Toward Enhancing Diabetes Self-Management with Personalization Through Human Digital Twins for Behavior Change

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Abstract. Patients with type 2 diabetes need to adhere to a healthy lifestyle to prevent suffering from short-term and long-term escalations. A key aspect of treatment is to supplement educational content with techniques for behavior change. Unfortunately, introducing change and maintaining it is notoriously hard. We explore a novel approach to personalization in the context of Human Digital Twins (HDTs), that facilitates a bidirectional data flow between patients and their digital counterparts. While current mHealth tools show potential, there is room for improvement in incorporating the concept of such twins and considering the complexity of behavior change. We developed a novel architecture that enables mHealth tools, through the lens of the Transtheoretical Model of behavior change, to focus on multiple stages of change and personalize functionalities based on an HDT model that is trained more holistically. Our modular HDT is made of three subcomponents: a health literacy model, a daily activities model, and a model of the user's player type. Our primary contribution is the demonstration of its relevance and feasibility toward the application of personalization for behavior change in patients with diabetes.

Keywords: Personalization · Diabetes · Self-management · Human Digital Twins · Behavior Change · Education · Health Literacy

1 Introduction

Diabetes is a prevalent chronic metabolic disorder that affects around 422 million people globally. It is characterized by elevated blood glucose levels that can cause long-term damage to vital organs [23]. Diabetes demands patients' proactivity

* Implementation of personalization through the incorporation of levels in the knowledge test tool based on one's health literacy level.

in their daily lives by being active, eating healthy, taking medication, and self-monitoring their blood glucose levels [12]. This proactivity requires patients to be effective at self-management. The self-management of a disease involves medical (e.g., taking medication), behavioral (e.g., adjusting old habits in the context of the disease), and emotional (e.g., dealing with feelings of frustration about the disease) management [8]. One of the most common challenges faced by patients with diabetes are linked to low health literacy (HL) about their condition [13].

Some tools aim to support diabetes self-management by regulating blood glucose levels automatically [5], tracking medication, physical activity, food intake, and promoting healthy behaviors. Despite being costly and challenged by a lack of care personnel, individual educational programs are more effective than programs offered to large classes. In a more scalable and cost-effective manner, edugames and mHealth apps could potentially improve knowledge, disease treatment, and management, thus the ongoing exploration of their potential to facilitate behavior change for good self-management of diabetes [6, 18].

Behavior change is a complex journey, where shifts in mindset and unforeseen challenges lead individuals to deviate from their intended behaviors [20]. An example of such a journey would be the following: An overweight man was advised to exercise more. He joined a gym and lost weight, but eventually dropped out of it due to social discomfort and regained weight. He started a cycle of exercising and dropping out, and, eventually, got stuck into never exercising again. One day, however, he was diagnosed with diabetes and had to suddenly learn how to manage his glucose levels and incorporate healthier habits.

The transtheoretical model of behavior change (TTM) is a theoretical framework for understanding and facilitating behavior change. It considers the complexity and variability of behavior change in its six discrete stages of change and introduces ten processes of change that work as strategies and independent variables that people need to use and adjust to move from one stage of change to the next and make progress [9]. Depending on the stage, certain processes are more efficient than others [9]. This model, "transtheoretical", integrates various psychological processes and principles (i.e., decisional balance theory, self-efficacy theory, cognitive-behavioral theory, and transtheoretical therapy), aiming to provide flexibility across a wide range of behaviors and populations. Individuals can have multiple attempts to transition from one stage of change to another, and the TTM takes the possibility of these attempts into account [20].

Pinpointing the stage of change an individual is in, is the biggest limitation of the TTM [9]. If the stage of change is unclear, it can be a challenge to personalize interventions, monitor progress, and allocate resources efficiently. Using data from multiple stages of change can be used to improve tools suited for other stages of change. This practice will be referred to as "cross-phase learning". Referencing the aforementioned example of the weight loss journey, learning that the man is reserved and felt unable to commit to the changes since they conflicted with his nature can be used to not only improve the interventions when he is in a contemplative stage but also once he decides to take action again. Furthermore, such learning can also be used to improve the new behavior change journey of glucose level management. This practice can potentially enhance the effectiveness of behavior change interventions by personalizing content delivery throughout both different stages of change and behavior change journeys. Personalization, within behavior change, by considering one's self-management skills, wellness knowledge, or education, has been increasingly recognized in fostering sustainable health outcomes [7]. To the best of our knowledge, cross-phase learning is yet to be explored in the aforementioned setting.

