. In context-aware mobile recommender systems, the most popular variables used for personalization, in addition to user preferences, are location [107], [111], [113], [122]–[124], time [107], [111], [113], [122]–[124], and weather [107], [111], [113], [122]–[124]). Other variables include e.g., temperature [124], moods of users [125], [126], and the presence of people nearby for group recommendation [127].

A significant amount of context-aware research has focused on inferring users' current states or activities, e.g., driving on a highway [128]–[133], social ties [109], [134], [135], and social interactions [128]–[131], [135]–[137]. Current technology is able to perform this type of inference with rather good precision with sensors embedded in mobile devices. Even spatio-temporal events such as "leaving home" or "returning from vacation" can be detected [133], [138]. These contextual features provide a good starting point for representing the social and physical environments of users in the virtual environment model.

Examples of context-aware mobile health systems include patient decision support systems such as the *DiabetesLivingAssistant*, which suggests adjusted insulin dosages based on users' current glucose measurements, activity levels, and planned meal

[4]http://chcr.umich.edu/mts.

[5]http://relationalagents.com/litebody.html.

schedules [139], and the *WellDoc Diabetes Manager*™[6] which provides food recommendations for adjusting the blood glucose levels of users. Virtual personal trainers, e.g., the *mobile personal trainer (MOPET*) [140], are another type of context-aware health systems, which provide real-time advice during exercise.

2) Acquiring Personal Profile Information: The information required for constructing user and context models can be collected explicitly by requesting direct input from users, or implicitly by observing the user-system interaction and the behavior of users [106]. Information of health behaviors and clinical risk factors has been acquired from PHRs [51], [121]. For instance, there are recommender systems that actively push healthcare related information such as medical updates to users based on their PHR or electronic medical records (EMRs) [114]. In addition, there are various questionnaires available to gather personal profile information directly from users (see Section II).

Determining user preferences or interests is increasingly done through inference by observing, for instance, the services chosen or places visited [107], [113], [122], users' web browsing activities, documents viewed, applications used [113], and stress levels [112], and by exploring users' social network profiles [127], social web content [51], social ties [122], and the content of e-mails and calendars [113]. However, also explicit inputs from users are widely used, e.g., through user ratings [107], [111], [122], [123]. Moreover, the knowledge level of users can be inferred implicitly based on, e.g., users' answers to exercises, time spent on reading certain content, or the number of actions required to achieve a certain task [106].

In context-aware mobile systems, user activities and states are commonly inferred from the accelerometer and audio data, and some systems complement this data with location information to deduce more complex activities [129]–[132]. Determining the social environment of users is usually based on audio data [129]–[131] combined with proximity sensing (Bluetooth) of people [128], [135]–[137].

3) Structure of User and Context Models: The most commonly used model structure for representing user features in user-adaptive web systems is to have overlays of feature domains, where each concept of the domain, e.g., knowledge fragment, object of interest, or goal item, is associated with a weight that represents the extent to which that concept applies to the person [106], [141]. Overlay models are relatively easy to develop, and they can represent user features at an accuracy level sufficient to enable advanced adaptation [106].

The simplest form of an overlay model is a set of concepts that are independent of each other, a vector model [141]. Although this model provides a powerful platform for maintaining a detailed picture of a certain user feature, the construction of the model requires observations about each of the concepts due to their independency. A more advanced form of an overlay model involves relationships between the concepts and thus allows interconcept inference [106], [141]. There are two main types of connected models: a tree-like concept hierarchy and a network of concepts. The links between concepts enable knowledge and interest propagation through inference. For instance, if users are observed to master certain concepts, it is likely that they master also the prerequisite concepts, or when users demonstrate lack of knowledge, the links can help to identify the concepts that most likely could remedy the situation [106], [141].

Representation structures used for modeling contexts include key-value models, markup scheme models, object-oriented models, logic-based models, and ontology-based models [118], [142]. Of these structures, ontology-based models are the most interesting. They represent descriptions of concepts and relationships between them. With ontology-based modeling, context can be described in arbitrary detail, organized hierarchically from generic to specific aspects of context. Ontologies are also flexible and extensible [143]. Many context models incorporate first a high-level ontology that represents the relations between the general contextual domains e.g., environment, location, user, or time, and then have a set of domain-specific ontologies [120], [133], [144].

In context-aware recommender systems, contextual and user-related information are mostly represented in hierarchical tree structures [145], i.e., in overlay models. However, ontologies can also be used to represent information in these systems [146].

4) Modeling User Preferences in Context-Aware Systems: User preferences are often context-dependent [120], [133], [144]. For example, one's willingness to go for a jog may depend on the weather, location, current activity, and company. Thus, in context-aware systems that consider user preferences, there is a need to define which preferences apply in which contexts. This can be achieved by maintaining a user profile that is divided into subprofiles, each subprofile containing the user preferences for a specific situation [144], [147], [148]. In the following, two examples of context-specific preference modeling are referenced.

The first example is a standard for designing and managing context-dependent user profiles for the personalization of eHealth systems and services [147], [149]. The standard allows the definition of several user profiles: a normal profile that is always active including static user information and situation profiles corresponding to the situations (e.g., in a meeting, travelling) the user has specific preferences for. Each profile is specified to store information, preferences and rules. A similar approach can be found in the User Profile Ontology with Situation-Dependent Preferences Support (UPOS). It is a user profile ontology, which describes context-dependent subprofiles [144]. It supports location and activity context dimensions and can be extended with other domain-specific ontologies. The authors have defined also a Mobile Ontology for mobile platforms.

5) Personalization: Selecting Appropriate Interventions: Matching appropriate interventions with the virtual individual and virtual environment models is a nontrivial task, which requires the use of appropriate methods, such as the ones developed for recommender systems. In the following, we will discuss three recommendation approaches: content-based, collaborative, and context-aware recommendation [145], [150].

In the *content-based approach*, the features of item profiles are compared with the interest profile of a user to find items that match user interests. However, the weakness of content-based recommender systems is in their tendency to overspecialize the item selection [151]. Due to the similarity-based nature of rec-

[6]http://www.welldocinc.com/

ommendation, the recommended items are usually very alike, lacking diversity, and thus limiting the choice of user.

The second approach, *collaborative recommendation*, is based on the knowledge of partial user preferences, i.e., user ratings for a subset of items in the item domain [145]. In these systems, the user ratings for items not rated by the user are predicted based on the ratings of other people that have similar interest or preferences [152]. Collaborative recommendation systems are built on the assumption that users with similar interests, i.e., with similar profiles, are likely to find the same resources interesting [116]. The best known methods for collaborative recommendation are the *k-Nearest Neighbor* (kNN) algorithms [152]. However, as for the content-based recommendation, collaborative recommendation also has its limitations: For large databases of user ratings, the processing time and memory consumption required for the neighborhood calculations can get high [152]. Furthermore, the power of collaborative recommenders to provide successful recommendations depends on the availability of a critical mass of users [150]. One way to overcome the problems related to the content-based and collaborative recommendation approaches is to combine aspects from these two into a hybrid system [150].

The third approach, *context-aware recommender system* (CARS), is a new and underexplored area [145]. CARS can be categorized in two groups: 1) recommendation via context-driven query and search and 2) recommendation via context preference elicitation and estimation. The context-driven query and search approach is analogous to the traditional content-based recommendation used in information retrieval systems. Systems using this approach use contextual information, obtained directly from the user or through sensing the environment, to search certain items (e.g., restaurants) and to present the best matching items as results (e.g., nearby restaurants that are currently open). The preference elicitation and estimation, which is analogous to the collaborative recommendation approach, represents a more recent trend [145]. In contrast to traditional recommender systems, CARS function in a multidimensional space.

F. Opportune Moments

PHGs should provide or recommend the selected interventions to users at moments when users are most receptive to interruptions and when they are in need of interventions, i.e., at *opportune moments*.

The most studied factors determining opportune moments for interruptions are the current activity of the user [153]–[158], social engagement of the user [153]–[158], and social expectations regarding the behavior of the user [153]–[159]. In general, users perceive context-aware interruptions less disruptive than random interruptions [156], and studies demonstrate that considering even some of the factors that determine opportune moments can be sufficient to achieve predictions regarding the interruptibility of a person with a high accuracy [153]–[155].

Consideration of the current activity of the user when determining opportune moments is especially important during mental tasks. Empirical studies show that interrupting users when they are in the middle of such a task may have a significant negative impact on the task completion time, error rate, and users' affective states [160]. More appropriate moments for interruptions would be during the transition points between tasks, when the current task performance is disrupted the least, to avoid burdening the user with additional mental load [160]. A common approach for detecting task transitions in mobile systems is to monitor the movements of users [155], [156], [158]. However, also the content of the interruption message matters, since one might be receptive to interruptions that are perceived as important or interesting, even when immersed in a task [157], [161].

Kern *et al.* [155] divide the concept of interruptibility into notions of personal interruptibility and social interruptibility. According to the authors, it is important to distinguish situations when a prompt will interrupt only the user from situations when also the nearby people will be interrupted. For example, when listening to a boring lecture, a user might be very receptive to interruptions. However, delivering an interruption with a loud notification sound in this context could be embarrassing to the user and disturbing to others. In addition, when engaged with social interactions users are less receptive to interruptions [156]. These examples demonstrate the importance of the social engagement and expectations factors. The social context influences not only the interruptibility of a person, but also the appropriate modality of interruption [155]. Selker [162] claims that in the future the social situation will become the most important factor to be considered when delivering interruptions with mobile devices.

Besides users' receptivity to interruptions, an equally important aspect to be considered is the moment when interruptions or interventions would be most needed or useful to users. Examples of such systems include a mobile stress management application that provides emotional regulation exercises to users at stressful moments [163], [164], and a user-adaptive reminder system that triggers reminders for medication intake and health related activities at moments when the user is in close proximity to the place where the task can be performed [158]. In drug treatments, the timing of drug delivery is crucial for achieving the optimal treatment effectiveness and minimizing adverse effects. Opportune moments in this context depend on factors such as the prescribed drug schedule (e.g., in the morning/evening, before/during/after a meal), usage of other drugs, and the patient's vital signs (e.g., blood pressure, blood glucose).

G. Gaps Between Existing Solutions and Requirements

In the following, we discuss the gaps found between the theoretical knowledge and the SoA of technology-enabled behavior change support. A strong theoretical basis is essential for technology-based interventions, but there is no single theory that covers the full complexity of behavior change support. The most fruitful results stem from deliberate and insightful combinations of ideas from various established theories and empirical evidence to a practical approach of studying the characteristics and needs of the users.

As expected, we were not able to find in the literature holistic health guidance systems with deeply personalized behavior change support and involvement of various coproducers along the lines envisioned in the PHG scenario presented in Section I. However, some interesting prototypes do exist. One example is a wellness self-management platform that provides dietary and exercise recommendations and suggests wellness and health services based on users' current location, activity state, intentions and preferences [165]. Another example is a universal remote controller for a home entertainment system that promotes nonsedentary activities by providing subtle clues that encourage alternative behaviors to watching TV at appropriate moments, i.e., when users are most likely to act upon the clues, e.g., during commercials or when shuffling through TV channels [166]. Additionally, wellness companies that claim to deliver personalized behavior change support to individuals exist, such as *Healthrageous*[7] and *HealthMedia*.[8] However, these solutions are still far from the PHG scenario.

Delivering appropriate interventions at opportune moments requires solid knowledge of effective strategies for different users in varying contexts. PHGs need to utilize established and proven intervention models to generate personalized intervention plans and update the BCS delivery processes continuously. Although most technology-based interventions have been based on behavioral theories, little work has been done in unifying the concepts and models to facilitate the reuse and dissemination of interventions. There is good empirical evidence of the effectiveness of technology-based interventions in general, but more detailed analyses of various elements which contribute to effectiveness have just recently begun to emerge. Instructions for developing, evaluating, and reporting Internet interventions [79], [94], as well as the development of comprehensive behavioral medicine ontologies [104] and increased attention to re-use of existing interventions [103], will improve the quality of studies and increase the body of knowledge of specific effective strategies. Finding common elements in existing interventions and utilizing them to build more complex, holistic BCS systems which support multiple behavior change is necessary for the realization of PHGs. Rigorous evaluation of theory-based interventions will also lead to improved theories, as their concepts and statements are put to test. Current health behavior models are not easily applicable to personalized and adaptive guidance within the changing contexts of everyday life [102], and improved models for dynamic and mobile interventions may need to be developed. Generalizability of results is also an issue; study samples have been biased towards female, Caucasian, well-educated, voluntary participants, who cover only a small part of all the possible personal profiles.

User-adaptive software systems already use several personal profile components that are required for building the virtual individual and virtual environment models, such as knowledge interests, personal traits, goals, current activity, social interactions etc. However, in addition to these, there are still many other variables to be included to the personal profile in order to be able to find the suitable interventions for a person. Such variables are, for instance, individual values, self-efficacy and attitudes towards health behaviors, ethnicity and religion, and barriers impeding healthy lifestyle. Furthermore, though methods exist for detecting social ties and social interactions, even more important is to understand how other people influence the health choices of a person. This would require maintaining at least partial virtual individual models of the friends and families of users. One practical way to do this could be the approach used in Darwin phones [167], where user models are exchanged between devices during social interactions.

PHGs should also be able to learn the behavior patterns or habits of users for predicting their intentions, behaviors and feelings. This knowledge is essential for identifying the moments when interventions would be especially helpful and effective. For example, a bad morning may overshadow the whole day and reduce one's motivation to eat healthily. However, research regarding opportune moments in terms of the usefulness or helpfulness of interventions is scarce, though delivering interventions at the least disruptive moments is widely studied. Moreover, high-level inference methods for predicting intentions and behaviors are still in their infancy, and this would require also more advanced context-aware sensing. A preliminary attempt for learning behavior patterns is presented in a recent study [168]. It should be acknowledged, though, that the current state of the context-aware research is already well developed, and accurate methods exist for somewhat complex inference, e.g., for detecting different social situations and user activities/states. This provides a good basis for the development of higher-level inference regarding intentions, feelings, and behavior patterns.

The algorithms utilized in recommender systems should be used as a starting point when developing the guidance engine of PHGs. As such these algorithms may be too simple, since they support only simple personal profiles of few variables. Furthermore, the collaborative recommendation algorithms might not be applicable at all for the purposes of PHGs, since they rely on finding users with similar interests. When aiming at something as complex as lifestyle management, each of us is unique with different motivational factors, underlying problems and barriers to address.

When constructing personal profiles, information about users and their environments should be collected as unobtrusively as possible, requesting only minimal amount of direct input from the users. Sensing is only one method for unobtrusive data collection for user profiling. A huge potential lies in utilizing the information collected by different coproducers, e.g., consumer records from shops and service providers, PHRs and EHRs. However, this requires a fully functional coproducer network, where coproducers receive value from sharing their data with the PHG users. The *Vitality corporate wellness program*[9] is an example of how the coproducer network could function in the wellness field. This network includes, e.g., fitness companies, shops, biometric screening retails, health clubs, and tracking devices[10]. The members of the Vitality program are encouraged to use these services at low cost, and the service providers share the consumer information with the Vitality program. Vitality uses this information to track healthy actions of its members and to motivate them to live healthily through rewarding.

Due to their continuous data exchange and synchronization, PHGs need to contain various interfaces to other systems in their architecture. The flow of information between systems requires standards for the content and distribution of messages. A lot of

[7]http://www.healthrageous.com/

[8]http://www.healthmedia.com/

[9]http://thevitalitygroup.com

[10]http://www.discovery.co.za

research has been done on the semantic interoperability front for PHR services, and the development of standards is well underway. However, the virtual individual model includes several concepts related to psychological and behavioral factors which are not included in current vocabularies and ontologies. Therefore, the development of PHGs will necessitate extensions to current standards.

Ethical aspects are obviously highly important in setting up systems which monitor users in their daily activities. The data collected by PHGs can be very sensitive and most people would want to have full control over what data is collected, who can access it, and who they share it with. The persuasive intent of PHGs should also be made clear to users to avoid deception or coercion. Moreover, access to technology and healthy options to choose from is not equal. Groups with highest risks may be those who do not have access to advanced technologies or live in environments which discourage healthy lifestyle, as it is e.g., for some ethnic minorities. The primary aim of PHGs should always be the empowerment of users and the improvement of their wellbeing, based on their free will.

IV. Health Outreach Ecosystem

The PHG scenario presented in Section I comprises on one hand the environment in which users navigate their health journeys, and on the other the PHGs that users use as navigation assistants. The environment comprises the coproducers that interact with users and thus influence their behavior and decisions, and the institutions that set the rules that govern activities in this Health Outreach ecosystem. The previous two sections focused on the design principles of Personalized HealthGuides, which should be fulfilled before users can and want to use such systems. This section looks at the other side of the coin, i.e., what is the business environment in which PHGs will be used, and more precisely, how is value created in this environment. The central tenet is that service providers should focus on value creation, because technology is merely an enabler for value creation. Doing so requires an understanding of the key concepts we introduce in this section: value and value creation through a service-dominant mindset [169], the business model as a blueprint [170] for value creation, service ecosystems [171] as the context for value creation, and the “rules of the game” [172] that create opportunities and barriers for value creation.

A. Value and Value Cocreation

Value is an elusive concept implying some form of an assessment of benefits against sacrifices [173]. Value has been emphasized as the key driver in reinventing health and healthcare by the foundational work of both Michael Porter [4] and Clayton Christensen [3]. In healthcare, value discussions are often dominated by Porter’s value-based healthcare model, which focuses on redefining healthcare through value-based competition [4]. This view defines value “as patient health outcomes (benefits) achieved relative to total cost (sacrifice)”. While Porter’s view on value is appropriate within traditional healthcare settings, it is not applicable to the Health Outreach ecosystem. The main rationale for this is simple: maximizing patient health outcomes relative to cost (value) will not lead to healthier behaviors. Hence, if we want to change the health behavior of individuals, we need to define value and its creation differently.

Discourse on value and value creation is topical in service marketing and management research. Much of the recent interest has been driven by the introduction of *service-dominant (S-D) logic* [169]. S-D logic is a mindset for a unified understanding of the purpose and nature of organizations, markets and society. Its foundational proposition is that organizations, markets, and society are fundamentally concerned with the exchange of service—the process of using one’s resources for the benefit of another entity [174]. Although S-D logic has to date received little attention in the healthcare domain, the lens through which it views value and value creation provides a more suitable foundation for the Health Outreach ecosystem, because it emphasizes two critical aspects required for disease prevention to be effective.

Firstly, prevention services in the Health Outreach ecosystem will only be effective if customers accept the value proposition of service providers, i.e., are willing to “do the job” [3]. S-D logic argues that the customer is always a cocreator of value [174]. Value creation is interactional as it is created jointly and reciprocally in the interactions between providers and beneficiaries [175]. This argument challenges the distinct roles of producers and consumers where previously producers were seen as the sole creators of value which customers then “destroyed” by consuming a service or good [175]. The acute care model of healthcare follows this view where the patient’s role in value creation is secondary to the input of medical professionals who create value by “curing” the patient. Patient empowerment deals with facilitating and supporting patients to reflect on their experience of living [176]. The S-D logic notion of value cocreation takes this further and argues “there is no value until an offering is used, i.e., the offering is actually experienced” [177]. Successful prevention services in the future will, therefore, go beyond thinking of patient or customer empowerment, into designing their offerings around the customer.

Secondly, prevention services will only be effective if providers know what value propositions customers are willing to accept, i.e., “what are the jobs customers want to do?” The fact that customers and suppliers think in different ways was observed by Drucker [178] long ago who argued “the customer rarely buys what the business thinks it sells”. In other words, customers and suppliers often have a different perception of an offering’s value proposition and, hence, value. Service-dominant logic argues that value is uniquely and phenomenologically determined by the beneficiary, because value is idiosyncratic, experiential, contextual, and meaning laden [174]. Customers are not passive, but instead they actively coconstruct their own consumption experiences, and as a result cocreate unique value for themselves [179]. Prahalad and Krishnan [180] refer to this shift as “$N = 1$,” where value will be based on the unique, personalized experiences of consumers, and company focus moves from masses to a focus on the centrality of the individual. For service providers this means going beyond mass customization into personalization based on understanding the behavior, needs, and skills of individual consumers [180]. The benefits of personalization have already been recognized and several ICT solutions (see Section III) have adopted a

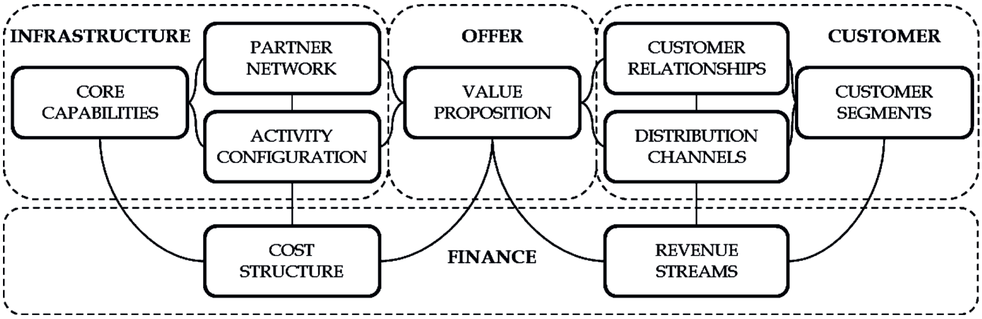

Fig. 3. Components of a conceptual business model.

personalization approach. However, in practice personalization often manifests itself through design related choices in the production of a service, something close to customization. Successful prevention services of the future will go beyond this and offer personalized value propositions that are built on understanding the unique, personalized needs of customers, hence, facilitating the creation of experiences for customers.

Finally, long-term success for prevention service providers in the Health Outreach ecosystem requires emphasizing a value-in-use perspective over a value-in-exchange perspective, because they reflect different ways of thinking about value and value creation. A firm's competitive advantage is said to depend on its ability to create more value than its rivals [181], [182]. However, a distinction can be made between two forms of value: exchange-value and use-value [174], [175]. Service-dominant logic relates an exchange value or the value-in-exchange view to what it refers to as goods-dominant (G-D) logic [183]. In G-D logic value creation usually occurs through a series of activities performed by the firm [175]. This firm created value is then embedded in products or services which are distributed to the market in exchange for a fee [175]. Service-dominant logic on the other hand emphasizes use-value or value-in-use [175], where customers as cocreators are central contributors to the value-creation process, and where providers and beneficiaries integrate their resources and apply their competences [175]. A value-in-use perspective reflects thinking of customers as cocreators and value as something unique to the individual [174]. Although we argue for a value-in-use perspective in the Health Outreach ecosystem, value-in-exchange remains an important component in the cocreation of value [175] by securing the sustainability of value proposing service providers. As Grönroos argues, in the long run "no or low value-in-use" equals "no or low value-in-exchange" [184].

B. Business Models as Blueprints for Value Creation

One of the key arguments for the sluggish development of the PHS market has been said to be the lack of sustainable business models [185]. While this statement summarizes much of the problems in the current field, it does not help to recognize the root causes behind the problems. A key reason for this is that we do not share a common understanding of what a business model means. This common language is a prerequisite for creating sustainable business models on a large scale. The concept business model became a "buzzword" during the internet boom [186] and has since become increasingly popular [187]. Schafer *et al.* found that although numerous business model definitions have been suggested, no generally accepted definition has surfaced [188]. However, a theme uniting these various perspectives is value creation. Initially, business model literature emphasized exchange-value, as business models were believed to illustrate "how firms planned to make money long-term, using the Internet" [189]. Where this view emphasized an exchange-value perspective, currently literature also recognizes the creation of customer use-value as a central part of the business model. For example, Chesbrough and Rosenbloom [190] argue the business model is a mediating construct between technology and value, where they consider value as an economic concept primarily measured with what a buyer will pay for a product or service. However, they also state that "the business model starts by creating value for the customer and constructs the model around delivering that value". Osterwalder and Pigneur [191] argue similarly that business models should describe what value is provided to customers (value-in-use), how this is done, and with which financial consequences (value-in-exchange). These two perspectives to value have led to a common misconception related to business models, in that many discuss business models when they only mean parts of a business model [192]. An example of this is using the concepts revenue model and business model as synonyms. Where the business model consists of components related to value creation and value capture, the revenue model focuses only on the value capture components. Fig. 3 presents a conceptual business model [191], [193]. Firstly, business models are developed around the value proposition which Christensen *et al.* [3] define as a product or service (offering) that helps customers complete a job they have been trying to do more effectively, conveniently, and affordably. Hence, customers and how customers are reached must also be parts of the business model as "a business model should explain how a firm creates value to its customers" [194]. Secondly, in order to create this value, firms need resources and capabilities to perform activities that enable producing the offering. These activities can be performed by the firm itself or the offering can be coproduced with partners in the firm's network including customers. Hence, capabilities, resources, and the value network are components of the business model. Finally, a business model should also explain how the firm yields a profit from this [194], i.e., captures value. The financial elements of a business model include the revenue streams or revenue model, and the cost structure which is dependent on how the firm's activities are organized in producing the offering.

C. Service Ecosystems as Locus of Value Creation

Healthcare, and especially healthcare ICT, has recently adopted the concept of ecosystem. Compared to how popular the concept has become, it is rarely asked what an ecosystem actually is, and what it means for individual actors. Thus far the dominant view has been to link ecosystem with interoperability and Personal Health Records. Focus has been placed on integrating products or services into what are referred to as "personal health ecosystems" [195].

Where the ICT view conceptualizes ecosystems as interoperable products and services [195], various other streams conceptualize ecosystems as interconnected actors [171]. Moore [196] was the first to use the ecosystem concept. He defined a "business ecosystem" as an economic community supported by interacting organizations and individuals. Recently S-D logic has defined service ecosystems as "spontaneously sensing and responding spatial and temporal structures of largely loosely coupled, value-proposing social and economic actors interacting through institutions, technology, and language to coproduce service offerings, engage in mutual service provision, and to cocreate value" [171]. Where the ICT view focuses on "how" services are connected from a technological perspective, business literature goes beyond this by placing emphasis on how the actors who create these services are connected. Furthermore, in the case of S-D logic the definition also discusses why actors connect [171]. This broader view to ecosystems will enable seeing opportunities for cocreating value, which are not as easily visible with the ICT lens.

The increased interest in ecosystems and other forms of inter-organizational networks, such as value networks [3], value constellations [197], service systems [198], business nets [199], and market configurations [200], stems from changes in the business environment and competitive landscape, which have had an effect on how value creation is perceived. Key changes include globalization, deregulation, and technological change [201]. Currently many streams of research argue that the locus of value creation is shifting from residing within firm boundaries to being something that is considered to be cocreated among actors within the networked market [194]. This shift means that the traditional dyadic perspective of inter-organizational exchange relationships is being replaced by a network perspective [202].

According to Prahalad and Krishnan [180] this shift, referred to as "$R = G$," is related to changing customer preferences. As company focus moves from masses to a focus on the centrality of individual customers and their experiences ("$N = 1$"), emphasis must shift from ownership of resources to access to resources, as no company alone can move from serving millions of customers to serving one customer [180]. For an individual actor this means that business models have to become more "open" [203] when increased competition pushes companies to concentrate on their own core competences [204] and to outsource other activities to partners and customers. These joint activities of the firm, customer or other network partners in creating the service offering are what S-D logic refers to as coproduction [175]. The business model of the focal actor defines how it interacts with other market actors [200]. It is the interface through which all interactions between market actors are conducted and, therefore, all interactions between market actors are in fact interactions between actors' business models [200].

D. Rules of the Game

All economic and social actors act in the context of society, culture, the economy, and politics [205]. Institutions that govern individual behavior and structure social interactions can be referred to as the "rules of the game" [172]. North argues "institutions are the rules of the game in a society or, more formally, are the humanly devised constraints that shape human interaction" [206]. The rules consist of formal legal rules and informal social norms that govern individual behavior and structure social interactions [206]. Where institutions are the rules of the game, organizations are the players [172] who will try to take advantage of the opportunities provided within a given institutional framework [207]. To put this in the context of the previous sections, actors will try to create value, for which the surrounding institutional framework will both provide opportunities and create barriers.

