Wearable Computing for Health and Fitness: Exploring the Relationship between Data and Human Behaviour

Hänsel, K; Wilde, N; Haddadi, H; Alomainy, A

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Wearable Computing for Health and Fitness: Exploring the Relationship between Data and Human Behaviour

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NATALIE WILDE, Queen Mary University of London
KATRIN HÄNSEL, Queen Mary University of London
HAMED HADDADI, Queen Mary University of London
AKRAM ALOMAINY, Queen Mary University of London

Health and fitness wearable technology has recently advanced, making it easier for an individual to monitor their behaviours. Previously self generated data interacts with the user to motivate positive behaviour change, but issues arise when relating this to long term mention of wearable devices. Previous studies within this area are discussed. We also consider a new approach where data is used to support instead of motivate, through monitoring and logging to encourage reflection. Based on issues highlighted, we then make recommendations on the direction in which future work could be most beneficial.

Additional Key Words and Phrases: Wearable Technology, Pervasive Sensing, Behaviour Change, Health Monitoring

1. INTRODUCTION

Within the health and fitness sector, the use of wearable technologies is a relatively new approach. Examples of health and fitness wearable applications include health monitors, fitness trackers and analysis aids. According to Orange [2014], fitness and medical wearables accounted for 60% of the wearables market in 2013 and it is predicted that the health wearables market will be worth roughly £ 3.7 billion by 2019. The ever growing popularity of smartwatches and fitness bands suggest that wearable health and fitness devices is a trend that is here to stay. The technology associated with these wearable devices is improving at a fast rate. Devices are becoming increasingly smaller and more energy efficient, making them better suited for continuously sensing and giving feedback.

Although the technology is improving and applications are evolving, ensuring long-term user retention is an issue that still remains. The dropout rate of health and fitness wearable devices currently stands at around 85% [Velayanikal 2014]. The lack of efficient data collection, utilisation and feedback may all contribute to the causes of this issue. Advanced intelligent sensing can log an individual's health data efficiently and in real time and can present the users with large amounts of data about their health. However, the meaningfulness of data can have a major effect on a user's behaviour. Poorly presented data or an overload of information can lead to an individual becoming confused and discouraged. This in turn leads to them abandoning their wearable device.

In this paper, we present an extensive survey of different approaches for data utilisation from wearable and mobile technology with regards to fitness and health behaviour change. We explore examples and studies of wearable devices used to promote health and wellness. We then point out different methods of utilising an individual's data to support positive behaviour change.

The rest of this survey is organised as follows. In Section 2, we focus on using data to encourage behaviour change through motivation and persuasive techniques, using gaming and social aspects to achieve this. We outline several psychological aspects and theories which surround technology driven behaviour change and present related projects. In Section 3, we focus on different approaches of data presentations to influence a person's behaviour. This includes the contextualised and adaptive presentations, as well as cognitive supporting ambient displays. In Section 4, we explain a more modern approach where data is used to support and facilitate human health behaviour. We outline studies conducted where data from wearable technology can support intrinsic driven behavioural changes. By analysing studies that have already been carried out in these areas, we highlight the challenges posed for the future of wearables in Section 5. Finally, in Section 6 we suggest areas and directions for future work that we feel would be beneficial to the field.

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2. PERSUASIVE WEARABLE TECHNOLOGIES FOR BEHAVIOUR CHANGE

Previous uses of health sensing data have shown it to have the power to drive behavioural change. Wearable applications can harness this power if they present data to the user in an effective way. One common aim of the wearable ecosystem providers is to create and maintain positive behavioural change for individuals. When looking into behavioural change, motivation is a key factor to consider. Nevid [2012] describes the term motivation as the *factors that activate, direct and sustain goal directed behaviours*. He further describes *motives* to be the needs or wants that drive behaviours. Motivation has the power to cause a person to start more healthy activities but also to continue and repeat these activity routines. If there is a lack of motivation or it is not used in the correct way, this can lead to opposite effects in an individuals behaviour [Arteaga et al. 2009]. This section outlines two of the biggest data utilisation methods used to create motivation; gamification and social influence.

2.1. Gamification

Gamification is a common way to motivate behavioural change. It refers to taking game design elements and applying these within other contexts. For example, rewarding an individual with *game points* if they eat healthy food for a day can motivate them and help develop a specific type of behavioural outcome [Deterding et al. 2011]. Gamification is a new concept and the exact origins are unknown. Pelling [2011] first used the concept of gamification within commercial devices. The main aim of his consultancy *Condura* was to incorporate gaming methodologies into businesses. Fogg [2002] describes the *Pocket Pikachu*, one of the first wearable devices that utilised gamification to become persuasive tool. The simple device includes a pedometer to measure the step count of the wearer. This data is then translated into game points which help the Pikachu to grow. Robson et al. [2015] state that presenting data and utilising it within a gaming context works well in encouraging behavioural change because it taps into an individual's motivational drivers; particularly their intrinsic motivations which is behaviour driven by internal rewards. Engaging motivation arises from within the individual because they enjoy the behaviour and experience it as rewarding [Cherry]. A comprehensive review by Seaborn and Fels [2015] highlights future directions in gamification research.

2.1.1. Motivational Affordances. Wearable applications utilise motivational affordances and gamification to motivate intrinsically. This includes emotionally positive stimuli like the use of badges, leader boards and challenges. Based on Hamari et al. [2014], the points system claims to be the most commonly used method. Bleecker et al. [2007] created a mobile based game *–MobZombies–* incorporating wearable sensors. The sensors provide accelerometer data which is used to move the virtual avatar. Physical movement by the player within the real world are translated into moves within the game. The main aim of the game is to run away from the zombies and collect points through body movement. Rewarding the player with points utilises features that the user is already familiar with and presenting data in this way ensures that the user gains instant gratification and motivation.

An issue that most of the motivational affordances have in common, is the *clouding* of the actual data. Health data is not directly presented to the user and the focus is on the rewards and achievements. There is evidence, that the removal of the gamification elements can have a negative impact on the usage of a system [Thom et al. 2012]. This indicates that the behavioural change is strongly connected to the presence of game elements. Further research is needed to establish long-term health behaviour outside of the game world. Furthermore, there is evidence that a special personality type prefers a certain motivational affordance and that applications should take this into account [Karanam et al. 2014].

Payton et al. [2011] developed a mobile game to reduce sedentary lifestyles in college students. *World of Workout* motivates the player to increase step count in small amounts throughout the day. The user can define a goal they wish to achieve and the mobile phone application generates suitable *quests* for the player to complete. The user's step count is calculated by using the *iOS shake event* and is then related to the set goal. Rewarding feedback is provided to the user when a goal is reached. The game was found to have a positive effect on participants, with players finding it fun and enjoyable to play. Feedback from other players suggested that they would enjoy a feature to share their data outside of the game. This could include the possibility of posting achievements on Facebook or Twitter.

Other wearable devices have also looked at levering extrinsic motivation. Brown [2007] describes extrinsic motivation to be where an individual is motivated by external factors. This can be by earning tangible rewards such as money or psychological rewards like praise. An example of a device that utilises rewards is the *Mymo*. Developed by *Tupelo*[1], the activity tracker allows users to cash in their steps to earn rewards such as mobile talk time and airline miles [Velayanikal 2014]. But other studies suggest that the use of extrinsic motivation may have flaws. Greene and Lepper [1974] state that when an intrinsically motivated task, such as drawing for children, is rewarded externally, it can be harmful. It leads to people expecting external rewards all the time and can have a detrimental effect on the individuals intrinsic motivations.

2.1.2. Social Incentives. Harnessing the power of others is important in gamification. Ali-Hasan et al. [2006] state that single player games can lead to the user feeling isolated. To avoid this, some gamification strategies include social incentives. There are two main incentives used – competition and cooperation. Competition can be created by comparing data of two users against each other within an application. In 2010, Clawson et al. created a mobile game where players have to dance in time to get points. Two people wear wireless sensors around their ankles that contain accelerometers to measure movements. This data is then translated into game points. Clawson et al. concluded that comparing an individual's data to others within a gaming context can heighten the motivation to dance more and get physical active.

