A contextual Hybrid Intelligent System Design for Diabetes Lifestyle Management

Maaike H. T. de Boer[1], Jasper van der Waa[2], Sophie van Gent[2], Quirine T. S. Smit[1], Wouter Korteling[1], Robin M. van Stokkum[3] and Mark Neerincx[2,4]

[1]dep. Data Science, TNO, The Hague, The Netherlands
[2]dep. Human Machine Teaming, TNO, Soesterberg, The Netherlands
[3]dep. Risk Analysis for Products in Development, TNO, Utrecht, The Netherlands
[4]Technical University of Delft, Delft, The Netherlands

Abstract

In the past few years, the research field of Hybrid Intelligence (HI) has progressed due to an increased human-centered focus on AI. In this paper, we propose a function design for embedding a hybrid intelligent system in the context of a societal relevant use case - lifestyle support for Type 2 Diabetes patients. The novelty of this paper is that we used co-design sessions with diverse stakeholders, such as general physicians, lifestyle coaches, diabetes researchers and healthcare IT professionals, to come to this design.

We explain our vision on HI for this use case and highlight key functions in that vision: 1) a support function to construct and update a holistic patient profile through inclusive and longitudinal personalized interaction; 2) a patient prioritization function for a consultation with a healthcare professional (HCP); and 3) a function enabling the shared decision-making on the goals the patient should pursue. These functions are designed with the context of users and system in mind, accounting for the unique contextual factors that make each diabetes patient unique and in need of context-aware support. In future work, we create a demonstrator based on this design and evaluate it with end users, ultimately improving quality of life of diabetes type 2 patients and supporting the work of HCPs.

Keywords

Hybrid Intelligence, Human-Machine Interaction, Human-Centered AI, Machine Learning, Knowledge Representation

1. Introduction

As of 2019, more than 703 million people were aged over 65 and it is expected this will more than double to 1.5 billion in 2050 [1]. Many elderly suffer from diseases such as Type 2 Diabetes as a result of a life lived in urban surroundings with an unhealthy lifestyle and environment [2]. These statistics suggest a future where the quality of life of millions is decreased drastically as they grow older. Furthermore, affordable healthcare is under immense pressure due to these developments. Many chronic diseases such as diabetes type 2, cardiac diseases and chronic obstructive pulmonary disease (COPD) are caused primarily due to lifestyle choices. Therefore, adapting a healthy lifestyle could help combat the challenges facing affordable care in the future. Technology and digitisation can be a solution to motivate people to change their lifestyle to prevent or mitigate the effects of lifestyle related diseases like diabetes [3]. However, many of such tools fail over time as they do not account for a patient's context, show a novelty effect that wears off quickly [4], and lack integration in a patient's life and the healthcare support they receive [5].

A more personalized, persistent, intelligent and integrated digital support is needed to adhere to the complex context of a patient's lifestyle. Hybrid Intelligence (HI) could provide such a solution [6], entailing Artificial Intelligence (AI) that augments the human healthcare information and knowledge processes concerning a patient's self-care. A HI system uses AI and interaction technologies that explicitly accommodates human intelligence or cognition, such as shared mental models, mutual explanations, human-in-the-loop machine learning and interactive feedback. We argue that a holistic perspective is needed to design effective support functions that account for the social-economic context of patients and healthcare professionals. For example, when a patient has a low social-economic status, a lifestyle change can be out of reach due to a lack of understanding how lifestyle affects their health, limited finances to eat healthier or become more active, reduced access to quality care, social connections demotivating any contact with healthcare professionals or to enact a lifestyle change, and a lack of a long term view due to pressing current problems such

MRC 2023 – The Fourteenth International Workshop Modelling and Representing Context. Held at ECAI 2023, 30.09.-5.10.2023, Kraków, Poland.
maaike.deboer@tno.nl (M. H. T. d. Boer); jasper.vanderwaa@tno.nl (J. v. d. Waa)
0000-0002-2775-8351 (M. H. T. d. Boer); 0000-0003-4648-2220 (J. v. d. Waa); 0000-0003-2815-9024 (S. v. Gent); 0009-0008-8890-4261 (Q. T. S. Smit); 0000-0001-8269-4402 (W. Korteling); 0000-0002-1988-9896 (R. M. v. Stokkum); 0000-0002-8161-5722 (M. Neerincx)

as debts and unemployment.

