Is there an Optimal Technology to Provide Personal Supportive Feedback in Prevention of Obesity?

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***Abstract*— Obesity is a global challenge that affects health and wellbeing worldwide. In this position paper, we review the digital technology used in prevention of obesity and present the proposed STOP project that integrates state-of-the-art wearable technology, chatbot, gamification data fusion, and machine learning with the aim to provide personalised supportive feedback for preventing obesity and maintaining healthy weight. Implication of sensitive data with General Data Protection Regulation (GDPR) is discussed. We conclude that machine learning plays an important role in data fusion, analytics, and providing optimal messaging tailored design to support healthy weight.**

Keywords*— *obesity, prevention, machine learning, chatbot, gamification, data fusion, supportive personalised feedback

I. Introduction

Obesity is defined as having excessive body fat and this excess is conventionally indicated by a Body Mass Index (BMI) of 30 or more. Although there are other, more direct, measures of body fatness, BMI is widely accepted as a de facto standard for estimating body fat and a method for screening weight categories. Associated to obesity is the concept of overweight, indicated by a BMI between 25 and 30, which frequently ends up in obesity. Many studies include overweight as associated to the problems inherent to obesity.

Obesity is a serious problem in most developed countries and now also in developing countries. Recent estimations indicate that about 1,8 billion people are currently overweight and about 650 millions of them are obese. Worldwide, it is estimated that over 115 million people suffer from obesity-related problems[1]; and the percentage of population suffering obesity nearly doubled between 1980 and 2008. According to the WHO, around 51 % of the European Union countries' population aged 18 and over are overweight and 20% (men) to 23% (women) are obese[2].

While efforts have been made to promote healthy living and prevent obesity or overweight, it still remains challenging to provide effective personal feedback to maintain healthy weight. In this paper, it will be discussed the applicability of recent technology in the light of the *STop Obesity Platform* (STOP) project. The STOP Obesity project is being developed to support people with obesity (PwO) by offering improved access to information on better nutrition habits, under supervision of healthcare professionals. In this paper, we firstly review the related work in weight management using digital technology in Section II. In Section III, the proposed STOP platform is presented. Section IV discusses the implications of sensitive data processing followed by summary to conclude the paper.

II. Related work

Some studies have been done on the effectiveness of weight management programs. Kerri identifies some key points to take care [1]:

A. There should be a behavioural component that addresses behavioural change on the user (helps individuals to modify what they eat, their activities and their thoughts about excess weight).

B. There should be a process that encourages self-monitoring of individual data. This helps people to identify a behaviour that would be positive for them.

Another study compared three different approaches to deliver weight loss program [2]: by Facebook posts (material + videos), by Facebook posts + feedback, and by waiting list control. The study suggested that the more persuasive components were involved, the better the weight loss results.

In the market, there are a lot of solutions that have a good success. One of them is called "**iBitz**"[3]. This app is addressed for children and has an active connection with a fitness tracker named "**iBits Kits Pedometer**". The steps that are counted from the tool has a feedback in the app as rewards in a gamification approach. The more activities the

1 https://www.who.int/nutrition/topics/obesity/en/
2 http://www.euro.who.int/en/health-topics/noncommunicable-diseases/obesity/data-and-statistics

3 http://geopalz.com

children do, the more points they gain. The points are converted into different rewards on the basis of the parents' preferences.

Another important success story is about the app for iOS and Android named "**Habitica**"[4]. This app is a free habit-building and productivity app that treats the user life like a game, in a gamified approach. Inside the game, the app provides rewards and punishments in order to motivate the user, applying a social network that amplifies this motivation. The app is very simple and easy-to-learn, with a minimal interface. The aims of the app are to assign some goal achievements in order to become healthy, hard-working and happy. Habitica app is not only addressed for health or fitness purposes, but it involves all the elements of the live, from the daily home-works, to the reading of a book, or the time-slot for free time and friends.

Another relevant app is called "**My Diet Coach**[5]". This app provides a virtual coach that assists the user in the daily diet. One interesting aspect of this app is related to the use of pictures to represent the "old" user and the "new" user in order to motivate who are using the app. In addition, the app proposes to use to collect pictures, that are useful in a second moment for a comparison with the subsequent shape.