Within healthcare, new entrants outside the regulated health scheme are often faced with high entry barriers due to the border between regulated health services and so-called market driven services. This has made it difficult to realize opportunities for value creation. In fact, where firm and industry boundaries have become increasingly blurry in many sectors [208], healthcare more often than not, can still be described as a relatively closed system where coproduction [174] between traditional healthcare organizations and new entrants is scarce. Healthcare has been characterized as a highly institutionalized sector [209]. Its distinct boundaries have, therefore, to a large extent been set by healthcare's "rules of the game". North has argued that institutions, i.e., rules are not necessarily or even usually created to be socially efficient. Rather they, or at least the formal rules, are created to serve the interests of those with the bargaining power to create such rules [172]. Within healthcare licensure and the presence of asymmetric information has led to a concentration of decision making to medical professionals to the extent that is has been referred to as professional dominance [210]. As a consequence, medical associations have accumulated substantial political influence, as well as secured a legal monopoly for medical practice [210]. While this position enables substantial bargaining power in creating new rules, it does so to sustain old rules as well. The rules ultimately determine the design of health systems. Hence, if improvements in chronic care cannot be achieved by further stressing current systems, because the fundamental problem is the system's design itself [211], then we should conclude that the current "rules of the game" are not equipped to meet the challenge of chronic diseases.

When previously the healthcare industry was said to exhibit "dynamics without change" [212], more recently changes have occurred in many areas from the delivery of services to mechanisms used to pay for them [209]. However, while a certain degree of change is always present, the speed at which this change has occurred has not matched the external pressures healthcare systems are faced with. Healthcare systems are social systems, and therefore change does not occur instantaneously as the system's structures display recalcitrance and inertia [209]. Greenwood and Hinings [213] argue that while change in healthcare does not come easily, when existing structures and beliefs are severely undermined or challenged, profound change can occur rapidly. To date, this has not been the case. Whether this is due to the bargaining power of the medical professional to sustain current rules, the system's inertia towards change, or the fact that healthcare systems are succeeding better than ever in what they were designed to do to respond to acute illness is not relevant. What is relevant is that tackling the "tsunami" of chronic diseases requires a significant change to the status quo. If this change does not come within the current healthcare system, then it will have to come from outside it. The game will have to be changed.

E. Implications for Health Outreach Ecosystem

The Health Outreach ecosystem focuses on customers and coproducers, not patients and healthcare service providers. ICT is an enabler of the ecosystem, with its core concepts and foundation being based on value and value creation. ICT integrates the ecosystem actors and realizes the "$N = 1$" and "$R = G$" shifts that need to be pursued in concert [180]. The key thing to understand is that the ecosystem deals with the health choices and everyday lives of individuals. The behavioral choices we as individuals make are estimated to have a 60% effect on our health while the healthcare system itself only accounts for 10% [214]. Thus, nonhealthcare actors (including the users) have potentially a much stronger influence on people's behavior. These coproducers offer services in the everyday life of the PHG users.

For the Health Outreach ecosystem to have the systemic impact societies are in need of, they have to be aligned so that actors within each line work together and coproduce. This means bundling of service offerings to create ecosystems of coproducers within sectors that impact the health behavioral choices of individuals. These sectors include but are not restricted to education, media, food and beverage, consumer electronics, sports, leisure, and tourism.

From an individual service provider's perspective, it is the business model that enables connecting the dots between the two shifts by conceptualizing how unique value is cocreated with customers, and how coproduction among network partners enhances an actor's ability to do so. Business models are the way to translate this new kind of health thinking into practice. One of the key business model changes required on a general scale is to move from traditional healthcare-driven value propositions, which promise better health in the long-run, to propositions that emphasize short-term benefits based on unique experiences of consumers but combined with long-term health effects.

However, business model changes alone are not enough. Achieving systemic change and creating healthier environments will require both a bottom-up approach led by innovative service providers and also a policy-driven top-down approach creating favorable "rules of the game" for coproducers. Otherwise, the result will be merely "happy islands" of wellbeing services and individual success stories, but not the kind of societal change in the scope societies are in need of.

V. Conclusion

We are faced with a potential "tsunami" of chronic conditions and diseases. Current healthcare systems and health promotion campaigns are not able to tackle this challenge. The commonly offered solution to this is the empowerment of people to manage their health with ICT-enabled services. This stems from the fact that most chronic diseases could be prevented or at least their onset delayed, if we would lead a healthy lifestyle. Schools have a crucial role in educating people about health consequences, but this initial awareness is often not enough when faced with challenges and temptations in everyday life.

What we need are PHGs that complement health policy and health promotion activities, not replace them. The "job to be done" is to develop solutions that can persuade users to change their lifestyles voluntarily and to maintain that course. This means that the success of PHGs depends on whether the users will use them; simple statement with a lot of content, as demonstrated by the scenario presented in Section I, and the analysis of the state of the art in Sections II–IV. The lessons can be summarized along two axes, namely the technology axis of building PHGs and the business or ecosystem axis in which PHGs are used. Along the technology axis the challenges are as follows.

1) The theory base needs further work. At the moment no single theory is able to explain behavior or successful behavior change interventions. Furthermore, people usually have multiple behaviors that need to be changed. We need to combine existing theories and intervention models, test their statements, reuse effective elements, and learn from experience.
2) PHGs must be deeply personalized in order to be capable of assisting users in health navigation. The personal characteristics of users are not static. They depend on a number of internal and external parameters. A dynamic ontology based virtual individual model of the user is needed. Although a lot of work is being done in the field of recommender systems, they are not focused on profiling for behavior change. Profiling is the area in need of most work.
3) PHGs must also be context-aware. We need a dynamic virtual environment model to represent the context around the user. There is good work done in context-awareness in other application areas. What is needed is to apply these to the CPH network.
4) Opportune moments and channels for delivering appropriate support to users is another area in need of more experimental research.
5) PHGs need to support user mobility 24/7. The architecture of PHGs thus needs to be explored from two viewpoints: distribution and synchronization of the processes that acquire and maintain the virtual individual and virtual environment models, communicate with the coproducers, and provide guidance at opportune moments.

Along the Health Outreach ecosystem axis the challenges are as follows.

1) The Health Outreach ecosystem cannot be created by healthcare payers and providers alone, because investing enough healthcare funds in disease prevention is not possible in the present healthcare systems. The way out of this vicious circle is the introduction of new actors. The coproducers could change the way the "prevention game" is played. The Health Outreach ecosystem is therefore a disruptive scenario for the future. It presents an alternative mental model for the prevention game and opens up new avenues for further discussion. With new players bearing the risk, we might finally see some return from prevention.
2) Nevertheless, healthcare is a partner in the ecosystem. The interventions must be based on best practice evidence. Furthermore, healthcare professionals have a central role in coaching people towards healthy lifestyles and in the management of chronic conditions.
3) We need to collect clinical evidence that the ecosystem approach is working, i.e., able to reduce the disease burden caused by chronic diseases. The problem with this is that the lead time until a diagnosis can be made can be several tens of years. Therefore randomized clinical trials are not possible. Instead, pseudo-parameters (like weight, amount of exercise, stress levels etc.) could be utilized as endpoints, as we know that there is a cause–effect relationship between these and chronic diseases.
4) Finally, in order to create a trusted relationship between users and service providers it is not enough to handle safety and privacy aspects only in the technical architecture of the ICT-enabled services and PHGs. Instead, these need to be considered at the overall ecosystem as part of the "rules of the game" issues.

Value-in-use underpins the CPH environment both from the personal and ecosystem perspectives, as it is the users who ultimately decide if they use the PHG services. This implies the need of a coherent, trusted offering, and bundling of the Health Outreach ecosystem services. We need to merge long-term healthcare-driven criteria with consumer-driven ones, which are short-term and user experience-driven. Furthermore, lifestyle management implies the need of a continuum of the offering in time and space. This can be achieved in a sustainable mode only by networked organizations. Similarly, the need for personalized health guidance can be achieved in a sustainable mode only by an ethical and evidence based approach. ICT is the key enabler for interaction and integration.

Parallel to the bottom-up approach a policy-driven top-down approach is needed. The risk of letting such complex new market evolve only by niches and silo-styled policies is that we will face the raise of the exact opposite of "societal changes", enlarging the gap between the richer and the poorer, the healthier and the unhealthier in an ethically and financially unsustainable scheme. Thus, in order to achieve an epidemiologically significant impact in society, we are in the need to change the "rules of the game" and design highly visible cross-market and societal incentives that will enable short to medium term stakeholder interests to be aligned in the direction of value cocreation on the larger scale and long-term payback model of primary prevention.

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PUBLICATION
II

Exploring Associations Between the Self-Reported Values, Well-Being and Health Behaviors of Finnish Citizens: Cross-Sectional Analysis of More Than 100,000 Web-Survey Responses

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Original Paper

Exploring Associations Between the Self-Reported Values, Well-Being, and Health Behaviors of Finnish Citizens: Cross-Sectional Analysis of More Than 100,000 Web-Survey Responses

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Abstract

Background: Understanding the relationship between personal values, well-being, and health-related behavior could facilitate the development of engaging, effective digital interventions for promoting well-being and the healthy lifestyles of citizens. Although the associations between well-being and values have been quite extensively studied, the knowledge about the relationship between health behaviors and values is less comprehensive.

Objective: The aim of this study was to assess retrospectively the associations between self-reported values and commitment to values combined with self-reported well-being and health behaviors from a large cross-sectional dataset.

Methods: We analyzed 101,130 anonymous responses (mean age 44.78 years [SD 13.82]; 78.88%, 79,770/101,130 women) to a Finnish Web survey, which were collected as part of a national health promotion campaign. The data regarding personal values were unstructured, and the self-reported value items were classified into value types based on the Schwartz value theory and by applying principal component analysis. Logistic and multiple linear regression were used to explore the associations of value types and commitment to values with well-being factors (happiness, communal social activity, work, and family-related distress) and health behaviors (exercise, eating, smoking, alcohol consumption, and sleep).

Results: Commitment to personal values was positively related to happiness (part r^2=0.28), communal social activity (part r^2=0.09), and regular exercise (part r^2=0.06; P<.001 for all). Health, Power (social status and dominance), and Mental balance (self-acceptance) values had the most extensive associations with health behaviors. Regular exercise, healthy eating, and nonsmoking increased the odds of valuing Health by 71.7%, 26.8%, and 40.0%, respectively (P<.001 for all). Smoking, unhealthy eating, irregular exercise, and increased alcohol consumption increased the odds of reporting Power values by 27.80%, 27.78%, 24.66%, and 17.35%, respectively (P<.001 for all). Smoking, unhealthy eating, and irregular exercise increased the odds of reporting Mental balance values by 20.79%, 16.67%, and 15.37%, respectively (P<.001 for all). In addition, lower happiness levels increased the odds of reporting Mental balance and Power values by 24.12% and 20.69%, respectively (P<.001 for all).

Conclusions: The findings suggest that commitment to values is positively associated with happiness and highlight various, also previously unexplored, associations between values and health behaviors.

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KEYWORDS

value orientation; happiness; health behavior; healthy lifestyle; cross-sectional survey

Introduction

Background

Suboptimal health behaviors are significant determinants of poor health outcomes. However, the adoption of healthy lifestyles has not been sufficient at the population level, and obesity levels are increasing worldwide. In addition, the burden of mental health problems is growing [1,2]. Personal electronic health (eHealth) and mobile health (mHealth) interventions have great potential in empowering individuals to take care of their health and well-being in a cost-effective way [3,4]. However, the problem of low user engagement commonly prevents these interventions from achieving their full potential [4,5].

Various computer-tailored eHealth interventions have demonstrated that personalizing the content to the characteristics of individual users tend to be efficacious for promoting healthy behaviors [4,6,7], though engaging the unmotivated proportion of the population, not actively interested in their health, is always challenging [8]. The common tailoring variables found in eHealth or mHealth interventions are health behaviors and the readiness to change behavior [9,10], and some have also considered demographics, clinical risk factors, and personal information needs [11]. However, addressing the motivational factors that influence the attitude toward a healthy lifestyle by personalizing interventions to match the needs, motives, and preferences of individuals could result in more engaging and effective health interventions [4,12]. It is well known, for example, from the experiments conducted based on the theories of reasoned action and planned behavior, that the attitude one holds toward a behavior is one of the key determinants for forming the intention to engage in the behavior (or readiness to change the behavior) [13,14].

Values act as guiding principles in life by determining what is important to people [15,16]. According to Schwartz and Bilsky [17], "values (a) are concepts or beliefs, (b) about desirable end states or behaviors, (c) transcend specific situations, (d) guide selection or evaluation of behavior and events, and (e) are ordered by relative importance." Values are considered as rather stabile motivational characteristics of people, which are related to personality traits [18,19], although changes in value priorities may take place because of changes in life and social conditions [15,18]. As values by definition reflect the motives, needs, and preferences of people, and thereby are one of the factors influencing attitudes [14,20], personalizing eHealth and mHealth interventions according to values may increase the appeal of the interventions and result in higher user engagement. This type of approach has been successfully applied in social marketing, where the message is tailored to the needs and preferences of different target groups [12,21].

To effectively utilize values for personalizing eHealth and mHealth interventions, understanding the relationships between values, well-being, and health behaviors is important. Results of previous studies regarding healthy and unhealthy values in terms of well-being are quite inconsistent (eg, [22-24]), and studies focusing on the relationship between values and health behaviors are sparse. This paper aims to contribute to the knowledge of the associations between values and commitment to values combined with well-being and health behaviors observed in the Finnish population.

Previous Work

Commitment to Values and Well-Being

Previous research indicates that living up to the values one holds important is beneficial for subjective well-being (SWB) [22,25,26]. SWB has been considered as a scientific term for happiness, which comprises 3 primary components—positive affect, negative affect, and life satisfaction [27]. Sharing similar value priorities with one's social group seems to enhance SWB, as the prevailing environment supports the value-congruent behavior of the person [22,28] and fosters positive interpersonal relationships [29]. Similarly, having values that conflict with social norms may hinder value-congruent behavior [30] and pose a negative influence on SWB [22]. Moreover, people are not always aware of their true, intrinsic value priorities, and differentiating personal values from social expectations may be challenging [26]. Hence, the cognitive process of value clarification and the conscious decision to behave according to or commit to one's values are sometimes needed for increasing value-congruent behavior and improving well-being [31]. Value clarification and commitment to value-congruent behavior are central concepts in the so-called third wave of cognitive-behavioral therapies [32], which have been effective in treating mental health problems (eg, [33]).

Value Types, Well-Being, and Health Behaviors

Schwartz value theory [34] is an extensively studied value classification system, which originally defined 10 broad value types based on the basic human needs, representing different motive orientations. The values form a circumplex structure with 2 axes—openness to change versus conservation and self-transcendence versus self-enhancement. Schwartz value types and the value structure have been recognized and verified in more than 65 different countries. Therefore, the theory is considered as near-universal and applicable across different cultures [34-36]. However, individual differences in the perceived importance attributed to each value type can be substantial [30]. More recently, a version of 11 Schwartz value types has been applied in research, where the Universalism value is divided into 2 subtypes—Nature and Social concern (eg, [37-39]).

A significant amount of research has been focused on the relationships between distinct value types and SWB, (eg, [19,23,24,40,41]). On the basis of the nature of the motivational goals underlying the values, it has been theoretically postulated that values expressing intrinsic goals of autonomy, relatedness, and competence [42] as well as growth needs [18], that is, Self-direction, Stimulation, Universalism, Benevolence, and Achievement, should enhance SWB [22,23]. In contrast, values expressing extrinsic goals such as wealth and fame [42], or deficiency and self-protection needs, that is, Power, Security, Conformity, and Tradition, should have a negative impact on SWB [23,24]. These assumptions were based on early findings, which indicated positive associations of intrinsic goals [43,44] and negative associations of extrinsic goals [43] with SWB.

Recently, Sortheix and Schwartz [24] theorized that values expressing person-focused growth needs (ie, Stimulation, Self-direction, and Hedonism) and the need for relatedness (Benevolence) should be positively associated with SWB. The authors found empirical support for these associations in their large, cross-cultural sample of 32 countries. However, earlier findings regarding the associations between value types and SWB have been quite inconsistent [19,22-24,41]. The most consistent evidence can be found for the negative relationship between valuing Power and SWB [24]. In addition, the observed correlations between the value types and SWB have been mostly weak or moderate [19,22-24,41]. The inconsistent findings could be partly explained by the differences found in socioeconomic and cultural contexts, which can either support or constrain individuals in pursuing their values. For instance, the observed relations of Tradition, Universalism, and Achievement with SWB seem to be opposite in countries with high versus low socioeconomic and egalitarian development [24,45].

The research regarding the associations between value types and health behaviors is sparse and scattered across different behaviors. Most of the studies focus on eating habits (the consumption of fruit and vegetables, calorie-dense food, or meat; and eating out habits) and substance usage (alcohol, tobacco, or drugs). Among Australian participants, Universalism has been observed to be associated with healthy eating habits [46-49], and Hedonism may be associated with overeating [30]. The associations between values and substance usage have been studied particularly among adolescents. One study observed that smoking behavior was related to valuing broadmindedness, independence, and freedom as well as disvaluing obedience [50]. Another study found that extrinsic aspirations (eg, wealth, fame, and public image) were associated with substance use [51]. However, Young and West [52] concluded in their longitudinal study that values may not predict youngsters' substance use in the long term.

Some studies report a relationship between values and stress-enhancing, exercise, or certain high-risk health behaviors. Valuing health seems to be more related to behaviors that are preventive of direct (eg, drunk driving and smoking) than indirect (eg, seat belt usage and health information seeking) health risks [53]. Furthermore, a study among youngsters found that the (negative) correlations between valuing exciting life and reporting health-risk preventive behaviors were higher than the (positive) correlations with valuing health, whereas for middle-aged adults valuing health was more related to direct health-risk preventive behaviors than valuing exciting life [54]. In eastern and central Europe, risky sexual behavior has been found to have a moderate but consistent relationship with Achievement, Power, Hedonism, Stimulation, and Self-direction [55]. Hedonism may be associated with stress-relieving (relaxing) behavior, whereas Achievement appears to be associated with stress-enhancing behavior (taking on many commitments) [30]. Universalism has been observed to be associated with regular physical activity [47].

Except for the cross-cultural study of Sortheix and Schwartz [24], the reviewed studies regarding values, well-being, and health-related behaviors were relatively small, involving some hundreds of participants. Furthermore, the studies involved mostly younger adults (students) or teachers, thereby limiting the generalizability of the results. Overall, the evidence for associations between values and well-being is still quite inconsistent, and comprehensive research focusing on a multitude of health-related behaviors is lacking.

This Study

This study aims to discover the associations between self-reported values (commitment to values and value priorities), perceived well-being, and various self-reported health behaviors from a large, cross-sectional dataset of open Web-survey responses, available from more than 100,000 Finnish citizens. The data were collected as part of the Finnish Happiness-Flourishing Study (FHFS), which was a national effort to promote mental well-being and healthy behaviors in the Finnish population [56]. The survey included questions assessing various dimensions of well-being and several different health behaviors. The measures for well-being factors included happiness, depression, life satisfaction, impact of major negative and positive life events on happiness, family- and work-related distress, and communal social activity. The health behavior–related factors comprised exercise, intake of fruits and vegetables, sleep hours, alcohol consumption, and smoking. The data regarding personal values were unstructured including free-text responses.

We adopted an exploratory approach for the data analysis to study whether (1) commitment to values was related to well-being, (2) certain value types could be considered healthier than others in terms of their associations with well-being or health-related behaviors, and (3) previous findings could be replicated with the extensive data at hand. On the basis of previous research, we hypothesized positive associations between well-being and commitment to values [26] as well as between well-being and the value types reflecting intrinsic goals of relatedness and person-focused growth needs [24,43]. Value types reflecting extrinsic aspirations or deficiency needs were expected to be negatively associated with well-being [24]. Associations between value types and health-related behaviors were also expected, especially between Universalism, healthy eating, and regular exercise (eg, [47]).

Methods

Study Design

The data were collected at the public website of the FHFS campaign over the period of 1 year, between 2009 and 2010 [56]. FHFS was a national effort to promote mental well-being and a healthy lifestyle in the Finnish population. The study campaign was implemented in collaboration among the National Institute for Health and Welfare, Duodecim Medical Publishing Ltd, a Finnish television (TV) production company (Tarinatalo), and the national public broadcasting company (YLE). The campaign produced a reality TV series about happiness and depression, where celebrities were learning happiness-related skills. The series attracted roughly 250,000 weekly viewers. The FHFS website and the Web survey were part of the campaign (see Multimedia Appendix 1 for the FHFS survey items in Finnish). The FHFS Web survey was advertised during the series episodes and at the website of the broadcasting company. It was freely available to all Finnish-speaking individuals having access to internet. The purpose of the Web survey was to allow participants to measure their happiness levels with the Happiness-Flourishing scale [56] and to encourage them to identify the key sources in life that contributed to their happiness. However, the survey also involved questions about a variety of other well-being factors and health behaviors. On the website of the FHFS survey, it was clearly stated that the collected data would be used for creating public summary reports regarding happiness and the related factors.

The study we conducted was a retrospective and explorative data analysis of the FHFS campaign data, which was driven by our hypotheses regarding the associations between values, well-being, and health behaviors.

Participants

Altogether, 139,462 anonymous responses were received to the Web survey. The respondents, who did not provide their age or gender, or reported ages below 18 or above 110 years, were excluded from the analyses of discovering associations between variables. In addition, the responses that involved 2 or more unrealistic values for numeric variables were considered unreliable and hence excluded from the study sample. If a response involved an implausible value for 1 numeric variable only, this value was treated as a missing input. The numeric values were considered unrealistic if they did not fall into the following variable-specific ranges—alcohol consumption (0-150 units/week), smoking (0-100 cigarettes/day), weight (30-250 kg), height (70-220 cm), body mass index (BMI, 10-50 kg/m^2), sleep hours (3-16 hours/day), years of education (from 9 years to the current age of the respondent minus 3, “age-3” years; the compulsory education in Finland takes 9 years), and income (0-5,000,000 Euros/year). After applying these exclusion criteria, 101,130 responses remained in the study sample, of which, 62,625 responses included a list of personal value items. The basic demographics of the study sample are provided in Table 1.

Materials

Well-Being Factors

Perceived happiness was measured using the Happiness-Flourishing scale [56] (Cronbach alpha=.93), which involves 10 items evaluated with a 7-point Likert scale. The score is the sum of the item-specific answers ranging from 10 (*very unhappy*) to 70 (*very happy*). Depression was measured with the Depression Scale [57] (Cronbach alpha=.92). Life satisfaction was assessed by the 7-point Likert-item “How satisfied are you with your life situation right now” (1= *completely unsatisfied* and 7= *completely satisfied*). The validity of employing single-item measures for life satisfaction has been shown in the study by Cheung and Lucas [58].

The impact of major positive and negative life events on happiness was assessed in 3 parts. First, it was enquired whether one had experienced in the past significant negative (eg, divorce, loss of a loved one, prison sentence, unemployment, or serious illness) or positive (eg, new relationship, marriage, retirement, childbirth, new job, or work promotion) changes in life that still mattered. Second, the perceived significance of the reported event was assessed with the item “Estimate the influence of the life event on your happiness nowadays,” having a response scale from 1 (*no influence*) to 10 (*significant negative* or *positive influence*). Finally, the timing of the event was enquired with 5 predefined response options (*within the past 6 months, 1 year, 2 years,* or *5 years,* and *earlier*).

Family- and work-related distress as well as communal social activity were addressed with the following questions: “Do you experience problems in your relationship with your partner?” (problems with partner),“Have your children caused you particular problems?” (problems with children), “How often are you troubled with having to push yourself to the limit in order to cope with your present job or work load?” (work stress), and “How often do you participate in communal social activities or events related to e.g. handicrafts, culture or religion?” (communal social activity). The response options for these questions are presented in the Results section.

Table 1. Self-reported demographics of the respondents included in the study sample (N=101,130).

Characteristics	Valid, n (%)[a]	Proportions, %
Gender	101,130 (100)	
Male		21.12
Female		78.88
Age (years)	101,130 (100)	
18-29		17.12
30-44		30.37
45-54		24.60
55-64		21.22
≥65		6.70
Years of education[b]	86,698 (85.73)	
<12 (comprehensive school)		13.48
12-14 (upper secondary education)		27.10
15-17 (bachelor's degree or equivalent)		35.04
>17 (master's or doctoral degree)		24.39
Gross household income (Euros/year)	89,821 (88.82)	
0-17,999		24.94
18,000-35,999		24.79
36,000-59,999		21.12
≥60,000		29.15
Body mass index (kg/m^2)	99,434 (98.32)	
<18 (underweight)		1.70
18-24.99 (normal weight)		50.63
25-29.99 (overweight)		31.49
≥30 (obese)		16.19

[a]Proportion of respondents with data available.

[b]The education level (in parenthesis) is estimated based on the Finnish education system.

Health-Related Behavior

Physical activity level was assessed with the question "On the average, how much do you exercise or strain yourself physically during your leisure time?" with 4 response options defined by the Gothenburg Scale [59]. According to World Health Organization's global physical activity recommendations, people should do moderate-intensity activities for at least 2.5 hours per week or vigorous-intensity activities for at least 1 hour and 15 min per week to gain health benefits [60]. Overall, 3 of the 4 response options (performing at least 4 hours of moderate-intensity activities per week, 3 hours of fitness training per week, and athlete training several times a week) indicated of meeting the public health recommendations for physical activity and thus were interpreted as regular exercise and dichotomized into a binary variable.

Healthy eating habits were assessed with the following 2 questions: "On the average, how often do you eat fresh fruits or berries?" and "On the average, how often do you eat fresh vegetables" with 4 response options (*less than once a week, 1-2 times per week, 3-5 times per week, once a day,* and *more often*). According to public health recommendations, people should consume at least 5 portions of fruits and vegetables per day [61]. Thus, the response options of the 2 questions were combined into a binary variable, describing the daily consumption of vegetables, fruits, or berries (healthy eating).

Sleep duration was assessed with the open question "On the average, how many hours do you sleep?" Sleeping 7 to 8 hours per night was regarded as a healthy amount of sleep [62] and dichotomized into a binary variable. Alcohol consumption was assessed with the open question "How many units of alcohol do you drink per week?" accompanied with an explanation for an alcohol unit (1 unit is equivalent to 10-14 g of pure alcohol such as 0.33 L of average-strength beer [4%-7%], 12 cL of wine [10%-15%], or 4 cL of spirits [35%-40%]; [63]). Smoking was assessed with the open question "How many cigarettes, cigars, or pipefuls do you smoke per day?," and a binary variable was created for representing nonsmoking.

Personal Values

The FHFS Web survey was not designed for the purpose of value research; hence, it did not include a validated value survey for assessing personal values. Commonly used tools for value research include the 57-item Schwartz Value Survey (SVS) [34,35] and the Portrait Value Questionnaire (eg, PVQ-21) [64], which define values as "guiding principles in your life" or concepts that are important in one's life. In the Web survey, the respondents were asked to define the key ingredients of their happiness and were presented with a predefined set of value items via an interactive user interface that allowed to name or choose up to 20 values. A library of more than 200 value items was available in the Web-system, and the respondents could select values from this library as well as freely enter their own items. The predefined value items were presented via a space-like animation, where items from the value library appeared and disappeared in a random order, attempting to resemble twinkling stars in the night sky. The respondents could select values from this value-space by clicking the appearing terms; type words into a search box with predictive text input utilizing the library; or alternatively, enter text from outside the library.

In spite of not employing a traditional value survey, we consider the collected data to represent a good approximation for personal values for the following 2 reasons: (1) one's "key ingredients of happiness" are most likely personally important concepts in life, just like values are important [15-17]; and (2) exposing the respondents to a predefined library of value items provided a clear clue about the type of data expected from them. Similarly, in the SVS, a list of value items are presented to the respondents [34,35].

Finally, the commitment to live up to one's personal values (commitment to values) was assessed with the 7-point Likert-item "I have firm values that I strive to nurture" (1= *I totally disagree* and 7= *I totally agree*).

Statistical Analysis

Associations With Commitment to Values

The statistical analyses were performed with the IBM SPSS (version 20) and the free R (version 3.3.1) statistical software. The connections between commitment to values and variables related to well-being factors and health-related behaviors were assessed with multiple linear regression. Visual inspection, pairwise correlations (Pearson and Spearman), descriptive statistics, and principal component analysis (PCA) were used to identify mutually strongly correlated variables among the well-being factors and health behaviors. Depression (r_{81124}=−.78, P<.001) and life satisfaction (r_{91876}=.72, P<.001) correlated strongly with happiness. According to the results of PCA, these variables appeared to align along a common dimension—all had high loadings (.93 for happiness, −.90 for depression, and .87 for life satisfaction) on the same, single component, which explained 80.57% of the overall variability in the data. Variables that did not correlate strongly with each other ($|r|$<.4) were included in the regression model as independent variables. Among the 3 highly correlated variables, only happiness was chosen to be included in the regression model to avoid the problem of multicollinearity. The other variables included were problems with partner, problems with children, work stress, communal social activity, regular exercise, healthy eating, healthy amount of sleep, nonsmoking, alcohol consumption, age, and gender.