Ali-Hasan et al. [2006] discusses *Fitster*, a mobile social fitness application that incorporates large scale competitiveness. It includes an online dashboard which contains the daily step count and activity data of the users friends. The application accommodates the light-hearted competition that can take place between befriended groups to motivate physical activity. The application is socially oriented and takes this further by allowing users to actively challenge another member to walk a set amount of steps within a given time. The introduction of timing can apply pressure for the user to perform specific behaviours. Although this may not make it as enjoyable, it may increase motivation.

The second social incentive is cooperation, where users can merge their data together to achieve or succeed within a gaming context. Ahtinen et al. [2010] created and trialled *Into*; a social mobile wellness application. In the application physical activity data from individuals all merges together. This then aims to encourage physical activity in all group members. The game contains virtual trips between cities in the world made up of step count goals. The player and their group can work together to achieve a goal and gain rewards whilst travelling around the world virtually. The social aspects of the application and the merging of data were found to be beneficial for users.

But which social incentive is the most influential? Chen and Pu [2014] noticed that many games focus on the competitive element of gaming. They developed a mobile application to find out which social incentive is most influential and observed how players reacted to data presented in three gamification modes. This included competition, cooperation and a hybrid of the two. The application included a messaging service, allowing pairs of users to talk to each other. Users could communicate either to help, support or to taunt one another. The aim of the game is for the users to input data in the form of step counts to fulfil a daily step count goal. The amount of steps that the user has to do is dependant on the group mode set up. One hundred percent is the need in competition mode and 50/50 in cooperation mode. Results showed that all modes caused people to increase their daily activity but cooperation was more powerful than competition. The most popular messages sent between users were of encouragement as opposed to taunts.

2.1.3. Real versus Virtual Worlds. More recently gamification has started merging data from the real world with the virtual world within the game. Mobile games developed by Macvean and Robertson and Chuah et al. in 2012, created virtual game maps using location and movement data from the phone to bridge the gap between the real and gaming worlds. The user must physically move around their environment to earn rewards. The audio augmented *Zombies, Run!*[2] game motivates runners by playing zombie noises through the headphones while they are on a run. These noises are supposed to create the immersive feeling of being hunted and motivate the user to run faster.

Freegaming by Görgü et al. [2010] is an interactive game using augmented reality through the users mobile phone camera. It places information and directions over real life footage of buildings and landmarks as the user views them in real time. The aim of *Freegaming* is to motivate outdoor exercising. This is achieved by presenting data about the user's status and environment itself in an immersive way. Based on this information, the app suggests workout routines to the user. As a result of the study, the author suggests that presenting data within an familiar environment can have an influence on an individual's behaviour. For example, if they know the running route and the rough distance in advance, it may convince them more than going into it blindly.

[1] www.tupelolife.com/
[2] www.zombiesrungame.com

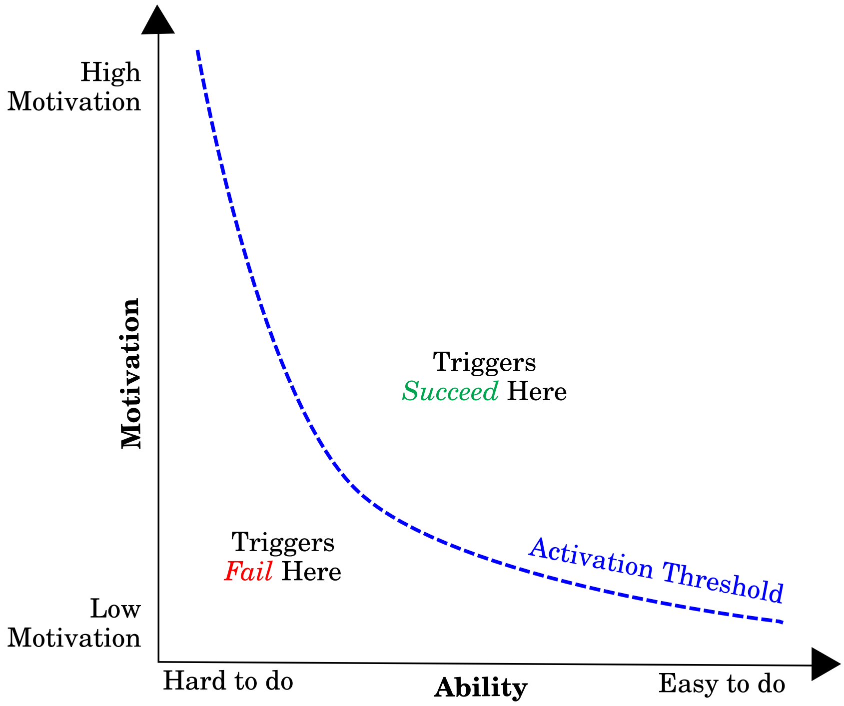

Fig. 1. Foggs Behaviour Model (Adapted from [Fogg 2009])

2.1.4. Foggs Behavioural Change Model. Data within a gaming context can change behaviour in a positive way. It achieves this by linking the motivational affordances used to behavioural outcomes. These are then fed back to the player through the outcomes of the game. Hamari et al. [2014] state that earning rewards from achieving exercise goals leads to enjoyment. This acquired enjoyment could lead to them doing more physical exercise each day. The use of gamification places the user right at the centre of the ecosystem. Their own self-created data becomes their motivator.

The behavioural change model described by BJ Fogg [2009] can provide answers on how gamification works (Figure 1). The model states in order for an individual to carry out a specific type of behaviour, three things need to be present at the same time. Firstly, the individual must believe they have the ability to carry out the behaviour. They must also have the motivation to carry out the action and they must receive a trigger to do so. Gamification aims to increase motivation through use of points, leader boards and rewards created from data. The trigger to carry out behaviour happens whilst the player is in the game itself. Nobody wants to lose and this triggers people to carry out the actions.

2.2. Social Influence

Social influence means having the capability to have an effect on another humans behaviour. Motivation is an internally generated motive to do something. But influence comes from external sources, as a result of interacting with others [Rashotte 2007]. For example, recommendations by friends likely lead to an desire to try out or buy the same thing. Instances like this sway our own ideas, actions and behaviours on a daily basis. Ledger and McCaffrey [2014] state social factors to be important for our health. Social connections with others are a basic need as food and shelter. There is strong evidence to suggest that our behaviours are shaped by the behaviour of our family, friends and even the people we work with.

Social influence can also be a key factor in the adoption of new health behaviours. Intille [2004] explains how an individual's behaviour can reflect that of their peers. Sticking to a diet can be easier for the individual if they have friends that also engage in healthy behaviours. Having friends that eat bad foods around you can cause unwanted temptations. Various wearable applications offer the functionality to share health data through online social networks. This allows competition or comparisons to happen between all members of the social group. This can lead to members of the group reflecting upon themselves and wanting to change their behaviours [Ananthanarayan and Siek 2012]. There are many different types of social influence, outlined below. For each of these types, data is manipulated in a different way, as explained.

2.2.1. Normative Influence. The first type of social influence utilised in wearable devices is normative influence. Asch [1951] explains how normative influence causes an individual to alter behaviour. An individual conforms to a groups social norms in order to be liked and accepted within the group. Within wearable applications, a type of informal conformity called *social proof* is often used [Aronson et al. 2009]. Developed by Cialdini and Garde [2006], social proof explains how, in times of uncertainty, an individual observes the reaction of others. They will then base their own behaviours upon their observations. Chang [2012] created a social food journalling application called *Food Fight*. The mobile application allows the user to take pictures of the food they eat and share this with other app users. *Similarity* is one of the factors that increases the effectiveness of social proof [Cialdini and Garde 2006]. We are more likely to be influenced by people we believe to be similar to ourselves. User's goal data is used within the *Food Fight* app to match people that have similar goals. The pictures that the users share become part of a timeline called the *food feed*. Within this timeline other users can vote up pictures that they like. As most of the users on the app aim to eat healthy, this means that the most popular images are usually healthy foods. If an individual is unsure of what to eat for lunch they may look at popular up voted images for ideas. This may influence them to try healthier options if they see it is a popular choice.