One way of achieving personalization is through Digital Twins (DTs). DTs are defined as a real space containing a physical entity and a virtual space including a representation of the physical entity, with bidirectional data flow between both entities that allows for synchronization. Human Digital Twins (HDTs) are a subtype of DTs where the physical entity represented is a human [14]. HDTs can potentially promote behavior change to ease effective self-management of chronic diseases, such as diabetes, which can lead to improved health outcomes and, consequently, improved quality of life [4]. HDTs offer the opportunity to create a real-time understanding of how medical treatments can be improved by behavior change interventions. By monitoring in real-time the effectiveness of such interventions, treatments can be better tailored to an individual's needs [19].

We present a tool, a Human Digital Twin (HDT) system, that serves as the means through which we facilitate the delivery of personalized content, in the form of gamified levels, considering cross-phase learning, to patients with diabetes navigating behavior change in their self-management journey, while also enabling further personalization opportunities in a health-promoting tool.

2 Related Work

2.1 mHealth apps and Edugames for diabetes

To understand the characteristics of available mHealth apps and games that aid the self-management of diabetes, a literature review was performed. mHealth apps built for diabetes can assist self-management by offering features related to monitoring blood glucose levels. Some other characteristics are reminders, educational content and dietary advice, sharing and connectivity, insulin dose suggestions, calculations, social features, and gamification elements. Other mHealth apps, while not diabetes-specific, can still be valuable tools for these patients as they can facilitate dietary control, medication tracking, or physical activity monitoring. Our inclusion criteria considered mHealth apps that were updated from 2020 onward, that have been involved in trials or scientific studies, and that offered, at least, one tracking feature. Out of the 22 mHealth apps found, 10 met our inclusion criteria. While some of the apps claim to offer personalization, we failed to identify explanations or clarifications on the applied strategies.

Similarly, many edugames have been created to educate patients with diabetes about their condition in a fun way. The inclusion criteria considered those released or updated from 2013 onward that have been involved in trials or scientific studies. Out of the 31 edugames found, 11 met our criteria. From these games, gamification elements, feedback mechanisms on the player's performance on topics related to diabetes, real-life simulations, integration with real data, social interaction by allowing multiplayer mode or social features, parental involvement, personalized features, and individual models, could be identified.

2.2 HDTs architectures and considerations

To develop an HDT, an exploration of relevant literature on proposed architectures and considerations was undertaken to establish a robust foundation.

There is a meta-model that describes both DTs and HDTs grounded in systemics [15]. The meta-model emphasizes the importance of considering both the environment of the twinned system and the environment of the DT itself. A DT system comprises machine-executable or interpretable models describing relevant aspects of the twinned system, the DT, and their environments. Data, including data storage, interfaces, and specialized functions, are integral components. Furthermore, the DT system is introduced as an aggregation of physical systems and DTs with a specific objective. On another note, the HDT inherits properties from the DT and relies on a human model composed of aspect models that formalize dimensions such as physical, physiological, cognition, behavior, personality, emotion, mood, motivation, and ability.

An architecture based on other established architectures for DTs has also been proposed [11]. It includes a unique ID, data of the represented human, models of the represented human, definition of relations with other DTs and between models. HDTs also require different interfaces, namely for co-simulation (and determining the behavior of an HDT in interaction with a DT, or the other way around), data acquisition, and models and data accessibility, considering access rights and security measures due to the sensitive nature of this content.

3 Methods and Materials

3.1 HDT Tool Architecture and Component Selection

To enable a more transparent and modular development of HDT-based personalization techniques, we conceptualized an architecture that combines a *health promoting tool*, *educational tool*, and *knowledge test tool* to demonstrate the novel concept of "cross-phase learning" in an HDT. We describe the architectural components and tools we selected for the sake of prototyping.

GameBus (Health Promoting Tool) GameBus is an mHealth platform designed to aid in the creation, execution, and assessment of a wide range of health promotion campaigns. It offers a customizable app that can be used to turn existing perceived obligations for cognitive, physical, and social tasks into a gaming experience. It also rewards teams for playing together, even if the activities among players differ, in a personalized gaming experience [22]. Moreover, the GameBus platform allows the embedding of mini-games in its framework and enables in-game actions to be rewarded within the platform. For that, it offers various game mechanics (e.g., points attribution, leaderboards, levels, and loot boxes) and 'social media'-inspired functionalities (e.g., likes and comments for one's activities, teams, and chats).

SugarVita (Educational Tool) SugarVita is an educational virtual board game, designed for educating newly diagnosed patients with diabetes [3]. SugarVita simulates the day-to-day challenges that diabetic patients face during their lives. The goal is to keep the blood sugar levels in a healthy range for as long as possible [3]. For the envisioned HDT, player behaviors within the edugame should sometimes be based on the patient's actual behaviors, but by default, such behaviors are now selected randomly.

SugarVita integrates E-DES, a scientifically developed blood glucose level simulator that provides real-time blood glucose level based on carbohydrate ingestion, physical activity, medication consumption, and stress [1].