One-third of the responses (27,599 out of 82,919), which involved self-assessments regarding commitment to values, had at least 1 of the independent variables missing. Instead of omitting these responses from the regression analysis, multiple imputation (MI) with fully conditional specification (FCS), available in SPSS, was used. MI with FCS is a statistically valid method for creating imputations in large complex datasets that involve both continuous and categorical variables [65]. All the independent variables were included in the imputation model, and 5 sets of imputations were created. For the integer-valued scale variables, the imputed values were rounded. The highest proportion of missing values (20,765/101,130, 20.53%) was imputed for nonsmoking. For most of the other variables, the proportions of missing (imputed) values were less than 5%. The regression analysis was applied on the imputed dataset. The results are presented via the unstandardized beta (B) and its 95% CI. Furthermore, squared semipartial correlations (part r^2) were calculated separately for each independent variable, adjusted for age and gender, and reported as a measure for the effect size.

The association between commitment to values and the impact of major life events on happiness was assessed separately from the model presented above to involve the timing of the events as a controlling factor. Linear regression was used to study whether commitment to values, controlled for age, gender, and the timing of a major life event, was associated with the impact of the life event. Distinct regression models were built for negative and positive life events. These analyses were performed using the original data, as the impact of major life events was not part of the imputation process. Compared with the other variables of interest, only a small proportion of the responses were related to major life events—altogether, 28,709 and 29,671 responses were included in the analyses regarding negative and positive life events, respectively.

Classification of Value Items

The reported value items were classified into value groups based on the Schwartz value theory. Altogether, 779,392 value items described with 23,552 different terms or expressions, including the items with typing errors, were reported in the study sample. Typing errors and infrequent entries were discarded by selecting only those items for classification, which occurred at least 50 times in the data, resulting in 723 different terms.

The classification procedure was conducted in 2 phases. The first phase was performed manually by AH. Obvious synonyms and words, which could be clearly identified to belong under a superordinate category, were renamed with a descriptive common term. For instance, the synonymous words "buddies," "good friends," "friendship," and "friend" were renamed as "friends," and the words "wife," "husband," "spouse," "boyfriend," and "girlfriend" were renamed as "partner." After the renaming procedure, the number of distinctive terms was reduced to 472. This set of terms was then grouped according to the 11 Schwartz value types [37-39] and the related 57-item SVS [34,35]. The words having the same meaning with a Schwartz value item as defined in the SVS were located under the corresponding Schwartz value type. However, many of the reported terms were not represented in the list of Schwarz value items, and language-specific nuances introduced some uncertainty for the matching. Hence, additional non-Schwartz value groups were created for the terms that described similar concepts but could not be matched with any of the Schwartz value items with a complete certainty. Even rather alike concepts were grouped separately to minimize the information loss at this point, despite increasing the likelihood of resulting in highly correlated value groups. As a result, 27 non-Schwartz groups were created in addition to the 11 Schwartz value types.

The second phase of the classification procedure was computational, aiming at investigating whether (1) some value groups correlated strongly with each other and, therefore, could be merged or (2) some value items should be relocated to a different group. The manually classified value items were transformed into a matrix, where the columns represented value types and the rows represented the number of value items each respondent had reported per value type. PCA based on the promax oblique rotation method was used to identify highly correlated dimensions in the value matrix and to verify the appropriate grouping of value items. Only the respondents who had more than 90% of their value items classified with at least 4 classified value items were included in the PCA to diminish the impact of the possible nonsense responses on the classification. The details of the PCA procedure are explained in Multimedia Appendix 2. As a result, the number of non-Schwartz types (groups) was reduced from 27 to 20. Finally, the value types were recoded into binary variables (0=*no items reported* and 1=*at least one item reported* for the value type).

Associations With Value Types

Logistic regression was used to study the relationships between the 20 most common value types observed in the study sample and the following well-being and health behavior–related factors: happiness, regular exercise, healthy eating, nonsmoking, and alcohol consumption. Only the respondents who had reported at least 4 value items considered in the value classification were included in the analysis (55,539 out of the 62,625 responses available). This restriction was made to decrease the probability of including nonsense responses that were provided without actual contemplation, for instance, for testing the interactive user interface. Separate logistic regressions were performed for each pair of well-being or health behavior factor and value type, having the binary value type as the dependent. The analyses were adjusted for age and gender. For reference, similar analyses were performed to assess the relationships between the selected well-being or health behavior factors and reporting value items in general (ie, at least 4 classified items) with 92,394 eligible respondents. The results are presented using odds ratios (ORs) with the corresponding *P* values.

Results

Statistics of the Responses

A slight majority (52.06%, 43,166/82,919) of the population reported strong commitment to values, and most (63.57%, 64,286/101,130) of the respondents provided a list of their personal value items. A slight majority (51.56%, 48,785/94,617) reported to be happy, though many suffered from work stress and experienced problems with their partners every now and then. Most of the respondents (59.73%, 60,403/101,130) did not share their experiences regarding major negative or positive life events. A clear majority reported healthy behaviors. The descriptive details of the responses are presented in Table 2.

Table 2. The self-reported mental well-being and lifestyle characteristics in the study population (N=101,130).

Variable	Valid, n (%)[a]	Proportions, %
Commitment to values (scale 1-7)	82,919 (82)	
Weak (1-3)		7.21
Moderate (4-5)		40.73
Strong (6-7)		52.06
Number of reported value items	101,130 (100)	
None		36.43
1-3		6.03
4-13		47.62
14-20		9.91
Happiness (score 10-70)	94,617 (93.6)	
Unhappy (10-30)		5.59
Neutral (31-50)		42.46
Happy (51-70)		51.56
Impact of major negative life events (scale 1-10)	39,016 (38.58)	
Weak (1-4)		34.73
Moderate (5-7)		38.93
Strong (8-10)		26.34
Impact of major positive life events (scale 1-10)	40,727 (40.27)	
Weak (1-4)		3.94
Moderate (5-7)		21.24
Strong (8-10)		74.83
Problems with partner	97,809 (96.72)	
Not in a relationship		26.62
Never		22.16
Sometimes		43.87
Almost all the time		7.35
Problems with children	97,903 (96.81)	
No children		33.56
Rarely or never		45.52
Sometimes		14.24
Almost all the time		6.67
Work stress	97,303 (96.22)	
Not working or studying		13.85
Rarely or never		24.35
Sometimes		38.60
Almost all the time		23.20
Communal social activity	98,872 (97.78)	
At least once a week		27.49
At least once a month		25.53
Once or twice a year		22.60
Rarely or never		24.39

Variable	Valid, n (%)[a]	Proportions, %
Regular exercise	99,580 (98.47)	
Yes		76.51
No		23.49
Daily intake of vegetables, fruits, or berries	97,621 (96.53)	
Yes		62.25
No		37.75
Sleep 7 to 8 hours	98,502 (97.40)	
Yes		74.17
No		25.83
Alcohol consumption (units/week)	92,285 (91.25)	
0		28.24
1-5		44.37
6-10		16.23
11-16		5.91
>16		5.26
Nonsmoker	80,365 (79.47)	
Yes		81.47
No		18.53

[a]The proportion of respondents with data available.

Associations With Commitment to Values

A significant regression equation was found ($F_{20, 82898}$=2123.11, P<.001, adjusted r^2=0.34) for demonstrating the associations between commitment to values and various well-being and health behavior–related factors. The regression results are presented in Table 3. Among all the variables, happiness showed the strongest (positive) association with commitment to values (part r^2=0.28). Involvement in communal social activities (summed part r^2=0.09), regular exercise (part r^2=0.06), and daily intake of vegetables, fruits, or berries (part r^2=0.04) were also positively but weakly associated with commitment to values. Problems with partner, problems with children, work-related stress, healthy amount of sleep, smoking, alcohol consumption, age, and gender were not associated with commitment to values.

Commitment to values was inversely associated with the perceived impact of major negative life events (B=−0.35, 95% CI −0.37 to −0.33, part r^2=0.03) and positively associated with the perceived impact of major positive life events (B=0.28, 95% CI 0.27 to 0.30, part r^2=0.04) on happiness, after controlling for age, gender, and the timing of the events. Both regression models were significant ($F_{8,28701}$=20427.54, P<.001, adjusted r^2=0.85 and $F_{8,29663}$=97850.55, P<.001, adjusted r^2=0.96 for negative and positive life events, respectively), though the associations were very weak.

Table 3. Linear regression results regarding the associations between commitment to values and various well-being and health behavior–related factors (n=82,919).

Variable	B (95% CI)	Part r^{2} [a]
Intercept	2.51 (2.46 to 2.57)	— [b]
Gender (reference=male)		
Female	0.11 (0.09 to 0.12)	0.006
Age (years)	0.00 (−0.0 to 0.0)	0.009
Happiness score	0.06 (0.06 to 0.06)	0.281
Problems with spouse (reference=not in a relationship)		
Never	−0.04 (−0.06 to −0.01)	0.014
Sometimes	−0.07 (−0.09 to −0.05)	0.001
Always	0.04 (0.01 to 0.07)	0.004
Problems with children (reference=no children)		
Never	0.01 (−0.01 to 0.03)	0.003
Sometimes	0.00 (−0.02 to 0.03)	0.000
Always	0.08 (0.04 to 0.11)	0.001
Work stress (reference=not working or studying)		
Never	−0.06 (−0.08 to −0.03)	0.008
Sometimes	−0.06 (−0.09 to −0.04)	0.002
Always	−0.02 (−0.05 to 0.01)	0.003
Communal social activity (reference=less than yearly)		
Weekly	0.39 (0.37 to 0.41)	0.050
Monthly	0.27 (0.25 to 0.29)	0.029
Yearly	0.15 (0.13 to 0.17)	0.010
Regular exercise (reference=no)		
Yes	0.35 (0.33 to 0.36)	0.055
Daily intake of vegetables, fruits, or berries (reference=no)		
Yes	0.20 (0.18 to 0.22)	0.035
Sleep 7 to 8 hours (reference=no)		
Yes	0.00 (−0.02 to 0.02)	0.009
Alcohol consumption (units/week)	−0.01 (−0.01 to −0.01)	0.010
Smoking (reference=yes)		
No	-0.01 (−0.03 to 0.01)	0.009

[a] Obtained from separate regression models for each variable, adjusted for age and gender.

[b] Not applicable.

Associations With Value Types

The classified value items covered 94.30% of the 779,392 value-related words or expressions reported. The classification resulted into 11 Schwartz and 20 non-Schwartz value types. However, in this paper, we report results regarding the value types that were expressed at least by 10% of the eligible respondents, that is, all the 11 Schwartz value types and 9 non-Schwartz value types (see Multimedia Appendix 3 for the definitions and exemplary value items for these value types). The 3 most common value types represented in the study sample were the appreciation of Loved ones (non-Schwartz), Hedonism (Schwartz), and Health (non-Schwartz). The most common value type, Loved ones, was reported by 73.13% (40,616/55,539) of the respondents. The prevalence of different value types are provided in Multimedia Appendix 4. The median number of value items classified under the value types was 20 items (range: 1-47 items). Most people used 1 to 2 value items to express a value type, but several value items were also used. For instance, Loved ones could be expressed with a single item "family," or with several items such as "father," "mother," "little sister," "big brother," and "child."

The observed associations between value types and happiness; exercise; intake of vegetables, fruits, or berries; alcohol consumption; and smoking are summarized in Multimedia Appendix 4. The value types having the most significant and extensive associations with happiness and health behaviors, after controlling for age and gender, were Power (social status, dominance—Schwartz), Mental balance (self-acceptance—non-Schwartz), and Health. Smoking; irregular intake of vegetables, fruits, or berries (unhealthy eating); irregular exercise; a 10-unit decrease in the happiness score; and the increase of alcohol consumption by 10 units per week increased the odds of reporting Power values by 27.80%, 27.78%, 24.66%, 20.69%, and 17.35%, respectively. A 10-unit decrease in the happiness score, smoking, unhealthy eating, and irregular exercise increased the likelihood of reporting Mental balance-related values by 24.12%, 20.79%, 16.67%, and 15.37%, respectively. Regular exercise, nonsmoking, and the daily intake of fruits, vegetables, or berries (healthy eating) increased the odds of valuing Health by 71.71%, 39.96%, and 26.76%, respectively.

Other meaningful associations between value types and happiness or certain health behaviors were observed for Tradition (commitment to traditions or religion—Schwartz), Universalism-nature (Schwartz), Stimulation (exciting life—Schwartz), Conformity (with social norms—Schwartz), and the appreciation of Loved ones and Culture (non-Schwartz). The decrease of weekly alcohol consumption by 10 units increased the likelihood of valuing Tradition by 29.30%. Regular exercise increased the odds of reporting Universalism–nature values by 26.09%. Smoking increased the odds of reporting values related to Stimulation and Conformity by 22.62% and 20.48%, respectively, whereas nonsmoking increased the likelihood of valuing Loved ones and naming Culture values by 18.34% and 15.12%, respectively. Unhealthy eating increased the likelihood of reporting Conformity values by 19.46%, whereas healthy eating increased the odds of naming Culture and Universalism–nature values by 15.20% and 13.94%, respectively. A 10-unit increase in the happiness score increased the odds of valuing Loved ones by 17.23%.

A 10-year increase in age increased the odds of naming Conformity values by 29.43%, whereas a 10-year decrease in age increased the odds of valuing Work (non-Schwartz) by 19.12%. Women were more likely to value Home (non-Schwartz), Loved ones, Universalism–nature, Quality of relationships (non-Schwartz), and Health than men with increased odds by 91.19%, 69.73%, 59.74%, 41.06%, and 31.85%, respectively. For men, the odds of reporting Intellectualism (non-Schwartz), Perseverance (non-Schwartz), Conformity, and Achievement (Schwartz) values were increased by 62.52%, 53.54%, 37.80%, and 28.75%, respectively.

In general, women were more likely to report value items than men with the increased odds of 77.08%. There were no major differences observed in the age, happiness, and health-related behaviors between the respondents who reported values and those who did not.

Discussion

Principal Findings

We explored whether the self-assessed commitment to one's values and the reported value items were related to self-reported well-being and health behavior–related factors in a large, cross-sectional sample of Finnish citizens. In our analyses, perceived happiness was considered as the main measure of well-being. As hypothesized, commitment to values was positively, and strongly, associated with happiness. The presumed associations between the value types and happiness were partially supported by our findings. Furthermore, several associations between different value types and health behaviors were observed.

Comparison With Previous Work

Commitment to values was explored in relation to various well-being and health behavior–related factors. In addition to observing a strong relation between commitment to values and happiness, we discovered that commitment to values was positively associated with frequent communal social activity, regular exercise, and the daily consumption of fruits, vegetables, or berries, though these associations were much weaker compared with happiness. Furthermore, commitment to values seemed to diminish the impact of major negative life events on perceived happiness and strengthen the impact of positive events but with weak associations. Family- and work-related distress, sleep hours, smoking, and alcohol consumption were not associated with commitment to values.

None of the Schwartz values, considered to express the intrinsic aspirations for relatedness and autonomy, or the person-focused growth needs (Stimulation, Self-direction, Hedonism, and Benevolence) were positively associated with happiness, which is somewhat at odds with previous findings [22-24]. However, the appreciation of Loved ones (non-Schwartz value) was positively, although weakly, associated with happiness. We consider valuing Loved ones to express the intrinsic aspiration relatedness—the need to connect with and care for others [42]. Thus, this finding supports earlier observations regarding the positive relation between the aspirations for relatedness and SWB [43,44]. Interestingly, Benevolence was not associated with happiness, though conceptually it may seem similar to Loved ones. Apparently, the motives behind these 2 value types differ somewhat from each other—Valuing Loved ones may reflect both the desire to enhance the welfare of others and the personal need for company, whereas Benevolence values may express mostly the former motive. Hence, valuing Loved ones might express relatedness more fully than Benevolence. However, in the traditional value surveys, these 2 motives are not differentiated from each other.

The Schwartz value Power (social status, wealth, and dominance), considered to express extrinsic aspirations, was negatively associated with happiness, which is consistent with previous findings [24]. In addition, Mental balance (self-acceptance—non-Schwartz) values were negatively associated with happiness. In the study sample, Mental balance values reflected the active process of learning to survive with external pressures, manage stress, and accept one's incompleteness, which we consider to express deficiency needs. Hence, the finding regarding Mental balance is aligned with the previous results indicating that expressing deficiency needs is negatively associated with SWB [22,24,43].

Our findings confirm many of the previous results regarding the associations between value types and health behaviors but also suggest new, previously unexplored associations. We found that Power, Mental balance, and Health (non-Schwartz) values had the most significant and extensive associations with several health behaviors. Unhealthy behaviors (smoking; insufficient intake of vegetables, fruits, or berries; and irregular exercise) were more prevalent among the respondents who reported Power or Mental balance values compared with those who did not report them. In addition, Power values were associated with slightly increased alcohol consumption. Extrinsic aspirations such as wealth and public image have been previously observed to be related to substance abuse [51]. Furthermore, regular exercise and nonsmoking were considerably more prevalent among respondents who reported Health values compared with those who did not, and healthy eating habits were also related to valuing Health. Likewise, positive associations between valuing Health and reporting healthy behaviors have been observed before [53,54].

In addition, we observed associations between several other value types and selected health behaviors. Reporting Tradition (commitment to traditions or religion—Schwartz) values was associated with decreased alcohol consumption. Conformity (with social norms—Schwartz) and Stimulation (exciting life—Schwartz) values were associated with smoking. The link between smoking and Stimulation values has also been observed before [54]. The appreciation of Universalism–nature (Schwartz) value was associated with regular exercise and healthy eating, though the association with healthy eating was weak. Previously, it has been observed that Universalism values, in general (nature and social concern), are related to healthy habits [46-48]. Our results suggest that this may be true particularly for the nature dimension of Universalism.

Significant gender differences were observed for value priorities. Women especially valued Home (non-Schwartz), Loved ones, and Universalism–nature values, but Quality of relationships (non-Schwartz) and Health values were also important. Men especially valued Intellectualism (non-Schwartz) and Perseverance (non-Schwartz) values, but Conformity and Achievement (Schwartz) values were also common. These results are consistent with the past research on gender differences in personality types (see eg, [66]). At the population level, it has been observed that women score higher in nurturance, gregariousness, and neuroticism traits and seem to be more sensitive to emotions than men. Men tend to be more assertive and intellectually or idea oriented than women. Though these differences have been shown to be pervasive across cultures, they are modest when compared with the individual variation within each gender [66]. Regarding the observed age differences in this sample, Conformity values were more prevalent among older respondents and Work (non-Schwartz) values among younger respondents.

Each of the 11 Schwartz value types were represented in the study sample, but 9 additional value types, reported at least by 10% of the study population (n>5554), were also identified. This finding is unsurprising, as the Schwartz value theory was developed to represent distinctive motive orientations within and across cultures instead of representing all the possible human values [34,35]. Schwartz et al acknowledge that other values do exist, but their meaning may vary considerably between cultures or individuals [36,67]. For instance, valuing health could express either Security (avoiding illness) or Hedonism (enjoying the pleasure of a healthy body) [36].

Strengths and Limitations

The study is unique in terms of the large sample size and diverse data, including information about various well-being and health behavior–related factors, coupled with personal values. Most of the previous, relevant studies have been restricted regarding the sample size and have involved mostly students or teachers. A welcome exception to these limitations is the recent, large, cross-cultural study of Sortheix and Schwartz [24], which focuses on the associations between value types and SWB. This study covers a broader set of aspects by also including self-reported health behaviors and commitment to values. The age distribution in this sample was representative of the Finnish working-age population at the time of the study. However, the sample is biased toward female respondents and the education level of the respondents was higher than in the general population (Statistics Finland Web database, years 2009-2010 [68]), which is important to keep in mind when considering the generalizability of the results.

We note that the Web survey received responses from people who were attracted by the FHFS campaign, and many of them might have followed some episodes of the happiness-related reality TV series. Thus, especially those people who had a special interest in their well-being, and/or were seeking ways to improve their happiness, might have noticed the survey. Furthermore, those respondents who actively followed the TV series might have already learned some strategies to improve their happiness before answering the Web survey, which could be reflected in their responses, for example, in the value items reported. The social-desirability bias could have also influenced the respondents to evaluate their state of well-being and health behaviors in a more positive light than in reality. However, as this study does not seek to estimate the state of well-being or the value distribution in the population, we consider that the abovementioned matters do not have a significant influence on the results. Although the distributions for happiness, healthy behaviors, and commitment to values were positively skewed, the employed measures captured enough variability to reveal associations between values, happiness, and health behaviors. Furthermore, a variety of value types, covering all the Schwartz value types, was represented in the sample.

We acknowledge that the employed nonvalidated, uncontrolled method for collecting personal values, and assessing commitment to values with a single-item measure could reduce the reliability of the results. However, our study is not the first of a kind to extract knowledge about values from unstructured data and apply the Schwartz value theory in an unconventional setting. Bardi et al [69] measured the national patterns of Americans' values from newspaper texts by utilizing a value lexicon they derived based on SVS and demonstrated the validity of their approach. Our methods share similarities with their approach, though our study setting was considerably more controlled, as the collected data were closely related to personal values. The single-item measure for commitment to values might have been interpreted slightly differently among the respondents, for example, providing a low score could mean unfamiliarity with the concept of values in general or awareness of one's values without commitment to them. Nonetheless, the measure was associated positively with the happiness scale, and the observed association was strong.

The major differences between the employed and traditional value surveys are related to the value definition (ie, the question format), survey structure, and the importance ratings of the value items. In the FHFS Web survey, values were defined as the "key ingredients of happiness," whereas traditionally they are defined as the "guiding principle in your life" or concepts that are important in one's life [34,35,64]. We suggest that in practice, these definitions are sufficiently similar to each other, as the concepts that produce happiness must also be personally important; therefore, people strive to fulfill them in their choices in life, which is characteristic to values [15-17]. According to the qualitative research of Delle Fave et al [70], the terms used by lay people to describe happiness involve concepts very similar to value items, such as stability, respect to others, just society, harmony, joy, achievement, and autonomy. Moreover, in the Web survey, the respondents were exposed to a predefined library of value items, which provided a clear clue about the type of data that were expected from them. However, responses were not restricted, so people could decide for themselves as to which items were worth reporting. Thus, it is reasonable to assume that the values reported were somehow personally meaningful and hence important.

The value classification scheme was partly subjective, as many of the value items were manually located under Schwartz value types based on the reasoning of one person (AH). However, the exemplary list of value items defined in the 57-item SVS [34,35] was strictly followed; only the items for which obvious, conceptual counterparts could be identified from the SVS were located under Schwarz value types. In addition, PCA was used to verify the hypotheses regarding the appropriate grouping of the remaining ambiguous items.

Despite the abovementioned limitations, the study has the following strengths, which reduce the potential variability and bias in the results. First, we have addressed the main challenges posed by the uncontrolled and unstructured nature of the data in the employed analysis methods. Second, we have a large sample size that is likely to compensate for some of the shortcomings. Conclusions at the population level have been drawn before also from large datasets collected in uncontrolled, scientifically nonvalidated settings, for example, regarding the sleep quality among the users of commercial wearable devices [71]. Third, our interpretations are based on effect sizes rather than on statistical significance in terms of *P* values. Fourth, the resulting value classification is consistent with the results of previous work, as each of the 11 Schwartz values were represented in the study sample. Furthermore, many of the non-Schwartz values, which emerged from our study, are consistent with the classification of Delle Fave et al [70], which is based on qualitative and unstructured data, similar to ours.

Implications

Understanding the connections between values, well-being, and health-related behaviors could provide valuable insight for the development of engaging eHealth and mHealth interventions that are effective in promoting behavior change and well-being. This large study replicates many of the previous findings related to the associations between value priorities, well-being, and health behaviors and highlights the positive relationship between commitment to values and happiness. In addition, because of the qualitative and unstructured data on values, we found previously unexplored associations—pondering over mental balance issues appeared to be negatively associated with happiness and several health behaviors. Gender differences in reporting values were stark; women emphasized "soft" values (eg, nurture, nature, and health), whereas majority of men reported "hard" values (eg, persistency, achievement, and influence). Valuing Loved ones emerged as a separate value from Benevolence and was associated with happiness, whereas Benevolence was not.

Though this study does not determine causal relations between values and the factors related to well-being and health behaviors, the strong motivational nature of values in guiding attitudes and behaviors, in general, suggests that values could predict behavior, at least via attitudes [17,20,30]. The observed positive association between commitment to values and happiness supports the previously suggested benefits of encouraging value clarification and value-congruent behavior in mental health interventions [31]. Furthermore, knowledge of the associations between values and health behaviors could help identify some of the reasons why one is not motivated to lead a healthy lifestyle, which would enable personalizing interventions to tackle these barriers. People endorsing values that express strong deficiency needs may have more pressing needs to attend before they are able to focus on healthy behaviors. These observed associations between unhealthy behaviors and reporting Mental balance values support this line of thinking. As values reflect the motives, needs, and preferences of people, they could also be utilized for reframing the goals of health behavior change in a more personally appealing way, attempting to create positive personal outcome expectations (ie, behavioral beliefs) associated with healthy behaviors, which in turn would result in a more favorable attitude toward taking action [14]. This type of approach may help engage the unmotivated proportion of the population, not actively interested in health benefits. For example, presenting healthy lifestyle as a means for increasing productivity at work and professional influence might appeal to people valuing Power.

These results along with the motivational nature of values indicate that it is worth to explore how values could be used to personalize and reframe behavior change goals in eHealth and mHealth interventions, and whether this approach would be effective in increasing user engagement at the individual level. The population-level knowledge provided by this study could be utilized in formulating educated hypotheses on how addressing values in eHealth and mHealth interventions may influence user engagement. However, testing these hypotheses would require rigorous research with well-defined, controlled study settings.

Finally, we consider this study as a successful demonstration of the potential of exploiting data collected in uncontrolled settings. Nowadays, the challenge of refining knowledge from unstructured and incomplete data has become ever so relevant, as data from citizens are becoming increasingly available because of the digitalization of societies. This development also provides interesting opportunities for studying the preferences, attitudes, and behavior of citizens.

Conclusions

This large study suggests that commitment to values is positively associated with happiness and replicates many of the previously observed relationships between value priorities and factors related to well-being and health behaviors. Previously unexplored associations between values, health behaviors, and happiness were also found. Health, Power, and Mental balance values were most relevant in terms of happiness and health behaviors. The results could be utilized in formulating educated hypotheses on how addressing values in eHealth and mHealth interventions may influence user engagement to be tested in controlled study settings.

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Authors' Contributions

AH, ME, IK, PM, HJ, and MP contributed to the conception or design of the work; AH and EH performed the data analysis and interpretation; AH drafted the article; and all the coauthors critically revised the paper and have approved the final version for publication.

Conflicts of Interest

None declared.

Multimedia Appendix 1

The Finnish Happiness-Flourishing Study (FHFS) Web Survey.

[PDF File (Adobe PDF File), 66KB-Multimedia Appendix 1]

Multimedia Appendix 2

Details of the principal component analysis (PCA) procedure applied for the classification of value items.

[PDF File (Adobe PDF File), 21KB-Multimedia Appendix 2]

Multimedia Appendix 3

Definitions of the value types expressed by the respondents.

[PDF File (Adobe PDF File), 73KB-Multimedia Appendix 3]

Multimedia Appendix 4

Associations between value types, happiness, and health behavior-related factors.