However, none of them are interoperable with an overall support platform and therefore, all of them work in isolation creating a management overhead on the side of the user who has to deal with a growing number of non-interoperable Information and Communications Technology (ICT) applications. Besides this, these applications fail to employ interoperability with state-of-the-art fitness sensing hardware as well as cutting edge user interface paradigms like, e.g., conversational chatbots and applied games. Besides this, a lot of actions exist in the market which could benefit from ICT support in many forms. This ICT support would become interoperable, if a unified platform would exist. Finally, they do not cover the full scope of possible support dimensions yet.

III. OVERVIEW OF THE STOP PROJECT

According to a 2016 Lancet publication [1], there are now more overweight or *People with Obesity* (PwO) globally than normal weight people are, with one in eight of the world's adult population classified as obese in 2014. Wherein, Obesity is defined as fat accumulation leading to a *Body Mass Index* (BMI, is a simple index of weight-for-height that is commonly used to classify overweight and obesity in adults. It is defined as a person's weight in kilograms divided by the square of his height in meters (kg/m2)[6]) of 30 or more. If projected to 2025, global obesity levels are set to reach 18% in men and surpass 21% in women. The cost of obesity is estimated at $2 trillion - equivalent to 2,8 per cent of the world's economic output, the study found. In fact, obesity is a major risk factor for a number of chronic diseases, including diabetes, cardiovascular diseases and cancer, whereas the work on obesity care related topics is highly connected to further urgent health related challenges. STOP is a H2020 RISE project funded by European Commission to address the challenge of preventing obesity.

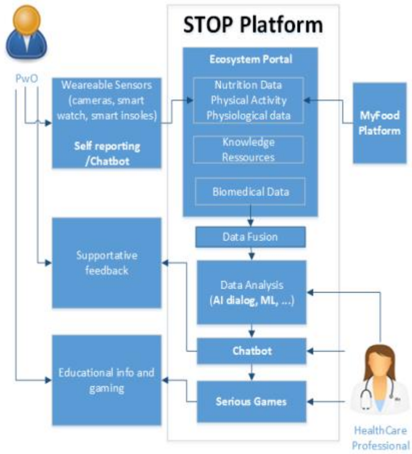

Figure 1: Overview of the STOP platform

The STOP project aims to establish a data and knowledge ecosystem as a basis for the STOP portal to enable healthcare Professional in decision support and PwO's in analysis and feedback of health information to optimise healthy nutrition. This includes exposed interfaces to capture additional personal exercise and nutrition information and provide intelligent interactive communication with users, besides access to information from a broad range of relevant knowledge bases to support decision making of Healthcare Professionals. To reach this goal we aim to develop a secured multiclient web-based portal, integrating several Machine Learning (ML) based support tools.

A. Data Collection

Data used in this study include 1) physical activity data collected by wearable sensors such as fitbit wrist bands, smart watches, and smart mobile phones; 2) nutrition information provided retailers and self reporting; 3) physiology information, such as BMI, heart rate, blood pressures by measurement; and 4) other self-reporting data, such as physical activities that are not recorded by sensors, feedbacks.

B. Data Fusion

The STOP platform foresees the transmission of sensor data from wearable sensors into the platform, in order to analyse PwO health data history to provide supportive feedback. A broad range of available devices could act as a sensor. In STOP we will only apply, these sensors that capture data of a person that suffers from obesity and could be used for the creation of supportive feedback (e.g. physiological data). However, it is considered to use sensor data from different devices (e.g. a smart watch and insoles)

4 https://habitica.com/static/home
5 https://apps.apple.com/us/app/my-diet-coach-weight-loss/id552341639