This paper aims to show how Hybrid Intelligence can serve as a solution for large societal problems by incorporating human context. We present three functions encapsulated in a HI system derived from a co-design process to support a long-lasting lifestyle change to prevent, reverse or mitigate diabetes in patients. This co-design process was followed with diverse stakeholders to arrive at human-centred and context-aware designs of AI-based functions. The three designed functions are; 1) a support function to construct and update a holistic patient profile through an inclusive and longitudinal personalized interaction to capture the patient's context; 2) a patient prioritization function to support healthcare professionals (HCP) to plan consultations with patients who need it the most; and 3) a function enabling the shared decision-making between patient and HCP on what goals the patient should pursue. These functions attempt to combine the patient's context captured in their profile with what is medically the best course of action. The resulting HI system consists of a three-fold interaction between AI system, patient and HCP. These functions require the integration of technologies such as Hybrid AI [7], counterfactual explanations [8], user modelling [9] and personalized conversational AI [10].

In the next section we explain related work in Hybrid Intelligence. Section 3 dives into Type 2 Diabetes. Section 4 explains our co-design process, the resulting identified functions and our vision how a HI system can be used in this use case. Section 5 concludes this paper.

2. Related Work

Hybrid Intelligence (HI) combines human and artificial intelligence, utilizing the complementary capabilities of each to realize the best overall performance for the stakeholders at the level of individuals, groups and society; a joint human-AI performance that is better than each of the two could realize separately [11, 6, 12]. HI is an emerging research & development (R&D) field and, consequently, few comprehensive applications have been implemented yet [13].

Three levels of HI can be distinguished to relate, assess and plan for R&D progress [6]. Higher levels entail greater mutual complementation of the human and artificial intelligence in comprehensive human-AI collaborations, in which the joint performance substantially exceeds the best individual performance of the AI and human. Hybrid AI (HAI) frameworks have been proposed and developed that combine data- and knowledge-driven methods and models in decision-making processes [7, 14, 15]. Such HAI frameworks can discover patterns from data not yet known to experts while at the same time incorporate the knowledge of those experts. This capability is deemed necessary for AI systems to be effective in the healthcare domain [16], and can already result into joint performances that exceed the individual performances of AI or human experts [17].

The first level of HI centers on *explainability*: the AI system and involved humans can explain themselves effectively to facilitate knowledge transfer [18]. An AI system typically takes the role of advisor at this level (i.e., suggests a patient to be more active). Explainable AI (XAI) is needed to establish appropriate levels of understanding and trust, and a responsible human-AI collaboration [19, 20]. Technologies to generate counterfactual explanations for instance, allow humans to probe the behaviour of an AI system [21]. XAI is increasingly applied within the healthcare domain (i.e., see the review by Adadi and Berrada [22]).

The second HI-level centers on *interactivity*: the AI system and humans closely interact with each other to arrive at a common decision. This level expands on knowledge transfer towards collaborative decision making, where the AI system can arrive independently at decisions. Often a shared-decision making (SDM) approach is taken, in which clinicians and patients share their best available options and patients can achieve informed preferences [23]. SDM is considered to improve patient autonomy and control in decision-making, by helping to fit decisions more adequately to their values [24]. HI can assist both patient and clinician in collecting all the relevant information and can continually adapt to new patient's needs and clinicians insights. For that, the decision-making process has to be designed, for instance with team design patterns [25, 26]. With the development of sophisticated language models, conversational agent technologies offer more inclusive ways for human-AI interactions, such as a digital coach for low-literates [27] and chatbots for inclusive learning [28]. This technology leads to new opportunities to support user groups with a low digital literacy with AI systems [29, 30]. An example of this is the HELENA support tool, which gathers patient information through a conversational agent [31].

Finally, the third HI-level centers on *symbiosis*: the collaboration between AI system and human achieves a high degree of interdependence and adaptivity that results in intricate joint decision-making. This requires personalization, as both the human and the system need mutual updates. Each patient has a different context, and based on that different needs and goals. The potential to aid to those specific contexts is widely recognized [32, 33, 34]. With AI and data science granting the opportunity to predict health-related outcomes for patients, personalization of information seems to be an excellent opportunity to improve understanding and acceptance by patients [35]. Also, generic information is harder for patients to apply to their own situation [36].

As one of the first of its kind, the PAL system integrated the HI-enabling technologies to support the diabetes self-management of children with Type 1 Diabetes Mellitus [37]. In a participatory socio-cognitive engineering process, the AI-agents were developed as partners in a hybrid human-AI team (HI-level 1), consisting of these agents, the children, health-care professionals and parents, to enhance this self-management. The AI modular system consisted of a common ontological knowledgebase, and HAI-models for the (joint) decision making and reasoning processes (e.g., for the conversational agent and robot, time-line, educational games, and dashboard modules) [38].