[PDF File (Adobe PDF File), 81KB-Multimedia Appendix 4]

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Abbreviations

eHealth: electronic health
FCS: fully conditional specification
FHFS: Finnish Happiness-Flourishing Study
mHealth: mobile health
MI: multiple imputation
OR: odds ratio
PCA: principal component analysis
SVS: Schwartz Value Survey
SWB: subjective well-being
TV: television

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Appendix 1

The Finnish Happiness-Flourishing Study (FHFS) Web-Survey

Happiness-Flourishing Scale:
01: Kuinka onnellinen olet yleisesti ottaen
1 = En lainkaan onnellinen – 7 = Hyvin onnellinen
02: Kuinka usein olet kokenut onnen hetkiä
1 = En koskaan – 7 = Hyvin usein
03: Kuinka hyvin olet voinut toteuttaa kykyjäsi ja lahjojasi
1 = En lainkaan – 7 = Poikkeuksellisen hyvin
04: Kuinka valoisana näet tulevaisuuden
1 = En lainkaan valoisana – 7 = Hyvin valoisana
05: Kuinka mielekkäänä ja tarkoituksellisena koet elämäsi
1 = En lainkaan mielekkäänä – 7 = Hyvin mielekkäänä
06: Kuinka arvokkaaksi koet elämäsi
1 = En lainkaan arvokkaaksi – 7 = Hyvin arvokkaaksi
07: Kuinka hyvin koet hallitsevasi elämääsi
1 = Heikosti – 7 = Erittäin hyvin
08: Koetko olevasi onnellisempi kuin muut tuntemasi ihmiset
1= En lainkaan onnellisempi – 7 = Erittäin paljon onnellisempi
09: Missä määrin koet, että sinulla on annettavaa muille ihmisille
1= Ei lainkaan annettavaa – 7 = Erittäin paljon annettavaa
10: Missä määrin olet saavuttanut sisäisen rauhan
1 = En lainkaan – 7 = Täydellisesti

Life satisfaction related questions:

et01: Kuinka tyytyväinen olet läheisiin ihmissuhteisiisi juuri nyt?
et02: Kuinka tyytyväinen olet taloudelliseen tilanteeseesi juuri nyt?
et03: Kuinka tyytyväinen olet elämän olosuhteisiisi yleensä juuri nyt?
et04: Kuinka tyytyväinen olet omaan terveyteesi yleensä juuri nyt?
et05: Kuinka tyytyväinen olet läheisesi terveyteen yleensä juuri nyt?

et01-et05
1 = Erittäin tyytymätön – 7 = Erittäin tyytyväinen

et06: Kuinka kovaa tai helppoa elämäsi on juuri nyt?
1 = Erittäin kovaa – 7 = Erittäin helppoa
et07: Kuinka ikävää tai iloista elämäsi on juuri nyt?
1 = Erittäin ikävää – 7 = Erittäin iloista

Depression Scale (DEPS)
dep01: Olen kärsinyt unettomuudesta
dep02: Olen tuntenut itseni surumieliseksi
dep03: Minusta on tuntunut, että kaikki vaatii ponnistusta
dep04: Olen tuntenut itseni tarmottomaksi
dep05: Olen tuntenut itseni yksinäiseksi
dep06: Tulevaisuus on tuntunut toivottomalta
dep07: Elämästä nauttiminen on tuntunut mahdottomalta
dep08: Olen tuntenut itseni arvottomaksi
dep09: On tuntunut, että kaikki ilo on hävinnyt elämästä
dep10: On tuntunut, että alakuloisuuteni ei ole hellittänyt edes perheeni tai ystävieni avulla

dep01–dep10
1 = Erittäin paljon – 4 = Ei lainkaan

Happiness skills related questions
ot01: Omistan suuren osan ajastani lähimmäisilleni
ot02: Olen hyvin kiitollinen kaikesta saamastani ja saavuttamastani
ot03: Muiden ihmisten auttaminen on minulle ominaista
ot04: Suhtaudun tulevaisuuteen hyvin luottavaisesti
ot05: Haluan elää juuri tätä hetkeä
ot06: Ulkoilen, liikun tai urheilen säännöllisesti
ot07: Minulla on pysyviä arvoja, joita pyrin edistämään
ot08: Koen vastoinkäymiset haasteina
ot09: Uppoudun usein työhöni ja askareisiini niin, että aika unohtuu
ot10: Anteeksiantaminen on minulle helppoa
ot11: Saan voimaa hiljentymisestä ja mietiskelystä
ot12: Minulla on selkeitä tavoitteita elämässäni

ot01–ot10
1 = Täysin eri mieltä – 7 = Samaa mieltä

Gender: 1 = nainen, 2 = mies

Age: Minkä ikäinen olet

Height: Kuinka pitkä olet (cm)

Weight: Kuinka paljon painat (kg)

Postal code: Postinumerosi kaksi ensimmäistä numeroa

Income: Kuinka suuret olivat taloutesi kokonaistulot viime vuonna bruttona (euro)

Household size related questions
01: Taloudessasi asuu, itsesi mukaan lukien ___ aikuista
02: Taloudessasi asuu, itsesi mukaan lukien ___ lasta

Years of education: Kuinka monta vuotta olet yhteensä käynyt koulua tai opiskellut päätoimisesti

Exercise: Kuinka paljon keskimäärin liikut ja rasitat itseäsi ruumiillisesti vapaa-aikana
1 = Vapaa-aikanani en paljonkaan liiku
2 = Vapaa-aikanani kävelen, pyöräilen tai liikun muulla tavalla vähintään 4 tuntia viikossa
3 = Harrastan vapaa-aikanani varsinaista kuntoliikuntaa vähintään 3 tuntia viikossa.
4 = Harjoittelen vapaa-aikanani kilpailumielessä säännöllisesti useita kertoja viikossa rasittavia urheilumuotoja.

Financial situation: Onko taloudellinen tilanteesi nyt parempi vai huonompi kuin aikaisemmin
1 = paljon parempi
2 = hieman parempi
3 = suunnilleen samanlainen
4 = hieman huonompi
5 = paljon huonompi

Problems with spouse: Onko sinulla vaikeuksia tulla toimeen puolisosi kanssa
1 = En ole parisuhteessa
2 = Melkein koko ajan
3 = Joskus
4 = Ei koskaan

Problems with children: Onko lapsista aiheutunut sinulle erityisiä vaikeuksia
1 = Minulla ei ole lapsia
2 = Melkein koko ajan
3 = Aika usein
4 = Joskus
5 = Harvoin
6 = Ei koskaan

Vegetables consumption: Kuinka usein keskimäärin syöt tuoreita vihanneksia tai juureksia
1 = Harvemmin kuin kerran viikossa
2 = 1-2 päivänä viikossa
3 = 3-5 päivänä viikossa
4 = Päivittäin

Fruits and berries consumption: Kuinka usein keskimäärin syöt tuoreita hedelmiä tai marjoja
1 = Harvemmin kuin kerran viikossa
2 = 1-2 päivänä viikossa
3 = 3-5 päivänä viikossa
4 = Päivittäin

Work stress: Miten usein sinua kiusaa se, että joudut pinnistämään voimasi äärimmilleen pystyäksesi selviytymään nykyisestä työstäsi tao työmäärästäsi
1 = En ole ansiotyössä, enkä opiskele päätoimisesti
2 = Melkein koko ajan
3 = Aika usein
4 = Joskus
5 = Harvoin tai ei koskaan

Communal social activity: Kuinka usein osallistut seura- tai yhdistystoimintaan, harrastat esim. kädentaitoja tai kulttuuria tai käyt uskonnollisissa tilaisuuksissa
1 = Kerran viikossa tai useammin
2 = Kerran kuukaudessa tai useammin
3 = Kerran tai muutaman kerran vuodessa
4 = Harvemmin tai en koskaan

Binge drinking: Kuinka usein juot alkoholijuomia niin, että tunnet itsesi päihtyneeksi
1 = Ainakin pari kertaa viikossa
2 = Ainakin kerran viikossa
3 = Ainakin kerran kuukaudessa
4 = Harvemmin kuin kerran kuukaudessa

Alcohol consumption: Kuinka monta annosta alkoholia juot viikossa

Smoking: Kuinka monta savuketta, sikaria tai piipullista poltat päivittäin

Total cholesterol: Mikä oli viimeisin kolesteroliarvosi, kokonaiskolesteroli (10* mmol/l, esim 57 = 5,7 mmol/l)

HDL cholesterol: Mikä oli viimeisin kolesteroliarvosi, HDL-kolesteroli (10* mmol/l, esim 14 = 1,4 mmol/l)

Sleep hours: Kuinka monta tuntia nukut keskimäärin

Questions about major negative life events:

01: Onko sinulle tapahtunut jokin huomattava kielteinen tai rankka elämänmuutos joka vaikuttaa yhä

1 = Asumusero
2 = Avioero
3 = Lapsen kuolema
4 = Läheisen perheenjäsenen kuolema
5 = Ystävän kuolema
6 = Puolison kuolema
7 = Vankilatuomio
8 = Työstä erottaminen
9 = Loukkaantuminen
10 = Vakava sairastuminen
11 = Perheenjäsenen sairastuminen
12 = Muu, mikä?
13 = En tahdo kertoa

02: Milloin
1 = Puolen vuoden sisällä
2 = Vuoden sisällä
3 = 2 vuoden sisällä
4 = 5 vuoden sisällä
5 = Aikaisemmin

03: Arvioi elämänmuutoksen vaikutusta onnellisuuteesi nyt
1 = Ei vaikutusta – 10 = Suuri kielteinen vaikutus

Questions about major positive life events:

01: Onko sinulle tapahtunut jokin huomattava myönteinen elämänmuutos joka vaikuttaa yhä
1 = Uusi ihmissuhde
2 = Avioliitto
3 = Eläkkeelle siirtyminen
4 = Lapsen syntymä
5 = Lapsenlapsen syntymä
6 = Muutto uuteen kotiin
7 = Opiskelupaikka
8 = Työpaikka
9 = Ylennys
10 = Palkankorotus
11 = Muu, mikä
12 = En tahdo kertoa

02: Milloin
1 = Puolen vuoden sisällä
2 = Vuoden sisällä

3 = 2 vuoden sisällä
4 = 5 vuoden sisällä
5 = Aikaisemmin

03: Arvioi elämänmuutoksen vaikutusta onnellisuuteesi nyt
1 = Ei vaikutusta – 10 = Suuri kielteinen vaikutus

Appendix 2

Details of the PCA Procedure Applied for the Classification of Value Items
Principal component analysis (PCA) based on the promax oblique rotation method was applied to investigate whether 1) certain non-Schwartz value groups could be merged with other value groups, or 2) some value items should be relocated to a different group. Before performing the analysis, the data were transformed into a value matrix, where columns represented value types and rows represented the number of value items each respondent had reported per value type. PCA was applied in numerous settings and the value matrix was accordingly, iteratively modified via the following steps: Each of the non-Schwartz value groups were explored one by one to verify whether their value items were adequately located by 1) dividing the non-Schwartz value group into subsets of items (usually 1-3 words) that strictly represented a single concept, 2) creating temporary value groups to the value matrix for each subset, 3) applying PCA to the modified value matrix, 4) merging the value groups in the matrix according to the PCA results, and 5) repeating the steps 3 and 4 until all the temporary value groups were merged with other groups, or no further merges were suggested by the PCA.

The number of components in the each PCA solution was defined based on the eigenvalue (0.98 – 1.0), scree plot, and the conceptual sensibility of the components. Only the value groups with communalities and maximum component loadings ≥ 0.3 were included in the final PCA solutions. Value groups were merged, if they were univocally loaded on the same component with loadings ≥ 0.4 amongst non-Schwartz value items (between temporary groups, or temporary groups and non-Schwartz groups), or with loadings ≥ 0.6 when Schwartz groups were involved (between temporary groups and Schwartz value types), and if the groups seemed conceptually compatible. These thresholds were defined based on the commonly observed loadings across different PCA settings and the conceptual sensibility of the components associated with varying loading magnitudes.

Altogether, PCA was applied in 33 different settings, where the non-Schwartz value group under investigation and the value matrix with the corresponding temporary value groups varied. The number of components in the PCA solutions varied from 7 to 16. The components of the different PCA solutions explained from 41% to 67 % of the overall variability in the value groups.

Appendix 3

Definitions of the value types expressed at least by 10% of the respondents (*n*=55,539[a]).

Value type	Conceptual definition	Exemplary value items
Power (S)	Social status and prestige, control or dominance over people and resources, *outward appearance*	Social power, authority, wealth, preserving public image, *elegance, attractiveness*
Achievement (S)	Personal success through demonstrating competence according to social standards, *skillful at solving problems, good standard of living*	Ambitious, successful, capable, influential, *expertise, analytical*, *pleasant housing conditions*
Hedonism (S)	Pleasure or sensuous gratification for oneself, *sentimentality, sense of humor*	Pleasure, enjoying life, self-indulgent, *intimacy, day-dreaming, playfulness, laughter*
Stimulation (S)	Excitement, novelty, and challenge in life	Daring, a varied life, an exciting life
Self-direction (S)	Independent thought and action – choosing, creating, exploring; *devotion to personally meaningful activities*	Creativity, freedom, independent, choosing own goals, curious, *self-fulfillment, inspiration*
Universalism – Nature (S)	Appreciation and protection for the nature, *enjoying the nature*	Protecting the environment, unity with nature, a world of beauty, *art, spending time in the nature, outing*
Universalism – Social concern (S)	Understanding, appreciation, tolerance and protection for the welfare of all people	Equality, social justice, wisdom, broadminded, a world at peace, *kindness, communication skills, rectitude*
Benevolence (S)	Preservation and enhancement of the welfare of people with whom one is in frequent personal contact	Helpful, honest, forgiving, loyal, responsible, *generous, empathic, unselfish*
Tradition (S)	Respect, commitment, and acceptance of the customs and ideas that traditional culture or religion provide	Devout, respect for tradition, humble, moderate, accepting my portion in life, *patriotism, hope, thankfulness*

Conformity (S)	Restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms	Self-discipline, politeness, honoring of parents and elders, obedient
Security (S)	Safety, harmony, and stability of society, of relationships, and of self	Family security, national security, social order, clean, reciprocation of favors, *piece of mind, financial security, accurateness, cautiousness, sensibility, patience*
Loved ones	Important people with whom one is in frequent personal contact	Partner, family, friends, siblings, grandchildren
Health	Health-conscious, interest towards a healthy lifestyle	Health, nutrition, fitness, healthcare
Mental balance	Knowing the self, accepting and appreciating the person one has become, nurturing mental well-being, defeating personal obstacles	Self-respect, spiritual growth, stress management, survival, being in control of one's life, peacefulness
Quality of relationships	Cultivation of relationships, interest to improve the quality of one's interpersonal relations	Companionship with partner, parenting, friendship, love, trust, respect
Culture	Attending cultural events, enjoying entertainment, producing art and handicrafts	Theatre, literature, travelling, music, dance, movies, creating artwork, handcrafting
Perseverance	Firm attitude in handling affairs, active and influential member of the society and communities	Persistency, fortitude, toughness, concentrating on the essential in problem solving, politics, community activities, desire to be heard and seen
Work	Special interest in work and studies	Occupation, workplace, studies
Home	Appreciation for home	Home
Intellectualism	Appreciation for intellectuality, idealism, and education; demand for progress and development in the society and the world	Spirituality, meditation, philosophy of life, education, internationality, public services

Notes. Schwartz values are denoted with (S).The definitions and value items for Schwartz values are adapted from [36] and completed with additional value dimensions and items (*in italics*) that were observed to reflect them in the present study.

[a]Includes the respondents, who reported at least four classified value items.

Appendix 4

Odds ratios (OR) regarding the associations between value types, happiness, and health behavior-related factors (n=55,539)[a].

Value type	Preval. (%)	Age (OR / 10 years)	Female (OR)	Happiness score (OR / 10 units)	Alcohol (OR / 10 units / week)	Regular exercise (OR)	Healthy eating[b] (OR)	Non-smoking (OR)
Loved ones	73.13	0.93***	**1.70*****	**1.17*****	0.96**	1.08**	1.10***	**1.18*****
Hedonism (S)	67.65	0.94***	0.91***	1.02*	1.07***	1.03	1.00	0.93**
Health	54.97	**1.12*****	**1.32*****	1.07***	0.93***	**1.72*****	**1.27*****	**1.40*****
Mental balance	52.78	1.04***	**1.17*****	**0.81*****	1.03*	**0.87*****	**0.86*****	**0.83*****
Universalism - concern and tolerance (S)	48.66	**1.12*****	0.92***	0.99	0.98	**0.90*****	0.94**	**0.86*****
Benevolence (S)	47.57	**1.19*****	**1.11*****	1.04***	0.93***	0.95*	**0.89*****	**0.85*****
Universalism – nature (S)	42.36	**1.13*****	**1.60*****	0.99	1.01	**1.26*****	**1.14*****	**1.12*****
Self-direction (S)	39.66	**0.90*****	0.92***	0.99	1.01	0.98	1.08***	0.99
Achievement (S)	38.55	**1.14*****	**0.78*****	0.91***	1.01*	0.91***	**0.91*****	**0.88*****
Quality of relationships	34.25	0.94***	**1.41*****	1.03***	1.00	1.00	0.98	0.94*
Security (S)	34.01	1.08***	0.92***	0.91***	0.98	**0.90*****	**0.88*****	0.92**
Culture	29.24	1.07***	**1.12*****	0.99	1.07***	0.98	**1.15*****	**1.15*****
Tradition (S)	25.61	**1.15*****	1.09**	1.05***	**0.77*****	0.96	0.97	**1.12*****
Power (S)	16.59	**0.90*****	0.92**	**0.83*****	**1.17*****	**0.80*****	**0.78*****	**0.78*****
Perseverance	16.39	0.98**	**0.65*****	0.95***	0.99	0.94*	0.92***	**0.87*****
Stimulation (S)	16.03	1.00	0.96	1.03*	1.03	1.05	0.97	**0.82*****
Work	15.92	**0.84*****	1.10**	**1.13*****	1.00	1.03	1.01	1.00
Home	14.77	1.02*	**1.91*****	**1.12*****	0.95*	0.95	1.02	1.14**
Intellectualism	13.31	**1.11*****	**0.62*****	1.01***	1.02***	0.91**	1.02*	**0.84*****
Conformity (S)	12.27	**1.29*****	**0.73*****	0.93***	0.96*	**0.89*****	**0.84*****	**0.83*****
Any values[c]	60.11	0.92***	**1.77*****	1.07***	0.92***	1.01	1.04*	1.05*

[a]The odds ratios are bolded for which the change in odds per unit is at least 10% and *P*<.001. Schwartz value types are denoted with (S).

[b]Daily intake of vegetables, fruits or berries.
[c]The respondents with at least 4 classified value items are compared with those who did not report any value items (n=92,394).
**P*<.05, ***P*<.01, ****P*<.001.

PUBLICATION
III

A Comprehensive User Modeling Framework and a Recommender System for Personalizing Well-Being Related Behavior Change Interventions: Development and Evaluation

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RESEARCH ARTICLE

A Comprehensive User Modeling Framework and a Recommender System for Personalizing Well-Being Related Behavior Change Interventions: Development and Evaluation

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ABSTRACT Health recommender systems (HRSs) have the potential to effectively personalize well-being related behavior change interventions to the needs of individuals. However, personalization is often conducted with a narrow perspective, and the underlying user features are inconsistent across HRSs. Particularly, theory-based determinants of behavior and the variety of lifestyle domains influencing well-being are poorly addressed. We propose a comprehensive theory-based framework of user features, the virtual individual (VI) model, to support the extensive personalization of digital well-being interventions. We introduce a prototype HRS (With-Me HRS) with knowledge-based filtering, which recommends behavior change objectives and activities from several lifestyle domains. With-Me HRS realizes a minimum set of important VI model features related to well-being, lifestyle, and behavioral intention. We report the preliminary validity and usefulness of the HRS, evaluated in a real-life health-coaching program with 50 participants. The recommendations were used in decision-making for half of the participants and were hidden for others. For 73% of the participants (85% with visible vs. 62% with hidden recommendations), at least one of the recommended activities was included into their coaching plans. The HRS reduced coaches' perceived effort in identifying appropriate coaching tasks for the participants (effect size: Vargha-Delaney $\hat{A} = 0.71$, 95% CI 0.59-0.84) but not in identifying behavior change objectives. From the participants' perspective, the quality of coaching improved (effect size for one of three quality metrics: $\hat{A} = 0.71$, 95% CI 0.57-0.83). These results provide a baseline for testing the influence of additional user model features on the validity of recommendations generated by knowledge-based multi-domain HRSs.

INDEX TERMS Behavioral sciences, digital health behavior change interventions, disease prevention, eHealth, filtering algorithms, knowledge based systems, recommender systems, user evaluation, user modeling.

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I. INTRODUCTION

In Europe, nearly 90% of the disease burden is attributed to chronic diseases, such as cardiovascular disease, cancer, and diabetes. Most of these diseases can be avoided or at least delayed with healthy behaviors. [1] Digital health behavior change interventions (DHBCIs), personalized to the needs and capabilities of individuals, have the potential to offer cost-effective solutions for empowering individuals to take care of their well-being [2], [3], [4]. Personalization can increase user engagement with digital interventions [3], [5], which is imperative for positive health outcomes. We consider personalized DHBCIs as adaptive interventions [6], [7] that aim to modify intervention content, dose, timing, or approach according to the characteristics of an individual users in order to achieve favorable behavioral or health outcomes.

Well-being is a broad concept comprising behavioral, mental, physical, and social dimensions. When attempting to improve well-being with the goal of preventing lifestyle-related diseases, several behavioral domains need to be taken into account, such as physical activity, dietary habits, sleep, smoking, alcohol consumption, stress management, work-life balance, and the cultivation of social relationships [8], [9]. Furthermore, the personal, social, and environmental factors that determine behavior [10], [11], [12] should be considered when personalizing health behavior change interventions. Individuals differ, for instance, in their behavior change needs, readiness to change behavior (intention), preferences, capabilities, and life situations, and their environmental and social circumstances vary. Each of these behavioral determinants either support or hinder change. In addition, the opportune moments to engage in behavior change activities differ between individuals, which calls for just-in-time adaptive interventions [7], [13].

Consequently, there are several aspects to consider when personalizing DHBCIs, including the a) identification of appropriate behavior change objectives and activities and the behavioral determinants to be targeted (i.e., personalization of the behavior change plan); b) adaptation of the selected objectives and activities based on individuals' adherence and the effectiveness of the activities; c) identification of appropriate educational, motivational, or feedback messages; d) identification of the opportune moments to deliver messages and prompts; and e) adaptation of the tone or style of interaction according to individuals' preferences and personalities.

As proposed earlier by Honka et al. [14], this type of extensive personalization requires the instantiation of a comprehensive user model, the so-called *virtual individual* (VI) *model*, which defines all the relevant knowledge constituents for intervention personalization. The VI model should cover the theoretical constructs of behavior change [10], [11], [12], since they define the behavioral determinants to be considered when personalizing DHBCIs, and thus, facilitate the identification of appropriate behavior change techniques (BCTs) [15], [16]. In this study, the VI model concept is further developed by proposing a theory-based framework of user features that support the implementation of extensively personalized DHBCIs.

In addition to the VI model development, we introduce a prototype health recommender system (HRS), using a standard recommendation approach, which recommends behavior change objectives and activities from various behavioral domains with the aim of promoting well-being and preventing lifestyle-related diseases. HRSs have been introduced as a promising solution for personalizing DHBCIs [5], [17], [18], but the existing applications rarely consider well-being from a multi-domain perspective (see Section II. Related work). In addition, the current HRS realizes a selection of the VI model features that we consider sufficient for serving the minimum requirements for personalizing multi-domain DHBCIs. The selected user model features are related to well-being, lifestyle, and behavioral intention. We study the impact of this minimum set of features on the performance of the implemented multi-domain HRS. Typically, HRS research focuses on the development of recommendation methods, although both the underlying user model and the applied recommendation method contribute to the suitability of recommendations. This study focuses on the user modelling aspect by providing baseline results for finding the most effective user features for personalization. Disease management systems are beyond the scope of the study.

II. RELATED WORK

A majority of HRSs that focus on promoting well-being and healthy lifestyle provide recommendations for physical activity (PA) or healthy diet or deliver tailored motivational messages for smoking cessation [17], [18], [19], [20]. Some have also addressed alcohol consumption [21], mental well-being [18], or sleep [22]. HRSs have been used for recommending personalized goals, healthy activities, peer support, and reliable health information and for selecting educational and motivational health messages or the appropriate timing for message delivery [5], [18], [20], [23]. For example, PA-related HRSs have recommended PA modes (e.g., running, walking, gym), intensities, or durations [24], [25], [26], [27]; personalized goals in terms of weight loss and calorie expenditure [24], [25]; [24], [25], [26], [27]; exercise buddies [27]; and suitable timings or places for exercise sessions [24], [26], [27]. Diet-related HRSs have recommended recipes, meal plans, restaurants, and healthy items from restaurant menus, and they have provided also nutritional advice [18]. For stress management, HRSs have recommended mental activities such as mindfulness, breathing, and cognitive exercises [28], [29] or activities related to PA, social engagement, and enjoyment [30].

Typical recommendation methods include content-based, collaborative, demographic, and knowledge-based filtering as well as hybrid approaches [23], [31], [32]. All of these methods have been employed also in HRSs that promote well-being and healthy lifestyle [5], [17], [18]. In content-based filtering, items that are similar to those rated positively by the user are recommended. In collaborative filtering, items that have been evaluated highly by other users sharing similar item preferences with the target user are recommended, whereas in demographic filtering, items preferred by other users sharing a similar demographic profile with the target user are recommended. In the knowledge-based approach, explicit knowledge about the user, derived, for example, from questionnaires or wearable devices, is used to filter suitable items. Cheung et al. [5] consider knowledge-based filtering especially appropriate for HRSs, and many of the implementations to date are based on this method [18]. In hybrid approaches, different recommendation methods are used. The majority of HRSs utilize hybrid methods [5], [18] such as in [30], [33], and [34]. In addition, both supervised and unsupervised machine learning have been utilized in HRSs [5], including random forests [28], reinforcement learning [24], [35], and neural networks [26].

Utilizing the methods of recommender systems for personalizing DHBCIs is appealing: Content- and knowledge-based filtering can efficiently generalize to a high number of user features compared to the traditional rule-based tailoring without considerably increasing the complexity of the system [36]. Furthermore, the combination of collaborative and demographic filtering can be used to collect the preferences of a group of people who share similar well-being issues and life situations, which can be used to recommend novel intervention items to a specific individual [5]. Hence, in terms of personalization, HRSs have the potential to consider well-being from a multidimensional viewpoint and harness the multitude of individual-specific factors that determine behavior for personalization.

However, to the best of our knowledge, HRSs based on such comprehensive user models have not been implemented. Typically, the user models have focused on a limited set of behavioral domains, often PA or dietary habits [17], [18], [20], and they do not cover any of the theory-based determinants of behavior [5], [37]. Some HRSs address one or two behavioral determinants. For instance, in [33], [38], and [39], smoking cessation messages are personalized according to the readiness to change construct. In [30], users' self-efficacy (i.e., belief in one's capability to perform the behavior under different circumstances [40]) and skills are leveraged to personalize stress management activities. A rare example of extensive theory-based personalization is provided by the smoking cessation application, Quit and Return [41], which addresses several constructs of the Integrated-Change Model (attitude, readiness to quit, self-efficacy, social support, action planning, and skills) [42]. Overall, examples of HRSs that are firmly grounded on behavioral theories are limited. The lack of multi-domain interventions and the insufficient consideration of behavioral determinants are major shortcomings for HRSs that aim to engage individuals in healthy lifestyle changes.

Furthermore, the user model features vary considerably across different HRSs, indicating a lack of common understanding of the important features. The typical (non-theoretical) feature types that have been used for personalization include basic demographics, such as age and gender (e.g., [25], [27], [33], [35], [39], [43], [44], [45]), health risks (e.g., [25], [27], [33], [43], [46]), and health behaviors (e.g., [20], [22], [24], [25], [27], [33], [35], [39], [43], [44], [45]). In addition, many HRSs utilize context-related features to determine opportune moments for delivering recommendations, of which location and the time of day are the most prevalent (e.g., [24], [26], [27], [28], [33]), but calendar availability [27], [28] and users' momentary activities [24], [26] have also been used in some examples. Considering user preferences (e.g., preferred PA modalities and time slots, dietary restrictions) [20], [25], [26], [27], [44], [45] and the usefulness or effectiveness of recommendations (either user-evaluated or inferred) [24], [28], [30], [35], [38], [43] are also quite common. Some HRSs consider mental states (e.g., stress level, mood) [28], [29], [47], social ties [27], [33], environmental conditions [22], [47], or personality traits [28].

III. OBJECTIVES

This study contributes to the development of personalized DHBCIs that promote well-being and prevent lifestyle-related diseases by guiding and empowering individuals to make healthy lifestyle changes. First, a comprehensive, theory-based VI model framework is introduced with practical user feature examples. The framework includes features that represent the psychological, social, and environmental factors determining behavior in the context of everyday life, and it considers well-being and healthy lifestyle from a multi-domain viewpoint. After defining the VI model, we describe the development of a prototype web-based HRS, called With-Me HRS, which implements a subset of the VI model features for personalizing the recommendation of behavior change objectives and activities. When generating the recommendations, several behavioral domains are considered, as opposed to most HRSs that have a restricted focus. Finally, we evaluate the preliminary validity and usefulness of With-Me HRS in a real-life remote health-coaching program.