Another factor that increases the effectiveness of social proof is *authority*. If an individual believes the information to be coming from a reliable and trusted source they are more likely to conform to it. Buttussi and Chittaro [2008] created *MOPET*, a mobile personal training application. The application takes in real time data about its user from wearable sensors. Analysed data is then used to present health and safety advice to the user. This advice comes from a personal trainer, which is visualised to the user via a talking 3D embodied agent. The belief that the information comes from a real personal trainer, can have an effect on how influential the information is. The user may be more likely to change their behaviour if they feel the advice is from a knowledgeable source.

2.2.2. Social Comparison. Another type of influence, proposed by Festinger [1954], is the theory of social comparison. It describes an individual evaluating their own opinions and abilities by comparison to others. This happens to reduce uncertainty and supports an individual learning to define themselves. In the wearable ecosystem this can mean comparing user data within a group. It can also include representing information in a way to encourage comparison to peers and promote self reflection. Lin et al. [2006] utilised social comparison to create a computer game called *Fish'n'Steps*. Within this game, the users wear pedometers which collect their daily step count. A higher step count leads to the growth of the user's animated fish character in the game. Social comparison comes into play when many players place their fish within the same bowl. This encourages the players to look at the growth of the others fish compared to their own. Presenting the step count data in this manner had a positive influence on the activity levels of the participants.

Bandura [2001] explains a similar theory called Social Cognitive Theory (SCT). SCT explains how we do not learn only from our own experiences, but from also observing those around us. Success of a friend losing weight by using an activity tracker could become driver for us ourselves getting the same tracker [Ledger and McCaffrey 2014]. Anderson et al. [2007] uses a wearable mobile device as a health promotion tool by utilising a groups collected data. *Shakra* calculates the daily exercise levels of users from the measured movement data. These daily exercise levels are then shared amongst the group of friends. The study found that this sharing of data was perceived positively by the participants. It helped them to reflect more upon their own exercise level data and encouraged behavioural change. If an individual finds that their friend with a figure they perceive as desirable is more active during the day, this may lead to the friend becoming a role model with an influence on the own behaviour. After reflection, the individual may choose to start walking more in hope to achieve a similar weight.

Social comparison has been shown to be a successful driver for health behaviour change, but there can be negative implications on a person's wellbeing and interpersonal relationships. These implications include decreased happiness [Lyubomirsky and Ross 1997] feelings of guilt and lying to others [White et al. 2006].

2.2.3. Social Facilitation. Zajonc et al. [1965] describe social facilitation, a type of influence where an individual's performance can be improved by the mere presence of others. This includes working with others within a team or by having an audience. Audience effect within wearable applications may involve sharing fitness data and goals with others. Sharing goals on social networks like Facebook increases the likelihood of an individual changing their behaviour to what they feel is acceptable because they feel a sense of commitment [Ledger and McCaffrey 2014]. The fear and guilt of letting others down by not achieving goals is a main driver of behaviour modification. Lim et al. [2011] created *Pediluma* which is a wearable device strapped to the user's foot. It takes the user's step count and maps it to a flashing LED light. The more steps the user takes, the more the device will flash. Social influence drives the decision to present data in this way. The ambient manner used to display the data results in the public becoming an audience. The individual may adjust their behaviour to ensure the data presented to the public is promoting a positive self image. The study found the device to increase the amount of daily steps taken. Public commitment was important in data representation with regards to changing a person's behaviour.

Zajonc et al. [1965] explain another type of social facilitation called co-action which describes the effect on the own performance when other people are carrying out the same task. Toscos et al. [2006] created an app called *Chick clique*. The application aims to motivate teenage girls to exercise more, through use of their fitness data. Data presented in the application levers the power of social relationships to bring about behavioural change. The app includes a leader board of each group members daily step counts. This encourages the girls to talk about health and fitness with each other and allows the application to become a persuasive social actor. Other wearable applications encourage co-action by motivating groups whilst they are physically together. Mauriello et al. [2014] designed and built a set of wearable, electronic textile displays. These displays support a group of people while they are running. Important running data obtained from sensors is displayed on e-ink screens attached to the back of the runners t-shirts. Their studies concluded that they improved motivation within the group and utilised social facilitation well. Karau and Williams [1993] also state that group members work harder on tasks if they perceive their contribution as instrumental to the desired team outcome. They will also work harder if they feel their peers are monitoring them.

The use of social awareness can increase the effectiveness of co-action techniques. Presenting other's data to the user allows them to sense other members feelings and perspectives and raises the awareness. This can lead to an individual having an active interest in others and how they are doing. Burns et al. [2012] created *Activmon* which is a wrist-worn device. Members of a group all wear the device and it contains a custom-built square LED screen. The device monitors each user's step counts. On the device, LEDs light up to correspond with the percentage obtained of the user's daily goal. The device displays the whole group's achievements on an ambient display. This allows the user to see how the group is doing as a whole but also individuals. Displaying other member's data can encourage an individual to become interested in how other members are performing. This encourages group motivation which could lead to behaviour changes within the whole group.

2.2.4. Social Impact. [Nowak et al. 1990] describe the theory of social impact which presents three factors that affect the amount of social influence. The first factor is*number of sources* for the influence. As the amount of people providing data increases, so does the influence exerted on each individual. This is evident in traditional support groups. The second factor is *strength*, which refers to the perceived importance of the feedback source. The more trusted the source providing feedback are to someone, the more likely they are to influence them. As mentioned earlier by Lin et al. [2006], *Fish'n'steps* placed many individuals fish in the same bowl. Family members fish were more influential than strangers when placed in the same bowl.

The last factor is *immediacy*, the closeness of the group both in time and space. Wearables open up opportunities for people to share data with others and be within the same shared digital space. Online social networks provide great opportunities to create these digital spaces. Lu and Lemonde [2014] developed an app called *UOIFit*. The mobile application aims to increase levels of activity amongst adolescents. The app collects fitness data of each of the users and shares this data to everyone through a *fit feed* tab. The app also allows users to exercise with each other remotely. This is an example of creating digital spaces for collaboration through data. Studies conducted into the app found social aspects to have a positive impact on an individual's behaviour. It increased the users' activity level and lowered their Body Mass Index (BMI).

2.2.5. Wearable Computers as Social Actors. Fogg [2002] talks about wearable technology becoming a social actor itself. He outlines the possibility of communicating with a wearable device becoming a more social experience for the user. Wearables themselves may be able to lever social influence. This social influence may persuade individuals to change their behaviours. Fogg highlights cues that can lead to a wearable becoming a persuasive social actor, the first of which is physical cues. The more attractive the interface of a device is to the user, the more of an impact it will make on the user (e.g. [Sonderegger et al. 2014; Chang et al. 2014]). The way that data represented aesthetically makes a great difference with regards to influence.

The second cue is psychological cues. This involves making the user believe that the application possesses emotions and feelings like a human. As Lin et al. [2006] showed, *Fish'n'steps* represents the collected activity data in the form of a fish avatar growing. This representation works well in developing a persuasive relationship between the user and their data. But as found in the study it can also have a negative effect on the user's behaviour. The user would feel responsible for the avatar when it was not growing or looking sad. This feeling of guilt would lead some people to avoid the application as they did not want to see an unhappy avatar.