6 WHO (2018) Obesity and overweight Factsheet. Available at: http://www.who.int/mediacentre/factsheets/fs311/en/

producing data of the same type (e.g. heart rate). Hence, the managed data within the STOP portal comes from distributed sources and are inherently of heterogeneous nature. To use these data, e.g., for generation of supportive feedback it first must be cleaned and fused on the signal level into a consolidated measure. Next, features could be extracted and a Feature Level Fusion (FLF) takes place. FLF in STOP is useful for, e.g., activity (e.g. lying, sitting, walking, or running) classification. Various ML techniques have been applied in this task already, like k-Nearest Neighbors (KNN), Decision Trees, Support Vector Machine (SVM), or Neural Networks incl. Deep Learning. For our work in STOP, multiple data streams from physical activities, captured by fitness sensors, will be fused. E.g. a smart watch (acceleration or heart rate), insoles (timing, balance, pressure, force, heart rate). The data will be *pre-processed* (e.g. deal weak signals and distortions), in a *Signal Level Fusion step* measures of same type (e.g. two heart rate measures) coming from several sensors, combined into a consolidated measure. Finally features will be extracted to recognize activities. As first results, the *Real World Data* [3] dataset will be used, for an initial requirement analysis and prototypical development. As a result we consider as minimal pre-processing steps resampling (adoption of the sampling rate), segmentation (decompose input in independent timeslots), and interpolation (replace missing values). Fusion implementation of pre-processed data will be first tested by simple weighted average and threshold based approaches. On gained insights more specific tests with more elaborated techniques as e.g. ML models will be implemented. For better interpretation and later validation of fused data we will furthermore investigate on strategies to implement as well a semantic integration (or semantic fusion) approach. This will attach further relevant contextual metadata (e.g. time of capturing, used sensors, applied cleaning, and fusion configuration and implementation) to the fused result.

C. Gamification

Gamification can be referred to as the process of using game elements like rewards, penalties, and competition, in a non-game environment in order to increase user's engagement. The impact of gamification systems in order to improve the target's motivation to execute some kind of tasks has been widely proven: Users involved into a gamification environment are not only more motivated, but also more engaged and more satisfied [4]. In particular, the applications of gamification techniques that aim to intervention on overweight obese children, adolescents, and adults provided effective results on 11 studies over 12 [5].

Since gamification seems to increase the overall usage experience of the system, it will be included into the STOP platform. Features will include progress bars, badges, rewards and leaderboards. Social role systems are important to keep the interest alive and has been proven that people's performances increase in a social competitive environment. We believe that introducing elements like data comparison and sharing, cooperation and competition, will help the users to reach their final goals.

D. Knowledge Resources

As for any weight-loss program, the STOP platform will be able to propose different diets to the final user. To do this, the MyFood (https://myfood.okkam.it/) dataset will be integrated into the platform. The database contains the information in different languages, as English, Italian, German, and Slovenian, about 13,500 dishes that are built on the base of 4,200 different ingredients with allergen information provided. The nutritional fact information will be extracted from the USDA Food Composition Database (https://ndb.nal.usda.gov/ndb/). The MyFood database comes with its own food ontology and knowledge base, a knowledge graph composed of entities, attributes, and constraints, connecting ingredients, products, producers, dishes, locations, and nutritional facts.

For dieting purposes, ML can be used to cluster foods and receipts into different groups in order to give to the STOP final user the possibility to map diets based on what best suits their preferences. This field has been widely studied by Ruan and Shao [6] using Support Vector Machines (SVM) and CNN with very high accuracy. In particular, the high precise categorization of the food will allow the STOP platform to automatically build diets for people who have specific allergies, who have religious and cultural limitations, or who follow particular lifestyles.

The STOP platform will update its data frequently in order to become more complete and precise during the time. The main problem in introducing new information in an existing system is the possibility to create duplicates. To avoid this, a component that is able to recognize if two entities refers to the same concept like the Okkam Entity Name System (ENS [7]) is required. The concept behind the ENS is that, given any representation of an entity, check if the entity is already available in a repository. If so, the entity will be updated with new information, otherwise a new entity is created. All data in the STOP platform will be treated as an entity, from users to devices, to food and receipts, in order to be able to merge the same concepts to a single unique entity. ML can support the ENS in its decisions and can be helpful to complete the missing entity information on the base of the one extracted from similar entities doing some inference on the data.

During the period of activity of the STOP platform, other kinds of knowledge, such as user activities and system logs, will be collected, processed, and visualised. This will be done with high performance modern technologies such as Elasticsearch[7], Logstash[8], and Kibana[9]. Monitoring can be really helpful to analyze what features are most used, what users like and dislike. Analysis of "in the wild" user log data has been carried out in other healthcare projects which provided key insights into usage patterns of healthcare apps and services [8]. A Health Interaction Log Data Analysis