3. Type 2 Diabetes

Diabetes is a major public health concern. The WHO observed 422 million patients world wide in 2015 [39], a number expected to grow to 642 million in 2040. Type 2 diabetes (T2D) accounts for roughly 95 percent of all cases. A patient with diabetes faces an up to four times the risk of developing heart disease [40]. Additionally, it is one of the main causes behind kidney disease and related deaths, amongst other health risks such as cataracts and others [41]. The major driver behind the large number of T2D is being overweight, approximately 60 percent of cases, caused by an unhealthy lifestyle [42]. Interventions aimed at weight loss and overall fitness increase have been shown to be excellent prevention strategies. Furthermore, they have shown to be beneficial in disease management for diagnosed patients, reduce risk of additional related disease such as kidney and heart disease and reduce the need for clinical treatments such as insulin [43]. However, large challenges remain in the uptake and prolonged use of such interventions, specifically when the aim is to create sustainable lifestyle change.

The challenge is then to help a patient change their lifestyle towards a more healthy one. Changing one's lifestyle is not an easy task [40]. Factors can vary from lack of understanding about the disease, deteriorating mental health, difficulties in the social setting such as loss of jobs, housing or other social challenges and bad habit formation, among others. To achieve a long-lasting change in lifestyle, a healthcare professional is required to know the complex factors underlying behavior patterns – alongside relevant medical data – to arrive at an advice for a lifestyle change that is both beneficial and attainable for the patient [44]. However, large scale behavior change interventions are difficult to implement in the regular health care setting. They are resource intensive, where resources of health care professionals typically are limited.

Technology driven lifestyle interventions have the potential to tackle these resource barriers. Advancements have been made in AI for digital health technology in recent years. Several studies have demonstrated the effectiveness for weight management and physical activity of highly tailored and adaptive digital behavioral interventions, such as goal setting, human-based phone coaching, weekly tracking, incorporating digital measures such as scales and wearable devices [45, 46, 43].

However, the majority of these interventions are data collection and prediction tools and offer minimal interactions with a patient (1). Furthermore, these AI systems struggle to go beyond what they have been trained to do (2). They cannot learn new concepts or adapt to a new user without manual intervening (e.g.: adding new features and updating the software) or adapt to a user over time. Finally, patient participation in the medical treatment process is often lacking, thus under-utilizing a potent source for motivation on the side of the patient (3) [47].

4. Hybrid Intelligence Function Designs for Diabetes Lifestyle Management

The goal of the designs is to overcome these three shortcomings of the current state-of-art mentioned in the previous section. We aim to demonstrate that AI-based support systems can progress towards advanced HI systems, in which AI-technology truly collaborates with patients, their doctors, specialists, family and friends and potentially others, thus interacting possibly with a patient's entire context. This way, long-lasting changes in a patient's lifestyle can be established to prevent diabetes, to maintain or increase their quality of life, to prevent additional diseases from occurring, and potentially to put the diabetes in remission [48].

To show the potential of HI, two sessions were held with general physicians (GPs), lifestyle coaches, diabetes researchers and healthcare IT professionals. Co-design activities were used during the sessions to identify the main stakeholders of the use case and their problems. These problems were prioritized to select the stakeholder groups that would benefit the most from digital support. Aside from supporting the patient stakeholder group, support for the GP was identified as vital for achieving a long lasting lifestyle change. Personas were made for both. The patient persona described an older adult with critical health risks and difficult barriers such as low health- and digital-literacy as well as a low social-economic status. The GP persona described an expert in their field motivated to help patients to their best of ability but suffering from tremendous workloads[1]. This served as the basis

[1]The GP persona was driven by the Dutch healthcare system which experiences a shortage of personnel combined with an increase in patients.