Language is another cue, this can involve the application asking questions. Wearable applications can offer praise which is common among health and fitness applications. The wearable collected data can be used to determine when praise should be given. Using data to create a conversation with the user is important in influencing long term behaviour change. Arteaga et al. [2010] created an application which uses a talking head to communicate motivational phrases and advice to the user at appropriate times. The use of a talking head made the application more anthropomorphic. This was perceived positively in studies and found to make a difference. Bickmore et al. [2008] conducted studies looking at virtual agents and how they were able to influence health behaviour change in more depth. The virtual agent talked to the user but also included non-verbal behaviour and facial expressions to communicate messages. These messages were based on data collected from the user. The agent was part of an application designed for use in the office. The application suggested short breaks to the user at timed intervals. Studies found that the more social the conversational agent was to the user, the more rests they were likely to take. Visualising data to a user in an empathetic way may encourage long-term compliance with new behaviours.

3. WEARABLE DATA REPRESENTATION

In current wearable applications, visual representations and methods of feedback are the most common way to communicate data to the user [Ludden 2013]. The way in which the raw data is processed and manipulated before it is presented to the user, plays a big role in how influential it can be. One of the issues raised by researchers in the health and personal data space is provision of meaningful data to the users and enabling Human Data Interaction [Haddadi et al. 2013].

Current step counters, pedometers and their accompanying applications struggle to provide long-term behaviour change. The users are still aware of the data provides of these devices, but it is not perceived as so meaningful and influential after six months [Ananthanarayan and Siek 2012]. Data representations need to emphasise the importance of being healthier in more intuitive and meaningful ways.

3.1. Adaptive and Contextual Data

Adaptive and personal data representations can be a powerful tool to deliver meaningful information from wearable devices. An individual's health and fitness is a personal issue to them, so the way of presenting the data should be just as personal. By making the representations user adaptive, a personal experience for each user can be offered. Intille [2004] conducted a study that looked into utilising just-in-time messaging of health information. The presentation of contextualised information at important decision times within the user's day proved to be effective and previous studies show that just-in-time persuasive interfaces can influence behavioural change.

A context aware system is able to tell what the user is doing from utilising and analysing sensor data. It can then use this to make motivational suggestions at specific, influential times in the day. Intille [2004] had four rules which they believed helped the data representation to be effective. The first rule was to keep the data representation as simple as possible. This ensures the user understands the data that's displayed to them as clearly as possible. Other rules include displaying data at appropriate times and in the appropriate place. This is to make it as easy as possible for the user to refer to the data within their day-to-day life. If the data representation is irritating to the user this can lead them to ignoring the device altogether.

Gockley et al. [2006] created a wearable device that contextualises sensor data. *Aviva* tracks the users' and their close friends' eating and exercise patterns. A wrist-worn, watch-type device shows the feedback to them. It aims to display qualitative and holistic data to the user, not just simply numbers from sensors. Experts suggested that displaying lots of raw unexplained data can lead to the user becoming discouraged [Gockley et al. 2006]. *Aviva* displays personalised, contextualised suggestions. For example, the user could be notified to 'eat a bag of nuts' as opposed to just telling them they 'need more protein'. This contextualising of data can be more persuasive when getting an individual to change their behaviour. Another way to contextualise data demonstrated by Macvean and Robertson and Chuah et al. in 2012. They suggest to give recommendations specific to the user's location. Making an application location aware can lead to it being more entertaining for the user as they feel they can relate to the data more easily.

Previous studies have shown personalisation to be an important factor for device usage and adaptations. Studies outlined by Ananthanarayan and Siek [2012] have shown that users want to create their own system to access their data. Users do not like having to use a predefined default form that everyone else uses as it does not feel personal. Ananthanarayan et al. [2014] developed

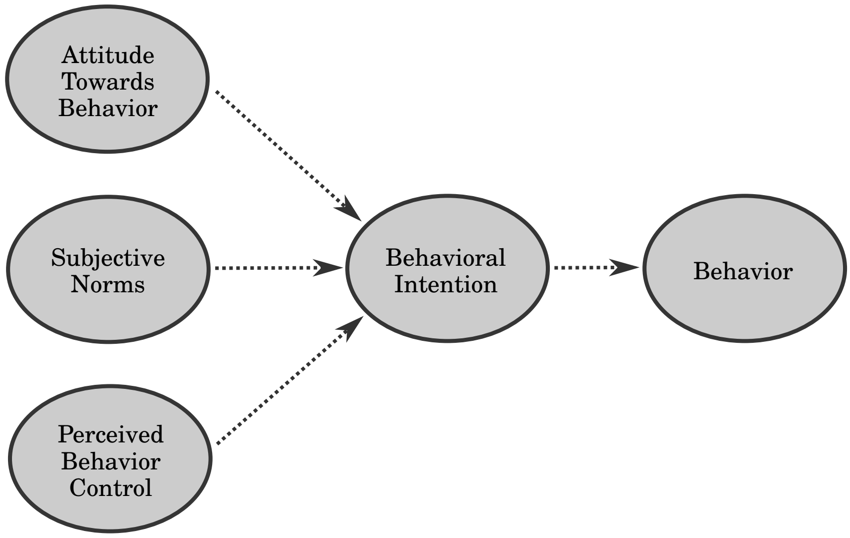

Fig. 2. Theory of Planned Behaviour

another wearable to look into the effectiveness self-crafted devices. The device the users could create held a set of sensors that tracked an individual's UV exposure. They found that people received the device well with people attaching it to their bags or even wearing it as an headband. Another device developed by Ananthanarayan and Siek [2010] looks into raising health awareness in children. They wanted to motivate them to think about their behaviour. It had a personalised build-it-yourself approach to the fabrication of the devices. All the components the device contained were *plug and play* in style. The children could attach components to a leather bracelet, including sensors and displays for feedback. The LED display changed colour dependant on the amount of exercise the child had done that day. Allowing individuality for data representation and form factor may make the device more meaningful to the user. This is because they feel they have created it so it may be more influential than a standard generic form.

3.2. Theory of Planned Behaviour

When thinking about how best to personalise data representation to make it as persuasive as possible, the Theory of Planned Behaviour (TPB) could be considered (Figure 2). Created by Ajzen [1991], TPB states that intentions are the best predictor of how an individual is going to behave in certain situations. For example, if we plan to do something we are more likely to go through with it. Three factors produce an individual's intentions to perform a specific behaviour. These are their attitude, subjective norms and perceived behavioural control. Behavioural attitude refers to how the individual feels about the behaviour. This includes affective attitudes which describe whether they feel they would enjoy doing it. Also, instrumental attitudes refer to whether they feel a behaviour would benefit them. Contextualising health data to make the user aware of the benefits may have an impact on the user's behaviours. Subjective norms deal with the support that we get from our friends, family and even the doctor. Injective norms involve others encouraging specific behaviours. An example of this is a friend making you go to the gym. Descriptive norms involve others actually engaging in a specific behaviour. This would involve your friend actually going to the gym with you. Wearable ecosystems have adapted the social aspect of sharing data to address these social norms. The final factor is the extent to which the individual believes that they can carry out the behaviour. This is influenced by how the data is presented to them. If a task sounds easy, an individual is more likely to engage in it.

Arteaga et al. [2010] developed a mobile phone application that considers TPB within its design. The app aimed to change an adolescents behaviour and get them to exercise more. They wanted to achieve long-term behavioural change as opposed to the short-term changes that other fitness games were producing. To design data representations that are engaging for teenagers, the system incorporated TPB principles. To stop the user getting bored of the game they decided it needed to take their personality into consideration. Everyone's preferences are different so they created a game that assesses the person's attitudes. Based on this assessment, it would suggest games that would be the most motivational and beneficial to them. Adjusting data representations around an individual's attitudes and personal traits can lead to stronger intentions for behavioural change.