7 https://www.elastic.co/products/elasticsearch
8 https://www.elastic.co/products/logstash
9 https://www.elastic.co/products/kibana

model has been developed to guide the workflow of user log analysis and entails data cleaning, preparation, modelling and evaluation phases. Descriptive, inferential statistics, and time series analysis can be used to reveal temporal patterns over hours, days, and months. Fourier analysis can be used to understand and extract frequency patterns. Moreover, whilst unsupervised ML (clustering) can be used to discover user types (archetypes), supervised ML can be used to predict these user types using features extracted from initial user interaction logs [9]. Daily activity information can be used (through ML techniques) to predict the long term success or failure of single users weight-loss program and, if necessary, correct the user's behaviour or propose different solutions. This kind of prediction has been studied by Xue et al. [10] who tried to predict obesity status using user's activity data using linear regressors and Recurrent Neural Networks (RNNs). Platform logs can also be analysed through ML techniques in order to detect system anomalies [11] using decision trees.

E. Chatbot and supportive feedback

Current solutions tend to generalize the obesity problem, proposing the same plan to each PwO. It is well known that each obese or overweight person needs to be treated differently with specific work plans. Emotions form the pillar of our social lives. People's ability to understand and express emotions allows them to form deep social bonds, navigate their social environment and pursue their goals. The basic emotions are discrete from one another, which makes it possible to analyse them more exactly.

Chatbots are becoming increasingly popular as a human-computer interface. The year 2016 was described as "The rise of the chatbot" and major companies including Microsoft, Google, Amazon, and Apple have all developed and deployed their own "personal digital assistants" or "smart speakers" which are platforms for chatbots (also known as voicebots). Interacting with a chatbot is arguably more natural and intuitive given that it is like human-human interaction when compared to conventional methods for human-computer interaction. Moreover, given that chatbots integrate with popular social media platforms such as Facebook Messenger[10] or Skype[11], users are not required to learn new unfamiliar interfaces or even download an app. Chatbots are intelligent systems capable of simulating conversation. Although intelligent systems have existed in one form or another since the 1960s, it is only in the last ten years or so that their popularity has increased. One of the potential selling points for chatbots is the fact that they are conversation-driven as opposed to being mouse-and-pointer-driven as is the case for conventional graphical user interfaces. As the vast majority of interactions with chatbots will be text- or voice-based, the user interface will therefore be very rudimentary, consisting of little more than a text entry box, chat window and a "send message" button in the case of software-based text-driven chatbots such as WoeBot, iHelpr [12] and WeightMentor [13]. Digital personal assistants or "smart speakers", such as Amazon Echo or Google Home will usually be controlled by little more than a microphone, loudspeaker, volume controls, and a mute button.

Natural language processing (NLP) is the brain behind the chatbot. Currently, there exists a variety of different NLP providers. They have different toolsets for making chatbots but the examples that will be discussed here are based around a system of utterances, intents, and entities. An utterance is the name given to whatever the user enters to the system. For example, "can I book an appointment this Thursday?" could be a user utterance for a chatbot that books a doctor's appointment. Intents are what chatbots are made up of. They refer to what is meant by the users' utterance i.e. their intention. The example utterance above could be part of a Book_Appointment intent. Entities allow information to be derived from an utterance by using intents. In the Book_Appointment example intent a required entity could be set that is the day of the appointment. The utterance would be parsed to find a day and, in this case, would see Thursday. Now the bot would know to look for an appointment on Thursday and could go about finding any free slots on that day. In the event that the user does not specify a day, the user could be prompted by the bot to ask for the missing entity. This is a rather simple example, but it highlights the basic structure of NLP systems that will be talked about here. In this section, two different NLP provider options are compared so that the reason why Dialogflow was chosen over Rasa can be highlighted.

Replika is a conversational agent (chatbot) that was created "by Eugenia Kuyda and Phil Dudchuk with the idea to create a personal AI that would help you express and witness yourself by offering a helpful conversation." There is no particular end user in mind here instead this bot asks questions of its user in an attempt to "get to know" them so that it can have meaningful conversations with them. Woebot, similar to Replika, is a chatbot focused on learning more about the user. However, while Replika is about gaining an AI companion, Woebot focuses more on helping its user to manage their mental health, something that will be quite useful when working with dementia sufferers. It makes use of cognitive behavioural therapy (CBT) techniques to guide its users towards improving themselves.

An intelligent use of chatbot technologies can be helpful in order to provide specific information requested by the users. This chatbot will be built up with the AI-based approach in order to be able to change its behaviour according to different users and program steps.