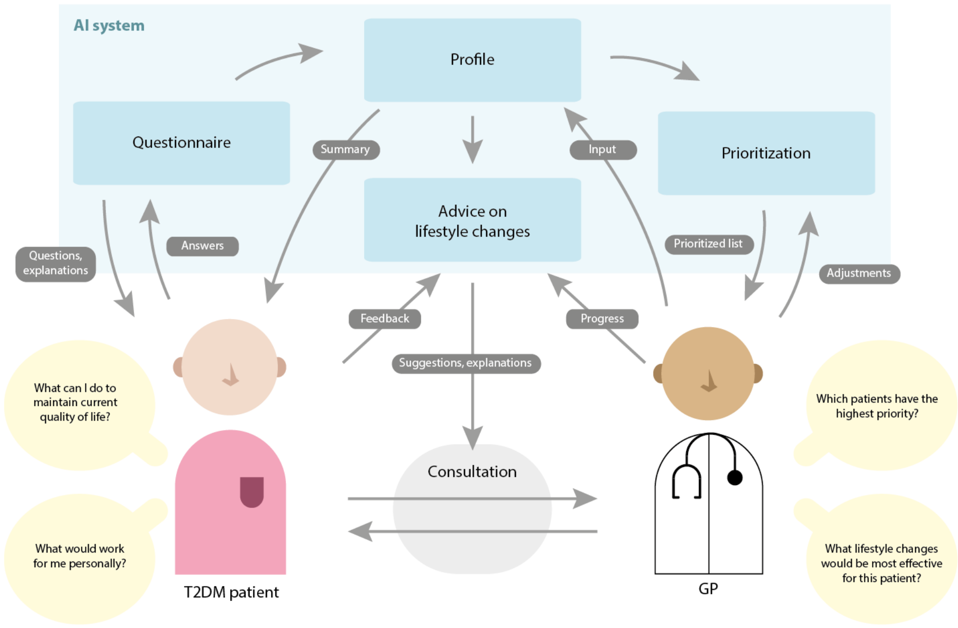

Figure 1: An overview of the main functions identified from co-design workshops with experts that rely on hybrid intelligence technologies. Depicted are the patient and general physician (GP) with their goals. The questionnaire and profile comprise the first function, the prioritization the second and the advice on lifestyle change the third.

for creating storyboards describing supportive functions for the patient and GP separately, and the consultation where both participate. With the help of these storyboards, AI and HI experts isolated functions that require advanced AI and interaction technologies. As such, a realistic readiness assessment and designs were made needed in the described use case.

Three means of digital support resulted from this process; 1) the creation and updating of a holistic patient profile on their social environment and values, 2) the prioritization of patients based on their need, willingness and readiness to change their lifestyle, and 3) providing advice on an appropriate lifestyle change. These three main functions are depicted in Figure 1 and explained in the following subsections. The next section describes the storyboard created based on these functions.

4.1. Patient Profile

The first main function serves as the basis for the other two. It consists of creating and updating a holistic profile about the patient. In particular a profile about their social environment (e.g., relations, financial status) and values (e.g., family, health). It was identified during the sessions that such a profile is vital to arrive at an effective and personalized lifestyle advice. As it uses the patient's context to signal if they are willing and capable of changing their lifestyle and what would motivate them to do so. However, there is often no time during a consultation to identify such elements besides discussing medical test results, symptoms and medication. Longer consultations or planning more of them is also not possible, as HCP often does not have the work capacity to do so. Instead, a functionality was defined and subsequently worked out by AI and HI researchers to create and maintain such a profile automatically.

This function was envisioned to conduct brief mixed-initiative interaction sessions with patients to construct a profile. This profile would need to model their current lifestyle, past attempts to change it, their drives to do so, and their barriers. These drives and barriers would be modeled as patient values and capturing the social and economic context of that patient. These system-patient interaction sessions would need to be inclusive and personalized, to fit with a patient's health and digital literacy.

Several HI technologies were identified to enable this envisioned functionality. First, the AI system would need to determine when a patient's profile is in need of an update. Then it would need to ask the patient follow-up questions to add or update any information. Where needed, the AI system would need to explain why it asks certain questions. It would need to do so in a way that motivates the patient to answer the question while ideally improving their health literacy. An ideal form to do is, is through brief conversations where AI system and patient can converse on raised topics related to their lifestyle and values while relating to their social and economic context. Through these conversations we foresee an accessible means for a patient to interact, as it requires little digital literacy [30]. Furthermore, the free format of text allows the AI system to adapt its questions and way of phrasing to the estimated language level for inclusivity and to maximize the acquired information. However, it does require an advanced conversational AI technology combined with reasoning about knowledge structures.

4.2. Patient Prioritization

A major challenge identified during the workshops was to reduce the workload of GPs while helping them integrate effective lifestyle advice in their consultations. To do so, a second function was envisioned that provides a way for the GP to prioritize patients based on their contextualized profile. This function allows the GP to take more control over their own workload by making informed decisions about when a consultation is needed. This could also prevent under- or over treatment. As a consequence, the GP's way of working changes. Currently they have periodically consultations with all patients, whether that timing is appropriate or not. With this change, they can consult patients who need it more often and patients that receive little to no benefit of them less often. We believe this could also make the work for a GP more enjoyable, as their consultations are likely to feel more effective and relevant.