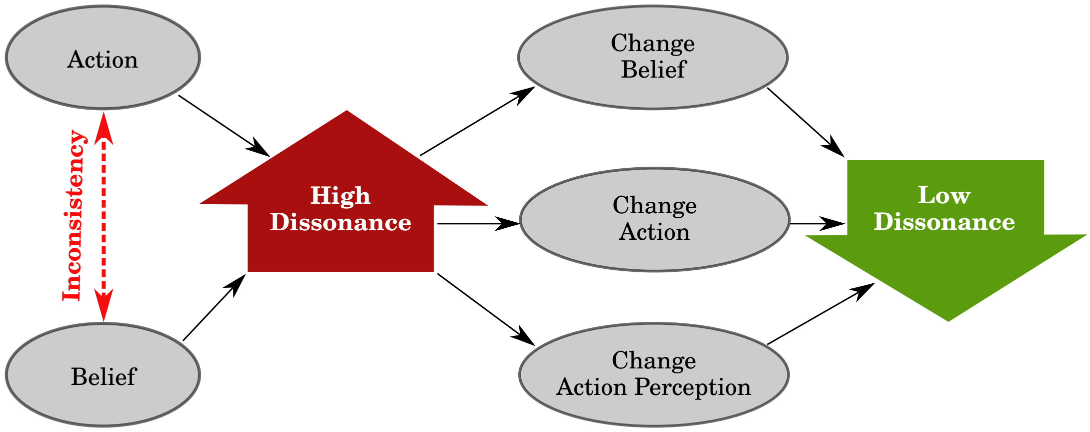

Fig. 3. Cognitive Dissonance Theory

3.3. Ambient Displays

We mentioned before that the way of presenting the data from wearable sensors to the users plays an important role in supporting long term health promotion. The displaying of numbers and figures may not be enough to encourage behavioural change. Fogg [2013] describes anecdotally how this may not be enough on its own. He owns a pair of scales which tweet out the weight to his Twitter account every time they get used. Although this automated process was supposed to motivate through social facilitation, it was not motivational to him and he did not pay much attention to it. The scales barely attracted his interest and therefore did not encourage him to want to lose any weight. Ananthanarayan and Siek [2012] state that wearable technology has the capacity to track difficult metrics such as heart rate. But there are questions around exactly what value this data has in motivating change. The subtle and ambient presentation of the data can be a key to motivate and subconsciously trigger a behaviour change.

When presented with a lot of complex information an individual can lack the cognitive capacity to process it. Ham and Midden [2010] show that ambient displays can be more persuasive because they do not require the user's conscious attention and use little cognitive resources. Studies conducted have found that the use of simple displays for information have more effect on an individual's behaviour than displaying numerical values. Modern health wearable devices have started to harness the power of using ambient ways to display data. Consolvo et al. [2008] developed an early example of such an application. *Ubifit* is a mobile application that includes a glancable display. This display is a non-literal representation of the physical activity that the user has done. It also represents the goals that they have achieved. The display contains a metaphor of a garden and the user gains more flowers by exercising more. They gain butterflies in their garden for achieving goals. The application collects data from sensors on the users body. It then analyses the data to change the aesthetics of the garden display throughout the week. From studies they discovered that participants did find the display motivating. They agreed that the metaphorical representation of their data helped them to focus on their goals. Lin et al. [2012] presented another similar application called *BeWell+*. The metaphor of fish within a fish bowl is used. The more fish it shows, the more physical and socially active the users have been. It also gives feedback on sleep quality by changing the light in the underwater world. This application gives unobtrusive feedback whenever the user glances at the screen of the phone. This subconsciously promotes healthier behaviour and wellbeing. Fortmann et al. [2014] created *Waterjewel*, a wrist worn device which aims to influence the user to drink more water throughout the day. It has a light up display that indicates to the user how much of their daily goal they have already achieved. The device also flashes every 2 hours as a nudge to tell the user to drink more water. Studies conducted with the device found it was successful in promoting healthy drinking behaviour. Users did drink more water when wearing the bracelet then when not.

3.4. Cognitive Dissonance

When thinking about the reasons that ambient ways of data representation are effective, cognitive dissonance theory (CDT) offers some insight (Figure 2). Created by Festinger [1962], cognitive dissonance theory refers to situations that cause a conflict for an individuals attitudes, beliefs or behaviours. As humans we have a inner drive to keep all three of these in harmony. Contradiction can lead to discomfort which causes the individual to change their behaviour to restore the balance.

Using displays and feedback techniques can also present data in a way to get the user to think of the long-term effects of their current short-term actions and cause the contradiction effect.

The *Fatbelt* created by Pels et al. [2014] is an example of CDT in action. The device looks into utilising isomorphic feedback to get the user to think of the consequences of their behaviours. The user wears the device around their waist. It uses physical feedback by inflating around the users stomach when they consume too many calories. This simulates the long-term weight gain associated with overeating. In tests the device contributed to a significant decrease in calorie consumption from the user. The use of data in this way leads to the user feeling that the device is an extension of their own body. This gives the wearable more emotional power over the user and their behaviour. Zhang et al. [2013] created a similar device which uses augmented reality glasses to represent potential UV damage on the users skin. It discouraged them from staying out in the sun too long as was also found to encourage healthy behaviour.

Both techniques made the users more aware of the future consequences of current unhealthy behaviour. This makes them feel uneasy about continuing the behaviour.

3.5. Triggering Habits

Presenting meaningful data to the user is encouraging in promoting behaviour change, but presenting it in a way to compliment behavioural change processes is the most effective method to use. Fogg [2013] suggests behavioural change is systematic. He also suggests that motivation is not enough to sustain long-term behaviour change. Fogg created *Tiny Habits*, tiny life changes that become automatic. For example he decided to do two push ups every time after he went to the toilet. He increased this slowly everyday until he was able to do 20 pushups a day. Wearable applications and the presentation of data should not place importance on motivating the individual. They should instead accommodate letting the natural processes emerge. He quotes that an application can *'plant a seed in the right spot and it will grow without coaxing'*.

Rajanna et al. [2014] created an application called *Step up life*. The application uses the suggestion of small contextually suitable activities at regular intervals. *Step up life* promotes brief bursts of physical exercise after periods of inactivity. It does this by sending data in the form of on screen nudge reminders. Suggesting small behaviour changes to the user leads to the incorporation of these changes into the users daily lifestyles. The changes seem easy to do by the user so they are more likely to lead to long-term behaviour change than setting up unrealistic goals.

4. SUPPORT OF BEHAVIOUR CHANGE

Methods of using wearable device applications to drive behaviour change have proven to work well in previous research. But the feasibility of such methods in ensuring long term retention is an area that needs further research. Recent studies focus on using the data that wearable technology provides to support individuals with behaviour change. Fogg [2013]showed concerns about technology focusing on *motivation* for behaviour change for the western culture. He believes that systems that *support* behaviour change would be much more successful in the long term. Similarly, Deci [2012] states in his TED talk: 'Don't ask how we can motivate people. That's the wrong question. Ask how we can provide the conditions within which people can motivate themselves.' Wearable products are starting to support instead of drive behaviour and are utilising data with the aim of influencing our inner abilities to change behaviour.

4.1. External and Self-Monitoring

This section focuses on the use of wearable technology to monitor health and wellbeing. These aspects can be monitored by the user themselves or by an health professional such as their doctor. We shortly outline sensing technologies used to provide health related data. We then focus on the use of data for self-reflection which can help improve self-understanding. This increased self-understanding can lead to an individual making changes in their everyday behaviours.

4.1.1. Health Monitoring. The increasing accuracy and portability of health monitoring sensors is promoting less obtrusive data collection and enables long term health monitoring[Pantelopoulos and Bourbakis 2010]. There are many examples where wearable technology is used successfully in monitoring an individuals recovery from illnesses and rehabilitation [Patel et al. 2012]. Data provided by wearable devices allow this monitoring to happen remotely. An example of this could include a medical professional being able to monitor patients without them having to be in the hospital. This is advantageous because the patient can benefit from healing at home. Being at home is more comfortable for them and this can lead to improved healing compared to a recovery in hospitals. Remote monitoring also cuts costs for the healthcare system because hospital stays are shorter.