The present work aims to advance a common understanding of the user features required for the extensive personalization of DHBCIs, which is currently lacking especially in the HRS research field. Furthermore, an example of a HRS that considers well-being and healthy lifestyle comprehensively, beyond only PA and dietary habits, is introduced. This kind of multi-domain interventions are novel in the HRS literature, and the current study provides baseline results regarding the personalization of such interventions.

IV. METHODS: IMPLEMENTATION AND EVALUATION

A. VIRTUAL INDIVIDUAL MODEL

To define the key constituents of the comprehensive VI model, we sought to identify various factors governing behavior and behavior change from the theories explaining health behavior. Many of the theories have overlapping constructs, but behavioral scientists have attempted to reach a consensus about the most important ones [10], [40]. Based on the comparisons of theories conducted by behavioral scientists [10], [40], [48] and a review into the fields of psychology, behavioral economics, and social marketing (e.g., [49], [50], [51], [52], [53]), Honka et al. [14] formed a synthesis of the key determinants of behavior. We utilized this synthesis to define the VI model constituents. In addition, the stage of change construct defined by the Transtheoretical Model (TTM) of behavior change [49] was included into the VI model, as it is widely used to explain the multistage process of change [54]. The stage of change construct describes one's readiness to change behavior (i.e., the behavioral intention or motivation). Finally, the principles of evidence-based intervention planning for health promotion [10], [55], [56] were considered when designing the VI model. Specifically, the following questions guided the selection of VI model constituents:

1) What are the risk behaviors to be addressed (e.g., unhealthy eating rhythm, insufficient sleep, lack of exercise)?
2) How motivated a person is to modify these behaviors (e.g., based on TTM [49])? Are they aware of the need to change behavior?
3) Which determinants of behavior should be addressed for increasing motivation and eliciting behavior change (e.g., outcome expectations/attitude, self-efficacy, social influence, perceived barriers, environmental context)? [11], [14]
4) What are the factors that facilitate or impede behavior change (e.g., time and monetary resources, personal skills, environmental or social factors)? [11], [14]
5) What motivates and interests the person? How should intervention materials and messages be framed to increase motivation towards behavior change (e.g., elicit emotions vs. stick to facts, negative vs. positive framing [57], [58], [59])?
6) What are the opportune moments to provide support? [7]
7) What kind of behavior change techniques [16], [60] and activities are effective for the person?

To provide answers to the open questions, we identified four key, high-level elements that form the core of the VI model: *Health & well-being, Resources, Motives & preferences,* and *Behavior change needs and determinants*. These factors determine one's behavior change needs, the type of support needed, and personal interests and preferences, and they should be used to personalize the intervention content. Furthermore, we included an element describing the *Momentary context* to facilitate the identification of opportune moments for providing support. We also included *Intervention items* and *Progress evaluation* elements; the former describes the content of the personalized intervention, and the latter tracks the person's adherence to the intervention and the effectiveness of the intervention. Progress evaluation is important for identifying whether the intervention should be updated. Fig. 1 presents the VI model elements and the related feature types. In the figure, two additional blocks are visible: intervention items appropriate for other individuals similar to the target person and an intervention library defining the available items to select from. These blocks are not part of the VI model, though closely related, as data from similar individuals can provide added value for intervention personalization (via collaborative and demographic filtering) and the intervention library defines the space for personalization.

TABLE 1. Behavioral domains supported by With-Me HRS.

Health behavior and well-being domains	
Sleep sufficiency	Workload management
Sleep quality	Recovery from stress
Eating rhythm	Anxiety
Diet quality	Personal values
Emotional eating	Quality of relationship
Physical activity	Self-esteem
Alcohol consumption	Smoking

When populating the VI model elements with an individual's data, a digital representation of the individual, the *personal profile*, is formed. Detailed descriptions of the proposed VI model elements, the proposed feature types along with concrete feature examples, and the interrelations between the features are provided in Appendix 1.

B. WITH-ME HEALTH RECOMMENDER SYSTEM

1) OVERVIEW

With-Me HRS was developed to provide support in identifying appropriate coaching plans for the participants of an occupational stress management program that involved human coaching. It was designed to evaluate individuals' behavior change needs in terms of 14 behavioral domains related to well-being and healthy lifestyle (see Table 1) as well as to recommend suitable behavior change activities based on the identified needs and domain-specific readiness to change. It assisted health coaches in identifying suitable behavior change objectives and activities (i.e., coaching tasks) for the participants by providing a comprehensive overview of the analyzed behavioral domains and recommending activities accordingly.

The VI model feature types relevant to behavior change needs and readiness to change were selected for implementation in the With-Me user model (bolded in Fig. 1). We consider these aspects as the two most important feature types for the user models of multi-domain DHBCIs, since the first, obvious step in such interventions is to identify the appropriate behavior change objectives for an individual [60], and readiness to change appears to be the single best predictor for behavior [11]. In addition, feature types from the VI model's Resources element (Fig. 1) were implemented to reflect the characteristics of the stress management program's target population, consisting of individuals who were active in work-life and lived with a family.

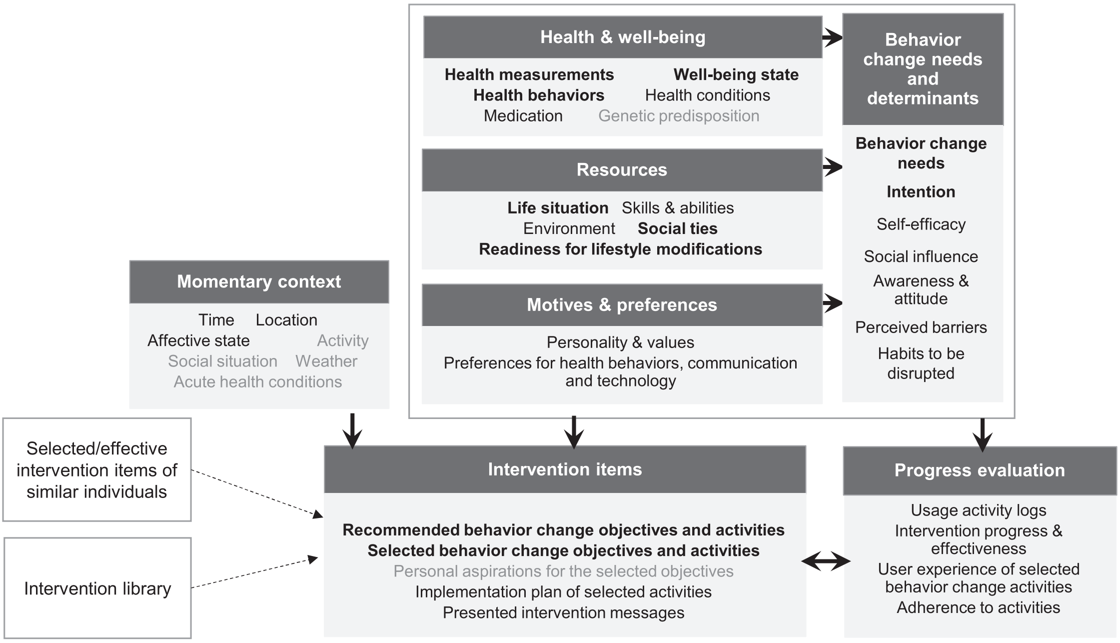

FIGURE 1. The high-level elements of the proposed VI model including the related feature types. The feature types that were included in the implementation of With-Me HRS are bolded, and the features that we consider promising for personalization but lacking a solid theoretical background or proven practical value are grayed out. The intervention item components are closely associated with the VI model but not part of it.

With-Me HRS was implemented as a web tool. It was integrated with the Movendos web-based health-coaching service (v1.27, Movendos Ltd.) [61] and the LimeSurvey online survey tool.[1] Together, these modules formed a digital health-coaching system. The content of the stress management program and the functionalities of the overall coaching system are described in [62]. In this study, we focus on the implementation of the HRS module only. Fig. 2 depicts the technical architecture of With-Me HRS and its connections to the other modules of the overall coaching system. The HRS was composed of *Personal profile, Profiler, Recommendation engine,* and *Intervention library* components.

The Personal profile included a user model that was associated with a database that populated the model's features with an individual's past and current data. The user model specified the features utilized for personalization and the structure of user data. The Profiler component analyzed the available data and created and maintained the Personal profile according to the data structure specified by the user model (see subsection Profiler below for details). The Personal profile provided a user-interface for coaches, which allowed coaches to examine the analysis results and to correct possible mistakes in the results. The data used for profiling were mostly collected with the online survey tool. In addition, objective indicators of physiological well-being and physical activity were provided by Firstbeat lifestyle assessment (Firstbeat Technologies Ltd.),[2] and they were manually entered into the HRS. Firstbeat lifestyle assessment is based on the analysis of heart rate variability and movement that are measured via chest electrodes.

Based on the constructed Personal profile, the Recommendation engine suggested behavior change activities from the Intervention library (see subsection Recommendation engine below for details). Only the most recent user data were used for recommendations. The Recommendation engine provided a user-interface for both coaches and individuals for presenting the recommended activities and enabling coaching task selection. The reference ids of the recommended and selected activities were stored in the Personal profile. Information about the selected activities was also transferred to the Movendos health-coaching service.

2) PROFILER

a: PERSONAL PROFILE

The Profiler populated the user model underlying With-Me HRS, thus forming the Personal profile. The user model covered a subset of the feature types included in the envisioned comprehensive VI model (Fig. 1): well-being state, health behaviors, health measurements, behavior change

[1] www.limesurvey.org

[2] https://www.firstbeat.com/en/wellness-services/wellness-professionals/individual-wellbeing/

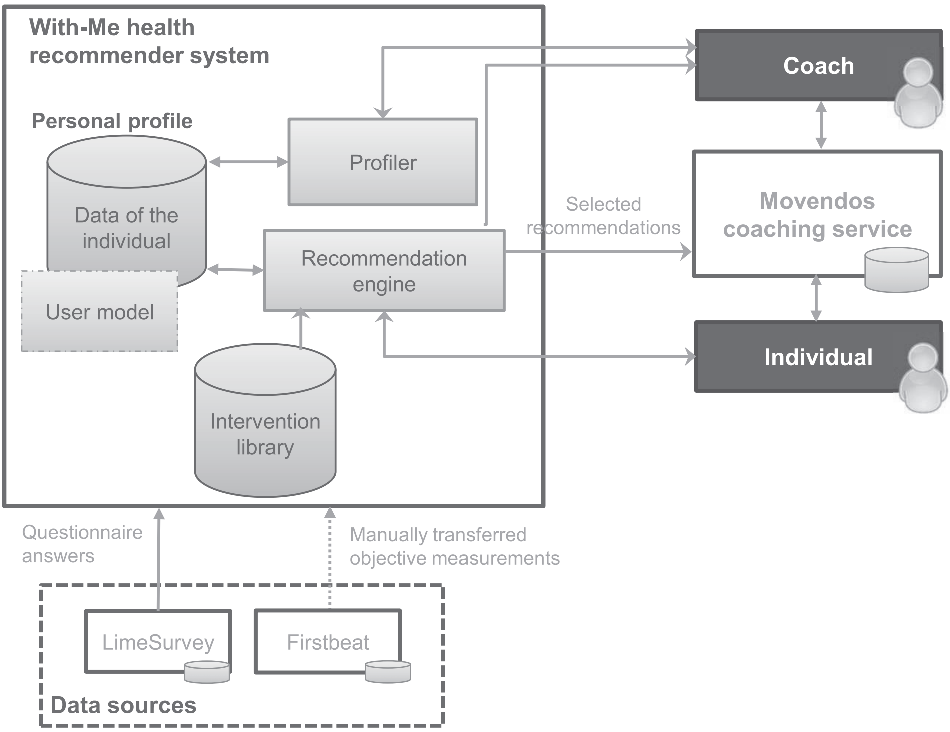

FIGURE 2. The architecture of With-Me HRS and its connections to the other modules of the overall digital health-coaching system that was utilized in the occupational stress management program described in [62].

needs, readiness to change (intention), life situation, social ties, and the reference ids of the recommended and selected items (see Appendix 1 for details). The Profiler analyzed data acquired via questionnaires (e.g., WorkOptimum for occupational health [63], Cognitive Fusion Questionnaire for anxiety assessment [64], and a modified version of the stages of change survey [65]) and, when available, via the Firstbeat lifestyle assessment conducted based on a 3-day measurement period. Based on the available data, the Profiler interpreted participant's behavior change needs and readiness to change regarding each of the 14 behavioral domains listed in Table 1.

The coaches could review the results of the Profiler's behavior change needs analysis via its user-interface. For each behavioral domain, the individual's need for change (5-point scale:1 = no need, 5 = strong need) and the readiness to change were presented. Readiness to change was categorized according to the TTM's stage of change construct (pre-contemplation, contemplation, preparation, action, maintenance [49]). The behavioral domains were presented in the order of importance by ranking them according to the behavior change need. In addition, the user-interface revealed per behavioral domain the original user data that were processed by the Profiler, i.e., the participants' self-reported values and Firstbeat indicators. The domains for which the Profiler was not able to assess the change need with high confidence were denoted with a warning sign to urge the coach to check the data behind the analysis and to modify the results if needed. Low confidence could be caused, for instance, by conflicting self-report and Firstbeat indicator values (see Appendix 2 for details).

b: USER MODEL'S DATA STRUCTURE

In addition to defining the features of the Personal profile, the With-Me user model specified the hierarchical structure of the features, their interrelations, and the common properties used to describe them. We implemented the hierarchical structure via three data layers: *original*, *integrated*, and *aggregated data*. The original data layer included original measures, provided directly by the available data sources (the participant or measurement device) and formed the bottom level of the hierarchy. The integrated data layer combined features representing similar concepts, and the aggregated data layer combined features describing different concepts into high-level summary features (Fig. 3).

The following properties were used to describe the features residing on the different layers: *timestamp* indicating when the value of a feature was acquired, *original value*

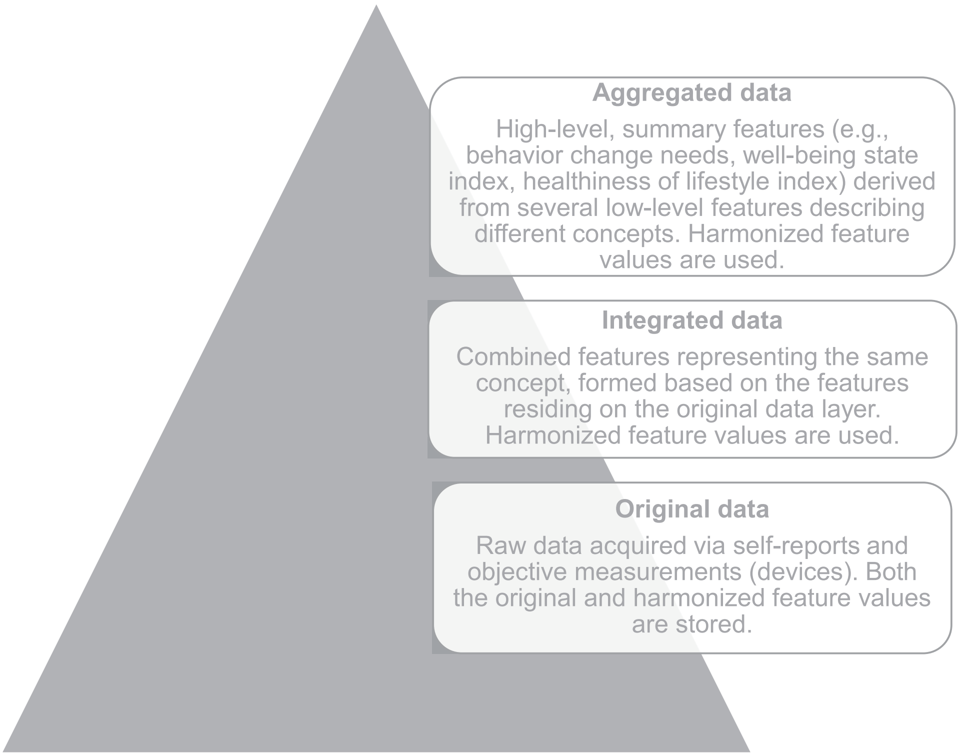

FIGURE 3. The hierarchical data layers of the With-Me user model.

of the feature (available only on the original data layer), *harmonized value* transforming the original feature value to a unified 5-point scale, *confidence* indicating the reliability of the feature value via a continuous scale from 0 to 1 (1 = highest reliability), and *source* denoting the origin of the feature value (participant's self-report, Firstbeat assessment, Profiler's analysis, or coach's modification). We used harmonized values to simplify the feature computations at the higher layers of data hierarchy and confidence values to determine the reliability of the Profiler's analysis results. In Appendix 2, we describe the data layers in more detail and the related data-processing algorithms executed by the Profiler.

3) RECOMMENDATION ENGINE

a: USER-INTERFACE

The Recommendation engine recommended behavior change activities (items) from the Intervention library based on the identified behavior change needs and readiness to change behavior, which were analyzed by the Profiler (but could be modified by the coach). The user-interface of the Recommendation engine presented the recommended activities and the items of the Intervention library to both the coaches and participants. In addition, the participants could propose at most three activities to their coaches to be included in their coaching plans, either from the recommended list of items or from the Intervention library, or alternatively, they could create custom activities. The coaches were able to view the proposed activities through the user-interface. The number of activities that could be proposed was limited to three, since for multi-domain behavioral interventions, including 2-3 behavior change objectives seems to be optimal in terms of intervention efficacy [66].

b: INTERVENTION LIBRARY

The Intervention library included over 100 items related to different behavior change activities. Each item was labelled by the behavioral domains it was supposed to target and the TTM's stages of change it was applicable to. A professional health coach was involved in designing the Intervention library. The activities were based on different behavior change techniques (BCTs) [16], and activities of varied difficulty or effort levels were included. Many of the activities utilized the Oiva web portal,[3] developed to promote mental well-being, which included short exercises based on the acceptance and commitment therapy [67]. Examples of the

[3]https://oivamieli.fi/

Intervention library items (and the related BCTs) include: ''Read an online article about the symptoms of stress and good practices for stress management'' (information about health consequences), ''Take a quiz for evaluating your alcohol consumption patterns'' (feedback on behavior), ''Get an exercise buddy'' (social support), ''Use Oiva to ponder the reasons that are keeping you from fulfilling your personal values in everyday life'' (pros and cons), ''Make a realistic list of work tasks for the upcoming work day'' (action planning), ''Keep a diary about eating habits for three days'' (self-monitoring), ''Keep fruits in sight and vegetables easily accessible at home'' (restructuring the physical environment), ''Wake up at the same time every day'' (habit formation), and ''Practice mindfulness skills with Oiva exercises'' (behavioral practice).

c: RECOMMENDATION LOGIC

With-Me HRS utilized the case-based recommendation technique of knowledge-based filtering [68], where items (or cases) that matched the behavior change needs and readiness to change of a participant (i.e., the target case) were retrieved from the Intervention library. Participants' behavior change objectives were determined by the behaviors that they had at least a moderate need for change. Only activities relevant to the objectives were considered for recommendation as explained in the following paragraphs.

Let us denote B as the set of 14 behaviors supported by With-Me HRS (see Table 2 in Appendix 2), $T = \{1, 2, 3, 4, 5\}$ as the set of the TTM's stages of change (1 = pre-contemplation, 5 = action), and I as the set of items included in the Intervention library. Each behavior was described in the Personal profile with a vector $\boldsymbol{b^i} = [b^i_{\text{str}}\ b^i_{\text{stg}}]$, where for a behavior $i \in B$, $b^i_{\text{str}} \in [0, 1]$ denotes the strength of the behavior change need (0 = no need, 1 = strong need) and $b^i_{\text{stg}} \in T$ denotes the stage of change for the behavior. Furthermore, each activity $j \in I$ was described in the Intervention library with the set of properties $\boldsymbol{A^j} = \{A^j_{\text{beh}}, A^j_{\text{stg}}, \text{opr\_A}^{\text{j}}\}$, where

1) $(A^j_{\text{beh}} \subset B, \leq)$ is a partially ordered subset of B including only those behaviors that are in the focus of activity j, ordered based on relevancy,
2) $A^j_{\text{stg}} \subset T$ is a subset of T, indicating the stages of change to which activity j is applicable,
3) $\text{opr\_A}^j \in \{\max, \min, \text{weighted}\}$ is an operator determining how to evaluate the combined relevancy of the set of behaviors A^j_{beh} in terms of the Personal profile: either all the behaviors $a^j_{\text{beh},n} \in A^j_{\text{beh}}, n \in \{1, \ldots, 14\}$ need to match the Personal profile (max); at least one of them needs to match (min); or the relevance of each behavior is weighted as such that the first item $a^j_{\text{beh},1}$ in the set matters the most and the other behaviors have a supporting role only (weighted).

For example, let us assume that the HRS supports only three behaviors: 1) physical activity, 2) relaxation, and 3) sleep. Let the Intervention library include an activity j' that is suitable for individuals who have challenges regarding relaxation or sleep and who are in the pre-contemplation, contemplation, or preparation stage. Thus, the activity j' has the properties $A^{j'}_{\text{beh}} = (2, 3)$, $A^{j'}_{\text{stg}} = \{1, 2, 3\}$, and $\text{opr\_A}^{j'} = \min$. Furthermore, we introduce an individual $\mathbf{P}$ with the profile

$$\mathbf{P} = \begin{bmatrix} \boldsymbol{b^1} \\ \boldsymbol{b^2} \\ \boldsymbol{b^3} \end{bmatrix} = \begin{bmatrix} 0.76 & 2 \\ 0.9 & 5 \\ 0.25 & 4 \end{bmatrix}, \tag{1}$$

which we use as an example for demonstrating the recommendation logic.

The recommendation logic was based on two similarity metrics, $\text{sim\_need}^j \in [0, 1]$ and $\text{sim\_stage}^j \in [0, 1]$, which together determined the suitability, $\text{sim\_total}^j \in [0, 1]$, of an activity j for recommendation (0 = low, 1 = high similarity). The sim_need^j metric described the similarity between the behaviors related to activity j and the behavior change needs identified in the Personal profile. The metric was based on the Manhattan distance between value pairs $\{(b^i_{\text{str}}, 1)\,|\,i \in A^j_{\text{beh}}\}$. Thus, only the behaviors relevant to activity j were considered. The general formula for the metric is

$$\text{sim\_need}^j = 1 - \left(\text{opr\_A}^j_{i \in A^j_{\text{beh}}} \left| b^i_{\text{str}} - 1 \right|\right), \tag{2}$$

where the operator opr_A^j determines how to combine the distances. If $\text{opr\_A}^j = \text{weighted}$, a weighted normalized Manhattan distance was computed with weights set according to the relevance of the behaviors denoted by the ordered set $(A^j_{\text{beh}}, \leq)$. In our example, the similarity between the behavior change needs of profile $\mathbf{P}$ and the behaviors relevant to activity j' is computed as

$$\text{sim\_need}^{j'} = 1 - \min\left(|0.9 - 1|, |0.25 - 1|\right) = 0.9. \tag{3}$$

The sim_stage^j metric described the similarity between the stages of change that activity j was applicable to and the set $T^j = \{b^i_{\text{stg}}|i \in A^j_{\text{beh}}\}$. T^j included the Personal profile's stages of change that corresponded to the behaviors relevant to activity j. If $\exists t^j \in T^j$ such that $t^j \in A^j_{\text{stg}}$, then $\text{sim\_stage}^j = 1$ (i.e., at least one matching stage was found). Otherwise, the closest values in both sets $t^{j*} \in T^j$ and $a^{j*}_{\text{stg}} \in A^j_{stg}$ were identified, and the similarity between them was computed as

$$\text{sim\_stage}^j = 1 - \frac{1}{4}\left| t^{j*} - a^{j*}_{\text{stg}} \right|. \tag{4}$$

In our example case, $T^{j'} = \{4, 5\}$. Hence, $T^{j'}$ does not share any common elements with $A^{j'}_{\text{stg}}$. The closest values in the two sets are $t^{j*'} = 4$ and $a^{j*'}_{\text{stg}} = 3$. Now,

$$\text{sim\_stage}^{j'} = 1 - 0.25 \times |4 - 3| = 0.75. \tag{5}$$

Finally, the overall suitability for activity j was computed as

$$\text{sim\_total}^j = 0.5 \times \left(\text{sim\_need}^j + \text{sim\_stage}^j\right), \quad \text{if } \text{sim\_need}^j \geq 0.5, \quad \text{otherwise } \text{sim\_total}^j = 0. \tag{6}$$

TABLE 2. Key steps of the recommendation logic.

Step #	Action
1	For each activity j, regarding the behaviors it focuses on, compute a) the similarity between the behaviors and the Personal profile's behavior change needs → sim_need^j ∈ [0,1], b) the similarity between the stages of change relevant to activity j and the Personal profile's readiness to change → sim_stage^j ∈ [0,1], c) total similarity: if sim_need^j ≥ 0.5, sim_total^j = mean(sim_need^j, sim_stage^j), otherwise sim_total^j = 0.
2	Preselect activities for which sim_total ≥ 0.5.
3	Randomize the order of the preselected activities, and sort them according to sim_total.
4	Recommend the top-20 items from the ordered list of activities.

Thus, only the activities that targeted the behaviors for which the individual had at least a moderate need for change were considered potentially suitable for recommendation. In our example,

$$\text{sim\_total}^{j'} = 0.5 \times (0.9 + 0.75) = 0.825. \tag{7}$$

The sim_total^j metric was computed for each activity $j \in I$, and the activities for which sim_total$^j \geq 0.5$ were preselected for recommendation. The order of the preselected items was randomized, after which they were sorted in descending order based on sim_total. Mixing the items ensured that activities addressing different behaviors were included at the top of the ordered list. Finally, the top-20 activities were selected for recommendation. The key steps of the recommendation logic are summarized in Table 2.

C. EVALUATION STUDY

The validity and usefulness of With-Me HRS were studied as a secondary objective of a pilot randomized controlled trial (RCT) [62], where technology-assisted and traditional telephone coaching for occupational stress management were compared in terms of intervention effectiveness and the time use of health coaches. The study was approved by the Ethics Committee of Human Sciences at the University of Oulu, Finland. Informed consent was obtained by regular mail from the individuals interested to participate in the study.

1) PARTICIPANTS AND PROCEDURES

Altogether 50 participants were recruited, who worked full-time (in the areas of information technology; education; culture; social, health, and customer services), reported a decreased state of well-being, lived in a relationship, and were motivated to enhance their well-being by making lifestyle changes or doing exercises related to mental well-being. The participants were recruited among the employees of the City of Oulu, Finland, most of whom worked in female-dominant occupations (e.g., teachers, nurses, social workers, etc.). Nearly all eligible participants were female (96.0%, 48/50), and their mean age was 46.40 years (SD 9.67). The participants were randomly allocated to two groups: one receiving technology-assisted health coaching via telephone ($N = 25$) and the other receiving traditional telephone coaching ($N = 25$). In terms of the scope of this paper, the relevant difference between the two groups was related to the usage of With-Me HRS in supporting the first two coaching calls. In technology-assisted coaching, health coaches utilized the HRS to define participants' initial coaching plans (*group with visible recommendations*), whereas in traditional coaching, the HRS generated recommendations, but they were not utilized in decision-making *(group with hidden recommendations*). Three health coaches were involved in the study, each having an equal number of participants from both groups. Further details regarding the participants and the study design are presented in [62].

At the beginning of the intervention, both groups answered an online questionnaire regarding well-being, health behaviors, and readiness to modify behaviors. The WorkOptimum assessment for occupational health [63] was part of the questionnaire. In addition, the group with visible recommendations conducted the 3-day measurements related to the Firstbeat lifestyle assessment. Based on the questionnaire answers and the selected Firstbeat indicators (available only for the group with visible recommendations), the HRS's Profiler component analyzed participants' behavior change needs and readiness to change (as described in Section IV.B).