The proposed intelligent chatbot will integrate the data collected and interpret the user's emotion to provide tailored feedback. will avoid some common errors and choose the right design features:

- Prevent:
  - o What are called "limbo" situations, where the uncertainty takes control of the dialog flow;

[10] https://www.messenger.com/

[11] https://www.skype.com

- tedious, monotonous, and boring conversations (or stateful conversations that never change during time);
- pretend to substitute health professionals or doctors.

- Nice to have:
    - Reinforcement learning → the ability to accept user's corrections over time to improve suitability of responses;
    - NLP processing in order to be able to read human text and understand sentences;
    - entity recognition to be able to understand that the analysed text is talking about an informative abstract category;
    - ML to learn how to respond to a user by analysing human agent responses;
    - intent recognition to be able to "guess" what the user is requesting (even if phrased unexpectedly);
    - dialog management to follow conversation history.

IV. Implications of Sensitive Data Processing

To provide a PwO with supportive feedback, the analysis of various kinds of personal information is required to monitor energy intake and expenditure and the impact to the weight management. Actually, there are two collection points foreseen during the project to capture personal data:

- A *Feasibility Study* (FS); the system will be used by subjects for one month (30 participants) to test the ease of use and to validate that the system is functions as per the design. This feasibility study will inform the sample size calculation for the randomized controlled trial.
- A pilot *Randomized Controlled Trial* (RCT); this trial will determine the effectiveness of an intervention. The purpose of this pilot RCT will determine the effectiveness of the newly developed system for overweight and obese adults to lose weight. This will last for three months with two-arm trial: 1. Intervention (n=20) and 2. Controlled (n=20).

However, new GDPR regulations are strict about processing personal data to various aspects. Like transparent and traceable data processing, anonymization, and data availability. Therefore, the STOP project consortium will collaboratively evaluate and document all data and data processing activities in a Data Management Plan (DMP), which will become the basis for a successive Data Protection Impact Assessment. STOP's DMP considers the four agreed decisions:

1. STOP is focused on physical health and wellbeing (e.g. overweight, minor obesity), but not physical illness related to obesity (e.g. diabetes or depression), hence STOP human subjects and chatbot/gamification users are not medical patients;
2. consortium decision to opt out of the EC Open Research Data pilot at contract negotiation stage;
3. raw and experimental STOP data such as user spoken dialogues with chatbots/gamifications will not be stored and managed long-term and certainly not after the lifetime of the project;
4. only three types of STOP data are stored and managed long-term by only two project partners in respect of Chatbot/gamification operation (Chatbot/Gamification Dialogue Management Action Plans, Chatbot/ Gamification Domain Knowledge, Chatbot/Gamification User Profiles).

To evaluate the ethics risks related to data processing activities within the STOP project, first, a detailed documentation of the background data and the related technological resources, that existed before the STOP project kick off and that will be brought to the project by the consortium partners, will be collaboratively identified and documented. Secondly, the same will be done for all foreground data/technology that is expected to come into existence during project duration of the project. Based on the results in this DMP, a detailed description of personal data protection and security measures will be set for all registered resources.

In addition, an Ethical Procedures Manual will be established during the early stages of the project. This will define all ethical procedures to be followed during interaction with any project participants, including users, researchers and staff of public places used for piloting, members of the public, etc. None of the research procedures to be used in the project will be invasive. Ethical issues may arise in the following areas of the project:

- Dealing with data breaches.
- Dealing with secure transmission of PwO data from connected health services.
- Dealing with PwO medical history.
- Dealing with data storage.
- Dealing with data analysis issues.
- Dealing with dissemination.

All individual studies involving primary data collection will receive ethical approval from an appropriate ethics committee, such Ulster University Research Ethics Committee. This research will be conducted adhering to GDPR 2018 and Data Protection Act 2018.

V. Summary

The decision on the application of ML approaches in the STOP project is challenging because of the nature of data types and data volume. However, the rapidly advanced ML techniques have demonstrated that its many advantages in healthcare and wellbeing, which will contribute to the success of the STOP Obesity project. The combination of all these ML approaches, from data collection, fusion, analysis, knowledge management, conversational agents to gamification systems, can concretely help in finding personalized solutions to improve patient lifestyle. Finally, an overall STOP privacy and data protection guideline must be in placed in order to work with sensitive data.

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