Table I. Common wearable sensors and example applications

Sensor	Measurement	Examples
Accelerometer	Is usually used to determine movements and activity by measuring the acceleration.	— Activity monitor: [Clawson et al. 2010; Bulling et al. 2014] — Movement execution in rehabilitation: [How et al. 2013; Nerino et al. 2013] — Habit tracking (smoking, food intake): [Lopez-Meyer et al. 2013; Amft et al. 2005] — Sports performance: [Spelmezan et al. 2009]
Stretch sensors (textile)	Stretch sensors are flexible sensors that change conductivity when stretched or bend.	— Measure angle of joints in rehabilitation: [Shyr et al. 2014] — Movement of the chest to determine respiration rate: [Qureshi et al. 2011]
Piezoelectric sensors (textile)	Piezoelectric sensors measure force/pressure applied to them	— Tracking of hits Taekwando [Chi et al. 2004]
Heart Rate sensor (ECG or PPG)	Heart Rate sensors can be used to measure the activity of the heart, which gives indication on health, energy expenditure or arousal levels. It can be measured with Electrocardiograms (ECG) or Photoplethysmogram (PPG)	— For more accurate calculation of Energy Expenditure: [Altini et al. 2013] — Fetal monitoring with special belt: [Fanelli et al. 2013]
UV sensors	Sense the amount of UV light	— For warnings when there is too much sun light exposure: [Zhang et al. 2013], Ananthanarayan et al. [2014]
GPS	GPS is used for localisation	— Used to contextualise other data: [Macvean and Robertson 2012] and [Chuah et al. 2012]

Wearable devices bring a wide variety of sensing to detect the amount, type and execution of movements. An overview of sensors and their application can be found in Table I. Accelerometers are devices which determine acceleration data and can therefore detect movements. These sensors are widely used for activity tracking [Garcia-Ceja et al. 2014]. They can be present in either in mobile phones or body-worn devices. Accelerometers form the basis for data collection in many commercially available activity trackers. Utilising Accelerometer data can identify activities such as walking, running, eating and drinking movements [Amft et al. 2005; Bulling et al. 2014]. They can even detect human behaviours such as smoking [Lopez-Meyer et al. 2013]. A clinician or the individual themselves can analyse the automatically recorded data. Analysis of behaviours and habits can help support a healthy behaviour change by forming a basis for services such as counselling or other intervention methods.

This also brings new possibilities to the physiotherapies after injuries or surgeries. How et al. [2013] created a mobile application called *MyWalk*. The application supports patients who have suffered from a stroke in the past. Step patterns of the wearer provided from the phones accelerometer detect gait asymmetry. If asymmetry exists, it lets them know that they need more training to establish a symmetry in their step pattern again. The mobile app offers different trainings modes and a overall score after each session. The user is able to view their score history to review their improvements. They can also share this score history with their therapist. The data collected from their training at home may help to enhance their physiotherapy sessions. Nerino et al. [2013] focused on the rehabilitation after knee surgery. They used accelerometers to collect data at different positions around the leg. They then used this data to monitor motor functions of the exercising patient. They created an application that included a coaching function, which would suggest exercises. There is also a video conferencing functionality for situations when the therapists is needed. Patel et al. [2012] presents a detailed review of wearable sensors that are currently used for rehabilitation and he especially identifies the trend of using ambient sensing for holistic home health monitoring and the need for a telepresence integrated in home monitoring systems.

Textile sensors and fabrics are other enablers for wearable technology in the healthcare sector. The combination of conventional, non-conductive fabrics with conductive materials have led to new sensor technologies [Marculescu et al. 2003]. These new technologies allow easy integration into textile products and garments. Stretch sensors are an example of these new technology. These sensors are able to collect data that can be used to monitor movements of joints in the body [Shyr et al. 2014]. Qureshi et al. [2011] used knitted stretch sensors to monitor breathing and Rai et al. [2013] used textile sensors to monitor neurological and cardiovascular biosignals. Textile sensors bring the possibilities of flexibility and unobtrusive integration into clothing. Where delicate and soft sensors are required, flexibility can be an advantage. An example of where this is important is textiles for newborn infants. Chen et al. [2010] developed neonatal babywear that measures the temperature of babies using soft textile sensors. The sensors were designed to be aesthetically pleasing but also as comfortable as possible for newborns to wear.

Another use case is the monitoring of health parameters to give the patient peace of mind and contact a medical professional in emergencies. Wearable sensors can be used to monitor pregnant women. Fanelli et al. [2013] monitored the fetal heart rate with a stomach belt. The designed the belt to be easy to put on to ensure it is easily useable at home. This reduces hospital visits during the pregnancy and make the pregnant woman feel calmer. There are several technologies for detecting seizures with wearable technology which could provide data to inform clinicians or family of a seizure. Patel et al. [2009] used accelerometer data and EEG brain signals to detect seizures with a 95% accuracy. The *Human+* platform created by Altini et al. [2011] uses various sensors like EEG, heart activity via ECG and skeletal muscle activity via EMG to obtain data and detect seizures. While these approaches are not very usable in everyday applications due to the use of EEG and ECG electrodes, the MIT Affective Computing group developed a seizure detecting wristband which uses Electrodermal Activity [Poh et al. 2012]. This research formed the foundation for the commercially available Embrace watch[3]. The watch has an accompanying app, which alerts parents or caretakers in the event of a seizure of the child or patient. Additionally it can be used to monitor stress and sleep levels. Wearable technology can be used to monitor behaviour and use the data to gain insight into health states of a person. Madan et al. [2010] looks at the usage of mobile phone data to detect the health status of an individual. The data is analysed to detect health conditions such as colds or depression. This application can form the basis for informing the users doctor of their condition. More broadly available mobile phone sensing can be used for epidemiological studies amongst large populations.

In healthcare it is often necessary to avoid unhealthy situations. Data provided by wearable technology can help identify unhealthy situations and environmental influences. One example is the UV sensing glasses from Zhang et al. [2013]. Too much sun exposure is widely known to be connected to skin cancer. These glasses keep track of the sun exposure and warn the user when they are at risk. Fabrizi [2014] presented a concept for a wearable textile flower. The flower is a visual representation of air quality data and can raise the awareness about unhealthy polluted air.

4.1.2. Quantified Self. The Quantified Self (QS) is a new movement supported by sensing data obtained from wearable devices. QS is part of the Personal Informatics, focusing on tools to support the personal growth and improvement and an individual. QS achieves this through use of technology in data collection and analysis and focuses on collecting data about ourselves with the purpose to reflect. Reflection can increase self-understanding about areas that need improvement in the future [Swan 2013].

Choe et al. [2014] state that health improvements are one of the most reported reasons for self-quantification and especially *activity* is a commonly tracked feature. Commercially available fitness trackers like *Fitbit* or *Jawbone*[4] allow daily assessment of steps and activity. Fitness watches, like the *Atlas*[5] promise the automation of workout logging, which is usually a manual task. It achieves this by using data to identify workout activities and repetitions. The consumer market for self-tracking wearable technology is ever growing. Tools like the open-source *Fluxtream*[6] support self-tracking by providing a platform for data aggregation and visualisation from multiple sources. It also supports the identification of correlations within the data.

Quantified Self can be a powerful tool to gain insights and drive behaviour changes within an individual. But it can requires skills to understand data fully to ensure long-term engagement. Choe et al. [2014] identifies two reasons why self-tracking often fails. One is that too many things are tracked and the effort is relatively high to track these. Automated data capturing and simple tracking mechanisms can ease the burden of tracking. The second reason is lack of knowledge about triggers and the context of the data. This confusion around the interpretation of data makes behaviour change difficult for the user. Self-tracking can be a powerful tool for reflecting and making us more aware of our own daily habits, patterns and performance. But at the current time, it

[3]https://www.empatica.com/product-embrace
[4]www.fitbit.com/ and www.jawbone.com/
[5]www.atlaswearables.com/
[6]www.fluxtream.org/

still requires a lot of effort, engagement and knowledge. Creating tools to ease these hurdles could assist us by identifying our own behavioural and habitual patterns. By presenting this data back effectively it could provide active support for self-improvement.