Finally, the game offers various gameplay options (i.e., solo play and multiplayer interaction). In our HDT vision, the edugame should take into account patient preferences and such preferences may also be learned from patient behaviors outside SugarVita (e.g., through interactions within a tool like GameBus). While SugarVita is embedded into GameBus as a mini-game, it does not yet personalize its educational journeys based on data from other apps or games.

Trivia Quizzes (Knowledge Test Tool) Educational tools like SugarVita could help model user literacy, however, they should also enable safe experimentation with unhealthy choices to learn about their potential impact more safely than experimenting in real life. Consequently, lifestyle choices within educational tools like SugarVita do not always reflect a patient's HL faithfully. Therefore, our HDT includes a separate knowledge test tool in the form of quizzes.

Several questionnaires are available to evaluate an individual's knowledge and numeracy skills in the context of diabetes. The GameBus platform includes a generic framework for including other games modularly. In particular, it enables the inclusion of other web-based games via its "mini-game" framework [22]. We cloned and updated an already existing Trivia mini-game that enabled us to test any type of knowledge through a Trivia Quiz [21]. Our updated Trivia includes quizzes based on common knowledge tests as well as questions from diabetes specialists in our network.

3.2 Mathematical Modeling of HDT Parts

This section describes briefly how we could combine data from the educational tool (i.e., SugarVita) and knowledge test tool (i.e., Trivia) to build a user-specific profile of player preferences and HL. In previous work, we have also demonstrated how player preferences can be derived from data of a health-promoting tool [16].

Data can be extracted from SugarVita (e.g., score, playtime, and actions) and provide insights into a player's behavior and what is valued within a game, which can be interesting for personalization purposes [10]. Data stored in GameBus from SugarVita was mapped into features for three player types (PTs) (i.e., competitive, explorer, and social). A mathematical model prototype was developed to quantify these PTs, acknowledging that a player can embody multiple types. Features underwent normalization using a MinMax scaler and were mapped into the three PTs, with assigned weights reflecting their significance to each type. The resulting scores were calculated using a weighted average.

HL involves the skills required to access, comprehend, assess, and effectively use health information to make informed decisions. In our approach, HL was considered to be partly based on patient behaviors in an educational tool like SugarVita and complemented with a knowledge test tool. Similar to the PT scoring, the extracted HL features were normalized, assigned weights, and computed through a weighted average. Nevertheless, there was a need to integrate a fairness factor, to adjust imbalances as positive and negative weights were assigned to the features. In the end, three different HL scores were available: one from the educational tool, another from the knowledge test tool, and a grouped one.

4 Results

We developed an HDT prototype, represented in Figure 1, that outputs up-to-date information on the player's characteristics and HL level by incorporating data from both an educational tool (i.e., SugarVita) and a knowledge test tool (i.e., Trivia). A user can choose to play SugarVita, as presented in Figure 2, or play the developed Trivia mini-game, as presented in Figure 3, through two different possible paths: with or without hints. Nevertheless, for the player to be able to use hints, points must be earned first. These are rewarded by playing SugarVita, answering correctly to Trivia questions (without hints), or performing other relevant activities (e.g., related to physical activity or nutrition) within GameBus, as demonstrated in Figure 4. While the user benefits from these tools, in the background two models are profiling the player's preferences and HL levels that are constantly being updated, which enables integration of personalization.

When players play SugarVita, they must follow a predefined path in the tile game, as presented in Figure 2. However, in this pathway, there are moments where players have the freedom to select, for instance, from three distinct paths (i.e., work-related, outdoor, or home-based paths). For example, if a player chooses a work-related path, the feature "number of times a work-related path was chosen" will increase. Currently, we have assigned a weight of 0.5 to that feature for the social player type but a weight of 0.1 and 0.05 for competitive and explorer, respectively. That means when a player does work-related activities their player type becomes more social since it has a higher weight compared to the other types. A list of all features and their assigned weights is available online [17]. Markedly, as new data is generated from SugarVita sessions, the scores for each player type (and HL level) will be dynamically adjusted.

When playing the Trivia game, a player faces questions from one of three difficulty levels, tailored to their HL level. This personalization is achieved through three distinct question databases, each with a specific difficulty level. The player's HL level is determined by an HL score attribute obtained from the HDT, accessible online. This score influences the Trivia game's selection of the appropriate question database. Additionally, with a script that generates the three levels of Trivia, we successfully adapt the game's content to match the player's level.

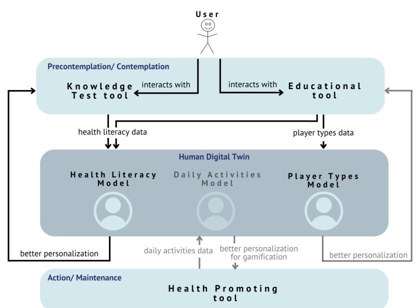

Fig. 1. Realization status of the HDT prototype. The grayed-out arrows and elements are beyond our demonstration of relevance and feasibility.