For the group with visible recommendations, the coaches prepared for the first coaching call by exploring participants' results regarding Profiler's behavior change needs analysis (via its user-interface) and Firstbeat lifestyle assessment (in a portable document format, PDF). The Firstbeat assessment results were provided also to the participants before the first coaching call. During the call, participants' behavior change needs were discussed, and a high-level behavior change objective was agreed upon (e.g., sleep better, manage workload, eat healthier). The coaches also instructed the participants to preselect one to three behavior change activities from the HRS as their preferred coaching tasks before the next coaching call, which was scheduled after two weeks. The activities could be selected either from the recommended list of items or the Intervention library, or the participants could create custom activities. The coaches were asked to make corrections to the Profiler's needs analysis immediately after the first coaching call, in case they found any inconsistencies between the analysis results and their discussions with the participants to ensure that the HRS's recommendations were up to date before the participants were exposed to them. During the second coaching call, the coaching tasks preselected by a participant were either confirmed by the coach or adjusted in mutual agreement. The agreed tasks formed the initial coaching plan for the participant.

For the group with hidden recommendations, the coaches did not utilize Profiler's needs analysis when preparing for the first coaching call. Instead, they received the results of the WorkOptimum questionnaire in a PDF report. The report was also provided to the participants before the first coaching call. During the call, participants' behavior change needs were discussed. In addition, on the contrary to the other group, the initial coaching plan, including the behavior change objectives and coaching tasks, was already set during the first call. With-Me HRS did not influence the decision-making, as neither the coaches nor the participants examined its outputs when making the coaching plan. However, immediately after the coaching call (and after the coaching plan was set), the coaches were asked to review the results of the Profiler's needs analysis so that the generated recommendations could be validated with all the participants, not limited only to the group with visible recommendations.

2) MATERIALS AND OUTCOME MEASURES

The evaluation study aimed to assess the preliminary validity and usefulness of With-Me HRS. The primary outcome for validity was the proportion of participants for whom recommended activities were included in the coaching plan. We also examined the proportion of participants (for the group with visible recommendations) who preselected activities from the recommended list of items as their preferred coaching tasks. In addition, we examined the number and type of changes made by the coaches to the results of the Profiler's behavior change needs analysis to understand whether the employed profiling algorithms included systematic flaws. The usefulness of With-Me HRS was studied by assessing the ease of coaching from the perspective of coaches and the quality of coaching from the participant viewpoint.

The validity of the HRS was evaluated based on coaches' self-reports and the information stored in the Personal profile database. For each of the 14 behavioral domains (Table 1), immediately after the (first) coaching call, the coaches were asked to record on a paper form a) whether they were able to evaluate the domain (need and readiness to change) based on the discussion they had with a participant, b) whether they made modifications to the Personal profile regarding the domain, and c) justifications for the modifications. In addition, the coaches were asked to write down the coaching tasks included in the participant's coaching plan (after the first or second coaching call depending on the group). From the database, metrics were retrieved regarding the changes made by the coaches to the results of the Profiler's needs analysis, the activities recommended by the Recommendation engine, and for the group with visible recommendations, the activities preselected by the participants.

The usefulness of the HRS from coaches' perspective was evaluated with the following two questionnaire items: (1) *"During the coaching call, it was easy to identify the behavior change needs and objectives for the client*." (ease of identifying participants' needs) and (2) "*During the coaching call, it was easy to identify suitable coaching tasks for the client.*" (ease of identifying coaching tasks). The participants' opinions were collected with the following items: (1) *"My coach understood my well-being related needs with ease."* (ease of explaining needs), (2) *"My coach helped me realize new areas for improvement that are important for my well-being."* (improved self-awareness of needs), and (3) "*I am satisfied with the coaching call(s).*" (satisfaction with coaching calls) Each item was measured on a 5-point Likert-scale (1 = completely disagree, 5 = completely agree). For the group with visible recommendations, the coaches assessed the ease of identifying participants' needs and coaching tasks immediately after the first and second coaching calls, respectively, whereas the participants provided their assessments after the second coaching call. For the group with hidden recommendations, all the assessments were conducted after the first coaching call.

3) DATA ANALYSIS

For assessing the validity of the recommendations, we considered only those participants for whom the coaches had reviewed the results of the Profiler's needs analysis and recorded the selected coaching tasks. We compared the recommendations to the selected coaching tasks but did not expect exact word-to-word matches, since coaches typically used much shorter names for the tasks than was used in the Intervention library's item descriptions. Therefore, for instance, "zumba two times a week" (coaching task) was matched with "I will start an exercise hobby" (recommended item), or "walking" (coaching task) was matched with "I will take 7000 steps per day" (recommended item). Furthermore, we excluded from the comparison five coaching tasks that were not part of the Intervention library, as our aim was to validate the recommendation algorithm, not the content of the Intervention library. To evaluate the changes made to Profiler's analysis results, we categorized them into three groups to describe the reasoning behind the changes: a) the participant's situation had changed after answering the online questionnaire utilized by the Profiler, b) the Profiler's profiling logic was suboptimal in terms of the input features or their weights (see Appendix 2), or c) the reason was unclear. The categorization was conducted based on the justifications provided by the coaches for the changes, the selected coaching tasks, participants' answers to the online questionnaire, and Firstbeat indicators (when available).

The usefulness of the HRS was evaluated by comparing the group-level medians of the coaches' and participants' self-assessments (coaches' ease of identifying participants' needs and coaching tasks; participants' ease of explaining needs, improved self-awareness of needs, and satisfaction with coaching calls) between the groups with visible and hidden recommendations. In addition to medians, the first (Q1) and fourth (Q4) quartiles of the self-assessments are reported. The Mann-Whitney U test was conducted to determine the statistical significance of between-group differences. The differences were considered statistically significant at an alpha level of 0.05. The Vargha-Delaney $\hat{A}$ measure of stochastic superiority [69] is reported as an indicator of the between-group effect size coupled with the 95% confidence interval (CI). The effect size computations were performed with the rcompanion package of the free R statistical software (version 4.0.5). The 95% CIs were computed using the bootstrap procedure (see e.g., [70]).

V. EVALUATION RESULTS

A. VALIDITY

Complete and valid data were available for 41 (out of 50) participants for assessing the validity of the recommendations. For 73% (30/41) of the participants, at least one of the recommended activities was included into the coaching plan. The proportion of participants with a recommended activity selected as a coaching task was higher for the group with visible recommendations (85% or 17/20) than for the group with hidden recommendations (62% or 13/21). However, also the number of coaching tasks was higher for the group with visible recommendations (median 3.0 tasks [Q1 2.8; Q4 3.0] vs. median 1.0 task [Q1 1.0; Q4 2.0]). Of the participants for whom two or more coaching tasks were defined, 53% (10/19) of the group with visible recommendations and 43% (3/7) of the group with hidden recommendations had at least two of the tasks selected from the recommended activities. Furthermore, the recommendations appeared highly suitable for the participants of the group with visible recommendations, as 90% (18/20) of them suggested to their coach to include at least one of the recommended activities in their coaching plans, and 50% (10/20) proposed to include three recommended items (the maximum number of items).

Regarding Profiler's behavior change needs analysis, the coaches reported modification needs for 21 (out of 50) participants in terms of 1 to 3 (out of 14) behavioral domains per participant. For 16 participants, modifications were required because of a changed life situation. For seven participants, some of the modification needs were due to faults in the profiling logic, and for five participants the reasons for the modifications were unclear. Most of the modifications due to participants' changed situations were related to increased readiness to change behavior (reported for 14 participants), and some were related to behavior change needs (reported for 7 participants). According to the coaches' notes, the coaching call had had a positive influence on the motivation to change behavior for many participants, which explains the modification needs regarding the readiness levels. In addition, a delay of one to two months took place between the participants' profiling questionnaire answers and in scheduling the first coaching call, which may have made part of the Profiler's analysis results outdated.

The coaches' notes revealed also some improvement needs for the profiling logic regarding physical activity (PA) and sleep: It appeared that the profiling logic gave too much weight on the short-term (3-day) PA levels, assessed via Firstbeat indicators, compared to the self-reported levels (evaluated for the past month). This resulted in incorrect inference about the PA needs of the participants who were usually inactive but temporarily increased their activity levels during the Firstbeat measurement period. To infer the behavior change needs regarding sleep, separating sleep quality and sufficiency from each other was not sensible, as poor sleep quality had a direct impact on sleep sufficiency.

B. USEFULNESS

For the coaches, it was considerably easier ($\hat{A} = 0.71$, 95% CI 0.59-0.84) to identify appropriate coaching tasks for the group with visible recommendations than for the group with hidden recommendations. However, the coaches' perceived effort for identifying participants' behavior change needs was similar for the two groups. According to participants' self-assessments, the group with visible recommendations was considerably more satisfied with coaches' abilities to understand their well-being related needs ($\hat{A} = 0.71$, 95% CI 0.57-0.83) and moderately more satisfied with the coaching call(s) ($\hat{A} = 0.67$, 95% CI 0.53-0.80) and coaches' abilities to make them realize new, personally relevant behavior change needs ($\hat{A} = 0.69$, 95% CI 0.55-0.80) than the group with hidden recommendations. Hence, With-Me HRS appeared to be useful in improving coaching quality from the participants' perspective. The details of the between-group differences regarding the usefulness of the HRS are provided in Table 3.

VI. DISCUSSION

A. PRINCIPAL FINDINGS

We proposed a comprehensive, theory-based framework, the virtual individual (VI) model, to support the extensive personalization of digital health behavior change interventions (DHBCIs) for promoting well-being. In addition, we implemented a prototype health recommender system, With-Me HRS, which recommended a personalized set of behavior change activities. The user model underlying the HRS implemented a subset of the VI model feature types, of which health behaviors, well-being state, health measurements, behavior change needs, and readiness to change were utilized for personalization. The HRS supported a multi-domain intervention by considering various behavioral domains related to well-being and healthy lifestyle, namely sleep, physical activity, eating habits, alcohol consumption, smoking, workload management, recovery from stress, anxiety, self-esteem, personal values, and quality of relationships.

According to the conducted evaluation study in the health-coaching context, the recommendations were suitable for the participants, and at least one of the recommended activities was included into the personal coaching plans (from a maximum of three activities) for more than 70% of the participants. The results regarding the usefulness of With-Me HRS in supporting coaches' work were mixed, as the HRS reduced coaches' perceived effort in identifying appropriate coaching tasks for participants, but not in identifying their behavior change needs. From the participants' perspective, the usefulness of the HRS was clear, as the participants for whom coaches could utilize the HRS in decision-making

TABLE 3. Between-group differences regarding the usefulness of With-Me HRS.

Outcome	Visible recommendations Mdn (Q1;Q4)	Hidden recommendations Mdn (Q1;Q4)	*U*	$\hat{A}^{a}$ (95% CI)	*P*
Coach					
Ease of identifying participant's needs	4.0 (3.0; 4.0)	4.0 (3.50; 4.0)	340.0	0.57 (0.41-0.72)	.390
Ease of identifying coaching tasks	4.0^{b} (4.0; 5.0)	4.0 (3.0; 4.0)	182.0	0.71 (0.59-0.84)	.005**
Participant					
Ease of explaining needs	5.0 (4.25; 5.0)	4.0 (4.0; 5.0)	174.0	0.71 (0.57-0.83)	.004**
Improved self-awareness of needs	4.0 (4.0; 4.0)	4.0 (3.0; 4.0)	185.0	0.69 (0.55-0.80)	.01*
Satisfaction with coaching call(s)	5.0 (4.0; 5.0)	4.0 (3.5; 5.0)	195.50	0.67 (0.53-0.80)	.023*

The items were assessed by either coaches or participants and measured using a 5-point Likert-scale (1 = completely disagree, 5 = completely agree). Unless otherwise stated, N=24 and N=25 for the groups with visible and hidden recommendations, respectively.
[a]Vargha-Delaney $\hat{A}$ measure of stochastic superiority for effect size estimation. Limits for interpretation: 0.56 (small), 0.64 (medium), 0.71 (large) [69]
[b]N=25
*$p < .05$, **$p < .01$

were more satisfied with the quality of coaching than the participants with hidden recommendations.

B. RELEVANCY OF USER MODEL FEATURES IN PERSONALIZATION

In the past HRS research, the attempts to improve the performance of HRSs have mostly been focused on finding accurate recommendation techniques (e.g., [27], [30], [34], [44]), while user models have attracted less research interest, even though wisely chosen user features can increase the suitability of recommendations significantly, which is important for improved user engagement and a positive health impact. The VI model provides a common user model framework that serves different personalization goals by considering not only the health and behavior change needs of individuals, which are the most widely used features for personalization and, beyond doubt, the most important ones in terms of the expected health impact, but also various other factors that influence user engagement and intervention adherence. These factors enable to a) identify the right kind of support to be provided while considering users' preferences regarding alternative behavior change activities; b) identify the opportune moments for delivering support; c) associate the recommended behavior change activities with personally meaningful goals; and d) use persuasive message framing and the tone of communication that is perceived as pleasant and credible by the user.

Some of the proposed VI features that influence user engagement and adherence have been utilized in earlier HRSs. Of the context-related features, location and the time of day are the most widely used for determining the appropriate content to recommend and the opportune moments for recommendations, although other interesting features have also been used (e.g., current activity, affective state, weather, calendar availability) [24], [26], [27], [29], [33], [47]. The time lag between receiving and reading messages has been used to infer the best time to disrupt a user [39]. In addition, user preferences regarding physical activity (PA) modes and food items have been used to personalize recommendations [25], [26], [27], [44], [45]. However, we could not find examples that attempted to make behavior change objectives personally meaningful or which personalized the tone of messages. Value-based personal aspirations and personality traits were included as features to the VI model to serve these purposes. Values are personal beliefs of desired end states that guide behavior and choices [71]. Therefore, aligning health behavior change objectives with one's values may be motivating. Furthermore, framing messages based on personality or values has been shown to increase the persuasiveness of messages [59], [72], [73].

The VI model features describing personal resources and the determinants of behavior change are highly relevant for determining the type of support to be provided, as these summarize the key constructs found in different behavioral theories [10], [11], [14]. These features enable the adaptation of recommendations to individuals' readiness and capabilities to change behavior. When a person is not motivated to change behavior despite a clear health need, the features can be used to select intervention items that raise awareness of one's behavior change needs and strengthen one's capabilities. In a few HRSs, readiness to change has been used for personalization [38], [39]. In addition, knowledge of the factors influencing readiness to change (self-efficacy, attitudes/outcome expectations, social influence) and the possible barriers preventing good intentions from translating into actions (e.g., environmental constraints, lack of skills, old habits to be disrupted) are required to increase motivation and provide appropriate support [14], [40], [51]. The Quit and Return mobile application for smoking cessation [41] is a rare example of a HRS where various behavioral determinants are considered for personalization.

The progress evaluation features of the VI model facilitate the monitoring of individuals' adherence to recommendations and the effectiveness of the intervention. These features are useful for providing feedback to users, and more importantly, for the dynamic adaptation of intervention content. For instance, HRSs that focus on PA have adapted recommendations based on monitoring the effectiveness of past recommendations. In [35], users' PA levels were monitored after sending motivational messages, and effective message types were learned for each individual. In [43], the effectiveness of activities was determined by monitoring changes in health outcomes (blood pressure, body mass index, and waist circumference) across users. Then, those activities were recommended which appeared effective for the users sharing a similar demographic and health profile with the target individual.

We propose to include in the VI model features related to genetic predisposition as an experimental component. The idea of utilizing genetics for the personalization of health interventions is intriguing, as it might reveal which behavior change activities (e.g., dietary habits, exercise modes, sleep patterns) are most effective in reducing personal health risks of an individual. Some computer-tailored interventions already utilize genetic information, for instance, for personalizing exercise regimes or nutritional intake [74], [75]. However, genetic testing needs to become mainstream before the value of genetics in personalization can be appropriately studied.

C. STRENGTHS AND LIMITATIONS OF WITH-ME HRS

Most of the earlier HRSs have focused on only a few health behaviors (PA or diet), which is insufficient for the prevention of lifestyle-related diseases. With-Me HRS took a comprehensive approach by acknowledging various behavioral domains that contribute to well-being and healthy lifestyle. However, modifying all the possible unhealthy habits at once is unrealistic [66], and the unhealthiness of behavior varies between different domains across individuals. Hence, before recommending actual behavior change activities, a high-level assessment of behavior change needs across different domains should be conducted, which ideally should result in a few selected behavior change objectives. With-Me HRS provides an example developed towards this direction. However, the HRS did not recommend activities in a similar detail as some previous examples have recommended, such as specific PA intensities or durations or certain food items and proportions to be included in meals [18], [25], [27]. Detailed recommendations were not crucial, since the usage context of the HRS involved human experts who could provide personal guidance during the coaching calls for performing the recommended activities. For a fully stand-alone HRS, recommending detailed activities would become more important.

In the HRS research, employed recommendation methods are often described, whereas details of the underlying user models and the available items to be recommended are rarely provided, although the user model, recommendation method, and intervention library together determine the accuracy and suitability of the recommendations. Therefore, to accumulate knowledge of the most effective personalization techniques, details regarding all these three aspects should be reported. In the present work, we provide information on the user model features used for personalization, how the features are measured, and the algorithms used to process raw measurements into features (Appendix 2), in addition to describing the recommendation method and intervention library items. Other examples of detailed user model descriptions are provided in [25] and [43]. Regarding the intervention library, it is important to ensure that the available items are varied enough for catering to the needs of different individuals. In our case, a professional health coach was involved in designing the content of the intervention library, who ensured that the activities typically used in human-delivered health-coaching for the behavioral domains supported by With-Me HRS were included.

In the With-Me user model, a harmonized value scale was used to describe the values of well-being and health-related features. Using harmonized values, when possible, can simplify aggregated feature computations (e.g., in terms of behavior change needs) and add flexibility to the resulting personal profile by allowing data source independent analysis. For instance, when several alternative devices or questionnaires can be used to measure the same concept of interest, such as PA level or sleep duration, harmonized values allow switching the data source without having to modify the computation logic of higher-level features. We chose to use a 5-point scale for the harmonized values, since the behavior change needs, which was the most relevant aggregated feature type in With-Me HRS, were described with such a scale. The use of a more fine-grained scale was not considered to provide additional information value for recommending activities. However, for some other use cases, using a 5-point scale for harmonized values may compress the original data too much, and using a 7- or 10-point scale may be more appropriate.

With-Me HRS was designed to be used only at the beginning of the health-coaching program, which limits its usefulness as a stand-alone HRS for the long-term support of health behavior change. With-Me HRS was incapable of collecting user data actively on a regular basis and updating the recommendations accordingly. Although data updates were supported and they resulted in a new set of recommendations, the user model was unable to identify trends in the data, and past values were not considered in the recommendations. For stand-alone HRSs, the capability to dynamically adapt to individuals' evolving situations while also monitoring the effectiveness of the recommendations is imperative.

The With-Me user model implemented the proposed VI model only to a limited extent. Only the features that we considered the most important were implemented, namely, behavior change needs derived from the features describing well-being and health behaviors, and the readiness to change different behaviors. Particularly, features related to self-efficacy and skills were not implemented, although they are among the important predictors of behavior change [40], and the intervention library items were not graded by effort level. In the usage context of With-Me HRS, this limitation did not pose problems, as coaches were available to guide the participants in performing the activities. However, for a stand-alone HRS designed for long-term behavior change support, recommending activities with gradually increasing effort levels that match individuals' self-efficacy and skills could be useful.

D. INTERPRETATION OF EVALUATION RESULTS

Rather than seeking for the most accurate recommendation method, which is common in the HRS research, the purpose of the present study was to examine how well a standard recommendation method, which utilizes a minimum set of user features for personalization that we consider important (behavior change needs and readiness to change), performs in the novel context of a multi-domain, real-life intervention. Behavior change activities recommended by With-Me HRS were included into the health-coaching plans of more than 70% of the participants, which we consider as a reasonably good result achieved with the limited user model, especially when only half of the participants (and their coaches) were exposed to the recommendations. This result provides a reference baseline for testing the influence of additional user model features on the validity of recommendations.

We wish to raise awareness of the importance of conducting empirical studies that focus on finding the most effective user features for personalization. It may be wise to conduct these studies with standard recommendation methods for better comparison. We chose to utilize knowledge-based filtering, since it allows to personalize recommendations based on the specific characteristics of an individual [5], [18], which is especially important in health and well-being applications [5], [36]. Indeed, knowledge-based filtering has been widely used in HRSs before [18], and it can be considered as one of the standard approaches to which more complex, hybrid recommendation methods are compared.

We cannot compare our evaluation results directly to previous work as the methods and study settings used to validate HRSs are versatile. In Table 4, the validation approaches of some recent HRSs are summarized. According to the review by De Croon et al. [18], the majority of validation studies have been conducted offline without the involvement of real users (e.g., via simulated or existing datasets), or via single-session user studies and surveys. Studies involving users who use HRSs ''in the wild'' are less common, which is considered a major challenge in the field [18]. In offline studies, standard error metrics (precision, accuracy, recall, F1-score, etc.) are commonly used to measure the performance of recommendation algorithms [18]. In real-life studies, these metrics are inconvenient because requiring users to rate all the available items for identifying the true negatives and positives would significantly increase user burden and hamper the real-life setting. Instead, user satisfaction with the recommended items (e.g., [33], [38], [44]), self-reported or observed compliance to recommendations (e.g., [24], [30], [35]), and changes in health outcomes (e.g., [24], [38], [46]) have been reported for assessing the suitability of recommendations. In addition, user experience, perceived usefulness, and usability of HRSs are typically assessed, but with varying self-report scales or interview questions [18].

In the present study, we assessed the suitability of recommendations by monitoring the number of recommended behavior change activities that were selected to the participants' coaching plans. While this is a stronger indicator for suitability rather than merely measuring user satisfaction with recommendations, the most reliable approach for validation, however, would be to assess the impact of recommendations on participants' behavior, i.e., evaluate participants' adherence to the selected activities. As continuous monitoring of behavior was not implemented in With-Me HRS, we were not able to evaluate participants' actual adherence to the recommendations. Nevertheless, some indications of adherence may be inferred from the results of the related pilot RCT [62], which describes the outcomes of the health-coaching intervention where With-Me HRS was utilized as a technological component. According to the results, participants' self-reported diligence in performing the selected coaching tasks at the beginning of the intervention was slightly better in the group receiving (visible) recommendations compared to the participants who were not provided the opportunity to examine the recommendations (group with hidden recommendations).

Even though the coaches considered With-Me HRS useful for identifying suitable coaching tasks for the participants, it did not seem helpful for identifying behavior change needs. Perhaps, participants' behavior change needs were straightforward to identify during the coaching calls per se, as the individuals participating voluntarily in the health-coaching program likely had a good idea of the areas they wished to improve already beforehand. Hence, it may seem from the coach's perspective that additional support for identifying participants' behavior change needs was not needed. However, the participants for whom coaches utilized With-Me HRS for decision-making evaluated coaches' abilities to understand they behavior change needs and make them realize new, important areas for change higher than the group with hidden recommendations. Thus, it seems that the Profiler's user-interface encouraged coaches to analyze participants' behavior change needs systematically across different behavioral domains when making decisions on coaching objectives, which resulted in improved participant satisfaction. The coaches may have even tried to convince participants about their most important behavior change needs indicated by the Profiler. However, we do not know how much of the improved participant satisfaction was mediated by the heart rate variability based Firstbeat lifestyle assessment, which was provided only for the group with visible recommendations.

TABLE 4. Recommendation and evaluation approaches in recent HRS studies.

Authors	Recommendation items	Algorithm	Comparative algorithms	Study setting	Evaluation metrics
Alcaraz-Herrera *et al.* (2022) [44]	Meals, physical activities	Hybrid: collaborative filtering inspired genetic algorithm	Simulations with and without collaborative filtering and with varying genetic operators	Offline simulations & user study (*N*=205)	Aptitude, user satisfaction
Torkamaan *et al*. (2022) [30]	Stress management activities	Hybrid: content + knowledge (case) based filtering	Content-based filtering	Real-life (*N*=49)	User-reported compliance to recommended items, user experience
Hors-Fraile *et al*. (2022) [33]	Messages for smoking cessation	Hybrid: knowledge (case) based filtering + demographic-based collaborative filtering	Knowledge (case) based filtering	Real-life (*N*=371)	User satisfaction, user engagement, user-reported smoking abstinence
Ribeiro *et al*. (2022) [45]	Weekly meal plans (recipes)	Knowledge (constraint) based filtering	None	Offline (simulated data)	User satisfaction, recommendations meeting nutritional goals, variability in recommendations
Starke *et al.* (2021) [34]	Recipes	Hybrid: content + collaborative filtering	Content-based and collaborative filtering, random item ranking (baseline)	Offline (existing dataset)	Precision, recall, mean absolute error
Ferretto *et al.* (2020) [43]	Physical activities	Hybrid: demographic-based collaborative filtering	None	User study with simulated data	User satisfaction
Dharia *et al*. (2018) [27]	Physical activity schedules (mode, duration, location, timing), fitness buddies	Hybrid: collaborative filtering + knowledge (constraint) based filtering	Simulations with varied similarity metrics applied in collaborative filtering	Offline (existing dataset), real-life (*N*=24)	Offline: root mean squared error, mean absolute error; Real-life: user experience

Finally, when interpreting the evaluation results, it is important to bear in mind that nearly all the study participants were women, and the results may not hold for men.

E. FUTURE WORK

We wish to call attention towards systematic, experimental research that seeks to identify the most relevant user model features for personalizing DHBCIs in terms of improving user engagement and delivering health impact. In addition, best practices for developing multi-domain interventions are needed. The introduced conceptual virtual individual model provides ideas of features to be experimented with, and the evaluation of the multi-domain With-Me HRS provides reference results for testing the influence of user features, beyond behavior change needs and readiness to change, on the validity of recommendations. The implemented With-Me user model should be expanded at least with features describing self-efficacy, skills, and the momentary context. Features related to self-efficacy and skills enable to recommend behavior change activities that are helpful but not too challenging, and knowledge about momentary context is required for providing support at opportune moments.

With-Me HRS was based on knowledge-based filtering, which is a straightforward approach for testing the impact of user features on the validity of recommendations. However, once the most impactful user features are identified, a hybrid method combining knowledge-based filtering with demographic-based collaborative filtering would be more appropriate. Such a hybrid method has also been suggested in [5]. Knowledge-based filtering could be used as a first step to identify the subset of recommendable items that match the most critical user features (e.g., behavior change needs, motivation and capabilities to change behavior, personal restrictions), whereas demographic-based collaborative filtering could be used as the second step to recommend items from the identified subset that were preferred by or effective for other users sharing a similar life situation with the target user. Knowledge-based filtering ensures that inappropriate or irrelevant items are not recommended, and demographic-based collaborative filtering reduces the risk of excluding highly suitable, novel items from the recommendations that may be missed by knowledge-based filtering, as it relies solely on expert knowledge (i.e., on the defined user features and the corresponding item labels). Therefore, this type of a hybrid method could facilitate extensive personalization even with a subset of the features proposed by the VI model framework.

With-Me HRS supported a multi-domain intervention, but the recommended behavior change activities were not very specific. In the future, it may be wise to implement multi-domain HRSs with two hierarchical layers to be able to provide domain-specific detailed recommendations efficiently. The top layer would be in charge of recommending behavior change objectives. The second layer could be built from domain-specific HRS submodules, which comprise specific user models and intervention libraries relevant to the domain in question. This approach would enable the modular development and usage of multi-domain HRSs. Submodules could be activated as need arises according to the identified behavior change objectives.

Finally, With-Me HRS was not designed as a standalone system, and it did not support dynamic recommendations that adapt to individuals' evolving situations and to the effectiveness of past recommendations. For standalone HRSs, it is imperative to monitor individuals' adherence to recommendations along with changes in well-being, behavior, and behavioral determinants. Part of the monitoring could be conducted via questionnaires, especially regarding psychological factors but, when possible, unobtrusive monitoring should be used (e.g., via wearable devices, smartphones, environmental sensors) to reduce user burden and subjective bias in self-reporting.

APPENDIX

Appendix 1: Elements of the virtual individual model

Detailed description of the proposed VI model elements, including the proposed feature types with concrete feature examples and the interrelations between the features.

Appendix 2: Data layers and profiling logic

Profiler's data layers and the data-processing algorithms executed by the Profiler are described in detail, including information on a) the user model features used for personalization, b) how the features are measured, and c) the algorithms used to process raw measurements into features.

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APPENDIX 1: ELEMENTS OF THE VIRTUAL INDIVIDUAL MODEL

We describe the elements of the proposed virtual individual (VI) model and explain their purpose of use in digital health behavior change interventions (DHBCIs). First, each element is described at a general level. Then, for the core VI model elements (Health & well-being, Resources, Motives & preferences, Behavior change needs and determinants), we describe the related feature types and provide examples of concrete features in Tables I-IV. The relevancy of the presented features varies according to the behavioral domains of interest. In the present work, the examples originated from the context of an occupational stress management intervention, targeting a multitude of well-being areas and health behaviors. Some of the features provided here as examples were implemented into the With-Me health recommender system (HRS). These are highlighted with ***bolded italics*** in the tables below.