This support would entail the AI system prioritizing each of the GP's patients based on how much they would benefit from their GP's lifestyle advice, based on the patient's profile. For example, when the profile indicates a failed lifestyle change, or when it shows a new or changed value such as "family support" or "improved financial situation". These kind of changes could all signal that the patient would benefit from advice, making a consultation on it more effective and rewarding for both patient and GP. However, the point was raised during the workshop that this prioritization would entail a combined data- and knowledge-driven approach. An AI system can learn from data what makes a patient willing to change their lifestyle, but new domain knowledge can also reveal similar incentives. This would also mean that the way in which the AI system prioritizes could change as it learns and that the GP is able to improve upon the knowledge the AI system uses.

The identified required HI technologies accommodate human and artificial intelligence, where the AI system is behaving both in data- and knowledge-driven ways, for example using rules based on expert knowledge and a machine learning model to predict an ideal visit frequency. In addition, the success of this function requires the AI system to explain how it arrived at a prioritization to allow for informed and responsible decisions what patient to invite. Similarly, the GP would need to be supported in adding or changing the knowledge the AI system uses. This way both AI system and GP can learn from each other and collaboratively arrive at a patient prioritization.

4.3. Advice on lifestyle changes

Currently a GP mostly discusses medical data, risks and lab results with patients. Based on the co-design activities this, however, seems to be changing towards discussing a patient's social-economic context as well as required lifestyle changes. We envision that the AI system can support in such consults by proposing potential lifestyle changes that are likely to be adopted by the patient and become a long lasting change. The AI system would provide this advice based on the patient profile and thus account for their social-economic context as captured in their drives, barriers, current lifestyle and past attempted changes. We argue that an advice based on such elements will support the GP in providing a more holistic and personalized advice. Furthermore, the AI system can readily involve the patient during this process by letting them explore potential changes that might fit them. Their feedback can be communicated to the GP, either just before or during the consult.

A three-fold interaction between patient, GP and AI system was designed during the workshops. The role of the AI system is to facilitate the collaborative decision making process towards a personalized advice for a lifestyle change. A wide variety of support was identified for the AI system to fulfil in this role. For instance, collect feedback from the patient before the consultation on likely changes to serve as input for the actual consult, provide explanations to both why certain changes may or may not result in a long lasting change for this patient, allow the GP to review the history of advised and attempted changes, and many more. Which of these functions are actually required should first be researched through more specific co-design sessions with the GP and patients.

Aside from these more complex functions there is a more basic functionality of the AI system inferring one or more potential changes that might be beneficial for that patient. This can already be developed with the help of Hybrid AI technologies and counterfactual reasoning to utilize both data- and knowledge-driven approaches to arrive at a counterfactual, i.e., a required lifestyle change. Furthermore, co-learning techniques can be used that allow both GP and patient to provide feedback on what lifestyle changes are desirable. Such feedback can be incorporated in the AI system's knowledge base, either

Figure 2: Screenshots from the storyboard, created with Scenes

temporarily for the consultation or become persistent new knowledge.

4.4. Storyboard

Once the initial ideas for the three different functions were formed, storyboards were created. Storyboards are a visual representation of showing how users are experiencing the problem space, and how they are trying to achieve their goals. It is a form of narrative prototyping, and is usually done early in the design process. In this use case, the storyboards helped to illustrate the context of all three functionalities, in order for them to be further specified. Based on the co-design sessions with the stakeholders, two personas were created that reflected the main stakeholders of the use case, being the patient and the GP. It is important to note that the persona representing the patient was based on the common issues that healthcare professionals painted. In further iterations, patients themselves should be included in the design process. During the process of making the storyboard, the AI system was added as a persona as well, in the form of a digital health coach, due to the degree of agency it has.

Although all three functionalities are represented in the storyboard, we choose to let it mainly revolve around the patient's experience, rather than the GPs. The reason for this is that the context of the patient is both a large contributor to the prevalence of DT2, as well as a part of the solution. In other words, contextual factors impair the adherence to lifestyle changes, but mapping these factors, and forming a patient profile can help dissolve this impairment. Hence, the aim of the storyboard was to illustrate how the patients' context impacts their interaction with the AI system, and how it can serve as a way to personalize interventions and therefore lead to sustainable behavior change.

The storyboard consists of four chapters. The first chapter introduces the patient (our persona named Kees), and reflects the challenges of having diabetes and pursuing behavior change (moving more). The second chapter shows the interaction between the patient and the AI system (named Freek), inviting the patient to have a conversation. The AI system is presented to the patient in the form of a digital coach, and asks the patient for their values (such as it is important to be able to play with grandchildren). After the patient shared some reasoning behind his behavior, the digital coach uses that information to give feedback and motivate the patient to help them reach their goals. The third chapter demonstrates the patient prioritization functionality, as it shows how the patient is pushed in the system of the GP, due to the identified motivation of that patient to improve their lifestyle. The fourth and last chapter shows the consult between the GP and the patient, and illustrated that both actors can benefit from the HI system, since the contextual factors of the patient are known to the GP and can therefore be more easily play a part in the conversation. A few screenshots of the storyboard are added in figure 2[2].