4.1.3. Sports Performance Monitoring. When it comes to sports, performance monitoring is essential in improving performance or preventing injuries. Using data monitoring can be useful for individual or even group performance.

Strohrmann et al. [2011] looked at the use of shoe sensors to access kinematic parameters of runners. This data can give an insight into the runner's performance and technique. This can help medical professionals and the runners themselves to analyse how effective the training was. The *Sensoria* fitness tracker works in a similar way[7]. The *Sensoria* tracker consists of a sock with textile pressure sensors and an attachable main unit for the data transfer to a mobile app. It can provide data about the performance during a run as well as feedback about the right running technique.

Spelmezan et al. [2009] looked at the use of force, bend and accelerometer sensors to track the movements of snowboarding beginners. The data collected is then shared with their trainers. The data helps the trainer to give more accurate feedback on the movements and technique of the snowboarder. They suggest a system like this could help in the teaching process. Chi et al. [2004] looked at the tracking of movements of Taekwondo players. They used piezoelectric sensors to detect forces applied by hits of the competitor. The system then counts the hits and calculates a score based on this information. This calculated data is then used as feedback for the athletes, trainers and the jury in competitions. Not just the performance of an individual is important. In team sports, the performance and communication of the whole team matters. Technological advances within networks and algorithms allow real-time assessment and remote monitoring of bio-signals within a group of athletes. Garcia et al. [2011] gives an example for using bio-signal sensing to monitor a group of soccer players.

4.2. Encouraging Reflection

Getting users to reflect upon their own behaviour can help them to stay on track. It can also help them to realign if they deviate from a specified behaviour. The visualisation of data is very important when encouraging reflection. [Sanches et al. 2010] developed a mobile application called *Mind the body* which is focussed on mental health and encourages the user to reflect upon both negative and positive aspects of their behaviour. Sensing data on skin conductance and heart rate are used to determine the stress levels of the user. The mobile phone app presents the stress levels in real time. Based on the user feedback during their study, they also offer a history to view past stress levels and support reflection.

Fortmann et al. [2013] conducted another similar study based around visualisation. They created a wearable bracelet device called *illumee*. Studies with the device proved that aesthetics play a major role on the level of impact an application or device makes on the individual. They built the device after considering previous research which stated that data displayed on the wrist is most influential [Harrison et al. 2009]. The device integrates a digital light that represents different aspects of a user's health. Aspects include for example sleep and activity levels. Kocielnik et al. [2013] focused on the long-term stress monitoring at the workplace. They used wristbands to monitor stress levels and combined it with data collected from online calendars to generate an aggregated view for self-reflection. This allowed workers to review the stress levels in different situations at the workplace. Interviews conducted with participants were promising and indicated that workers found it easier to identify stressful factors.

Another method that encourages reflection is by creating lifelogs. The aim of a lifelog is to record various aspects of a person's lifestyle. Gemmell et al. [2006] created one of the first technologies to support lifelogging. *MyLifeBits* creates a complete historical log of documents, websites, and other objects a person has encountered whilst using their computer. Ståhl et al. [2009] created *Affective Diary* which is a digital diary. The application has access to recorded stress data from sensors, mobile usage data, and photos. They present this data in a timeline which contains photos and arousal levels represented by shapes. They found that some users appreciated the application as it helped their self-understanding. Others experienced discomfort because the data shown highlighted bad moments.

But why is lifelogging so effective? A study conducted by Lindqvist et al. [2011] analysed the motivations behind people using Foursquare. Foursquare is a social network used on a person's mobile phone, allowing them to check themselves into places that they visit. They found that motivation to use the application came from an individual's desire to record all the places they have been. Later reflection and having the opportunity to share this data with friends is a key driver

[7] http://www.sensoriafitness.com/Technology

to use the app. To build upon the effectiveness of presenting data in a lifelog, Epstein et al. [2014] utilised the *Moves* mobile phone app[8] which records activity and location data on the phone. They developed *cuts* which focus on a subset of the data with a shared feature, e.g. days with the most physical activity or time to commute by the type of weather at the day. New visualisation offered new insights in the data for the user and were perceived positively.

4.3. Self-efficacy

Self-efficacy is a person's belief in their ability to succeed within a specific situation. Created by Bandura [1977], these beliefs are great drivers of how people think, behave and feel. A person with a strong sense of self-efficacy forms a strong sense of commitment to tasks and likes to master challenges. A person with a weak sense of self-efficacy would avoid challenging tasks altogether. In order to sustain long-term behavioural change, an individual's self-efficacy needs to remain high. Wearable applications are utilising data in an attempt to keep self-efficacy high. The most effective method for maintaining self-efficacy is mastery experiences. If an individual has success and an application makes them more aware of this, it can have a positive effect on their self-confidence. Wearable applications can give rewards when users have achieved their goals. Using data in a way to set realistic goals provides the most effective methods of support for the individual. Using unrealistic and generic goals within a system could set the user on a path where they are likely to not succeed. This can cause more damage than good. The *GymSkill* mobile application involves sensor data logging and activity recognition. The application works for an individual while they are balance board training. They use this to present the user with goals suitable for their ability. In testing users liked the personalised feedback and suggestions. This shows that there is potential for this type of system to support long-term behaviour change.

4.4. Social Support

Data from wearable sensors can be utilised to provide social support to the user. There are many different types of social support, the first of which is emotional support. This is the offering of support in the form of concern, affection and caring from others. This type of support makes the individual feel valued. They also feel that the behaviour they are carrying out is meaningful. Providing emotional support through a wearable interface may be positive in supporting behaviour change. It would be effective because it mimics the support that we get from our friends and family in everyday life.

Another type of social support is informational support. This involves offering advice and suggestions to someone to help them solve problems. Health and fitness wearables utilise informational support through the use of virtual trainers. Freyne et al. [2012] created an application which comprises of a weight management mentor that supports dietary changes. The application would take in data about what the user was eating. It would then analyse the collected data and make suggestions for changes to the user. They created two versions of the application. The full version offered suggestions and pushed these as prompts to the user. The other version was a simple base line application that did not have the pushing feature. The study found that users who had suggestions in the form of prompts sent to them lost more weight than those who were not prompted.

Companionship support gives an individual a sense of belonging. This involves encouraging the presence of others in shared social activities. Mueller et al. [2007] created a wearable device called *Jogging over a distance*. The device uses audio pace cues to allow two people to go on a run together when they were in two different geographical locations. The spatial sound lets the user know whether the other runner is jogging in front or behind them. They found that providing companionship support in this situation was very supportive. Users could find a person to run with of similar experience and at the time of day which was most convenient to them.

Polzien et al. [2007] aimed to investigate support offered through data provided by a wearable compared to support from a human being. Their study compared results of weight loss programs supported by counselling or supportive technology. The technology used was the *SenseWear Pro* wristband. This provided data to the user about their total energy expenditure and sleep efficiency. The study found that the group that used technology lost more weight within the 12 week intervention period. Those who had face to face conversations with a counsellor did not lose as much. Comparing the effectiveness over an even longer period would provide a more solid insight. The study also found that a mixture of using counselling and technology was not as effective as solely using one or the other. Merging computer and human systems effectively in order to support the individual could prove beneficial.

[8]www.moves-app.com

The timing of providing data to the user is an important factor to consider. Patel et al. [2015] suggest supporting new behaviours may be best facilitated by regular, appropriately framed feedback. This feedback should be presented at the times where the user is most likely to notice it. Carroll et al. [2013] looked at a device that senses emotional eating. The collected data is then analysed to find when the individual is most vulnerable to emotional eating. They then provide an intervention to support and stop them straying from healthy behaviours.

Using social support can also increase an individuals self-efficacy, a concept developed by Bandura [1977]. Social modelling is where the individual sees others they consider similar to themselves succeed. This makes them believe they have the ability to succeed, too. Another method used to increase self-efficacy is social persuasion. This is when a person posts an achievement to a social network and their friends and family like it, giving the individual a sense of 'belonging'. Social persuasion strengthens people's beliefs and helps to abolish any self-doubt they may have.