I. HEALTH & WELL-BEING

The Health & well-being element reveals the person's risks to develop lifestyle-related diseases or mental health issues, and the behaviors causing or aggravating these problems. It includes features describing the person's well-being (physical, mental, social), health risks, and health behaviors. This knowledge can help to identify one's behavior change needs and their relative importance for reducing the risks of lifestyle-related diseases and improving well-being. When possible, we propose to include objective measurements of well-being and behavior (e.g., sleep quality, stress, physical activity), in addition to subjective assessments. Including objective measurements from wearables may help to get a more complete picture of the person's situation, as wearables enable continuous monitoring and they are not influenced by the self-reporting bias [1]. Furthermore, vital signs and physiological measurements of health, such as blood pressure and heart rate variability, may reveal the need for a lifestyle change, of which the person would not be otherwise aware.

As the proposed VI model is designed for DHBCIs focused on disease prevention in a generally healthy population, it does not need to include details of possible medical conditions. However, knowledge of health conditions that pose restrictions on certain health behaviors, such as exercise intensity or dietary habits, is vital. In addition, if physiological signals are used as health measurements, knowledge of medications that may influence the signals may be required for correct interpretation. Finally, including features related to genetic predisposition might be interesting for the future, if genetic testing becomes mainstream. Genetic profiles could be used, for instance, for personalizing exercise regimes and nutrition intake [2], [3].

TABLE I
FEATURE TYPES OF THE HEALTH & WELL-BEING ELEMENT

Feature type	Feature examples
Health measurements: objective measurements that are relevant for the assessment of risks for developing lifestyle-related diseases or mental health problems. These can include physical measurements, vital signs and physiological measurements. The physiological measurements can be based on heart rate variability, electrodermal activity, skin temperature, brain waves etc.	Physical health index* Physical measurements - BMI (height, weight) - waist-hip ratio (waist and hip circumferences) Vital signs - cholesterol - blood pressure - fasting glucose - cortisol ***Physiological measurements*** - sleep latency - sleep efficiency - ***recovery during sleep*** - ***recovery during 24h*** - resting heart rate - momentary stress - fitness level
Health behaviors: assessment of habits relevant for preventing lifestyle-related diseases or mental health problems. We propose to prefer objective monitoring of behavior, such as the use of wearable accelerometers, over self-reports to reduce self-reporting burden and bias. However, self-reports should be collected, if the validity of the monitoring outcomes is uncertain (e.g., regarding automatically inferred sleep times).	Healthiness of lifestyle index* ***Physical activity*** - daily activity (e.g., via steps) - ***exercise habits*** (frequency, intensity, duration) ***Sleep habits*** - ***sufficiency of sleep duration*** - circadian rhythm - sleep hygiene (activities before sleep, sleeping conditions) - day-time naps ***Eating habits*** - ***diet quality*** - ***eating rhythm*** - ***emotional eating*** - binge eating ***Work-leisure balance*** - ***appropriateness of weekly working hours*** - ***sufficiency of quality leisure*** (pleasant social, physically active or mentally engaging activities) Amount of leisure time ***Alcohol consumption*** (frequency and amount) - risk for a drinking problem - binge drinking ***Smoking*** - ***usage of tobacco products*** - ***strength of nicotine addiction*** Other addictions (gambling, social media)

Table I continued…

Feature type	Feature examples
Well-being state: subjective health and well-being assessments relevant for mental health risk evaluation. Features combining the results of objective health measurements and subjective assessments are also located here; for instance, *stress level* and *sleep quality* could be such features.	Well-being index* Health - perceived health status - perceived fitness level ***Stress and recovery*** - ***stress level*** - ***perceived stress*** - ***perceived ability to relax*** - ***sexual desire*** - stressors ***Sleep*** - ***sleep quality*** - ***perceived sleep problems*** - ***perceived sleep sufficiency*** ***Psychological well-being*** - mood (positive - negative) - ***vigor*** - ***irritability*** - anxiousness - depressive mood - ***cognitive fusion*** - ***self-esteem*** - ***life satisfaction*** - ***sufficiency of time for important life areas*** - neuroticism - perfectionism - awareness of personal value priorities ***Work well-being*** - ***concentration ability at work*** - ***perceived time pressure*** (lack of time to finish work tasks properly, feeling of hurry) - ***perceived workload*** (e.g., needing to work over-time involuntarily) - work ability ***Social well-being*** - loneliness - having someone to confide in - ***quality of romantic relationship*** (e.g., regarding trust, sharing of responsibilities, enjoying time together, sharing similar values) - quality of family, friend, and work relations

Table I continued…

Feature type	Feature examples
Health conditions: conditions which pose restrictions on suitable lifestyle interventions e.g., regarding exercise or dietary changes.	Allergies (e.g., pollen, food) Physical disabilities (e.g., movement restrictions)
Medications: medications influencing physiological signals (e.g., heart rate) may need to be taken into account when interpreting the signals. This section is relevant, only, if health measurements include physiological signals.	
Genetic predisposition: indications of lifestyle-related disease susceptibility and effective lifestyle interventions. This is an exploratory feature type, which can be used to study the value of genetics in intervention personalization.	Family history of lifestyle-related diseases Genetic test results

*High-level features summarizing the person's overall situation over various individual well-being or behavioral features. We propose these features, as they could be useful for providing feedback to the person or other relevant stakeholders (e.g., health coaches), in addition to intervention personalization.

II. RESOURCES

The Resources element describes the general barriers and abilities, which hinder behavior change or support it. Resources can be related to the availability of time and money, often determined based on one's life situation; personal skills or abilities, such as psychological flexibility towards changes or time-management skills; nearby facilities and services determined by one's living and work environment; social ties; and the personal attitude towards lifestyle modifications in general.

Good intentions to make lifestyle changes do not translate into actions, if the person does not have the skills and abilities to engage with the new behavior and overcome the possible barriers hindering the change [4], [5]. Knowledge about one's resources can help to identify whether lack of skills or means are preventing the person from engaging in a target behavior, indicating the need to provide support for developing the required skills. Another important purpose of the Resources element is to facilitate the personalization of the recommended behavior change activities as such that they fit well to the person's everyday life and utilize the facilities and abilities readily available. The recommended activities should be easy enough to prevent the perceived cost of performing the activities from outweighing the perceived benefits, thus leading to a positive attitude towards the behavior [4]. For instance, the intervention could recommend muscle-training exercises at home, if the gym is far away and time is restricted, or instruct to buy frozen vegetables instead of fresh ones, depending on the availability of groceries at the nearby store. Furthermore, the knowledge of everyday routines can be used to identify the opportune moments to send prompts or other messages to the person.

TABLE II

FEATURE TYPES OF THE RESOURCES ELEMENT

Feature type	Feature examples
Life situation: features describing the current life situation of the person to which the behavior change plan should be adjusted. Knowledge of everyday routines can be used to identify the opportune moments for prompting the person about behavior change activities.	***Demographics*** - year of birth - ***gender*** Socio-economic status and life stage - years of education - household income level - ***occupation*** (student/in work life/retired/between jobs/home with kids etc.) - ***occupational position*** (knowledge/manual worker, professional, director etc.) - ***civil status*** (single, in a relationship etc.) Everyday routines - ***work schedule*** (part-time/full-time, day job, shift-work etc.) - childcare/school schedule - partner's work schedule - hobby schedule for the family
Skills & abilities: personal characteristics that facilitate behavior change. If the person is lacking some of the skills relevant for the behavior change objective, the intervention should first focus on strengthening the skills. Simultaneously, the intensity of behavior change guidance and the complexity of the recommended activities should be adjusted based on the current skill-level of the person.	Psychological abilities/attitudes - self-regulation - optimism - self-confidence - flexibility - determination - self-direction Coping skills - time management - stress management Technology usage skills relevant for the intervention - usage experience of different types of technology - apps/technology in use Practical skills - cooking - exercise skills (e.g., swimming, bicycling) - etc.
Environment: facilities, equipment and services readily available for engaging in healthy activities, which should be exploited in the recommended behavior change activities.	Physical activity options nearby - access to gym, exercise groups, nature, sport facilities - exercise equipment at home Readily available healthy food choices - lunch restaurants at work, grocery shops etc.

Table II continued…

Feature type	Feature examples
Social ties: people with whom one usually spends time. As positive social influence can increase one's motivation to change behavior [4], [6], involving one's family and friends in the change process may be beneficial.	***Household members*** Extended family (parents, siblings, grandparents/grandchildren) Friends (from work/hobbies/other connections)
Readiness for lifestyle modifications: the personal motivation towards making lifestyle changes in general. If the person is unwilling to make any kind of changes, it may be better to postpone the offering of a DHBCI until the person is more receptive to guidance.	***Readiness to make lifestyle changes*** Satisfaction with current health-related habits

III. MOTIVES & PREFERENCES

The purpose of the Motives & preferences element is to facilitate the personalization of the tone and style of intervention materials as well as the mode of communication based on one's interests, preferences, or personality. The appropriate tone (e.g., humorous, dramatic, serious), framing approach (e.g., gain-, loss-, or value-based framing), and the persuasion style (e.g., appealing to personal commitment, consensus with other people, or authority) for the intervention materials can be inferred based on personality and personal values [7]–[10]. Schwartz value theory is a good basis for the assessment of personal values, since the related value types have been shown to hold universally in different cultures and to influence behavior [11], [12]. Knowledge on personal values can be also used to motivate the person to strive for a behavior change objective by associating the objective with one's aspirations. Personal aspirations could act as a source of inspiration. For instance, for a family-oriented grandparent, introducing a lifestyle change as a means to gain more energy to spend time with grandchildren may be motivating, whereas for a person interested in their appearances, associating the change with a fresh and rested look may do the trick. Finally, personal preferences, for instance regarding exercise types or the taste for food, should be taken into account when recommending behavior change activities.

TABLE III
FEATURE TYPES OF THE MOTIVES & PREFERENCES ELEMENT

Feature type	Feature examples
Personality and values: features describing what motivates and interests the person, which can be used to tone and frame intervention materials in order to increase their appeal. The knowledge of personal values could be used also to motivate the person to commit to a behavior change objective.	Personality traits - Big Five traits [13]: extraversion, agreeableness, conscientiousness, emotional stability, openness to experience - sensation seeking - judging / perceiving - competitiveness - need for cognition / emotion [14] - monitoring / blunting [14] Schwartz values [15] - Security, Conformity, Tradition, Benevolence, Universalism, Self-Direction, Stimulation, Hedonism, Achievement, Power
Preferences: personal preferences to be taken into account when suggesting behavior change activities and interacting with the person.	Preferences for health behaviors - most/least favorite exercise types - most/least favorite dishes - morning/night person - etc. Preferences for communication and technology - mode: visual, text, audio, combined - timing for notifications and messages - wearables: willingness to use, preferred type (wristband, ring, belt-clip etc.) - etc.

IV. BEHAVIOR CHANGE NEEDS AND DETERMINANTS

For each behavioral domain supported by the DHBCI, the Behavior change needs and determinants element describes the theory-based factors predicting behavior change [4], [5], [16]. This knowledge can be partly inferred from the Health & well-being, Resources, and Motives & preferences elements. In particular, the Health & well-being features determine the behaviors for which the person has a high need for change.

The behavioral determinant *intention* defines the readiness to change behavior, which can be evaluated, for instance, based on the stage of change construct of the Transtheoretical Model (TTM) of behavior change [17]. Other determinants explain the formation of intention (*self-efficacy*, i.e., believe in one's capability to perform the behavior under different circumstances [4], *social influences*, *awareness* of the need to change behavior, and *attitude* towards the change), or the barriers preventing good intentions from translating into actions (*perceived barriers* or difficulties in *disrupting old habits*) [6]. For evaluating the person's level of awareness, we propose to compare the perceived importance to change behavior to the identified behavior change need. The Resources element may provide important knowledge regarding the barriers preventing behavior change, and the Motives & preferences element may explain attitudes.

The features describing behavioral determinants should be utilized for defining the appropriate behavior change techniques (BCTs) [18]–[20] to apply and the activities to recommend for the person. For instance, false beliefs should be corrected by providing correct information, perceived barriers should be addressed with solutions, and low self-efficacy could be improved by guiding the person towards change via tiny steps.

TABLE IV
FEATURE TYPES OF THE BEHAVIOR CHANGE NEEDS AND DETERMINANTS ELEMENT

Feature type	Feature examples
Behavior change needs: here the behavior domains supported by the DHBCI are specified. The importance of the need to change each behavior, inferred based on the Health & Well-being features (Table I), are described. The behavior change needs determine the behavior change objectives for the person.	***Behavior change needs*** - ***sleep*** - ***physical activity*** - ***eating habits*** - ***smoking*** - ***alcohol consumption*** - ***recovery from stress*** - ***workload management*** - ***quality of romantic relationships*** - ***clarification of personal values*** - ***anxiety*** - ***self-esteem*** - etc.
Determinants of behavior change: theory-based factors influencing behavior, evaluated for the behavior domains supported by the DHBCI. The determinants preventing behavior change should be addressed in the intervention.	***Intention*** (low - high) Self-efficacy (weak - strong) Social influence (unsupportive - supportive) Awareness - knowledge level (low - high) - perceived importance (low - high) Attitudes and outcome expectations (negative - positive) Perceived barriers Habits to be disrupted

V. MOMENTARY CONTEXT

The Momentary context element includes features that are required to determine the opportune moment to prompt the person to interact with the DHBCI. The prompt could be a reminder or an encouragement to engage in a behavior change activity, or a message providing feedback on progress, guidance, or information. At an opportune moment the person is receptive and available (mentally, physically, and socially) for an interruption or in a need of support [6], [21], and thus the probability of getting the person's attention is increased. For instance, when the person is being idle, it may be a good time to suggest activities that involve thinking and planning, or on the contrary, when the person is sick, delivering prompts to act should be ceased. The features describing opportune moments should include knowledge of the person's current state (e.g., time of day, activity, affective state) and environment (e.g., location, social situation). The detection of opportune moments is especially important if the intervention attempts to provide real-time support and guidance. For instance, when one is alone and feeling anxious, a prompt for a breathing exercise could be delivered.

VI. INTERVENTION ITEMS

The Intervention items element keeps track of the behavior change objectives and activities that have been recommended for the person based on the Health & well-being, Resources, Motives & preferences, and Behavior change needs and determinants elements; the items selected as part of the intervention; and the messages (reminders, encouragement, guidance, feedback) presented to the person while considering the Momentary context. Intervention items may also include the personal aspirations (derived from values) associated with the behavior change objectives (see section III), and the implementation plan for the selected behavior change activities. The implementation plan defines the order of executing the activities, the context to perform them (when, where, with whom), and instructions for performing them.

The behavior change objectives can be directly derived from the identified behavior change needs (see section IV). "Increase daily activity", "Get more sleep", and "Improve dietary habits" are examples of such objectives. Behavior change activities are means to achieve the selected objectives, such as "I will increase my daily steps to 5000", "I will go to bed by 11 pm on most days", or "I will enjoy at least two portions of berries each day". For the behavior change needs that do not interest the person in spite of a clear health need, the intervention could include consciousness-raising activities attempting to increase motivation [20]. For instance, "Improve awareness of the importance of sleep" could be an objective selected for a sleep-derived person, and a related subtle activity could be to prompt the person to reflect on their feelings after each night of a good quality sleep. Furthermore, associating personal aspirations, such as "I want to be more productive at work" or "I do not want to lose my temper with my children every day", with the behavior change objectives and activities might be motivating for the person.

We propose that all the intervention items (behavior change objectives, activities, aspirations, and messages) available for recommendation are located in an intervention library, separate from the VI model, to flexibly support different recommendation methods (knowledge, content, collaborative). Only the references to the items (e.g., via identifier codes) shall be maintained within the Intervention items element. To enable the recommendation of items that correspond to the personal profile, the items in the intervention library should be described with features similar to the VI model. For instance, the features for a behavior change activity item may include a) the behavior and behavioral determinants to be targeted by the activity, b) appropriate events for triggering a prompt regarding the activity (e.g., based on the momentary context, changes in behavior or well-being, completion of another activity), c) the typical performance schedule for the activity (one-time vs. repetition), and d) the optimal conditions for recommending the activity (e.g., life situation, preferences, personality). The library should also include information on the hierarchy and relations between the items, for instance, the activities related to specific objectives and the execution order of activities related to the same objective should be defined. For framing and personalizing the tone of messages, the library needs to contain alternative versions of the same message content.

VII. PROGRESS EVALUATION

The Progress evaluation element keeps track of the progress and effectiveness of the selected interventions so that the need to update or modify the intervention items could be recognized. The element maintains usage activity logs relevant for analyzing the person's progress in performing behavior change activities and identifying the engaging intervention components (e.g., the feedback messages liked or videos viewed). In addition, it includes information on the person's experiences regarding the behavior change activities (e.g., perceived importance and difficulty); adherence to the activities monitored based on the usage activity logs, connected wearables or questionnaires; and the effectiveness of the intervention. Intervention effectiveness could be inferred by monitoring changes in the Health & well-being, Resources (skills and abilities), or Behavior change needs and determinants elements.

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APPENDIX 2: DATA LAYERS AND PROFILING LOGIC

In the following, we describe the data layers of With-Me HRS's user model, the implemented user features regarding the Health & well-being and Behavior change needs and determinants VI model elements, and the related data-processing algorithms executed by the Profiler.

Original and integrated data layers

The original data layer included raw data provided directly by the available data sources (individual, coach, or measurement device). For features related to health and well-being, both the original and harmonized values were stored. The Profiler transformed the original values to a unified 5-point scale, which described individuals' situations with ordinal values ranging from 1 (bad situation) to 5 (good situation). Additionally, the Profiler determined a confidence value for each feature. For features based on single-item self-reports, the confidence values were set to 0.8, whereas for validated questionnaire scales, they were set to 0.9. These confidence values were chosen to account for the possible bias in self-reporting [14]. The confidence values for the utilized Firstbeat indicators were computed based on the percentage of missing heart rate values that were provided by the Firstbeat lifestyle assessment[1].

On the integrated data layer, combined features were formed based on the features residing on the original data layer that were related to the same concept. A combined feature represented a higher-level concept (e.g., the sufficiency of sleep, inferred based on the personal need for sleep and the time reserved for sleep) or it integrated values from different data sources (e.g., stress level determined based on subjective and objective measures of stress). For features describing higher-level concepts, the confidence values were taken as the minimum of the confidence values of the original features. For the integrated features, the confidence values were determined based on the agreement between the harmonized values of the original features: the more similar the values (e.g., between a self-report and an objective measurement), the higher the confidence.

Table I describes the health and well-being related features implemented by the user model of With-Me HRS as well as the rules used to harmonize the feature values, compute confidence values for the features, and derive features for the integrated data layer. Most of the described features reside on the original data layer. The features that are part of the integrated data layer are denoted by an asterisk (*).

TABLE I
THE IMPLEMENTED HEALTH & WELL-BEING FEATURES AND THEIR COMPUTATION

Feature type	**Feature**	**Interpretation of harmonized values (v)**	**Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$**
Health measurements	***Physiological measures***		
	Recovery during sleep	1 = poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = good	The feature is based on a 3-day Firstbeat lifestyle assessment [1]. It is determined by $\boldsymbol{X} = [x_1, x_2, x_3]$: proportion of *recovery during sleep* per day, available

[1] https://www.firstbeat.com/en/wellness-services/wellness-professionals/individual-wellbeing/

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
			from the Firstbeat report (amount of recovery during sleep) [2]. If $\text{mean}(\boldsymbol{X}) \leq 24$, then $v = 1$. If $25 \leq \text{mean}(\boldsymbol{X}) \leq 49$, then $v = 2$. If $50 \leq \text{mean}(\boldsymbol{X}) \leq 74$, then $v = 3$. If $75 \leq \text{mean}(\boldsymbol{X}) \leq 100$, then $v = 5$. If the number of measurement days < 3, then v is considered missing. $\text{Conf}(v)$ is based on the *missing heart rate %* provided in the Firstbeat report for each measurement day. If $\max(\mathit{missing\ HR}\ \%) < 20$, then $\text{conf}(v) = 0.01 \times [100 - \max(\mathit{missing\ HR}\ \%)]$. If $20 \leq \max(\mathit{missing\ HR}\ \%) < 80$, then $\text{conf}(v) = 0.01 \times [80 - \max(\mathit{missing\ HR}\ \%)]$. If $\max(\mathit{missing\ HR}\ \%) \geq 80$, then $\text{conf}(v) = 0$.
	Recovery during 24-hours	1 = poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = good	The feature is based on a 3-day Firstbeat lifestyle assessment. It is determined by $\boldsymbol{X} = [x_1, x_2, x_3]$: proportion of *recovery during 24h* per day, available from the Firstbeat report (amount of recovery) [2]. If $\text{mean}(\boldsymbol{X}) \leq 9$, then $v = 1$. If $10 \leq \text{mean}(\boldsymbol{X}) \leq 19$, then $v = 2$. If $20 \leq \text{mean}(\boldsymbol{X}) \leq 29$, then $v = 3$. If $\text{mean}(\boldsymbol{X}) \leq 30$, then $v = 5$. If the number of measurement days < 3, then v is considered missing. $\text{Conf}(v)$ is based on the *missing heart rate %* provided in the Firstbeat report for each measurement day (see *recovery during sleep*).

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
Perceived well-being	***Sleep***		
	Sleep quality*	1 = very poor 2 = somewhat poor 3 = not poor, not good 4 = somewhat good 5 = very good	Determined by X: *recovery during sleep* and Y: *perceived sleep problems*. Y is a compulsory feature. X is considered missing, if $\text{conf}(x) \leq 0.6$. If X is missing, then $v = y$; otherwise $v = \min(x, y)$. If both x and y are available, $\text{conf}(v) = 1 - \lvert x' - y' \rvert$, where x' and y' are min-max transformations of x and y to the scale [0, 1], respectively, i.e., the confidence increases as the similarity between x and y increases. If x is missing, $\text{conf}(v) = \text{conf}(y)$.
	Perceived sleep problems	1 = very bad problems 2 = rather bad problems 3 = moderate problems 4 = hardly any problems 5 = no problems	Self-report, $\text{conf}(v) = 0.8$.
	Perceived sleep sufficiency	1 = very insufficient 2 = somewhat insufficient 3 = not insufficient, not sufficient 4 = somewhat sufficient 5 = very sufficient	Self-report, $\text{conf}(v) = 0.8$.
	Stress and recovery		
	Stress level*	1 = very high 2 = somewhat high 3 = moderate 4 = somewhat low 5 = very low	Determined by X: *recovery during 24-hours* and Y: *perceived stress*. Y is a compulsory feature. X is considered missing, if $\text{conf}(x) \leq 0.6$. If X is missing, then $v = y$; otherwise $v = \min(x, y)$. The computation of $\text{conf}(v)$ follows the same logic as for *sleep quality*.

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
	Perceived stress	1 = very high 2 = somewhat high 3 = moderate 4 = somewhat low 5 = very low	Self-report, $\mathrm{conf}(v) = 0.8$
	Perceived ability to relax*	1 = very poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = very good	Determined by X: *ability to detach from work* and Y: *sufficiency of quality leisure*. $v = \mathrm{round}(\mathrm{mean}(x, y))$ $\mathrm{conf}(v) = \min(\mathrm{conf}(x), \mathrm{conf}(y))$
	Ability to detach from work	1 = very poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = very good	Self-report, $\mathrm{conf}(v) = 0.8$.
	Sexual desire	1 = poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = good	Self-report, $\mathrm{conf}(v) = 0.8$.
	Work well-being		
	Concentration ability at work*	1 = very poor 2 = somewhat poor 3 = not poor, not good 4 = somewhat good 5 = very good	Determined by X: *ability to maintain focus in challenging work tasks* and Y: Vigor. $v = \mathrm{round}(\mathrm{mean}(x, y))$ $\mathrm{conf}(v) = \min(\mathrm{conf}(x), \mathrm{conf}(y))$
	Ability to maintain focus in challenging work tasks	1 = very poor 2 = somewhat poor 3 = not poor, not good 4 = somewhat good 5 = very good	Self-report, $\mathrm{conf}(v) = 0.8$.
	Perceived time pressure	1 = high 2 = somewhat high 3 = moderate 4 = somewhat low 5 = low	Self-report, $\mathrm{conf}(v) = 0.8$.
	Perceived work load	1 = heavy 2 = somewhat heavy 3 = moderate 4 = somewhat light	Self-report, $\mathrm{conf}(v) = 0.8$.

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
		5 = light	
	Psychological well-being		
	Vigor	1 = very low 2 = somewhat low 3 = moderate 4 = somewhat high 5 = very high	Self-report, $\mathrm{conf}(v) = 0.8$.
	Irritability	1 = very high 2 = somewhat high 3 = moderate 4 = somewhat low 5 = very low	Self-report, $\mathrm{conf}(v) = 0.8$.
	Life satisfaction	1 = very unsatisfied 2 = somewhat unsatisfied 3 = moderately satisfied 4 = somewhat satisfied 5 = very satisfied	Self-report, $\mathrm{conf}(v) = 0.8$.
	Sufficiency of time for important life areas	1 = very insufficient 2 = somewhat insufficient 3 = not insufficient, not sufficient 4 = somewhat sufficient 5 = very sufficient	Self-report, $\mathrm{conf}(v) = 0.8$.
	Cognitive fusion	1 = very strong 2 = somewhat strong 3 = moderate 4 = somewhat weak 5 = very weak	Determined based on the Cognitive Fusion Questionnaire score (CFQ-7) [3], X: *CFQ-7 score*. If $7 \leq x \leq 11$, then $v = 5$. If $13 \leq x \leq 21$, then $v = 4$. If $22 \leq x \leq 28$, then $v = 3$. If $29 \leq x \leq 34$, then $v = 2$. If $35 \leq x \leq 49$, then $v = 1$. $\mathrm{conf}(v) = 0.9$
	Self-esteem	1 = very weak 2 = somewhat weak 3 = moderate 4 = somewhat strong 5 = very strong	Determined based on the Rosenberg Self-Esteem (RSE) scale [4], X: *RSE score*. If $0 \leq x \leq 9$, then $v = 1$. If $10 \leq x \leq 15$, then $v = 2$. If $16 \leq x \leq 19$, then $v = 3$. If $20 \leq x \leq 24$, then $v = 4$.

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
			If $25 \leq x \leq 30$, then $v = 5$. $\mathrm{conf}(v) = 0.9$
	Social well-being		
	Quality of romantic relationship	1 = very poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = very good	Self-report, $\mathrm{conf}(v) = 0.8$ [5].
Health behaviors	Physical activity		
	Exercise habits*	The physical activity categories are determined according to the Finnish physical activity guidelines for aerobic exercise [6]. 1 = inactive (< 10 min of moderate or vigorous intensity activities / week) 2 = slightly active (moderate intensity activities 10 – 59 min or vigorous intensity activities 10 – 29 min / week) 3 = moderately active (moderate intensity activities 60 – 99 min or vigorous intensity activities 30 – 49 min / week) 4 = somewhat active (100 – 149 min of moderate intensity or 50 – 74 min of vigorous intensity exercise per week) 5 = healthily active (≥ 150 min of moderate intensity activity or ≥ 75 min of vigorous intensity activity / week)	Determined by X: *physical activity level* and Y: *perceived physical activity level*. Y is a compulsory feature. X is considered missing, if $\mathrm{conf}(x) \leq 0.6$. If X is missing, then $v = y$; otherwise $v = \mathrm{round}(\mathrm{mean}(x, y))$. The computation of $\mathrm{conf}(v)$ follows the same logic as for *sleep quality*.