All in all, the storyboards have insight into how the interaction between the personas and the AI system could look like. By translating the use case into a tangible story, certain discussions emerged, on of them being that the context of the patient strongly hinders the reachability of the patient. This lead to the conclusion that adaptive timing is a very important feature, and that the AI system should learn when the patient is most likely to interact with the system. Another lesson was that the interaction itself is unlikely to sustain for our persona, is the conversation does not occur in a natural manner. The functionality of a dialogue agent was added to prevent the patient from dealing with complicated interfaces. Besides these insights, the storyboards also serve as material for future co-design sessions, to further iterate on them with different stakeholder sharing their perspectives.

5. Conclusion and Future Work

Hybrid Intelligence is claimed to serve as a solution for large societal problems. In this paper, we propose the designs of three support functions of an AI system in the context of HI to support a long-lasting lifestyle change for diabetes patients. Each of the functions have for the full complex context of a diabetes patient at its basis, something that is lacking in other AI-based support functions. The three functions were derived from two co-design sessions with diverse stakeholders: 1) a support function to construct and update a holistic patient profile through inclusive and longitudinal personalized interaction; 2) a patient prioritization function for a consultation with a GP or other HCP; 3) a shared decision-making function on the goals the patient can best pursue. These functions require a diverse set of AI and interaction technologies to be integrated, ranging from hybrid AI and explainability to conversational AI and co-learning. In future work, we plan to create a demonstrator based on this framework and test it with end users as well as further develop the HI concept in this domain but also other domains.

Acknowledgments

This research was supported by TNO's internal program APPL.AI[3]. We would like to thank the Hybrid Intelligence Centre of the Netherlands[4], our colleagues Jef van Schendel, Tjeerd Schoonderwoerd, Erik Boertjes, Tim van den Broek and the DIAMONDS team. In addition, we acknowledge the contributions of the involved domain experts from the UMC Amsterdam, Health Coach Program, ORTEC, Councyl, Almende and KPN.

References

[1] U. Nations, World population ageing 2019: highlights, New York (2019).

[2] S. Wild, G. Roglic, A. Green, R. Sicree, H. King, Global prevalence of diabetes: estimates for the year 2000 and projections for 2030, Diabetes care 27 (2004) 1047–1053.

[3] M. Changizi, M. H. Kaveh, Effectiveness of the mhealth technology in improvement of healthy behaviors in an elderly population—a systematic review, Mhealth 3 (2017).

[4] D. Katz, N. Dalton, B. Price, Failing the challenge: Diabetes apps & long-term daily adoption, in: International Conference on Advanced Technologies & Treatments for Diabetes, 2015, pp. 18–21.

[5] R. S. Istepanian, Mobile applications for diabetes management: efficacy issues and regulatory challenges, The Lancet Diabetes & Endocrinology 3 (2015) 921–923.

[6] Z. Akata, D. Balliet, M. De Rijke, F. Dignum, V. Dignum, G. Eiben, A. Fokkens, D. Grossi, K. Hindriks, H. Hoos, et al., A research agenda for hybrid intelligence: augmenting human intellect with collaborative, adaptive, responsible, and explainable artificial intelligence, Computer 53 (2020) 18–28.

[7] A. Meyer-Vitali, R. Bakker, M. van Bekkum, M. de Boer, G. Burghouts, J. van Diggelen, J. Dijk, C. Grappiolo, J. de Greeff, A. Huizing, et al., Hybrid ai: white paper, TNO Reports (2019).

[8] M. Prosperi, Y. Guo, M. Sperrin, J. S. Koopman, J. S. Min, X. He, S. Rich, M. Wang, I. E. Buchan, J. Bian, Causal inference and counterfactual prediction in machine learning for actionable healthcare, Nature Machine Intelligence 2 (2020) 369–375.