4.5. Biofeedback

Another important topic for supporting behaviour change is biofeedback. Biofeedback involves instant feedback on an individuals own biosignals. Biosignals are any signals within an individual that can be continually measured and monitored. Providing feedback ensures that the patient understands about the meaning of the signals as well as how to influence them. Appropriate visual cues and training can help the user to instantly adjust the behaviour to positively influence their biosignals. These adjustments can improve physical and mental health [Frank et al. 2010]. The use of wearable technology can help to bring the traditional biofeedback therapy to the home of the user. Normally this therapy would take place in a practice but now can be used on the move.

MacLean et al. [2013] created *MoodWings*, a project which uses biofeedback. The aim of the wearable bracelet was to make drivers aware of their current stress state while they are driving. When the driver was stressed, the butterfly's wings flapped faster. The feedback positively increased their task performance and driving safety. But they found showing feedback on a driver's internal state could make them feel even more stressed. Yu et al. [2014] presented a study looking at use of biofeedback to change the ambient environment. They used ECG sensors and the changes in heart rate to control the ambient lightning in the room. The aim was to help the user relax by actively trying to control their heart rate patterns. This subtle and intuitive interface was perceived more positively than usual Graphical User Interfaces.

5. CHALLENGES AND OPPORTUNITIES FOR FUTURE WORK

In the previous sections, we surveyed the current field of wearable technologies and applications with focus on health and fitness promotion. Different techniques and psychological concepts have been applied and they bring new opportunities and challenges along. In this section, we explain the challenges wearable technology faces at the current time. We also suggest areas of research that would benefit how data is obtained, utilised and represented in future wearable applications.

5.1. Encourage Self-Motivation

Most wearable devices aim to drive behavioural change through persuasion and creating motivation within an individual. We showed that they achieve this by using gamification, incorporating social incentives or persuasive data representation methods. We believe that there are issues with this approach of *machine made* motivation.

Constant motivation through external rewards can lead to the effect that we expect to get rewarded all the time to stay motivated. These external motivators can even spoil otherwise intrinsic and enjoyable task [Greene and Lepper 1974]. Wearable applications currently risk manipulating data beyond recognition, especially games.

In games, the actual sensing data is often not represented in a direct way to the user on the interface but instead it may be manipulated and hidden behind *game points*. In the short term, this can create motivation and a stimulus for the user to move in order to score points. But the behaviours may not be adapted by the users every day life outside of the game. Other studies have shown that the removal of the game elements lead to a decrease in usage of a system [Thom et al. 2012]. A similar effect could influence the long-term effects of gamified wearable applications. Further studies have to investigate long-term motivational consequences of game elements on health behaviour changes.

In section 2.1.4, we presented the Behavioural Change Model by Fogg [2009] which illustrates that a balance of high motivation or high perceived ability to execute a behaviour, in combination with a trigger is needed to facilitate behavioural change. Instead of persuading us to change, wearables should support self-motivation and raise awareness through providing a direct, positive link between changing our behaviour and the health outcomes. Technologies, which show us the consequences of unhealthy behaviour, like the *FatBelt* [Pels et al. 2014], could raise the awareness and our self-motivation to change and avoid unpleasant outcomes. Identifying these unhealthy behaviours and providing contextualised, meaningful alternatives could help to promote a better behaviour through internal triggered motivation.

5.2. Design to support and motivate long-term use

Long-term retention of health and fitness wearable devices is a big issue currently [Ledger and McCaffrey 2014]. The majority of the studies we present in this paper take place over a short time span. Studies conducted over longer time periods are scarce and hard to find. The development of future devices and future research should take this into consideration.

Long-term studies and the comparison of multiple approaches, like gamification and social incentives, could lead to insights on sustainable support for healthier behaviour. There is also evidence, that personal traits have to be taken into account (e.g. [Karanam et al. 2014]). Long term-studies could investigate these issues and help to develop a framework for the design of wearable health promotion applications which are optimised to support different personality types in the long term.

It is important to bring together researchers, designers and engineers with different background and expertise to address technological problems, like accurate sensing and battery life, device design and aesthetics, cognitive supporting visualisations, as well as psychological, behavioural concepts.

5.3. Personal but non-intrusive interfaces for data collection and analysis

Studies show that users want wearable health devices and applications to be personalised to their needs and situation [Ananthanarayan and Siek 2012; Gockley et al. 2006; Macvean and Robertson 2012]. Collecting and utilising data about the user's behaviour, personality and location can give insights in their needs and situation and support personalised and meaningful feedback.

Collecting data about the user's behaviour and health raises issues concerning privacy and practicability. How much data needs to be collected about a user in order to be able to give a reliable representation of the user's lifestyle? This includes and overview of their choices and overall health. Obtaining many different types of data can require a collection of different sensing methods. All of these sensors obtaining data may feel intrusive for the user. We feel there is an opportunity to study the correlation between the amount of data collected about someone and how effective it is at describing their health in general. Current systems require many data sources to built a context around an individuals health. These countless sources can include emails, sleep patterns and location. Some users may find these systems to be intrusive and may not be comfortable with giving all of this information away. These users should still be able to have access to a system that is customisable to their comfort requirements.

A compromise needs to be found between two elements. The first is the amount of data points a system collects to analyse. The second is the user's perception of personalisation. Can a system using minimal data input sources intelligently be just as personal as another with multiple inputs? Devices should not be intrusive, they should blend into the user's environment. Devices need to selectively analyse the minimal amount of data collected efficiently. Future work in this area will lead to integrated intelligent systems. These systems will offer a personal interface, regardless of the amount of data the user wants to provide.

5.4. Understanding not everyone wants and needs the same type of support

Most wearable applications offer motivation or support in one defined way. But the support offered may not be the most effective method for every person that uses the application. This leads to applications being limited to the amount of people that they can support. There is an opportunity to utilise data to find out which methods are most effective in supporting behaviour in each user. This could work well in is establishing the most effective social incentives to use within an application.

For example, one person may be motivated more by competing with their friends but another person may prefer working as a team to achieve goals [Chen and Pu 2014]. Some people may experience the self-monitoring and analysis of their own data as a sufficient tool to gain insight in their health and adjust their behaviour based on that. Other users may need active support from an wearable application through rewards, interventions or similar things. But little research has looked into providing appropriate methods support. A smart and adaptive system can analyse data and learn from the user's behaviour to work out an individuals support preferences.

6. DISCUSSIONS AND CONCLUSION

In this paper, we reviewed the current relationship wearable technology has with human behaviour. We focused specifically on methods of data collection, manipulation and representation in wearable ecosystems. As previous studies have shown, wearable applications and the data have the power to drive positive behaviour change within an individual. By utilising methods such as gamification and social interaction, motivation can be created. This motivation increases the possibility of someone changing their health behaviours for the better. But we have found issues with using wearable sensing data as a behavioural driver. Although studies have shown it to be effective in the short term, there are issues regarding data losing its meaning to the user over time. As a response to this, it has been suggested that data and data representations should act as a facilitator for behaviour change. This can be archived by encouraging reflection and presenting the health data to accommodate cognitive theories and support the natural behavioural change process. Using data as a facilitator is showing positive hope for the development of further health wearables, but we believe that even more research is needed.

Through outlining previous studies, we believe that there are many opportunities for further research. Personalisation is an area in which more research would be beneficial. A system that can adapt to the user and recognise their needs could help to form a long-term relationship between a user and their health data. Data meaningfulness needs to remain high to ensure long-term retention between the user and their device. We suggest ways that this could be done through non-invasive collection and intelligent interpretation of health data in a way to encourage self-motivation. Wearable systems need to offer a number of different data manipulation and presentation methods. The methods would then be chosen to reflect which process the system determined to be the most effective. Ideally, research needs to be conducted that can inform the design process of future wearable technology. Ensuring long-term retention needs to be considered from the very beginning of the development process to create effective systems.

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