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
	Physical activity level	1 = inactive (< 10 min of moderate or vigorous intensity activities / 3 days) 2 = slightly active (moderate intensity activities 10 – 19 min or vigorous intensity activities 10 min / 3-days) 3 = moderately active (moderate intensity activities 20 – 39 min or vigorous intensity activities 11 – 20 min / 3-days) 4 = somewhat active (40 – 59 min of moderate intensity or 21 – 29 min of vigorous intensity exercise in 3 days) 5 = healthily active (≥ 60 min of moderate intensity activity or ≥ 30 min of vigorous intensity activity / 3-days)	The feature is based on a 3-day Firstbeat lifestyle assessment. It is determined by $\boldsymbol{X} = [x_1, x_2, x_3]$: *physical activity points* per day, available from the Firstbeat report (active calories) [2]. If $\mathrm{sum}(\boldsymbol{X}) \leq 29$, then $v = 1$. If $29 < \mathrm{sum}(\boldsymbol{X}) \leq 59$, then $v = 2$. If $59 < \mathrm{mean}(\boldsymbol{X}) \leq 94$, then $v = 3$. If $94 < \mathrm{mean}(\boldsymbol{X}) \leq 129$, then $v = 4$. If $129 < \mathrm{sum}(\boldsymbol{X}) \leq 300$, then $v = 5$. If the number of measurement days < 3, then v is considered missing. $\mathrm{Conf}(v)$ is based on the *missing heart rate %* provided in the Firstbeat report for each measurement day (see *recovery during sleep*).
	Perceived physical activity level	See Exercise habits	Self-report, $\mathrm{conf}(v) = 0.8$.
	Sleep habits		
	Sufficiency of sleep duration*	1 = very insufficient 2 = somewhat insufficient 3 = not insufficient, not sufficient 4 = somewhat sufficient 5 = very sufficient	Determined by X: *personal need of sleep* and Y: *time reserved for sleep*. If $x - y > 2\text{h}$, then $v = 1$. If $1\text{h}30\text{min} < x - y \leq 2\text{h}$, then $v = 2$. If $1\text{h} < x - y \leq 1\text{h}30\text{min}$, then $v = 3$. If $30\text{min} < x - y \leq 1\text{h}$, then $v = 4$. If $x - y \leq 30\text{min}$, then $v = 5$. $\mathrm{conf}(v) = \min(\mathrm{conf}(x), \mathrm{conf}(y))$
	Personal need of sleep	HH:MM	$v = 7\text{h}30\text{min}$ as a default, $\mathrm{conf}(v) = 0.8$.
	Time reserved for sleep	HH:MM	Self-report, $\mathrm{conf}(v) = 0.8$.

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
	Eating habits		
	Diet quality: vegetable and fruit intake	1 = very low (less than weekly) 2 = low (once or twice a week) 3 = moderate (most days a week) 4 = close to sufficient (once a day) 5 = sufficient (5-6 portions a day [7])	Self-report, $\mathrm{conf}(v) = 0.8$.
	Diet quality: excessive intake of unhealthy foods	1 = very frequently (several times a week) 2 = somewhat frequently (once a week) 3 = moderately (few times a month) 4 = somewhat infrequently (once a month) 5 = rarely (less than once a month)	Self-report, $\mathrm{conf}(v) = 0.8$. We refer to unhealthy foods as highly processed foods, which are calorie-dense, but low in nutritional value, such as fast foods, and sugary or salty snacks [8].
	Eating rhythm	1 = very irregular 2 = somewhat irregular 3 = not regular, not irregular 4 = somewhat regular 5 = very regular	Self-report, $\mathrm{conf}(v) = 0.8$.
	Emotional eating	1 = very frequently (daily) 2 = somewhat frequently (most days a week) 3 = moderately (few times a week) 4 = somewhat infrequently (once a week) 5 = rarely	Self-report, $\mathrm{conf}(v) = 0.8$.
	Work-leisure balance		
	Appropriateness of weekly working hours*	1 = inappropriate 2 = somewhat inappropriate 3 = moderate 4 = somewhat appropriate 5 = appropriate	Determined by X: *weekly working hours* and Y: *flexibility in work schedule*. If $x = 5$, then $v = 5$. If $x \in \{3,4\}$ AND $y \in \{4,5\}$, then $v = 5$. If $x \in \{3,4\}$ AND $y = 3$, then $v = 4$. If $x \in \{3,4\}$ AND $y \in \{1,2\}$, then $v = 3$.

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
			If $x = 2$ AND y ∈ {4,5}, then $v = 3$. If $x = 2$ AND y = 3, then $v = 2$. If $x = 2$ AND y ∈ {1,2}, then $v = 1$. If $x = 1$, then $v = 1$. $\mathrm{conf}(v) = \min(\mathrm{conf}(x), \mathrm{conf}(y))$
	Weekly working hours	1 = very high 2 = high (> 48h) 3 = quite high 4 = close to normal 5 = normal (≤ 40h)	Self-report, $\mathrm{conf}(v) = 0.8$. Weekly work time > 40h is associated with increased prevalence of fatigue during work. Weekly work time > 48h is associated with increased prevalence of fatigue also on leisure days. [9]
	Flexibility in work schedule	1 = very poor 2 = somewhat poor 3 = moderate 4 = somewhat good 5 = very good	Self-report, $\mathrm{conf}(v) = 0.8$. The possibility to influence one's work schedule reduces the number of short-term sick leaves and improves work-leisure balance [9].
	Sufficiency of quality leisure	1 = very insufficient 2 = somewhat insufficient 3 = not insufficient, not sufficient 4 = somewhat sufficient 5 = very sufficient	Self-report, $\mathrm{conf}(v) = 0.8$.
	Alcohol		

	Consumption	1 = very high
		2 = high
		3 = moderate
		4 = low
		5 = no consumption
			Determined based on *gender* and the AUDIT-C questionnaire [10],
			X: *AUDIT-C score*.
			
			If $x = 0$, then $v = 5$.
			If $1 \leq x \leq 2$, then $v = 4$.
			If (female AND $3 \leq x \leq 4$) OR (male AND $3 \leq x \leq 5$), then $v = 3$.
			If (female AND $5 \leq x \leq 8$) OR (male AND $6 \leq x \leq 8$), then $v = 2$.
			If $x \geq 9$ ≥, then $v = 1$.
			
			$\mathrm{conf}(v) = 0.9$

Feature type	Feature	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
	Smoking		
	Strength of nicotine addiction*	1 = very strong 2 = strong 3 = weak 4 = very weak 5 = no addiction	Determined based on the short version of the Fagersröm test for nicotine dependence [11], X: *test score* and Y: *usage of tobacco products*. If $y < 3$ AND $x \leq 1$, then $v = 4$. If $y < 3$ AND $x = 2$, then $v = 3$. If $y < 3$ AND $x = 3$, then $v = 2$. If $y < 3$ AND $4 \leq x \leq 6$, then $v = 1$. If $y \geq 3$, then $v = 5$. $\mathrm{conf}(v) = 0.9$
	Usage of tobacco products	1 = regular (daily) 2 = somewhat regular (weekly) 3 = somewhat irregular (monthly) 4 = occasional (less than once a month) 5 = non-smoker	Self-report, $\mathrm{conf}(v) = 0.8$.

Aggregated layer

The topmost layer in the data hierarchy, the aggregated data layer, included features that summarized knowledge across different concepts based on the features residing at the original and integrated data layers. In the With-Me user model, behavior change needs were such aggregated features. The behavior change need was evaluated for each behavioral domain by comparing the similarity between two feature vectors: one describing the individual's current situation (object vector) and the other describing the optimal situation (reference vector). The vectors comprised features relevant to the specific domain. For instance, the need to practice relaxation skills was derived based on stress level, perceived ability to relax, irritability, work efficiency, and sexual desire, and the need to clarify personal values was derived based on life satisfaction and sufficiency of time for important life areas. The reference vector included the optimal values for each feature, thus describing the situation in which behavioral changes were not required. Normalized, weighted Manhattan distance was used to compute the similarity between the two vectors; the smaller the distance between them, the lower the need to change behavior. Furthermore, the confidence value for a behavior change need was determined based on the confidence values of the related features. Missing values in the object vector influenced the confidence negatively. The exact behavior change needs that were supported by With-Me HRS and the computation rules used for the needs and the corresponding confidence values are presented in Table II. Other possibly interesting aggregated features could be, for instance, lifestyle healthiness or well-being indices, which summarize the knowledge over various health behaviors or well-being domains.

TABLE II

THE IMPLEMENTED BEHAVIOR CHANGE NEEDS AND DETERMINANTS FEATURES AND THEIR COMPUTATION RULES

Feature type	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
Behavior change needs, B_i		
b_1: Improve sleep quality b_2: Reserve more time for sleep b_3: Increase physical activity b_4: Improve diet quality b_5: Improve eating rhythm b_6: Manage emotional eating b_7: Reduce alcohol consumption b_8: Cease smoking b_9: Practise relaxation skills b_{10}: Manage work load b_{11}: Improve the quality of romantic relationship b_{12}: Clarify personal values b_{13}: Practise cognitive defusion from negative thoughts b_{14}: Improve self-esteem	For each b_i, $v_i \in \{1, 2, 3,4,5\}$, where 1 = no need 2 = mild need 3 = moderate need 4 = rather strong need 5 = very strong need	Let the value v_i of a behaviour change need b_i be defined by n attributes $X_{i1}, X_{i2},..., X_{in}$. Let x'_{ik} be the min-max transformation to the scale [0,1] of attribute X_{ik}, and $w_{ik} \epsilon \{1, 2, \ldots ,10\}$ the weight term for X_{ik} denoting its relevance. The value $v'_i \in [0,1]$ of the behaviour change need b_i is computed as the similarity between a reference vector $\boldsymbol{r}$ of length n with all ones and an object vector $\boldsymbol{i} = [x'_{i1}, x'_{i2},..., x'_{in}]$ based on the normalized Manhattan distance: $v_i = \frac{\sum_{k=1}^{n} w_{ik}\lvert 1-x'_{ik}\rvert}{\sum_{k=1}^{n} w_{ik}}.$ If the value x_{ik} of the attribute X_{ik} is missing, x_{ik} and w_{ik} are ommitted from the computation. The value v'_i is mapped to the values $v_i \in \{1, 2, 3,4,5\}$ according to the following logic: If $0 \leq v'_i < 0.125$, then $v_i = 1$. If $0.125 \leq v'_i < 0.375$, then $v_i = 2$. If $0.375 \leq v'_i < 0.625$, then $v_i = 3$. If $0.625 \leq v'_i < 0.875$, then $v_i = 4$. If $0.875 \leq v'_i \leq 1$, then $v_i = 5$. The confidence score $\mathrm{conf}(v_i)$ should be influenced by the confidence values of the attributes $X_{i1}, X_{i2},..., X_{in}$ and missing data. Let $c_{ik} \in [0,1]$ be the confidence score for the attribute value x_{ik}. Let us define a binary function $f_i(k)$ to indicate whether the value x_{ik} of attribute X_{ik} is missing or not: $f_i(k) = \begin{cases} 0, & if\ x_{ik}\ is\ missing \\ 1, & if\ x_{ik}\ is\ defined \end{cases}$ Now, $\mathrm{conf}(v_i) = \frac{\sum_{k=1}^{n} c_{ik} w_{ik} f_i(k)}{\sum_{k=1}^{n} w_{ik}}$ Hence, $\mathrm{conf}(v_i) \in [0,1]$, and a missing attribute value of high relevance will have the largest influence on the confidence score.

Feature type	Interpretation of harmonized values (v)	Computation logic for value v, and for the related confidence score, $\mathbf{conf}(v)$
Determinants of behaviour change		
Intention for each behaviour change need, b_i	For each b_i, $v_i \in \{1, 2, 3,4,5\}$, where 1 = precontemplation 2 = contemplation 3 = preparation 4 = action 5 = maintenance	Based on the Transtheoretical Model (TTM) of behavior change [12], [13]. $\mathrm{conf}(\ v_i) = 0.8$

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PUBLICATION IV

Citizen-Centric Web-Based Health Profiling Service: A Service Concept and a Profiling Method

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Citizen-Centric Web-Based Health Profiling Service: A Service Concept and a Profiling Method

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Abstract— **Personalization of health interventions has been shown to increase their effectiveness. In digital services, user profiles enable this personalization. We introduce a web-based user profiling service, where citizens can 1) create various personal profiles, specific to certain health topics, by providing their personal data, 2) get summarized feedback on their health and behavioral determinants regarding each profile, and 3) share their profiles with health service providers. As part of the service, we define a profiling method that identifies the health needs and behavioral determinants of citizens, and highlights their most potential behavior change targets. The novelty in the service arises from allowing citizens to govern their health data, quantifying automatically various behavioral determinants, and summarizing aggregated knowledge efficiently via simple visualizations. The service aims to evoke personal awareness about behavior change needs and the factors influencing behavior, enable health service providers to develop and offer highly personalized, automated interventions, and facilitate time-efficient and transparent decision-making of health professionals. According to a preliminary concept evaluation with citizens (N=29), the presented profile feedback was perceived as interesting and intuitive.**

I. Introduction

Health interventions personalized based on citizens' health needs and behavioral determinants have been shown to be more effective than generic ones [1], [2]. Behavioral determinants explain the personal motivation and ability to modify behavior and are characterized e.g. by the readiness to change behavior, the perceived need for change, the confidence in succeeding with the change (self-efficacy), beliefs and attitudes, social influences, prevailing habits, personality, and contextual and environmental factors [5], [8], [10], [12]. It is acknowledged that the current level of personalization in public health interventions is not sufficient [3], [4], since these psychological, behavioral, and social abilities and barriers related to behavior change are hardly considered [5], [12].

Understanding behavioral determinants is important for both the citizens, and the health and well-being service providers. For citizens, being unaware of the various personal and external factors that influence behavior and the choices in daily life, can lead to frustration and lack of motivation after repeated failed behavior change attempts. On the other hand, health professionals need to have this knowledge about their clients in order to provide them with the right kind of guidance and support. Acquiring the required knowledge is typically done by interviewing clients [6], which is a time consuming, non-systematic and non-transparent method. Having the relevant information systematically recorded in an electronic format with the clients' health needs and behavioral determinants readily analyzed, could make following clients' progress more efficient, and enables health and well-being service providers to develop and offer partly or fully automated personalized interventions.

User profiles in the context of digital health and well-being services refer to a collection of user information, gathered from various data sources to enable personalizing health interventions to the needs and preferences of individual users [4], [5]. There are many ways of obtaining information about citizens' health, lifestyle, and behavioral determinants that can be used to create a profile. Firstly, numerous empirically validated questionnaires exist to assess the health conditions, health risks and lifestyles of a person (e.g. [7]). Moreover, behavioral sciences provide strategies for assessing individuals' behavioral determinants relevant to target behaviors, i.e. the readiness to change, and the abilities and barriers influencing the behavior change process. Particularly, the technique of Motivational Interviewing (MI) [8], [9] and the Transtheoretical Model (TTM) [10] are widely used. *Family check-up* (reachinstitute.asu.edu/family-check-up) is an example of a behavior change intervention for promoting parenting skills that utilizes MI and the evaluation of various behavioral determinants [14]. Many free questionnaires are also available on the Internet that produce profiles relevant for health behavior change (e.g. *Personality test*, www.16personalities.com, *Stickiness Quiz*, www.wellocracy.com).

Secondly, self-tracking apps and devices provide a useful source for behavioral information, as citizens are increasingly using them to monitor their health, well-being and lifestyles [4]. Currently, exploiting these kind of personal data by health service providers involves challenges related to privacy and interoperability. Improving the interoperability between various health and well-being services and giving the citizens the power to determine which service providers are authorized to access their data and for what purposes, i.e. following the *MyData* approach [11], is expected to create opportunities for health professionals to get a complete and accurate picture of their clients' health needs and lifestyles. For example, *Apple Healthcare* (www.apple.com/healthcare) was recently introduced to harness the data collected by Apple mobile apps and the Apple Watch for supporting the delivery of personalized care. However, forming a coherent picture from the multitude

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of available data sources can be challenging. This is a challenge also for the citizens themselves.

The aim of this article is to introduce the concept of a web-based health profiling service, designed primarily for citizens to help them understand comprehensively their behavior change needs and determinants. We present the core features of the service concept and the current implementation regarding the employed profiling method and the quantified profile metrics. We also present the results of a preliminary concept evaluation with citizens, conducted to study the feasibility of the concept and gather further development ideas.

II. The Concept: A Citizen-Centric Profiling Service

MyProfile is a citizen-centric web-based health profiling service, aiming at 1) raising citizens' awareness of the personally relevant targets for health behavior change by providing a comprehensive view of their current lifestyles and the determinants of behavior change, and 2) empowering citizens to manage their personal health data by allowing them to decide what purposes the data is used for and who can access it.

The core features of the *MyProfile* service concept include 1) offering a variety of profiles relevant to different health or well-being topics for citizens to choose from, 2) constructing personal profiles that quantify behavior change needs and determinants based on the data provided by citizens, either via digital questionnaires or authorized data transfer from other service providers (e.g. self-tracking apps, grocery stores), 3) providing summarized feedback regarding the resulting profiles, and 4) enabling citizens to share their profiles with health services that match their personal needs, when they wish to get personalized guidance or support for lifestyle changes. The profiles are designed to aggregate and present knowledge efficiently via simple visualizations and computed metrics. The following scenario illustrates the envisioned usage of the *MyProfile* service from the citizen's and service provider's viewpoints.

Hanna is a 32 year-old woman who works as a financial secretary. She considers herself slightly overweight, and she is unhappy with her physical appearance. Hanna is constantly trying to lose weight and even when she succeeds, she always fails to maintain her weight target. Hanna feels frustrated, as she does not understand what she is doing wrong.

With the MyProfile service, Hanna creates her Weight management profile by responding to a series of questionnaires and sharing the data from her fitness wristband. MyProfile identifies her current behavioral patterns, strengths and weaknesses. Hanna learns that, in overall, her exercise and eating habits are relatively healthy. She also realizes that her family's discouraging attitude towards exercise in general has a notable influence on her exercise motivation, and that she has the tendency for emotional eating. As MyProfile presents her recommendations about service providers that could support her in learning the weight management skills she is currently lacking, she feels empowered to know that there are new things to try and weight management is more than just counting calories. She grants access for two weight management service providers to her Weight management profile, so that they can directly offer her personalized services.

A weight management coach at the FeelGoodWeight service receives a notification about a new potential customer, matching their offering, who has shared a profile with them. The coach contacts Hanna to discuss their services and suggests a four-week program focused on emotion regulation and problem solving skills. Hanna is delighted to get such a well-targeted offer and signs up for the program

III. Technical Description

A. Implementation of the Service

A prototype of the *MyProfile* web-platform has been implemented, featuring profiles for two health topics: weight management and stress. Currently, the profiles aggregate knowledge based on questionnaires via quantified profile metrics, and provide visual and written feedback accordingly. Written feedback, containing knowledge and recommendations regarding a healthy lifestyle, is provided for each answered questionnaire.

The prototype provides an open application interface (API) to facilitate the integration of the computed profile metrics with 3rd party applications, if authorized by citizens. Alternatively, citizens can share their profiles manually with health professionals by downloading a summarized feedback report as a pdf-print. However, the recommendation of suitable health service providers based on the personal profiles, and integration with 3rd party applications have not yet been implemented.

B. Profile Constituents

The main constituents of the profiles comprise lifestyle and health information (e.g. sleep quality and duration, quality of diet, exercise frequency and intensity), behavior change needs, and behavioral determinants (readiness to change, motivation, self-efficacy, perceived importance, social support, skills, and environmental factors). In addition, the most potential health behaviors to target are highlighted, according to the identified behaviour change needs, abilities and barriers.

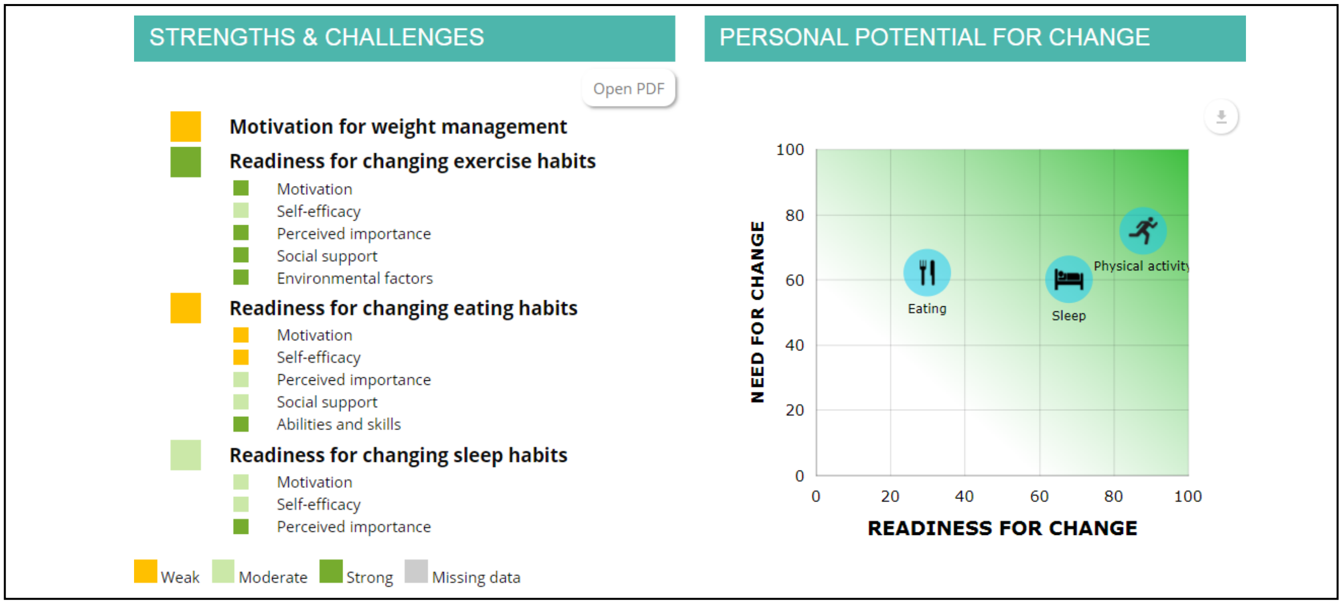
C. Profiling Method

The health behaviors, behavioral determinants, and data sources (i.e. the relevant questionnaires for the prototype) associated with a profile depend on the health topic in question. For instance, for the weight management profile, eating, exercise and sleeping habits are essential, whereas for the stress management profile, relaxation skills, awareness of personal values, and habits related to exercise, sleep and alcohol consumption are relevant. The assessment of behavioural determinants is done based on questionnaires, such as the ones developed for determining the TTM's stage or change [10] and the Readiness Ruler developed for MI [8].

For each behavior associated with the profile, citizens' behavior change needs, abilities and barriers are quantified, and the most potential behaviors to modify are indentified in the following way:

Let q_i denote the evaluation of the healthiness of a

Figure 1. Example visualizations from the Weight management profile for sleep, eating and exercise behaviors.



behaviour *i*, e.g. a score received for a questionnaire assessing the quality of diet in comparison to the recommended guidelines. Then, the behavior change need B_i for behaviour *i* is the min-max transformation of the value q_i to the scale [1,100], where 1 = *low* and 100 = *high* need for change.

Let d_{ij} denote the score of a questionnaire assessing how supportive a behavioral determinant *j* is for modifying the behaviour *i,* transformed to the scale [1,100]. For low values, the determinant is considered as a barrier, whilst a high value indicates that the determinant is an ability. Let w_j denote the importance of the determinant *j* in predicting behavior change. Then, R_i refers to the readiness to change behaviour *i*, and it is computed as the weighted average of w_j and d_{ij}.

Finally, the most potential behaviors to modify are defined by ranking the behaviors according to the formula (1) (applied Manhattan distance).

$$Rank(B_i,R_i) = 100 - \frac{w_B(100-B_i)+w_R(100-R_i)}{w_B+w_R}, \quad (1)$$

where w_B and w_R are weights for B_i and R_i, respectively, and $w_B < w_R$, since the readiness to change behavior predicts behavior change better than the perceived need for change (e.g.[10]). As a result, behaviors associated with a high need for change (i.e. unhealthy behaviors) and a high readiness to change are considered the most potential to modify, whilst the behaviors scoring low in both of these dimensions are considered as the least potential to target.

D. *Profile Visualizations*

The resulting profile metrics are presented through simple visualizations, aiming to provide concise feedback on personal behavior change needs and the behavioral determinants that hinder the change process (barriers) or facilitate it (abilities), thus making citizens aware of their personal strengths and challenges regarding behaviour change. In Fig. 1, two example visualizations are presented from the Weight management profile view, involving eating, exercise and sleeping habits. On the left, the states of the behavioral determinants for each behavior are presented. The color-coding associated with the determinants denotes whether the determinant is a barrier/challenge (yellow) or an ability/strength (dark green) in modifying the behavior in question. The visualization on the right side highlights the most and least potential behaviors to target along the 'behavior change need' (y-axis) and the 'readiness to change' (x-axis) dimensions. Behaviors that are placed near to the upper right corner of the graph are the potential ones to target due to the expected health benefits and the likelihood of succeeding with the behavior change.

IV. Concept Evaluation

A. *Objectives and Methods*

A qualitative concept evaluation was conducted for 1) evaluating the user experience of the profile metrics and visualizations, 2) evaluating the feasibility of the *MyProfile* service concept, and for 3) co-innovating appealing functionalities to the service together with end-users. The evaluation was conducted via online asynchronous focus group discussions in the spring 2016, over a three-week period. The group discussions took place in a web-based co-design platform, *Owela* (owela.fi/?lang=en) [13], which is based on a blog structure that consists of posts and comments visible to all participants. Participants were recruited for the discussions from the volunteer database of *Owela*.

The participants were first asked to register to the *MyProfile* service and use it freely, then provide feedback via *Owela* by participating in theme discussions that were facilitated by researchers. Using the service included answering well-being related questionnaires and examining the personal feedback presented in the Weight management profile. The participants were encouraged to discuss themes related to the user experience of the profile feedback, interesting profiling topics, and opinions about sharing data between *MyProfile* and other services, and to generate ideas about appealing features for *MyProfile*.

The concept evaluation involving human subjects was conducted in accordance with the principles outlined in the Helsinki Declaration of 1975, as revised in 2000.

B. Results

User Statistics: Altogether, 29 participants took part in the focus group discussions, 9 men and 20 women, mean age 57 years (range from 21 to 90 years).

Feedback on the Profile Metrics: The Weight management profile was perceived as interesting, and the accompanying visualizations (see Fig. 1) as easy-to-interpret. The visualization of the 'personal potential for change' was considered particularly interesting: "*Clear, interesting how the changes are visualized. Could the target levels for behavior change be also included in the picture as clearly?*"

Feedback on the Service Concept: As the idea of the service is to support versatile profiling topics, we presented some example topics for the participants to consider. Topics related to weight management, exercise, and the daily life rhythm were regarded as particularly as interesting: *"Exercise and diet are really important in affecting the quality of life. Improving time management in daily life, would provide more time to take care of them."* The service concept was thought to provide *"an incentive to improve all kinds of lifestyles"*, including topics such as grocery shopping habits and ecological footprint. Other topics of interest were related to personality, social activity and mental skills.

Sharing personal profiles with health professionals, particularly when visiting the healthcare center, was perceived as beneficial. The opportunity to transfer data to the *MyProfile* service from other health services or self-tracking devices, including vital signs such as blood pressure and blood glucose, was appreciated, since supporting the comprehensive monitoring and analysis of well-being was perceived as valuable. A few participants were worried about the possible misuse of their data - who may access the data and for what purposes. One participant did not see any use in the service.

V. *Development Ideas:* Suggestions for improving the service included updating personal profiles with recent data at least once in 6 months, providing recommendations regarding behavior change actions, and supporting self-care. The participants also expressed a need for considering in the profiles the current life situation, such as age, family situation, and changes in life. In addition, following the evolvement of the profiles over time and comparing personal results to one's peer group were considered motivating.

VI. Discussion

This paper introduced the concept of a citizen-centric, web-based health profiling service, *MyProfile,* and its first implemented prototype, together with the feedback received from end-users. As part of the service, a profiling method was implemented for identifying not only the health behavior change needs of citizens, but also the psychological and contextual determinants of behavior, which are often insufficiently considered in public health interventions and automated health services [3] - [5]. Moreover, the potential behaviors to modify are highlighted based on the identified health needs and behavioral determinants, hence enabling a holistic comparison between various competing behavior change targets.

The results of the concept evaluation suggest that citizens perceive the presented comprehensive analysis of behavior change needs coupled with behavioral determinants as feasible and interesting. The idea of importing personal health data to *MyProfile* from other services, and sharing personal profiles with health service providers received positive feedback, although the data security and privacy should be ensured to avoid any misuse of personal data. The monitoring of personal progress via evolving profiles and comparing personal profiles with one's peer group we requested as additional features.

In the next, revised version of the *MyProfile* service, we plan to introduce more profiling topics, offer the possibility to import data from self-tracking devices, support evolving profiles, and implement the recommendation of suitable health service providers based on the personal profiles.

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