[9] J.-P. Calbimonte, D. Calvaresi, F. Dubosson, M. Schumacher, Towards profile and domain

[2]https://experience.sap.com/designservices/scenes

[3]https://appl-ai-tno.nl/

[4]https://www.hybrid-intelligence-centre.nl/

modelling in agent-based applications for behavior change, in: International Conference on Practical Applications of Agents and Multi-Agent Systems, Springer, 2019, pp. 16–28.
[10] A. B. Kocaballi, S. Berkovsky, J. C. Quiroz, L. Laranjo, H. L. Tong, D. Rezazadegan, A. Briatore, E. Coiera, The personalization of conversational agents in health care: systematic review, Journal of medical Internet research 21 (2019) e15360.
[11] D. Dellermann, P. Ebel, M. Söllner, J. M. Leimeister, Hybrid intelligence, Business & Information Systems Engineering 61 (2019) 637–643.
[12] M. M. Peeters, J. van Diggelen, K. Van Den Bosch, A. Bronkhorst, M. A. Neerincx, J. M. Schraagen, S. Raaijmakers, Hybrid collective intelligence in a human–ai society, AI & society 36 (2021) 217–238.
[13] P. Hemmer, M. Schemmer, M. Vössing, N. Kühl, Human-ai complementarity in hybrid intelligence systems: A structured literature review., PACIS (2021) 78.
[14] D. Dellermann, A. Calma, N. Lipusch, T. Weber, S. Weigel, P. Ebel, The future of human-ai collaboration: a taxonomy of design knowledge for hybrid intelligence systems, arXiv preprint arXiv:2105.03354 (2021).
[15] M. van Bekkum, M. de Boer, F. van Harmelen, A. Meyer-Vitali, A. t. Teije, Modular design patterns for hybrid learning and reasoning systems: a taxonomy, patterns and use cases, Applied Intelligence 51 (2021) 6528–6546.
[16] M. Sharma, A. Kochhar, D. Gupta, J. A. Zubi, Hybrid intelligent system for medical diagnosis in health care, in: Hybrid Artificial Intelligence and IoT in Healthcare, Springer, 2021, pp. 21–49.
[17] C. Reverberi, T. Rigon, A. Solari, C. Hassan, P. Cherubini, A. Cherubini, Experimental evidence of effective human–ai collaboration in medical decision-making, Scientific reports 12 (2022) 1–10.
[18] J. van der Waa, Explainable Artificial Intelligence for human-AI collaboration, Ph.D. thesis, Technical University Delft, 2022.
[19] T. Miller, Explanation in artificial intelligence: Insights from the social sciences, Artificial intelligence 267 (2019) 1–38.
[20] J. van der Waa, S. Verdult, K. van den Bosch, J. van Diggelen, T. Haije, B. van der Stigchel, I. Cocu, Moral decision making in human-agent teams: Human control and the role of explanations, Frontiers in Robotics and AI 8 (2021) 640647.
[21] D. Dave, H. Naik, S. Singhal, P. Patel, Explainable ai meets healthcare: A study on heart disease dataset, arXiv preprint arXiv:2011.03195 (2020).
[22] A. Adadi, M. Berrada, Explainable ai for healthcare: from black box to interpretable models, in: Embedded Systems and Artificial Intelligence, Springer, 2020, pp. 327–337.
[23] G. Elwyn, S. Laitner, A. Coulter, E. Walker, P. Watson, R. Thomson, Implementing shared decision making in the nhs, Bmj 341 (2010).
[24] C. Charles, A. Gafni, T. Whelan, M. A. O'Brien, Treatment decision aids: conceptual issues and future directions, Health Expectations 8 (2005) 114–125.
[25] J. J. van Stijn, M. A. Neerincx, A. ten Teije, S. Vethman, Team design patterns for moral decisions in hybrid intelligent systems: A case study of bias mitigation, in: 2021 AAAI Spring Symposium on Combining Machine Learning and Knowledge Engineering, AAAI-MAKE 2021, CEUR-WS, 2021, pp. 1–12.
[26] J. van Diggelen, M. Johnson, Team design patterns, in: Proceedings of the 7th International Conference on Human-Agent Interaction, 2019, pp. 118–126.
[27] D. G. Schouten, F. Venneker, T. Bosse, M. A. Neerincx, A. H. Cremers, A digital coach that provides affective and social learning support to low-literate learners, IEEE Transactions on Learning Technologies 11 (2017) 67–80.
[28] S. Gupta, Y. Chen, Supporting inclusive learning using chatbots? a chatbot-led interview study, Journal of Information Systems Education 33 (2022) 98–108.
[29] K. Sriwisathiyakun, C. Dhamanitayakul, Enhancing digital literacy with an intelligent conversational agent for senior citizens in thailand, Education and Information Technologies (2022) 1–21.
[30] M. A. Neerincx, A. H. Cremers, J. M. Kessens, D. A. Van Leeuwen, K. P. Truong, Attuning speech-enabled interfaces to user and context for inclusive design: technology, methodology and practice, Universal Access in the Information Society 8 (2009) 109–122.
[31] M. Polignano, P. Lops, M. de Gemmis, G. Semeraro, Helena: An intelligent digital assistant based on a lifelong health user model, Information Processing & Management 60 (2023) 103124.
[32] A. G. Edwards, G. Naik, H. Ahmed, G. J. Elwyn, T. Pickles, K. Hood, R. Playle, Personalised risk communication for informed decision making about taking screening tests, Cochrane database of systematic reviews (2013).
[33] M. Jacobs, J. Johnson, E. D. Mynatt, Mypath: Investigating breast cancer patients' use of personalized health information, Proceedings of the ACM on Human-Computer Interaction 2 (2018) 1–21.
[34] S. M. Noar, C. N. Benac, M. S. Harris, Does tailoring matter? meta-analytic review of tailored print health behavior change interventions., Psychological bulletin 133 (2007) 673.
[35] S. Acharya, A. D. Boyd, R. Cameron, K. D. Lopez,