Listing 1.1. An example JSON response of the HDT API call that returns scores for HL (overall, Trivia, and SugarVita), and player characteristics (competitive, explorer, and social).

```
{
  "health_literacy_score": {
    "domain": {
      "name": "diabetes",
      "score": 0.5842929875077731,
      "sources": {
        "sugarvita": 0.8501221664178091,
        "trivia": 0.4070735349010824
      }
    }
  },
  "player_types_score": {
    "competitive": 0.1827407627244398,
    "explorer": 0.26896275411782167,
    "social": 0.020774595637334917
  }
}
```

Fig. 2. A screenshot of the SugarVita edugame.

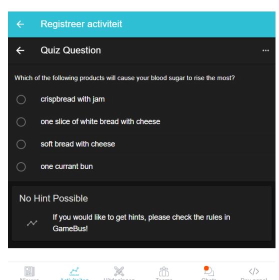

Fig. 3. A screenshot of Trivia.

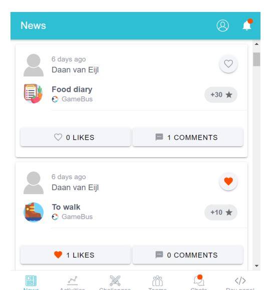

Fig. 4. A screenshot of Lifestyle data in GameBus news feed.

5 Discussion

Our key contribution is showing how diabetes-related tools can be integrated modularly within a novel type of HDT for personalized content delivery. The different tools have characteristics that can trigger specific processes, enable cross-phase learning, and enhance progression, as outlined in the TTM. Importantly, using one tool can impact all others, as they all access the separately hosted API for the HDT. Our results are an initial step toward HDTs that can effectively accompany individuals through their behavior change journeys.

Even though the three components that we have integrated largely serve as examples, our work does contribute also to using HL more explicitly in behavior change interventions regarding chronic diseases. For that, we have introduced a Trivia mini-game to assess an individual's level of HL about diabetes. This method incorporates verified or developed by professionals in the field questionnaires, offering a unique dimension to the assessment process.

Furthermore, our HDT system is also transparent on how the models operate, from detailing the data sources, the nature of their outputs, to the rationale behind their functionality. Such transparency aims to foster trust among users, differentiating our system from others that claim to offer personalization without explanations of their methods. Nevertheless, there is a need for a more in-depth assessment of the features extracted. This step will provide a deeper understanding of their effectiveness and how they contribute to behavior change. Additionally, although a method for calculating user characteristics and HL scores has been presented, such an approach is not essential to user modeling but rather an example of how such modular infrastructure can be exploited and leveraged to facilitate modeling. On another note, there is potential for enhancing the system by incorporating not only different ways of modeling but also more types of models, such as the Daily Activities represented in Figure 1.

6 Conclusion

We attempt to address the dynamic nature of behavior change by introducing a pioneering HDT system that draws data from diverse data sources spanning various stages of behavior change at the same time and profiles the users into competitive, social, and explorer, while also assessing their HL levels. With access to this continuously updated information, it is possible to constantly fine-tune personalization (e.g., adjustments in the educational or knowledge test tool).

This paper establishes a proof of concept for an integrated HDT framework for the delivery of personalized content in a diabetic's patient behavior change journey, that can be extended to other domains as well. Our contribution paves the way for future exploration of cross-phase learning and offers a promising direction for enhancing the effectiveness of behavior change interventions, in particular, a more promising self-management of diabetes, by understanding users' preferences and using it toward personalization.

7 Future Work

To reinforce the data-driven insights on the PTs and HL score from SugarVita, GameBus properties can be enhanced so more features can be extracted (e.g., differentiating if a user is playing against a digital profile or real players), enabling better analysis of the user's profile. Further research regarding the relevance of the features can also optimize the reliability of the HDT.

As presented in Figure 1, the Daily Activities model based on data from GameBus has not yet been developed, however, could contribute to a more comprehensive HDT. Furthermore, exploring the use of GameBus' social and competitive elements (e.g., likes, leaderboards, etc.) and integrating such data into the PTs model could lead to valuable insights. We envision competitions across clinics where each strives for the best results, for instance, regarding diabetes HL. This approach ignites inter-clinic competitions and encourages cooperation among patients from the same clinic, ultimately enhancing the HL journey for all and positively impacting intrinsic motivation and performance [2].

Lastly, the insights gained from HDT results could be explored for more personalization within the different tools (e.g., a less social player might experience a customized GameBus interface, where features such as 'likes' remain hidden).

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[4] Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the EU or the European Health and Digital Executive Agency. Neither the EU nor the granting authority can be held responsible for them.

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