P. Martyn-Nemeth, C. Dickens, A. Ardati, B. Di Eugenio, Incorporating personalization features in a hospital-stay summary generation system, in: Proceedings of the 52nd Hawaii international conference on system sciences, 2019.

[36] M.-A. van Stam, H. G. van der Poel, J. R. Bosch, C. N. Tillier, S. Horenblas, F. Mols, N. K. Aaronson, Prevalence and correlates of mental health problems in prostate cancer survivors: A case-control study comparing survivors with general population peers, in: Urologic Oncology: Seminars and Original Investigations, volume 35, Elsevier, 2017, pp. 531–e1.

[37] M. A. Neerincx, W. Van Vught, O. Blanson Henkemans, E. Oleari, J. Broekens, R. Peters, F. Kaptein, Y. Demiris, B. Kiefer, D. Fumagalli, et al., Socio-cognitive engineering of a robotic partner for child's diabetes self-management, Frontiers in Robotics and AI 6 (2019) 118.

[38] F. Kaptein, B. Kiefer, A. Cully, O. Celiktutan, B. Bierman, R. Rijgersberg-Peters, J. Broekens, W. Van Vught, M. Van Bekkum, Y. Demiris, et al., A cloud-based robot system for long-term interaction: Principles, implementation, lessons learned, ACM Transactions on Human-Robot Interaction (THRI) 11 (2021) 1–27.

[39] K. Ogurtsova, J. da Rocha Fernandes, Y. Huang, U. Linnenkamp, L. Guariguata, N. H. Cho, D. Cavan, J. Shaw, L. Makaroff, Idf diabetes atlas: Global estimates for the prevalence of diabetes for 2015 and 2040, Diabetes research and clinical practice 128 (2017) 40–50.

[40] J. M. Spahn, R. S. Reeves, K. S. Keim, I. Laquatra, M. Kellogg, B. Jortberg, N. A. Clark, State of the evidence regarding behavior change theories and strategies in nutrition counseling to facilitate health and food behavior change, Journal of the American Dietetic Association 110 (2010) 879–891.

[41] R. Saran, B. Robinson, K. C. Abbott, L. Y. Agodoa, P. Albertus, J. Ayanian, R. Balkrishnan, J. Bragg-Gresham, J. Cao, J. L. Chen, et al., Us renal data system 2016 annual data report: epidemiology of kidney disease in the united states, American journal of kidney diseases 69 (2017) A7–A8.

[42] K. G. M. M. Alberti, P. Zimmet, J. Shaw, International diabetes federation: a consensus on type 2 diabetes prevention, Diabetic Medicine 24 (2007) 451–463.

[43] L. Van Rhoon, M. Byrne, E. Morrissey, J. Murphy, J. McSharry, A systematic review of the behaviour change techniques and digital features in technology-driven type 2 diabetes prevention interventions, Digital health 6 (2020) 2055207620914427.

[44] V. J. Strecher, B. McEvoy DeVellis, M. H. Becker, I. M. Rosenstock, The role of self-efficacy in achieving health behavior change, Health education quarterly 13 (1986) 73–92.

[45] E. Everett, B. Kane, A. Yoo, A. Dobs, N. Mathioudakis, et al., A novel approach for fully automated, personalized health coaching for adults with prediabetes: pilot clinical trial, Journal of medical Internet research 20 (2018) e9723.

[46] A. Michaelides, C. Raby, M. Wood, K. Farr, T. Toro-Ramos, Weight loss efficacy of a novel mobile diabetes prevention program delivery platform with human coaching, BMJ Open Diabetes Research and Care 4 (2016) e000264.

[47] D. Lee, S. N. Yoon, Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges, International Journal of Environmental Research and Public Health 18 (2021) 271.

[48] J. Kelly, M. Karlsen, G. Steinke, Type 2 diabetes remission and lifestyle medicine: a position statement from the american college of lifestyle medicine, American journal of lifestyle medicine 14 (2020) 406–419.